Neural dynamics of social behavior

An evolutionary and mechanistic perspective on communication, cooperation, and competition among situated agents

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Steffen Wischmann

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1. Gutachter: Prof. Dr. rer. nat. Frank Pasemann
2. Gutachter: Prof. Dr. rer. nat. Wolfgang Alt

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“*The most exciting phrase to hear in science, the one that heralds new discoveries, is not ‘Eureka!’ (I’ve found it!), but ‘That’s funny…’*”

Isaac Asimov

Summary

Social behavior can be found on almost every level of life, ranging from microorganisms to human societies. However, explaining the evolutionary emergence of cooperation, communication, or competition still challenges modern biology. The most common approaches to this problem are based on game-theoretic models. The problem is that these models often assume fixed and limited rules and actions that individual agents can choose from, which excludes the dynamical nature of the mechanisms that underlie the behavior of living systems. So far, there exists a lack of convincing modeling approaches to investigate the emergence of social behavior from a mechanistic *and* evolutionary perspective.

Instead of studying animals, the methodology employed in this thesis combines several aspects from alternative approaches to study behavior in a rather novel way. Robotic models are considered as individual agents which are controlled by recurrent neural networks representing non-linear dynamical system. The topology and parameters of these networks are evolved following an open-ended evolution approach, that is, individuals are not evaluated on high-level goals or optimized for specific functions. Instead, agents compete for limited resources to enhance their chance of survival. Further, there is no restriction with respect to how individuals interact with their environment or with each other.

As its main objective, this thesis aims at a complementary approach for studying not only the evolution, but also the mechanisms of basic forms of communication. For this purpose it can be shown that a robot does not necessarily have to be as complex as a human, not even as complex as a bacterium. The strength of this approach is that it deals with rather simple, yet *complete* and *situated* systems, facing similar real world problems as animals do, such as sensory noise or dynamically changing environments.

The experimental part of this thesis is substantiated in a five-part examination. First, self-organized aggregation patterns are discussed. Second, the advantages of evolving decentralized control with respect to behavioral robustness and flexibility is demonstrated. Third, it is shown that only minimalistic local acoustic communication is required to coordinate the behavior of large groups. This is followed by investigations of the evolutionary emergence of communication. Finally, it is shown how already evolved communicative behavior changes during further evolution when a population is confronted with competition about limited environmental resources. All presented experiments entail thorough analysis of the dynamical mechanisms that underlie evolved communication systems, which has not been done so far in the context of cooperative behavior. This framework leads to a better understanding of the relation between intrinsic neurodynamics and observable agent-environment interactions.

The results discussed here provide a new perspective on the evolution of cooperation

because they deal with aspects largely neglected in traditional approaches, aspects such as embodiment, situatedness, and the dynamical nature of the mechanisms that underlie behavior. For the first time, it can be demonstrated how noise influences specific signaling strategies and that versatile dynamics of very small-scale neural networks embedded in sensory-motor feedback loops give rise to sophisticated forms of communication such as signal coordination, cooperative intraspecific communication, and, most intriguingly, aggressive interspecific signaling. Further, the results demonstrate the development of counteractive niche construction based on a modification of communication strategies which generates an evolutionary feedback resulting in an active reduction of selection pressure, which has not been shown so far. Thus, the novel findings presented here strongly support the complementary nature of robotic experiments to study the evolution and mechanisms of communication and cooperation.

Parts of this thesis have been published in (Wischmann et al., 2005, 2006; Wischmann and Pasemann, 2006; Wischmann et al., 2007b; Hülse et al., 2004, 2007a).

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"Every decade or so, a grandiose theory comes along, bearing similar aspirations and often brandishing an ominous-sounding C-name. In the 1960 it was cybernetics. In the '70s it was catastrophe theory. Then came chaos theory in the '80s and complexity theory in the '90s.

[...] reductionism may not be powerful enough to solve all the great mysteries we're facing: cancer, consciousness, the origin of life, the resilience of the ecosystem [...] What makes all these unsolved problems so vexing is their decentralized, dynamic character, in which enormous numbers of components keep changing their state from moment to moment, looping back to one another in ways that can't be studied by examining any one part in isolation [...]

Chaos theory revealed that simple nonlinear systems behave in extremely complex ways, and showed us how to understand them with pictures instead of equations. Complexity theory taught us that many simple units interacting according to simple rules could generate unexpected order. But where complexity theory has largely failed is in explaining where the order comes from, in a deep mathematical sense, and in tying theory to real phenomena in a convincing way."

Steven H. Strogatz (2003, p. 285-286)

Chapter 1

Introduction

Social behaviors, such as cooperation, competition, and communication, pervade the animal kingdom. They can be found among higher organisms, from human to insect societies, and even among unicellular individuals. One of the best studied example is the slime mold *Dictyostelium discoideum* (Bonner, 1967; Goldbeter, 1996; Marée and Hogeweg, 2001). It is remarkably representative for how complex global behavior patterns can emerge from local interactions between rather simple individuals. If food supply is sufficient, each amoeba acts by its own, independently from other members of its species. If food sources become rare, the developmental phase toward a multicellular organism begins. It starts with aggregation patterns of many individuals resulting in concentric cycles and spiral structures. Then a transition occurs, $10,000$ to $100,000$ individuals form a motile, slug like, multicellular organism. In the final stage, initially identical cells differentiate into different types of cells. Some individuals form a stalk and others a fruiting body, which contains the spores, on top of that stalk. Eventually, the spores are released and the development of new unicellular amoebas starts again, completing the life cycle.

A considerable amount of research has been done to understand the mechanisms that underlie this fascinating pattern formation process (for an overview see Camazine et al., 2001). Principles were found which are fundamental for explaining collective behavior of natural societies as self-organized processes. Global complex structures emerge from the interactions among lower-level components. There is no global knowledge, each individual can access only *limited local information*, that is, with just a few sensor modalities it can sense changes in its immediate vicinity only. Most important for the aggregation process of *D. discoideum* is the detection of cyclic adenosine monophosphate (cAMP) concentrations within an individual's surrounding. The molecule cAMP is enzymatically synthesized from ATP and used by most organisms for intracellular signal transduction. For *D. discoideum* it additionally serves as a medium for extracellular communication. Each individual reacts to specific spatial and temporal patterns of cAMP by segregating additional cAMP and by moving toward a cAMP gradient in the environment. This positive feedback mechanism gives rise to the fascinating pattern formation process, an excellent example for a further principle of self-organized collective behavior: Each individual obeys a limited set of rather *simple behavioral rules*. The global structure, that emerges from these rules, *accomplishes some function*. That is, it allows a group to solve particular problems which are impossible to handle for a single individual; in our example, maintaining reproductive success of a slime mold population when food supplies become depleted. Such group behavior is *flexible* in a way that it is adaptive to novel environmental conditions. And it is *robust*, that is, the global structure remains stable even when several individuals fail or miss perform.

Natural evolution has developed a vast diversity of similar collective phenomena in animals based on those fundamental principles of biological self-organization (Camazine et al., 2001). For instance, the astonishing behavior of fireflies during mating where thousands upon thousands of individuals flash in synchronized unison (for an overview see Buck, 1988). Fish schools seem to act as a super organism, where millions of individuals move cohesively, while the group can execute rapid and effective responses to predators (Partridge, 1982). Ants and termites are able to collectively build huge nest architectures with highly sophisticated and complex internal structures which serve for storing, and even growing food, breeding, and defending predators (Wilson, 1971; Gordon, 2000). In all those examples the actual individual mechanisms which give rise to the global structure are clearly different, but the system as a whole can in general be characterized by the aforementioned principles of self-organized collective and social behaviors.

Explaining the evolutionary origins and mechanisms of cooperation still persists as a grand challenge for evolutionary biology (Levin, 2006). Influenced by game theory, first proposed by John von Neumann (1928, see also von Neumann and Morgenstern, 1944), John Maynard Smith (1982, see also Maynard Smith and Price, 1973) laid the ground for most modern research in evolutionary biology with respect to the development of social behaviors (e.g., Maynard Smith and Szathmáry, 1995; Axelrod, 1997; Nowak, 2006). Although research in this direction has provided fruitful insights, for instance, into the evolutionary development of cooperation and communication, the used formal models focus on ultimate explanations, that is, on clarifying the evolutionary causes, which include several important aspects such as genetic relatedness (Hamilton, 1964) or the cost of signals (Maynard Smith and Harper, 2003). As a drawback of this formal modeling, individuals are mostly treated as rather abstract and idealized agents, often with a limited set of predefined basic behaviors and interaction rules. Consequently, they are limited in giving proximate explanations, that is, explaining the underlying mechanisms of behavior, may it at a genetic, molecular, or neural level. Only very recently, microorganisms draws the attention of researchers to study the evolution of social behaviors from an *evolutionary and a mechanistic perspective* (e.g., West et al., 2006b; Keller and Surette, 2006), a complementary approach already demanded by Niko Tinbergen (1963) or Ernst Mayr (1961).

Leaving the evolutionary perspective aside for a second and asking questions about possible general mechanisms which determine the behavior of an individual, whether it is a single cellular bacteria, an insect, or even a human, we find a growing field of research which claims that behavior emerges from, mostly non-linear, dynamical processes intrinsic to an individual and from reciprocal dynamical interactions with environmental entities. The vast diversity and intriguing complexity of processes observed in biological organisms poses the problem of generalization. Using the language of dynamical systems theory as a qualitative description of macroscopic changes in complex organizations promises to provide useful analogies between seemingly different systems (for an overview see Tschacher and Dauwalder, 1999, 2003).

Considering dynamical systems to describe behavior is one constituent part of what we want to propose here as a unified methodology for studying the evolution *and* individual mechanisms of social behaviors; a methodology very different from the traditional game-theoretic approaches in evolutionary biology. We will make a great leap from biological organisms to artificial agents, that is, robotic models. The idea of using robots as simplified models to study adaptive behavior goes back to the era of cybernetics, and in particular to the pioneering work of Grey Walter (1953) and Valentino Braitenberg (1984). Nowadays this idea is further pursued in fields as behavior based robotics (e.g., Brooks, 1999), biorobotics (e.g., Webb, 2001), or evolutionary robotics (e.g., Harvey et al., 2005; Nolfi and Floreano, 2000). Research in those fields draw the attention to *situatedness* and *embodiment* (e.g., Pfeifer and Bongard, 2006) as fundamental principles of the mechanisms that underlie behavior, principles already proposed by Maturana and Varela (1980, 1987) to be essential for living beings as well.

Being situated means that intelligent and adaptive behavior emerges from agent-environment interactions, and the nature of these interactions is determined by the embodiment of an agent. In other words, the whole body of an agent with its sensors and actuators, and not only its nervous system, embedded in a dynamic environment is fundamental for its behavior. Situatedness and embodiment are largely neglected in game-theoretic approaches toward understanding the evolution of social behavior.

This thesis "Neural dynamics of collective behavior" follows a combined evolutionary and mechanistic perspective to study cooperation, communication, and competition among situated agents. It aims at the development of distributed and decentralized autonomous artificial systems, in particular, robotic systems controlled by artificial neural networks, which are based on the aforementioned fundamental principles: Self-organized collective behavior of situated agents whose behavior emerges from the dynamical processes intrinsic to their control structures and from dynamic agent-environment interactions. Behavior emerges as an outcome of dynamical systems, and here in particular from the dynamics of recurrent neural network models. *These dynamical systems are parameterized* through the sensors of an agent. They are driven by the sensory experience of an agent which is reciprocally coupled with the environment through the action of that agent and, therefore, changes dynamically.

Such dynamical systems are developed by artificial evolution where the reduction of our preconceptions, which may constrain the behavioral outcome, plays a crucial role. Artificial evolution as a synthetic methodology with minimized bias is used to circumvent the frame-of-reference problem (Clancey, 1989), especially the perspective issue, which is undeniably problematic in mathematical models of animal behavior: Many aspects are unavoidably preconceived which the modeler thinks are important for the artifact of investigation. In this thesis, we artificially evolve behaviors, phenomenological similar to animal behaviors, where the underlying mechanisms matter indeed only to the evolving agents instead to us as an observer. This is not as trivial as it may intuitively seem. We have to abandon the perspective that evolution optimizes particular functions. Natural selection solely acts on the survivability and reproductive success of biological organisms. The challenge is to develop such general selection criteria for artificial systems.

The novelty of the methodological approach presented in this thesis is that it unifies and strictly obeys the following constituent parts:

- *Completeness* always demands complete brain-body-environment systems.
- *Complexity out of local simplicity* follows the principles of biological self-organized collective behavior.
- *Dynamical systems* presuppose that coordinated behavior is a global outcome of local, mostly non-linear, dynamical processes.
- *Reduction of preconceptions* demands minimizing predefined constraints and our assumptions about the evolution of particular behavioral aspects.
- *Comprehensibility* demands that every developed system is analytically feasible at every level of detail.

Especially the last aspect, comprehensibility, is highly important throughout the whole thesis. The common denominator of complex systems is the difficulty to understand them in every detail. In 1999 renowned scientists from different research fields, such as biological signaling, nervous systems, chemistry, physics, and economy, contributed their viewpoint on complex systems to a special issue of the journal *Science* (vol. 284:5411, p. 79-109, 1999). What they all have in common is the absence of a general definition which declares a system as complex or not. For instance, Weng et al. (1999) describe a complex system in a general sense as "a system or component that by design or function or both is difficult to understand and verify."

In general, a complex system is characterized by two main properties: *emergence* and *self-organization*. Emergence points to the appearance of global behavior patterns that can not be anticipated from the knowledge about the system's components alone. In this sense, a car would be also a complex systems, it is not enough to know everything about every single component, it is also necessary to know how those parts interact with each other. However, the second property, self-organization, disqualifies a car as a complex system. A self-organizing systems exhibits a global behavior pattern without any reference to this pattern, that is, it emerges solely from the interactions between the parts of a system, and the rules which specify those interactions are based on local information only and are not given by any external controller or planner (Haken, 2004; Nicolis and Prigogine, 1989; Camazine et al., 2001). That's why an ant colony is a self-organizing system, and a car is not.

Here, we start with simple systems and gradually increase their intricacy while maintaining full comprehensibility. Thus, we approach complex systems bottom-up by systems which successively get more complicated, that is, by sophistication without loosing analytical feasibility. However, this inevitably entails necessary simplifications at all levels. The used robotic models are far away from the complexity of even the simplest biological organisms, as well as the neural network model, the environments robots are acting in, and the evolutionary algorithm. Thus, the work presented here is limited in that it cannot explain details of the actual mechanisms that underlie specific animal behaviors or their evolutionary development. Nevertheless, by following our methodological aspects we are forced to avoid idealization, and we study –at a somewhat abstract level– systems which face similar real-world problems as animals.

Thus, simplification, not idealization, is the important key to our contribution to the understanding of social behaviors.

Understanding demands comprehensibility of the whole system, that is, understanding every single part and how these parts fit together. This thesis with its concrete examples offers an incremental approach of increasing individual and environmental complexity and at the same time we can reduce our preconceptions about social behaviors, and we can demonstrate that the resulting systems exhibit phenomenological similarities to biological systems.

The development and analysis of such systems may help us:

- to understand better the link between control dynamics, individual behavior, and social behaviors,
- to clarify the role of the sensory-motor loop,
- to identify important structural changes during the evolutionary development of communication where cooperative behavior may be based on,
- and to pinpoint in how far coordinated behavior is a reflection of environmental complexity rather than of complexity at the individual level.

Ultimately, the present study aims at achieving truly open-ended and creative evolutionary scenarios (Taylor, 2001; Bianco and Nolfi, 2004) where significantly novel behaviors and behavioral mechanisms can be expected. For that aim two aspects are required. First, individuals are not evaluated on certain higher level goals and are, therefore, not optimized for specific functions. Instead, evolving individuals compete for limited resources to increase their own viability. Second, individuals are not restricted in how they interact with their environment or with each other. And they are not restricted in using specific sensory or motor capabilities in predefined ways.

The thesis discusses the advantages and drawbacks of such a modeling approach toward the evolutionary development of cooperative and collective behavior in artificial societies. Several experiments will approach questions about the evolutionary origins of novelty, the way how local dynamical processes lead to global coordinated behavior among interacting situated agents, and the role of different forms of communication as the basis of cooperative behavior.

The aim of this thesis is *not* to prove that the proposed method constitutes a better approach compared to traditional methods of evolutionary biology. It rather attempts to provide a new and, hopefully, complementary perspective on the evolution of communication and cooperation.

1.1 Original contributions

There already exists a considerable amount of research employing artificial agents to study the emergence of social behaviors (for overviews see Wagner et al., 2003; Cangelosi and Parisi, 2002; Steels, 2003). We will refer to particular related studies when discussing our experiments. However, only a part of related research considers situated and embodied agents, as for instance robotic systems. Even less involves dynamical systems, as for instance recurrent neural networks, to control the behavior of single agents. And to our knowledge, the experiments presented here are the first which entail thorough analysis of the properties of dynamical systems that underlie collective behavior to clarify the relation between intrinsic neurodynamics and observable agent-environment interactions. So far this was only done by a few studies considering the behavior of single agents (e.g., Beer, 2003b; Hülse, 2007).

Thus, here we are able to clarify which behavioral aspects of socially interacting agents can be accounted to *internal neural mechanisms* and which to *sensory-motor interactions* between an agent and entities of its environment. Both are, as we will show, heavily intertwined which supports theories arising from modern embodied cognitive science (for overviews see Clark, 1996; Hendriks-Jansen, 1996; Sharkey and Ziemke, 2000; Riegler, 2002; Pfeifer and Scheier, 1999).

Simplicity of neural control. What we can show is a remarkable simplicity of neural control when interactions with the environment are taken into account. Generally, evolution heavily exploits the dynamics of agent-environment and agent-agent interaction and, therefore, minimizes the complexity at the individual level (here, complexity of neurodynamics). Concrete findings include the emergence of sophisticated spatial aggregation patterns determined by rather simple individual behaviors, cooperation without explicit communication by means of environmental changes induced by single individuals, and the important, otherwise usually neglected, role of sensory noise for specific signaling strategies. A further novel finding is the repeated evolution of synchronization mechanisms to coordinate signaling among many interacting individuals, reducing the interference of too many simultaneously emitted signals.

Multimodality of neurodynamics. Intriguingly, throughout all experiments we repeatedly discover a notable multimodality of very small neural structures. That is, small subnetworks possess rich dynamical properties in form of different attractor domains, which allow versatile behaviors through the sensory-motor coupling of an agent. This could be shown before only in a few cases and only for behavior of single agent (e.g., Beer, 2003b; Hülse, 2007). However, demonstrating this in multi-agent systems has not been achieved so far. Here, especially the example given in Chapter 7 has to be emphasized. A two-neuron subnetwork enables individuals to show several sophisticated communication strategies, such as signal coordination, cooperative intraspecific communication, and, most intriguingly, aggressive interspecific signaling. It can be shown that the reciprocal coupling of an agent with its environment via its sensory-motor system realizes transitions between these different sub-behaviors through switching between different domains of periodic and quasi-periodic attractors within the neural system.

The role of evolutionary diversity. Only a very few related studies show open-ended evolution characteristics (e.g., Bianco and Nolfi, 2004). Especially the experiments presented in Chapter 6 demonstrate that evolution with minimized preconceptions results in a diversity of solutions to the same problem. By thoroughly analyzing representative solutions with respect to their neural mechanisms, we discover fundamentally different principles.

To our knowledge, for the first time we can show that some solutions show an intrinsic robustness to specific environmental changes, which did not occur during the evolutionary development. By knowing the exact mechanisms, we are even able to explain the mechanistic reasons for this robustness. Interestingly, communication strategies which rely on rather indirect mechanisms outperform other solutions when confronted with novel environmental conditions. *Indirect communication* is characterized by individuals who communicate through their actions within a shared environment, which are not identifiable as communication as such because they mainly serve other behavioral purposes. In contrast, *direct communication* occurs when only dedicated channels, that is, sensors and motors explicitly designed for communication, are used. Both forms are investigated and their influence on the robustness and flexibility of a group is tested with the result that, in general, indirect forms of communication significantly increase flexibility and robustness, thus, the adaptability of interacting agents.

Counteractive niche construction. By investigating how communication strategies and neural systems do evolutionary change when a population is confronted with competition for the same limited resources, the results presented in Chapter 7 are, to our knowledge, the first in the literature which demonstrate counteractive niche construction (Odling-Smee et al., 2003) based on an evolutionary change of communication. Individuals evolved in form of punctuated equilibrium (Eldredge and Gould, 1972) where long periods of stasis were followed by rather short periods of sudden changes. We observed two major behavioral transitions. First, evolving individuals discovered, as expected, a new environmental niche. Surprisingly, evolving individuals then changed their behavior in a second transition by displaying aggressive signaling against competitors and, consequently, excluding them from their original niche. Thus, evolving individuals created an evolutionary feedback where they actively changed their selection pressure through a behavioral change.

1.2 Thesis outline and related publications

Chapter 2 introduces the historical background of the different methodological aspects employed in this thesis. We briefly review the fields of cybernetics, biorobotics, behavior based robotics, embodied cognitive science, dynamical systems theory, and evolutionary robotics, and relate them to our study. This is followed by five chapters discussing concrete examples of evolved collective behaviors in multi-robotic systems.

The work described in Chapter 3 investigates the evolution and mechanisms of cooperation without dedicated communication channels, that is, the emergence of indirect communication. We also show the difference between centralized and decentralized control approaches. Partial results of this chapter are published in (Wischmann et al., 2005; Hülse et al., 2004).

The unpublished results of Chapter 4 demonstrate how complicated spatial aggregation patterns emerge from simple local behavioral rules, such as repulsion and attraction. It also shows how these rules are implemented in surprisingly small neural structures. The basic neural control elements were inspired by results which are published in (Hülse et al., 2004, 2005).

The work presented in Chapter 5 originated from strong collaborative efforts with Martin Hülse, who, inspired by the work of Arthur Winfree, proposed to develop experiments which involve internal neural rhythms distributed among many individuals. In Chapter 5 we show how such individual neural rhythms become locally synchronized among interacting individuals through simple acoustic signals giving rise to coordinated and functional group behavior. The implemented mechanism is highly robust and scalable with respect to the spatial range of interactions and the number of interacting agents. Most of the work in Chapter 5 is published in (Wischmann et al., 2006; Hülse et al., 2007a) and the ideas of internal rhythms were further pursued by Martin Hülse and are published in (Hülse et al., 2007b).

The experiments discussed in Chapter 6 realize open-ended evolution characteristics and concern the emergence of communication from an unconstrained evolutionary process. Interestingly, similar signal coordination mechanisms evolved as we purposefully set up in the experiments of Chapter 5, but this time signal synchronization evolved without biasing it. Furthermore, we show how open-ended evolution gives rise to significantly different solutions to the same problem. It is the first time that sensory noise is identified to be highly relevant for communication. We also discuss the relevance of indirect and direct communication mechanisms with respect to robustness to novel environmental conditions. Most of this work is published in (Wischmann and Pasemann, 2006, 2007; Wischmann et al., 2007b).

The work described in Chapter 7 naturally follows from the experiments discussed in Chapter 6 by introducing competition between two populations for the same limited food sources. To investigate how communication changes under competition, one of the populations was allowed to evolve. For the first time we show counteractive niche construction by the development of aggressive communication strategies. The evolving population does not only adapt its communication to exploit a new environmental niche, but it also actively changes its selection pressure through aggressive signaling against a competing population. Part of this work is published in (Wischmann et al., 2007a,b). Based on the ideas of open-ended evolution presented in Chapter 6 and 7, first experimental results with an asynchronous and distributed evolutionary algorithm are published in (Wischmann et al., 2007c).

Chapter 8 reviews the main contributions of this thesis and concludes with a discussion about their biological relevance for our understanding of the evolution of cooperation and communication.

Chapter 2

A unified approach to study cooperative behavior

In the following we are going to motivate our research from biological studies of cooperation and communication, and give arguments for the unified methodology employed here to investigate the evolution and the mechanisms of cooperation and communication in artificial societies.

2.1 Behavior of interest: Cooperation and communication

Cooperation as one aspect of social behavior can be found at almost every level of complexity within biological organisms. The extraordinary introductory example of the slime mold (see p. 19) showed that cooperation among unicellular organisms can significantly increase their survival success. Indeed, social behavior is a widespread phenomena among microorganisms (for reviews see Keller and Surette, 2006; Wingreen and Levin, 2006; West et al., 2006b) and it is even proposed to be at work among cancer cells (Axelrod et al., 2006). Cooperation is also considered as one possible driving force toward the evolutionary transition from unicellular to multicellular organism (Pfeiffer and Bonhoeffer, 2003).

The most studied species which exhibit cooperation are social insects. Here we cannot give a comprehensive overview of this large field of research. We therefore refer the interested reader to the textbooks of Wilson (1971, 1975), Gordon (2000), and Camazine et al. (2001). Among the many fascinating behaviors of social insects, probably one of the most intriguing principles first discovered in ants, is the concept of *stigmergy* (Grassè, 1959; Theraulaz and Bonabeau, 1999). Stigmergic behavior refers to indirect communication mechanisms in self-organizing emergent systems. Individuals communicate not directly with each other, as it is the case, for instance, in honey bees (von Frisch, 1967) or food and alarm calls among vertebrates (Maynard Smith and Harper, 2003), instead they communicate indirectly via local modifications of their environment. An example is the pheromone trail laying of ants or termites. With these mechanisms ants and termites do not only forage efficiently, they are also able to build highly complex nest structures composed of pillars, arches, and a sophisticated network of tunnels and chambers.

However, cooperation does not only occur among members of one species. Endosymbiotic relationships (Wernegreen, 2004), the mutual benefits between plants and pollinators (Cook and Rasplus, 2003), fungus farming ants (Aanen and Boomsma, 2006), or the highly complex social interactions among fish species (Bshary et al., 2002) are just a few examples of interspecific cooperation.

Explaining the evolution of cooperation (Hamilton, 1964) and competition (Gause, 1934) is still a great challenge for evolutionary biology (Trivers, 1985; Wilson, 1975). A lot of research has already been done to explain it in terms of fitness benefits for socially interacting individuals (for overviews see Sachs et al., 2004; Lehmann and Keller, 2006; West et al., 2007). Analytical models and agent-based simulations in the realm of game theory are the most common tools to approach this challenge, and they successfully predicted necessary preconditions and different strategies for the evolution of cooperation (see, for instance, Nowak, 2006; Axelrod, 1997). However, one drawback of game-theoretic approaches is that they often assume fixed and limited rules and actions that agents can choose from. Here, we propose a combined evolutionary simulation modeling approach (Belew and Mitchell, 1996; Burtsev and Turchin, 2006) based on robotic systems (Harvey et al., 2005; Nolfi and Floreano, 2000) controlled by recurrent neural networks with complex dynamics (Pasemann, 2002) to investigate how small robotic societies develop cooperative behavior based on implicit and explicit communication, and how they adapt their behavior under varying environmental conditions such as interspecific competition. Apart from the evolutionary perspective, we are especially interested in the dynamical processes required at the individual control level to exhibit cooperative behavior and communication among situated agents.

2.1.1 Definitions

Social behavior can be categorized as shown in Table 2.1. Does the behavior of the focal individual, the actor, benefits only itself and has negative effects on another individual, the recipient, it is called selfish (Hamilton, 1970). If it is only beneficial to the recipient, it is referred to as altruism (for an overview see West et al., 2006a). Spiteful behavior has negative effects on both, the actor and the recipient (for an overview see Gardner and West, 2006). The behavior is mutually beneficial if it has positive effects on both (Connor, 1995).

Cooperation is then defined as a behavior which must be beneficial for the recipient (if exclusively, than it is altruism), but it could also be beneficial for the actor (i.e.,

Table 2.1: Categories of social behavior depending on positive (+) and negative (−) fitness consequences for the actor and recipient (Hamilton, 1964, 1970; Sachs et al., 2004; West et al., 2007). Cooperation includes mutual beneficial and altruistic behavior.

	mutual benefit	altruism	selfishness	spite
effect on actor	+	−	+	−
effect on recipient	+	+	−	−

mutually beneficial). However, West et al. (2007) emphasize that this definition of cooperative behavior might be too general. They give the vivid example of an elephant producing dung which is beneficial for a dung beetle. It is obviously not useful to declare behaviors like this cooperative. To narrow the definition, behavior is seen as cooperative if it is selected for because of its beneficial effects (Connor, 1995; Sachs et al., 2004). What we will focus on in this thesis is the evolution of *mutually beneficial cooperative behaviors*.

A further distinction of social behavior based on selection forces in the context of communication is made by Maynard Smith and Harper (2003), they distinguish *signals* from *cues*. A signal is defined as "any act or structure which alters the behavior of other organisms, which evolved for this effect, and which is effective because the receiver's response has also evolved". A cue is "a feature of the world, animate or inanimate, that can be used by an animal as a guide to future action". From this perspective also the stigmergic behavior of ants relies on signals (i.e., pheromones) even though they communicate rather indirectly by modifying their environment, whereas the smell of the elephant's dung is a cue for the dung beetle. Therefore, the elephant-beetle relationship cannot be classified as social behavior.

Important for this thesis is the definition of cooperation as behavior that evolved for its beneficial effects. This includes signals, which convey information either directly or indirectly.

2.1.2 Mechanistic and evolutionary approaches

In their review about social evolution theory for microorganisms, West et al. point to the complementary nature of research in microbiology and evolutionary biology:

> "Evolutionary biologists and microbiologists typically study behaviours or traits from different perspectives. Evolutionary biologists are primarily concerned with the fitness consequences or survival value of a behaviour, which are called ultimate explanations: why has this behaviour been selected for by natural selection? Microbiologists are primarily concerned with proximate explanations: what molecular and genetic mechanisms govern the particular trait or behaviour? The crucial point here is that these methods are complementary and not alternatives."
>
> *West et al. (2006b, p. 599)*

Later, the authors emphasize the need for a complementary approach by referring to a highly influential paper of Tinbergen (1963). Tinbergen discussed the synergistic benefits of studying behavior from different perspectives with the example of black-headed gulls that remove eggshells from their nest. From a mechanistic, i.e. proximate, perspective this behavior can be explained by the fact that individuals react with an instinctive behavior of removing light weighted white colored objects which have frilly edges. From an evolutionary, i.e. ultimate, perspective this behavior is reasonable because it prevents aerial predators from easily finding the gull's brood. Both explanations are complementary and show what Dobzhansky (1973) phrased as "nothing in biology makes sense except in the light of evolution". The strong interrelation between proximate and ultimate explanations was also discussed by Mayr (1961).

In the context of cooperation and communication this kind of complementary research started to grow only very recently. To our knowledge the most promising efforts are currently spent at the level of microorganisms (West et al., 2006b; Keller and Surette, 2006; Wingreen and Levin, 2006). There are two reasons: First, a lot of microbiological research already revealed in detail the physiological processes of intracellular as well as extra-cellular signaling (see, for instance, Waters and Bassler, 2005); second, microorganisms offer exceptional opportunities to test evolutionary hypothesis because of their generation span and the ease of experimenting under controlled laboratory conditions. For instance, very recently researchers in the field of biophysics started to develop silicon chips as microhabitat patches for bacteria populations as *E. coli* (Keymer et al., 2006). Such an amazing new technology may offer experimental setups, inspired by the theoretical findings of evolutionary biology, to study evolutionary dynamics while, for instance, fitness landscapes may be arbitrarily changed by the experimentalists. Thus, it may become possible to test evolutionary models and hypothesis *in vivo* where everything is indeed more complex than *in vitro*, yet especially this complexity entails what we are most interested in.

However, despite of the tremendous progress which has been achieved so far in understanding the molecular mechanisms of bacterial signaling, describing the *complete* mechanisms of even a single cell, whose physiological responses to internal or external signals are governed by complex dynamical networks of interacting genes and proteins, is still a major challenge (see Tyson et al., 2003; Andrews and Arkin, 2006; Tyson, 2007, and references therein).

Organs are composed of myriads of interacting cells, individuals of interacting organs, societies of interacting individuals, and ecosystem of interacting species. Thus, an exact proximate explanation of cooperation or communication is unfeasible.

Here, a ‘slightly’ different approach is taken to investigate cooperation and communication from various perspectives, we use artificial societies composed of robots. The experiments presented in this thesis are full of abstractions and simplifications concerning biological behavior and evolution. However, we try to unify several different perspectives into one methodological approach under the premise to reduce the mechanistic complexity of cooperative behavior to a level at which it is still analytically feasible in every detail. The perspectives we want to bring together are:

- **The cybernetic perspective.** We will use robots as complete physical models to study basic animal-like behaviors, persistently taking into account the important role of sensory-motor feedback loops for individual behavior.
- **The dynamical systems perspective.** We stress that behavior in general arises from mostly non-linear dynamical processes at the individual control level as well as at the interaction level between an individual and its environment and other individuals.
- **The evolutionary perspective.** Non-trivial behavior, such as cooperation, communication, or competition, can emerge from an open-ended evolutionary process where individuals are evolved, but not for achieving high-level goals.

In particular, the proceeding chapters are dedicated to the following questions:

- How can cooperation evolve in agents which lack the ability to communicate explicitly? (Chapter 3)
- What are the minimal requirements to achieve basic coherent collective behavior? (Chapter 4)
- How can we coordinate functional behavior among many agents relying on simple local communication? (Chapter 5)
- Which forms of communication emerge in an unconstrained evolutionary process? (Chapter 6)
- How does communication in a species change when confronted with niche competition? (Chapter 7)

In the remainder of this chapter we will give a historical and technical introduction of the different methodological aspects relevant for this thesis and arguments why this complementary approach is reasonable to study adaptive behavior in the context of cooperation and communication.

2.2 What robots can tell us

2.2.1 Biologically inspired robotics

Biologically inspired robotics, also called *biorobotics*, becomes an ever growing research discipline. It is motivated by the assumption that animals and robots have in common general properties of adaptive behavior. Both have a sensory-motor and an autonomous control system to carry out various behaviors and tasks in complex and dynamic environments, which is the reason why robots are suggested as simulators or physical models of animals to address specific biological questions (Webb, 2001; Beer et al., 1998; Ijspeert et al., 2007). Therefore, biorobotic research promises to understand "natural systems by building a robot that mimics some aspects of their sensory and nervous system and their behavior" (Lambrinos et al., 1997).

Although we can not give an comprehensive overview on this topic (for reviews see Dean, 1998; Meyer, 1997; Beer et al., 1998; Bekey, 1996; Webb, 2001), at least we want to mention one highly successful study recently published by Franceschini et al. (2007) to illustrate the potential of this approach. They built a micro-helicopter navigating with a minimal optic-flow sensor that is similar to insects. This machine is controlled by a visual feedback loop as hypothesized from biological studies of insect flight. The experiments helped to understand previously unexplained findings of visual guided performances in insects, such as how honeybees land with a constant slope, descend in a headwind, or drown while flying over water. Other examples of robots serving as physical models of particular behavioral aspects include investigations of the chemotaxis of nematodes (Morse et al., 1998) or the phonotactic behavior of crickets (Reeve and Webb, 2003).

As for any kind of modeling, biorobotics has the problem of underdetermination: "the performance of similar behavior is never sufficient to prove the similarity of mechanisms [which leads to] inevitable difficulties in drawing strong conclusions about biological systems from the results of robot models" (Webb, 2001). Thus, the biorobotics approach is still highly debated (see commentaries on Barbara Webb's (2001) target article in Behavioral and Brain Sciences, vol. 24(6):1050-1087). However, since robots and animals often have to solve similar problems, for instance walking or flight navigation, biorobotic experiments already demonstrated that surprisingly simple control mechanisms can suffice (see for instance Collins et al., 2005; Franceschini et al., 2007). Obviously, robots are much simpler in their organization and structure than biological systems. However, because biorobotics takes an abstract rather than an analytical approach, it enables us to discover simpler solutions to problems in biology which is suggested to be a key advantage (Meyer, 1997). By simple we mean less complex than biological solutions and, therefore, easier to grasp and easier to understand. Thus, a major principle in biorobotics is simplification, i.e. abstraction, instead of idealization, which is claimed to distinguish it from pure simulations because abstraction...

> "[...] usually occurs by leaving out details, by substitution, or by simplifying the representation, rather than by idealising the objects or functions to be performed. Thus, even two-wheeled motor control has to cope with friction, bumps, gravity, and so on; whereas a six-legged computer simulation may restrict itself to representing only the kinematic problems of limb control and ignore the dynamics entirely. Different aspects of the systems are often abstracted to different degrees in biorobotics. Thus, models involving quite complex sensors often use very simple two-wheeled motor control rather than equally complex actuators."
>
> *Webb (2001, p. 1047)*

As much as it is an important methodological principle in this thesis, another important principle of biorobotics is the focus on *complete* systems:

> "Biorobotics researchers are generally more concerned with building a complete, but possibly rough or inaccurate model, than with strict accuracy per se. That is, the aim is to build a complete system that connects action and sensing to achieve a task in an environment, even if this limits the individual accuracy of particular parts of the model because of necessary substitutions, interpolations, and so on. [...] and we can learn more from several somewhat inaccurate models than from one incomplete one."
>
> *Webb (2001, p. 1048)*

Besides modeling particular aspects of animal behavior to improve our understanding of them, robots attracted also the interest of researchers from an evolutionary perspective, which promises to generate behaviors a priori unknown or at least unexpected. This led to the field of *evolutionary robotics.* Before we review work of this still young research discipline, we want to go sixty years back in time to the era of cybernetics because it is the origin of many principles currently ascribed to the study of behavior by using robotic systems.

2.2.2 Back to the roots: Cybernetics

The importance of models, as it is debated in the biorobotics approach, was already under discussion much earlier, for instance in the 1940s: "The best model of a cat is another or, preferably, the same cat." This popular quote is ascribed to Norbert Wiener who also coined the name *cybernetics* derived from Greek *kybernetes*, meaning steersman or governor. Wiener used this term to describe the study of teleological mechanisms not only of machines but also of animals (Wiener, 1948). The key to cybernetic research is the introduction of feedback loops, especially the emphasis on a tight coupling between sensing and acting was rather controversial to the standard view at that time, and even today it has not gained the required acceptance in every research field.

Apart from the work of Wiener (1948), Ashby (1952, 1956), and von Foerster (2002) probably the two most influential papers at the beginning of the cybernetics era were written by Rosenblueth et al. (1943) and McCulloch and Pitts (1943).

The work of McCulloch and Pitts (1943) provided the ground for most of artificial neural network models which exist nowadays. They reduced the characteristics of single neurons to an all-or-none response depending on stimuli provided by incoming synapses. In their highly simplified model, neurons are realized as threshold logic units, that is, their output is either zero or one depending on an excitation threshold. McCulloch and Pitts showed that any logical proposition can be encoded by an appropriate network, with or without circles, of their simplified neurons, and that different networks can have equivalent functions:

> "It is shown that many particular choices among possible neurophysiological assumptions are equivalent, in the sense that for every net behavior under one assumption, there exists another net which behaves under the other and gives the same results, although perhaps not in the same time."
>
> *McCulloch and Pitts (1943, p. 99)*

McCulloch and Pitts raised an interesting point, that different networks can exhibit similar behaviors. Recent findings in neurobiology affirm this phenomena. Even within the same population of a species, one can find different neural networks in different individuals leading to similar behaviors, and even at the level of single neurons it could be shown that spatially close neurons within the same cortical areas show similar behaviors with significantly different ion channel dynamics (for an excellent review on this topic see Marder and Goaillard, 2006). Throughout the experimental part of this thesis we encounter not only that different neural networks exhibit similar dynamics but also that completely different neural dynamics give rise to similar behaviors of our robotic agents.

On a more philosophical side, Rosenblueth et al. (1943) introduced teleology as purposeful behavior controlled by feedback. There, purposeful behavior especially presupposes the requirement of negative feedback, that is, (sensor) signals from a specific goal are used by a system to restrict its outputs not to go beyond that goal. Rosenblueth et al. emphasized one major aspect of cybernetic research: the focus on the effects of inputs on outputs in the sense that the output is desired or predictable by taking into account the concepts of feedbacks and transformations. Thus, they take a strong behavioristic perspective:

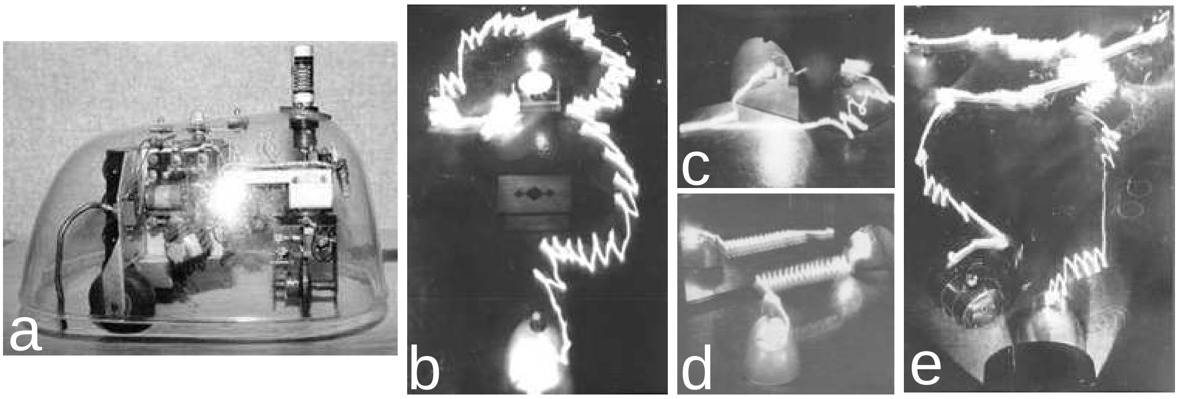

Figure 2.1: **Grey Walter's turtles.** A: One restored original turtle (© University of the West of England, Bristol) B-E: Original photographs of the turtles' behavior (© Burden Neurological Institute). A candle was fixed on top of a robot and long exposures were used. Thus, the light streak shows the path of the turtles. B: Elsie avoids an obstacle and seeks a light. C: Elsie moves into a hutch, that is, a recharging station. D: Elsie performs a mirror dance. E: Elmer and Elsie are interacting and dance with each other, but both loose interest when the light in the hutch switches on (since Elsie always worked better than Elmer, she takes the first place).

> "[. . .] what is meant by the behavioristic method of study omits the specific structure and the intrinsic organization of the object. This omission is fundamental because on it is based the distinction between the behavioristic and the alternative functional method of study. In a functional analysis, as opposed to a behavioristic approach, the main goal is the intrinsic organization of the entity studied, its structure and its properties; the relations between the object and the surroundings are relatively incidental."
>
> *Rosenblueth et al. (1943, p. 18)*

The omission of detailed structural mechanisms leads to a black-box perspective focusing on the behavior of a system rather than on its detailed structural properties. That is exactly what we find in the neuron model of McCulloch and Pitts (1943) which omits the exact biophysical mapping of biological neurons. Thus, we might characterize cybernetics as the study of behavior where the *what* matters most and where the exact *how* is rather irrelevant.

Interestingly enough, we find many of the concepts developed during cybernetics in modern research as we have already seen for biorobotics, and as we will see also for cognitive science and artificial life. Before we come to that, we want to exemplify the prevailing nature of cybernetics by the work of Grey Walter and Valentino Braitenberg.

Grey Walter's turtles and Braitenberg's vehicles

Using robots to understand animal behavior is actually not a modern trend. In fact, the neurophysiologist Grey Walter conducted pioneering work in this field already about sixty years ago, and we will see later that his experiments are very similar to the questions we are dealing with in robotics nowadays.

Grey Walter, well known for his work on the electroencephalogram, built rather simple machines (Figure 2.1a). He called them tortoises, which already exhibited conceivably sophisticated behaviors (Walter, 1950, 1951, 1953; Holland, 1997). The actuators of these machines consisted of three wheels, two for propulsion and one for steering, controlled by independent motors. The sensors were a light and a contact sensor. Energy was supplied by a telephone battery which made the machines truly autonomous in the sense that they behaved without human intervention and connections to external devices.

The control system was realized by an analog circuit with two vacuum tubes, which controlled the motors of the wheels and sensed the direction of sensor stimuli such as the physical contact with other objects or the direction and intensity of a light source. With this equipment the robots could actually perform only two behaviors: retreat when hitting an object and move toward a light source. However, such a robot could already integrate two conflicting behaviors such as obstacle avoidance and light seeking (Figure 2.1b) and even reach a charging station marked by a light source (Figure 2.1c) and, thus, autonomously maintain its energy, which is still a great challenge for modern robotic applications.

It became even more interesting when a head light was attached on top of a robot which turned on when a robot was in the "exploratory mode" and turned off when the light sensor detected a moderate light intensity. The robot could not sense its own light directly, but indirectly. For instance, confronting the robot with a mirror resulted in zigzag movements of the robot in front of its own image (Figure 2.1d). From a pure observational perspective, we might tend to describe this behavior as 'narcissism'.

Even more interesting behaviors emerged when two robots, Grey Walter called them Elsie and Elmer, were placed together in the same environment. In the absence of other light sources, the two robots approached each other and displayed "dancing patterns", they even lost interest in each other when an external light switched on which seemed to be more attractive than the other robot (Figure 2.1e).

All these different behaviors resulted from a very simple control circuit. What changed was the environment and, therefore, the sensory stimuli, which was also actively modified by the action of a robot, thus, closing the loop between the environment and the robot.

What is most intriguing when observing the experiments of Grey Walter is how we would describe the behavior of these robots without having any knowledge about their control system's design. It is intriguing because in biological system we are confronted with exactly the same problem: Observing behavior without knowing the exact underlying mechanisms. Thus, these experiments, as simple as they are, challenge our perspective on behavior. Just by observation, would we call the behavior of these creatures social? Is the creature hungry because it seeks a recharging station? Is it self-aware because it changes its behavior in front of a mirror? Indeed, we would not ascribe these attributes to the turtles of Grey Walter because we know that their behavior is easily explainable by the wires, lights, and bodies they consist of. However, these questions are fundamental, because they emphasize the frame of reference problem: What we might interpret as a complex behavior is actually based on very simple mechanisms. What we might describe as hunger is a simple phototactic response to the light in the charging station.

The main conclusion from these experiments is that complicated behavior patterns do not necessarily have to be caused by complicated nervous systems and that the interaction with the environment plays a fundamental role. Thus, Grey Walter offered us a new way of thinking about problems, in particular about the realization of seemingly complex behaviors. This is well reflected in the following quote of Herbert A. Simon, a pioneer in the field of artificial intelligence (see also Simon, 1969):

> "The way in which problems are represented has much to do with the quality of the solutions that are found. [...] The representation or 'framing' of problems is even less well understood than agenda setting. Today's expert systems make use of problem representations that already exist. But major advances in human knowledge frequently derive from new ways of thinking about problems."
>
> *Simon et al. (1986)*

Because of his 'naive' approach to build an autonomous robot without thinking too much about how to implement specific behavioral aspects, but rather to observe what is going to happen, Grey Walter with his simple machines discovered the emergence of fascinating behavior patterns under different environmental conditions. And these behaviors were based on very simple control systems. This brought to light the importance of sensory motor feedback generated through agent-environment interactions as a key to understand behavior.

Almost forty years later Valentino Braitenberg described which sophisticated behaviors can emerge from simple rules. After experimenting on real brains to find out how the mind is represented in our heads and at the same time reflecting on cybernetics, he wrote a wonderful book about what is nowadays known as Braitenberg-Vehicles (Braitenberg, 1984). He conducted thought experiments with machines, which, similar to Grey Walter's turtles, consisted of simple sensors, motors, and wires between them.

The first vehicle possessed only one sensor connected by one wire to one motor and could, however, already follow a gradient of heat. Taking this machine as a basis, Braitenberg equipped proceeding vehicles incrementally with more sensors and more motors. The wires between them became crossed, and some of them were made inhibitory. By connecting two sensors with two motors via two wires in different ways (crossed, uncrossed, inhibitory, excitatory), these still simple vehicles showed behaviors which could be interpreted as fear, aggression, love, and affection with an wandering eye. Later on vehicles were additionally controlled by simple neural networks of connected threshold units (McCulloch-Pitts neurons as described above), and the virtual engineer who built the machines on his lab table followed simple evolutionary concepts. He copied vehicles and incidentally made small mistakes in their wiring circuit. The ones who still managed to stay on the table 'survived' while others fell down and 'died'. Incrementally the internal wiring became more complicated and the sensors and motors more sophisticated leading to vehicles which behaved as they would possess sequential reasoning, free will, foresight, or egoism:

> "They move through their world with consistent determination, always clearly after something that very often we cannot guess at the outset - something that may not even be there when the vehicle reaches the place

> it wants to get to. But it seems to be a good strategy, this running after a dream. Most of the time the chain of optimistic predictions that seems to guide the vehicles's behaviour proves to be correct, and Vehicle 14 achieves goals that Vehicle 13 and its predecessors 'couldn't even dream of.' The point is that while the vehicle goes through its optimistic predictions, the succession of internal states implies movements and actions of the vehicle itself. While dreaming and sleepwalking, the vehicle transforms the world (and its own position in the world) in such a way that ultimately the state of the world is a more favorable one."
>
> *Braitenberg (1984, p. 83)*

The major conclusion which can be drawn from the thought experiments of Braitenberg[1] is that if we do not know how the vehicles are wired and if we can analyze them only by observing their behaviors, we might tend to describe their behaviors in psychological terms as used in the previous paragraph. However, viewed from the inside, the behaviors are caused by relatively simple networks. This brings us back to the frame of reference problem we get by solely observing behaviors. It leaves us often enough with the tendency to overestimate the complexity of the systems we observe (Braitenberg, 1984).

2.2.3 The frame of reference problem

The frame of reference problem is probably the most fundamental problem for the study of adaptive intelligent behavior; for both, research of artificial and animal behavior. It concerns the relation between the observer, the designer or modeler, the artifact, the environment, and the observed agent. Simon (1969) explained this problem vividly with his example of an ant wandering on a beach. The trajectory of an ant from a starting point to its nest looks, from an observer perspective, rather complicated and one might wonder how the ant's brain calculate the path around puddles, pebbles, and rocks. However, from the perspective of the ant the environment looks completely different, there are no rocks, pebbles, or puddles. All the ant can sense are obstacles which it tries to avoid by simple mechanisms similar to Braitenberg's simplest vehicles. Whenever the ant detects an obstacle to its right the ant turns left and vice versa. Because the environment is full of obstacles, the developing trajectory seems to be rather complicated. That is, the environmental complexity is a perquisite for the ant's complex behavior, which also heavily depends on the ant's embodiment. If the ant would be one thousand times larger in size, pebbles and puddles would be no obstacles any more, and the path of the ant would look rather straight, seemingly much simpler, even though the behavioral mechanisms and the brain of the ant are unchanged.

Clancey (1989) summarized the main aspects of the frame of reference problem as follows:

- **Observer versus agent perspective**: Descriptions of the behavior from an observer's perspective must not be taken as the internal mechanisms that underlie the behavior of an agent.

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[1] Note, that his experiments originated from, or at least were inspired by, neurophysiological findings (see Braitenberg, 1984, p. 95-144)

- **Behavior versus mechanism**: Behavior always results from system-environment interactions and is not explainable by internal mechanisms only.
- **Complexity**: The observable complexity of a particular behavior does not necessarily reflect the complexity of the underlying mechanisms.

The way how Grey Walter and Valentino Braitenberg designed their experiments clearly demonstrated those three issues. As we might now agree, robots as physical models might help us to overcome that problem, at least to a certain extent. Of course, we have to be careful. For instance, in the biorobotics approach we have to take care to put not too much of our assumptions about the mechanisms of the behavior of interest in the control system of the robot. This is an inevitable consequence of starting with behavioral analysis from the outside, from the external observer point of view; a warning also articulated by Delcomyn (2001) as a commentary to the article of Webb (2001):

> "A significant difficulty with most other forms of modeling, be they paper and pencil circuit diagrams or computer simulations of biological processes, is that they require the modeler to make many assumptions about factors that may influence the performance of the model but that are not directly a part of it."

In this thesis we will use evolutionary techniques to develop control architectures for robots with as few preconceptions as possible. Before we elaborate on this possible way to at least minimize our assumptions about adaptive behavior, we want to discuss briefly the revival of the cybernetic ideas in modern trends of robotic research and cognitive science.

2.2.4 Behavior based robotics and embodied cognitive science

Considering behavior as the essential key for building intelligent robots revived with great attention almost forty years after the first experiments of Grey Walter in a field now known as *embodied cognitive science* or *behavior based robotics* (Brooks, 1999; Arkin, 1998; Pfeifer and Scheier, 1999). Behavior based approaches mean "non-information-processing-based" in contrast to classical "knowledge-based" approaches of Artificial Intelligence (for an overview of these two fields see, for instance, Pfeifer and Scheier, 1999). A pioneer of this approach was Rodney Brooks with his subsumption architecture (Brooks, 1986), which probably is the most important approach in this field and, therefore, will be discussed in more detail[2].

The subsumption architecture shares with the cybernetic approach that it is designed on purpose, that is, certain control aspects are implemented with the expectation to fulfill a specific type of behavior. As much as the cybernetic approach, it relies on simple control elements and sensory-motor feedback loops as an integral part of intelligent behavior. The aim is to integrate particular sub-behaviors in one architecture

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[2] Opposed to the competitive method (only one sub-behavior affects the motor action) of Brook's subsumption architecture, Arkin (1998) proposed a cooperative method based on behavioral fusion via vector summation, that is, different sub-behaviors contribute to a motor action with different strength.

without centralized control. To do so, one would start with building the lowest layer, that is, to construct very few connections between sensors and motors (very much like the ideas of Braitenberg's vehicles) which realize, for instance, obstacle avoidance behavior. On top of the lowest layer you then start building layers for "higher" behaviors, for instance pushing a chair, or reaching a target. Different layers, or modules, are built independently of each other, that is, each module is directly coupled to sensors and motors. Constructed in this way, modules can serve as basic building blocks because each module realizes a specific sub-behavior which can be executed independently of other modules. However, to achieve a global coherent behavior, modules are eventually linked to each other, that is, modules can either suppress the input or inhibit the output of another module. For instance, the chair pushing behavior must inhibited the obstacle avoidance behavior. The direction of these links is usually from higher layers to lower layers. That is why we might say high-level layers subsume low-level layers. In Brooks' original subsumption architecture (1986), each layer resembles a finite state machine, that is, a computation device that changes its state depending on an input and its current state. States are finite in number and change according to predefined rules. However, using finite state machines is not essential to the idea of subsumption architectures as Brooks demonstrated later within the Cog project which focused on a humanoid robot controlled by layers of neural networks (Brooks and Stein, 1993).

In contrast to the functional decomposition of classical Artificial Intelligence approaches (for an overview see Pfeifer and Scheier, 1999), behavior based robotics switches the focus away from a central integration of information processing (the sense-think-act cycle) to sensory-motor couplings. Thus, it focuses not on brain-like centralized architectures but on the interaction with the environment, a principle with which we are already familiar from our discussion about cybernetics.

Brooks emphasized that intelligent behavior does not necessarily require reasoning (1991a) or symbolic representations of the world, at least at the level of insect like intelligence (1991b): "When we examine very simple level intelligence we find that explicit representations and models of the world simply get in the way. [...] The key idea here is to be using the world as its own model."

2.3 Situatedness, embodiment, and structural coupling

The early work of Brooks and others emphasized again two fundamental principles of adaptive behavior, *situatedness* and *embodiment*, principles which are also central to the current mainstream of *embodied cognitive science* (for an overview see Clark, 1996; Hendriks-Jansen, 1996; Sharkey and Ziemke, 2000; Riegler, 2002).

Situatedness emphasizes that an agent always has to be embedded in an environment, which is dynamically changing, which can be modified by the agent, and which can be sensed by the agent. Embodiment refers to the interaction between an agent's brain and its body. The body with its sensors and actuators is an essential part of an agent's behavior. Thus, being situated means that intelligent and adaptive behavior emerges from agent-environment interactions and the nature of these interactions is determined by the embodiment of an agent.

Situatedness and embodiment are also key elements of the autopoietic theory proposed by Maturana and Varela (1980, 1987). Their perspective on cognition is that "all living systems are cognitive systems, and living as a process is a process of cognition".

An autopoietic is, for instance, a unicellular organism, like an amoeba, is a network of molecular components which have their own properties and interactions with other components forming the metabolism of the cell. Metabolism, as a dynamic process, produces the constituent components of the network which in turn produces the very same components and the system's spatial boundary; it is a circular process where metabolism and boundary formation happen simultaneously. Thus, autopoiesis is a self-organizing recursive process where the system (the autopoietic unity) produces its own elements and boundaries–therefore, *auto* for self and *poiesis* for birth, creation, or production.

Maturana and Varela distinguish between the *organization* and the *structure* of an autopoietic system. Organization describes the totality of all relations between the components that build a unity, and structure describes a specific network at a specific time. That means, the structure of a system can change as long as its organization is maintained. Maturana and Varela (1987) used the example of a toilet to illustrate this difference. A toilet is organized in a specific way to fulfill its function. However, single components can be replaced by similar elements (e.g., a plastic by a wooden seat). This changes the structure but not the organization. Maintaining the organization requires adaptive behavior of an organism, which can be observed by us as a consequence of structural changes within the organism.

Autopoiesis is arguably one of the most important concepts in biology to define living (=cognitive) systems. Important for our discussion is that Maturana and Varela's autopoietic systems are *structure-determined*, That is, the state of a system is always determined from inside the system, from its structure (i.e., its components and their interactions). Changes are always made inside the structure. The outside can not determine the changes, it can only trigger them. In this sense systems have no inputs or outputs. Inputs are considered as perturbations and the output of a system is the *behavior* we can observe as a consequence of compensations made inside the system as a response to perturbations. These compensations are realized by structural changes, and perturbations are non-destructive as long as the organization of an organism is not destroyed. Note that this emphasizes again the perspective problem we have as an observer who can only see the consequences of the internal mechanisms.

To put that into the context of our discussion about situatedness and embodiment: An organism, or agent, is structurally coupled to its environment via parts of its body, its sensors and actuators (see Figure 2.2). Changes of sensory states are perturbations to the system which might be compensated by the control system (e.g., nervous system, hormonal system, or metabolism). The consequences of these compensations can be observed as actions of the system's actuators, and that is what we refer to as the behavior of an agent. This behavior can induce structural changes in the environment as well, which then can consequently again perturb the agent. Thus, the environment and the agent are structurally coupled. Therefore, the cognitive domain of an agent is characterized by its internal structure and its coupling with the environment, which is realized by the body of the agent. In this sense cognitive behavior can not be considered as a function of a particular part of an agent, such as its brain, it can only be discussed

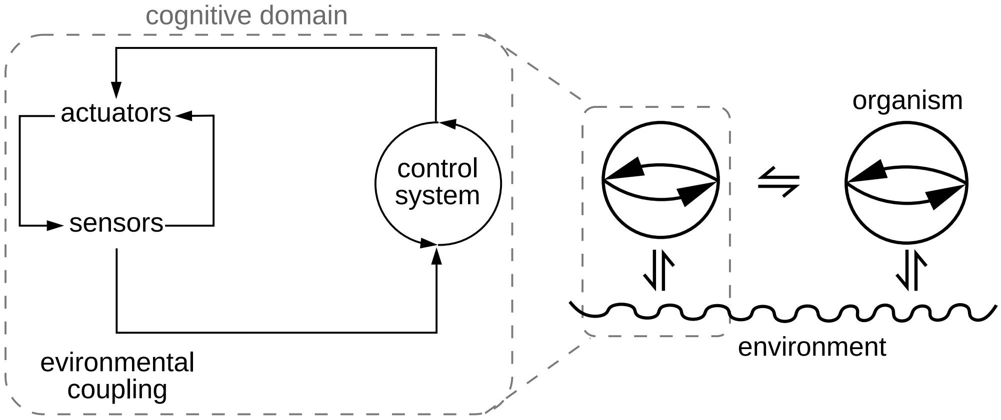

Figure 2.2: **Autopoiesis and structural coupling.** An individual consists of recursively coupled sensors, actuators, and a control system, which are all embedded in a body, separating the individual from the environment by a well defined boundary. The cognitive domain of an individual is defined by its body and the environment to which it is recursively coupled through its sensors and actuators. In the same way an individual is coupled to other individuals (right panel adapted from Maturana and Varela, 1987).

in the context an agent lives in. Part of this context includes also other agents. Agents are also structurally coupled with each other, that means, the compensation effects of one agent can become the perturbations for another agent and vice versa (Figure 2.2). This concept can be used to describe communication and social behavior in general (Maturana and Varela, 1987; Luhmann, 1990).

In this thesis we do not deal with autopoietic systems as defined by Maturana and Varela (1980). Instead, we are using robots, which entails that the components a robot exists of are not produced by the robot itself, which makes robots *allopoetic* systems (Maturana and Varela, 1980). That means, *we* design the sensors and actuators of our machine, and *we* define its boundary. In classical approaches to robot control and in the cybernetic and most of the behavior based approaches the rules which determine specific actions of an agent according to its sensor states are also predefined by *us*. The latter constraint will be tackled by the experiments described here, we try do avoid as many preconceptions as possible for generating adaptive behavior, mainly by the use of evolutionary techniques without explicit fitness functions. However, the robot and its body is still designed by us.

Therefore, we deliberately try to avoid the discussion about whether robotic systems can then ever be cognitive (for deeper discussions on that see, for instance, Keijzer, 2006; Sharkey and Ziemke, 2000; Di Paolo, 2005), which they can not from a strict autopoietic point of view (autopoietic=living=cognition). Thus, we think robots in the way they are currently built can not be cognitive. However, first approaches to realize artificial cell synthesis by self-assembling processes (Rasmussen et al., 2004; Buchanan et al., 2006) hint to a promising methodological direction toward creating artificial cognitive systems.

The experiments of this thesis are not aiming at revealing what makes an robotic

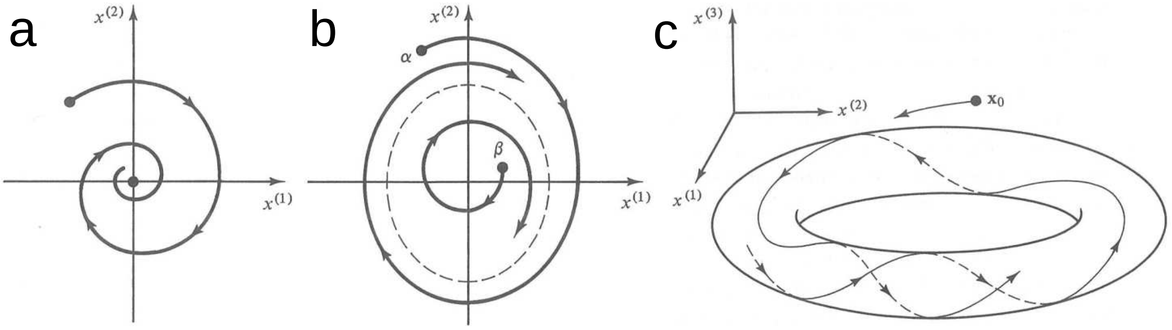

Figure 2.3: **Stable attractors of dynamical systems.** A: Point attractor. B: Limit cycle (dashed curve). C: Two frequency quasiperiodic orbit on a torus. (A-C: from Ott, 1993, © Cambridge University Press)

agent cognitive or not. We are aiming at the evolutionary emergence of adaptive behavior in groups of interacting agents. Therefore, besides the concepts of *situatedness* and *embodiment*, the description of *structural coupling* as mutual sources of perturbations between an agent and its environment or other agents is what we will use for the experiments in this thesis to describe and to explain the behavior of an agent. By explaining we mean we will try to reveal the internal compensation mechanisms which lead to a particular behavior. Here, these internal mechanisms are based on non-linear dynamical processes.

2.4 The dynamical systems approach

Dynamical systems became a quite sucessful tool to explain the behavior of complex biological systems, such as single neurons (e.g., Izhikevich, 2006), neural cuircuits (e.g., Rabinovich et al., 2006), the brain (e.g., Kelso, 1995), cognitive behavior (e.g., Port and van Gelder, 1995), developmental processes (e.g., Thelen and Smith, 1994), or population dynamics (e.g., Turchin, 2003). An increasing number of researchers suggest dynamical systems to use as a unifying framework for studying autonomous agents and embodied cognitive science in general (see for instance Beer, 2000; Steinhage and Schöner, 1997; Thelen and Smith, 1994; van Gelder, 1998; Pasemann, 1995b; Tschacher and Dauwalder, 1999, 2003). In the field of autonomous agents, it is mainly used as a descriptive tool, that is, for describing and analyzing the behavior of an agent as well as its underlying internal mechanisms.

Here, we can only give a very short introduction to the most important aspects of dynamical systems as they are used in this thesis. For more comprehensive introductions see, for instance, (Abraham and Shaw, 1992; Ott, 1993; Strogatz, 1994).

A dynamical system can be formally described as a triple (after Beer, 2000):

$$< T, S, \phi_t >, \tag{2.1}$$

where T is a ordered time set, S is the state space, and ϕ_t is an evolution operator. $S \rightarrow S$ transforms an initial state $x_0 \in S$ at time $t_0 \in T$ to another state $x_t \in S$ at time $t \in T$. S may be numerical or symbolic, continuous or discrete, finite or infinite-dimensional. T may be continuous or discrete. ϕ_t may be explicitly given or implicitly defined. This is a quite general description; finite state machines, cellular automata, Turing machines, or sets of differential or difference equations can be described in these terms.

Of major interest is the long-time behavior of a dynamical system. Examples of such long-time behavior are given in Figure 2.3. State variables move toward a steady state or point attractor (Figure 2.3a), toward a stable periodic orbit or limit cycle (Figure 2.3b), or exhibit quasi-periodic motions, in which states never repeat exactly, but neighboring trajectories remain neighbors, as shown for a torus in Figure 2.3c. We will mainly discuss these three types of behavior throughout this thesis. However, dynamical systems can also exhibit quite different characteristics, such as chaotic behavior or unstable limit sets (see, for instance, Ott, 1993).

At this point, we will describe the dynamical characteristics of the neural architectures used in this thesis. We will use probably one of simplest neuron model of recurrent neural networks that exists. Simplicity is an advantage because it means a fewer number of parameters which keeps the systems analytically feasible. These abstract neural systems, however, offer a rich set of dynamical behavior as we will see below. More realistic models such as the Hodgkin-Huxley model (Hodgkin and Huxley, 1952), its derivatives (FitzHugh, 1961; McCormick and Huguenard, 1992) or spiking models (Rieke et al., 1997; Gerstner and Kistler, 2002) may describe the dynamics of biological neurons better than the neuron model we will use. However, they are computational expensive and include too many variables which increases not only the difficulty, to evolve, but also the difficulty to analyze them in a behavioral context.

We are interested in which *neurodynamics* determine specific behavioral aspects of an artificial agent rather than the exact biophysical mechanisms of biological nervous systems. Thus, apart from using robots as physical models to investigate adaptive behavior, using a simplified neuron model is the second strong abstraction we make in this thesis.

2.4.1 Keeping it simple: The artificial neuron

Figure 2.4a shows a highly simplified illustration of the main components that constitute a biological neuron[3]. The dendrites transmit the activation from other neurons to the cell body. The corresponding synapses can have different strengths and can be either inhibitory or excitatory. Thus, the activity of connected neurons can have different influences. The cell body sums up the incoming signals, and at a specific threshold an action potential is elicited which propagates through the axon to other neurons. The following ‘crude’ abstractions are made for our artificial neuron model:

- Discrete time dynamics are used.
- Our network is synchronized, that is, the activity of all neurons is updated at the same time by summing up their inputs.

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[3] Here, we completely omit the biophysical complexity of biological neurons because it exceeds the scope of this thesis (for comprehensive introductions into neurophysiology see, for instance, Kandel et al., 2000; Churchland and Sejnowski, 1994).

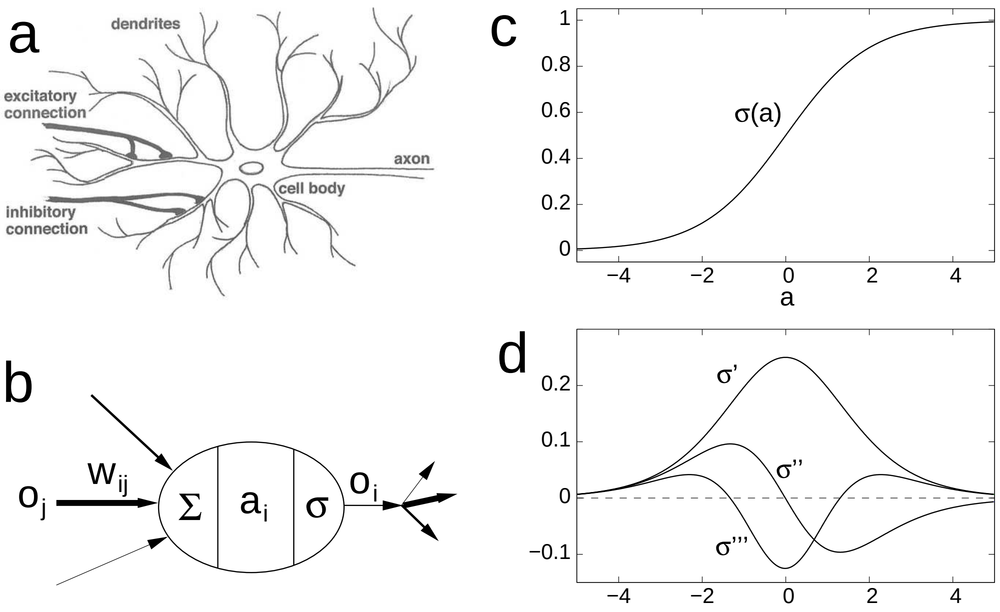

Figure 2.4: **The standard additive neuron model.** A: Illustration of a biological neuron (from Pfeifer and Scheier, 1999, ©MIT Press). B: The derived abstract artificial neuron model (modified from Pasemann, 1996). Synapses can have different strengths and can be excitatory or inhibitory (i.e., positive or negative w). C: Standard sigmoid transfer-function applied to a neuron's activity a to calculate its output $o = \sigma(a)$. D: Derivatives of the transfer-function.

- Information is only coded in the firing rate which is resembled by the output value of our artificial neuron.
- There is no time delay accounting for the time a signal needs to travel along the axon. Signals are transmitted within one time step.

Figure 2.4b illustrates an artificial neuron as it will be used here. The outputs o_j of other neurons are weighted by different strengths w_{ij} of the synapses, which can be either excitatory or inhibitory corresponding to positive or negative values of w_{ij}. The artificial cell body sums the incoming values to the activation a_i of the neuron. The output o_i of a neuron is calculated according to a sigmoid transfer function (Figure 2.4c). Therefore, the output of a neuron has a lower and upper saturation domain (zero and one for the standard sigmoid), which accounts for the fact that the firing rate of biological neurons is bounded as well.

Thus, our neuron model[4] corresponds to standard additive neurons with discrete time dynamics, and the activity of a neuron is then defined as:

$$a_i(t+1) = \theta_i + \sum_{j=1}^{n} w_{ij}\, f(a_j(t)) \ , \quad i = 1, \ldots, n \ , \tag{2.2}$$

---

[4] The neuron model used here is derived from the Naka-Rushton equation which is based on empirical neurophysiological data and describes the relation between stimulus intensity and the resulting firing rate (see Evans et al., 1993; Wilson, 1999).

where n is the number of neurons which are connected to neuron i, and θ_i is its fixed bias term. The output $o_i = f(a_i)$ of a unit i is given by a sigmoid transfer function. Here, this transfer function is either $f(a) = tanh(a)$ (i.e., $o_i \in (-1, 1)$) or the standard sigmoid $f(a) = (1 + e^{-a})^{-1}$ (i.e., $o_i \in (0, 1)$).

Figure 2.4d shows the first three derivatives of the standard sigmoid. The root of the second derivative indicates the linear domain ($a = 0$) and the roots of the third derivative indicate the domains of the strongest non-linearity ($a \approx \pm 1.5$). The same properties are obtained when using *tanh* as transfer function. Thus, both types of transfer functions have the same dynamic properties and, in fact, each can be transformed into each other (see Pasemann, 2002).

2.4.2 Everything is possible: Network architectures

Now that we have described the characteristics of a single neuron, the question is how to connect these neurons, that is, to choose a network topology.

The first and probably simplest type of artificial neural networks (ANNs) are feed-forward networks (FNNs), also called perceptrons. In FNNs information flows in only one direction. The simplest case would be a one-neuron network of the McCulloch-Pitts model (see p. 33). Such a neuron sums up all its inputs and at a given threshold it changes its output from zero to one. This kind of of single-layer perceptrons can be trained to learn linearly separable patterns (Minsky and Papert, 1969). By introducing layers, one can built so called multi-layered perceptrons (MLPs), where each neuron in one layer has directed connections to subsequent layers (Minsky and Papert, 1969; Hertz et al., 1991). It could be shown that MLPs with only one hidden layer and a sigmoid transfer function can approximate arbitrarily close every continuous function that maps intervals of real numbers to some output interval of real numbers. And that is exactly what MLPs are mainly used for, function approximation.

FNNs are characterized by a one-directional information flow. In contrast, in recurrent neural networks (RNNs) information can flow bi-directional. One of the simplest RNN model was introduced by Elman (1990). These networks are actually an extended version of MLPs. They consist of three layers: input, hidden, and output. Neurons in the hidden layer have connections to some neurons in the input layer, to the so called context sensitive neurons which maintain a copy of the previous values of the hidden neurons. These types of networks allow sequence-prediction, and Elman (1990) used them, for instance, to investigate human speech perception.

Another type of RNNs are Hopfield networks (Hopfield, 1982), which are fully connected without self-connections. The connections between two neurons are always symmetric. Hopfield networks guarantee that their dynamics always converge. They are often combined with Hebbian learning (Hebb, 1949) to realize content-addressable associative memory systems.

In this thesis we will use no specific type of architecture. That is, we will use RNNs of general types, ranging from fully-connected networks (including self-connections) to networks without any recurrent connections (i.e., FNNs). Not restricting network topologies and their parameters, offers the emergence of almost any kind of dynamical behavior, even with our simplified neuron model. This is important, since we want to find out which kind of dynamics are relevant for particular behavioral aspects, which can not be known beforehand. As we will see later the topology of our RNNs are also subject to evolutionary processes. However, first we want to discuss which dynamical properties we can expect from our networks with arbitrary topologies consisting of additive standard neurons with discrete time dynamics.

2.4.3 Two neurons are enough: Parameters and complex dynamics

The following considerations are derived from (Pasemann, 1995b, 1996). As we have seen the activity of a neuron in our neuron model (Eq. 2.2, p. 44) is characterized by the weighted input from other neurons and its bias term. The bias term can be substituted by an additional neuron with constant activity and a corresponding synaptic weight. In this case, the state of the neural system at time t is characterized by the activity of all neurons and the strength of all synapses, that is, by the activity vector $a(t) := (a_1(t), \cdots, a_i(t), \cdots, a_n(t))$ and the weight matrix $w(t) := (w_{11}(t), \cdots, w_{ij}(t), \cdots, w_{nm}(t))$. Thus, the state space S of the system is described by $S = A \times W$, where A is the activity space and W the weight space. The behavior of a system is characterized as the temporal change of neural activity described by the dynamics of A. The change of synaptic parameters, which realizes specific functionalities, is described by the dynamics of W.

As a further abstraction we assume that changes of neural activities occur on a much faster time scale than changes of synaptic parameters. Synaptic changes are usually associated with learning, which will not be considered in this thesis. Thus, synaptic strengths are control parameters of our neural system (Pasemann, 1996), and therefore belong to ϕ_t (Eq. 2.1, p. 42). These parameters will here be subject to an evolutionary development, as we will see in the next section. Because they do not change during the life time of an agent (i.e., no learning), we refer to the synaptic strengths as well as to the topology of an RNN as internal parameters to distinguish them from parameters which do change during the life time of an agent. These changing, or external, parameters are the sensor signals of a robot which generally represent the input of our neural systems.

Which kind of dynamics can we expect from our simplified RNN? The most common dynamics we will find with the experiments presented in this thesis are hysteresis phenomena and periodic oscillations. Figure 2.5 shows how these two phenomena can be realized by three very small RNNs with *tanh* as transfer function. The left panel shows two networks with similar dynamics. One network is a single neuron with an excitatory self-connection which receives an external input. In the corresponding bifurcation diagram we see a domain where two fixed point attractors co-exist ($-2.5 < in > 2.5$). If we start with a strong negative input signal ($in = -7$) and increase it slowly, we stay in the attractor of low activity until, at a critical value (≈ 2.5), the system suddenly changes to the attractor with high activity. If we then decrease the input signal again, the system suddenly changes to the attractor of low activity but at at a much lower critical value (≈ -2.5). Thus, co-existing attractors in an one-neuron module realize already a kind of short term memory via a hysteresis effect. Similar effects can be achieved with a two neuron-ring as shown in the left panel of Figure 2.5, which indicates already that different networks can exhibit similar dynamics. Hysteresis effects in small RNNs are formally described in (Pasemann, 1993, 1995b) and their

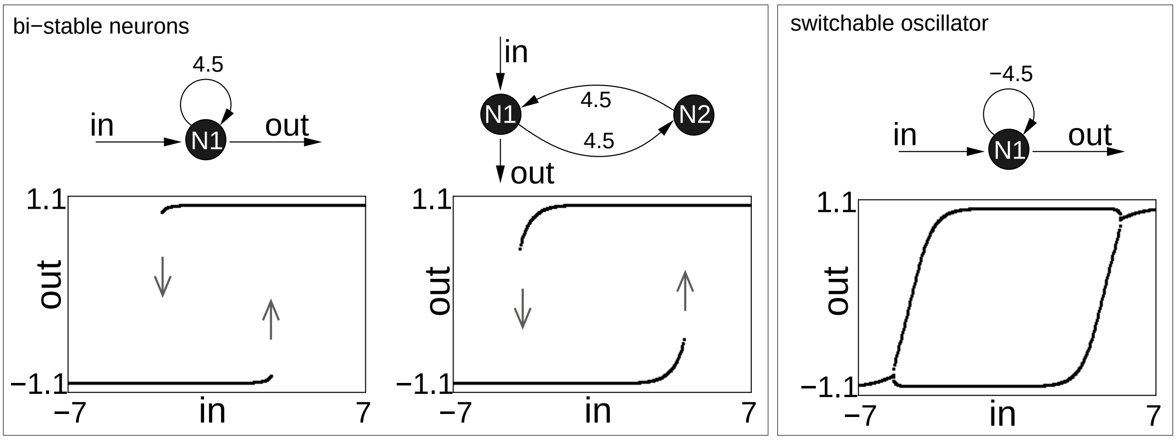

Figure 2.5: **Hysteresis and oscillations of small neural structures.** Left panel: Bi-stability of one neuron through an excitatory self-connection and in a two-neuron system through an even loop. Right panel: A switchable oscillator realized by one neuron with an inhibitory self-connection. Depending on the input signal strength the system ends either in fixed point domains or in period-2 attractors.

robotic applications to achieve robust obstacle avoidance is shown, for instance, in (Hülse and Pasemann, 2002; Hülse et al., 2004).

The right panel in Figure 2.5 shows how a single neuron with an inhibitory self-connection can function as a switchable oscillator. In the corresponding bifurcation diagram we see that for strong negative input signals the system stays in fixed point attractors of low activity. If we increase the signal, the system enters a domain of period-2 attractors at a critical value, the bifurcation point ($in \approx -5.4$). We can see how the amplitude of the oscillations increases very fast while increasing the input signal, stays in the same period-2 attractor for a large domain, and eventually switches back to a fixed point attractor with high activity (for $in > 5.4$). Periodic behaviors of small RNNs are formally described in (Pasemann, 1993, 1995a, 2002) and we will see many behavioral applications in this thesis.

Interestingly, already a two-neuron network can offer a rich repertoire of dynamical properties as we can see in Figure 2.6. Two neurons are coupled via an odd loop and each neuron has an inhibitory self-connection (such networks are formally described in Pasemann, 1995b, 1998, 2002). To each neuron an external signal is applied ($in1, in2$). For the given weight configuration (see Figure 2.6a), we can now determine the attractors in which the system ends when we vary $in1$ and $in2$. The result is shown in Figure 2.6b. We see that the attractor map is almost symmetrical, which is due to the almost symmetric weight configuration. We find domains of fixed point attractors (white regions), attractors with different periodicities (encoded by different colors), quasi-periodic and even chaotic attractors (black regions).

Figure 2.6c gives the bifurcation diagram for the parameter region marked with a white dashed line in Figure 2.6b. While $in2$ is kept constant, we vary $in1$ and observe the output dynamics at neuron $N1$. Now, we can see more vividly the meaning of the different colors in Figure 2.6b. We start with period-3 oscillations for $in1 = -2$, followed by several domains of quasi-periodicity and varying periodicity ($-1.6 < in1 <$

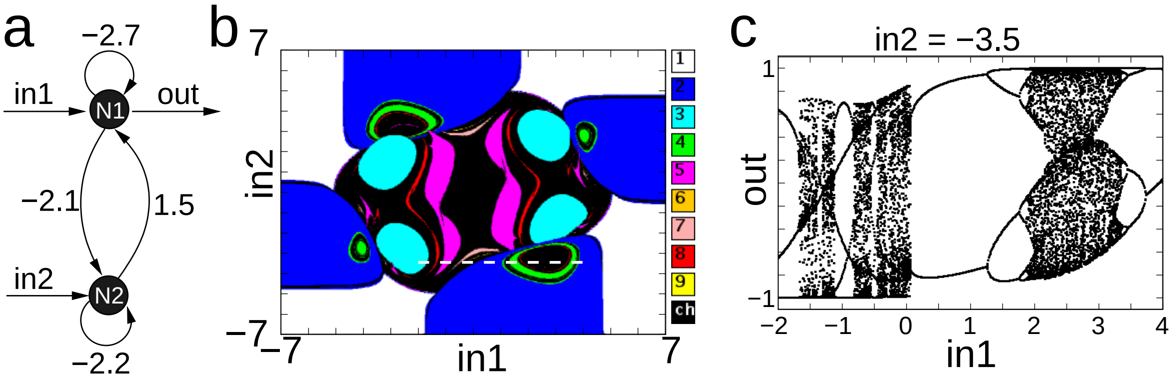

Figure 2.6: **Complex dynamics in a two-neuron network.** A: RNN with two inputs and one output (transfer function: *tanh*). B: Colors in the iso-periodic plot encode attractor domains of different periodicity (white indicate fixed point; black indicates either domains with periodicity > 9, or quasi-periodic, or chaotic behavior). C: The bifurcation diagram indicates behavioral changes of the system's dynamics depending on one input value ($in2 = const$; the white dashed line in (B) indicates the parameter domain).

0.1), reach a large domain of period-2 oscillations ($0.1 < in1 < 1.3$), get subsequently over period-doubling to a chaotic domain ($2 < in1 < 3.4$), and eventually reach, through period-halving, a period-2 attractor ($in1 = 4$). That means that even in very 'simple' networks we can discover a variety of dynamical behaviors even in a very narrow parameter range. However, the question remains whether or not such complex dynamics are necessary to generate adaptive behavior. We deliberately picked the example network shown in Figure 2.6a because we will encounter an identical configuration again in Chapter 7 as part of an RNN which realizes different aspects of interspecific and intraspecific communication, demonstrating that complex dynamics of small RNNs can be highly useful for different signaling strategies. These behavioral strategies strongly depend on the environmental context of an agent, and this context is represented by the input signals of its neural control system.

To relate this idea to the concept of structural coupling: The RNN represents the (control) structure of an agent. The agent senses its environment, which changes the input signals of its control structure (perturbations), which might change the internal dynamics (consider this as the compensation mechanisms as discussed in Section 2.3, p. 40). The results of theses compensation mechanisms, or dynamical changes, within the system can be observed at the output of the system, which corresponds to a particular action, or behavior, of the agent, and this action might again lead to changes of the input signals; thus, closing the loop.

So far we have seen that varying parameters of a neural system can either lead to a smooth transition or drastic change at bifurcation points (see Figure 2.6c). At this point, we have to emphasize again that we want to focus on the complexity of dynamical processes in the context of neural information processing instead on the physical complexity of neural correlates. Therefore, we argue that the simplifications we make with our neural model are reasonable, especially because we want to analyze the correlation between the intrinsic dynamical mechanisms and the observable behavior of an agent.

2.4.4 RNNs in the sensory-motor loop

We want to use RNNs as control systems for our robotic experiments. That means we have to connect them somehow to our robot's sensors and actuators. Sensor values are represented by the input units of a neural network (gray circles in Figure 2.7). Even though we will refer to these units as input neurons in the following, they differ with respect to other neurons. Input neurons realize linear buffers without a transfer function (i.e., $a_i = o_i$) and they have no incoming connections, thus, no feedback from other neurons. Specific signals from the physical sensors are usually linearly mapped to the range of the transfer function of the RNN. For instance, a physical infrared sensor measures distances to objects, a light sensor the illumination, a microphone measures sound intensities, and so on. Not only do the signals of these sensors vary in their signal range, they vary also from one robotic platform to another. For instance, a small robot, such as the Khepera$^{\text{TM}}$ robot, usually has very short range infrared sensors whereas a bigger robot, for instance the Koala$^{\text{TM}}$ robot, has long range infrared sensors. If we would just give the distance to an object as input to our network, it would be hard to transfer it from one platform to another without further modifications. If we, however, map the sensor signals always in the range of the transfer function, nets can be easily transfered between different robots with different sensor properties.

To give an example, Hülse and Pasemann (2002) developed a small-sized network which realizes highly robust obstacle avoidance behavior on the Khepera$^{\text{TM}}$, a tiny two-wheeled robot. The very same network was later used by Manoonpong et al. (2007) to implement obstacle avoidance on six- and four-legged walking machines. Thus, this network was implemented in three robots which differ significantly in their sensors and actuators. However, by keeping the input and output parameters of an RNN in the same range, it is possible to employ a network with a particular behavioral function on many different machines.

Except for the input neurons, all other neurons correspond to the neuron model described in Section 2.4.1 (p. 43). We refer to neurons whose outputs are taken as signals for the actuators of a robot as output neurons; other neurons are referred to as hidden neurons. Thus, the structure between hidden and output neurons define the dynamical properties (i.e., the system's attractor landscape) of the RNN and the input neurons provide the input signals of this dynamical system (see Figure 2.7). Such a system can behave very much like the small systems we discussed in previous section. The input signal can drive the system through different attractor domains which of course can change the behavior of output neurons and, therefore, change the actions an agents make in its environment which, in turn, affects its sensory states (that is what we refer to as the sensory-motor loop).

Let us take a simple example. Consider the one-neuron network with a bi-stable attractor domain given in the left panel of Figure 2.5 (p. 47). Suppose the input is the mapped signal provided by an infrared sensor on the left side of a wheel-driven robot. High values correspond to no object detection and low values to detection of very close objects. The output drives the right wheel where high values correspond to high

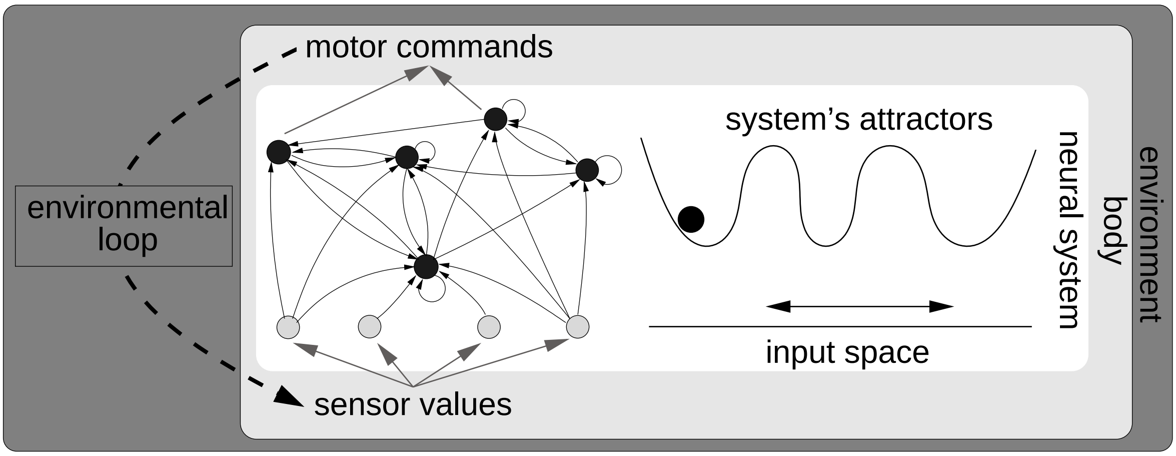

Figure 2.7: **RNNs embedded in the sensory-motor loop.** Grey circles represent input units which provide input signals to the neural network in form of mapped sensor values. Black circles represent neurons and from some of them the output is taken as command signals for the robot's actuators. Thus, the neural system is embedded in the body of the agent, which is embedded in the environment.

wheel speed and low values to low speed, respectively. If the robot now approaches an obstacle on its left side, the input would decrease slowly, but as we can see in Figure 2.5 (leftmost) the output stays high for a while. However, at a critical value it would jump to low output values, and this would consequently slow down the right wheel which leads to a right turn of the robot. Thus, the robot turns away from the obstacle, which consequently increases the activity of the input. However, the system jumps back to high output values at a much higher input value which assures a turning movement lasting long enough to move away from the obstacle.

Because of the positive self-connection of the neuron, we get the hysteresis effect, which realizes a large turning angle for robust avoidance behavior. At the same time, due to the self-connection, the system filters sensory noise quite efficiently. As we can see in Figure 2.5 (left), the input signal drives the system in an attractor of either high or low activity. Small random variations do not influence the output behavior, except at the critical points, but even there the system would jump from one attractor to the other once and then would stay there because of the hysteresis effect. Thus, this simple one-neuron module filters noise and realizes avoidance behavior to obstacles on the left side quite efficiently. In a similar way we could connect the right infrared sensor to the left wheel and thereby design a robot which would reliably explore its environment without bumping into obstacles or getting stuck in narrow corners (see also Hülse and Pasemann, 2002; Hülse et al., 2004). Considering Figure 2.7, the state of the infrared sensors represent the input space. Sensor changes drive the system through different attractors, which changes the output of the system and, thus, the behavior of the robot leading again to a change of its sensor values.

The control system described above is reminiscent of the simple Braitenberg controllers (see also p. 36), except that we have a bit more than mere input-output relations. Additionally, we also have internal dynamics, which do not only depend on the current sensor state, but also on its history.

Note, to increase the behavioral capabilities of a robot, one needs to add more sensors and motors, that is increasing the complexity of its sensory-motor coupling. Consequently, the input and output space of the control system would quickly get high dimensional in contrast to the small systems discussed above. However, the experiments in this thesis will show that such robots do not require much larger RNNs with respect to the number of hidden neurons or synaptic connections, as one might intuitively think. We will present examples of behaviors which go beyond simple tropisms, which are, however, determined by still very small RNNs. The main reason why small RNNs can realize a variety of interesting behavior is the richness of their dynamical properties, that is, already small modules possess a notable multimodality as we will see later on (especially in Chapter 6 and 7).

2.5 The evolutionary synthesis of behavior

So far we emphasized several times that we want to circumvent the perspective, or frame of reference, problem by using evolutionary techniques, that is, transferring the design of control architectures to a self-organizing process (Nolfi and Floreano, 2000). A secondary and more pragmatic reason for using artificial evolution lies in the intrinsic complexity when using RNNs as dynamical systems. As we have seen in the previous section, even small structures with specific parameter settings can exhibit non-trivial dynamical behaviors. It is almost impossible to decide which dynamical properties are of advantage, or required in the first place, especially when considering sophisticated behaviors, such as cooperation and communication.

Thus, artificial evolution implemented by evolutionary algorithms (EAs) seems to be a promising technique to develop RNNs for specific behaviors in a rather preconception-free manner. At the end of this thesis, we even want to go a step further. We will try to avoid almost *any* assumptions about what kind of behavior is of advantage for an robotic agent.

So far we motivated the use of robots as complete systems acting in the sensory-motor loop and recurrent neural networks as control architectures based on the principles of non-linear dynamical systems. In this section we will discuss why using evolutionary techniques to generate these RNNs is a compelling design method. Before we describe the setup as used in this thesis, we give a brief overview about commonly used EAs and the rising field of evolutionary robotics.

2.5.1 Evolutionary algorithms

In general, EAs are inspired by natural evolution, which includes the mechanisms of reproduction, variation via mutation and recombination, natural selection, and survival of the fittest[5]. The first scientific milestones in evolutionary biology clearly were the theory about natural selection and descent with modification proposed by Darwin (1859), and the discovery of Mendelian genetics (Mendel, 1866; Morgan et al.,

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[5] "Survival of the fittest" is often associated with Darwin, but it was actually coined by Herbert Spencer (1864) who drew parallels of his ideas about economics with Darwin's idea about natural selection.

1915). Here we just want to name three further fundamental steps in evolutionary biology without going into the details (for a comprehensive introduction see, for instance, Maynard Smith and Szathmáry, 1995). The first was made by Hamilton (1964) with his theory about "selfish genes" and kin selection which favors altruistic behavior among relatives. Later on Maynard Smith and Price (1973) introduced evolutionary game theory, which is now vastly used in current evolutionary modeling. The next fundamental step is the theory about quasi-species proposed by Eigen and Schuster (1979); it unified Darwian evolution with physical chemistry and information theory.

Returning to EAs: EAs became quite popular with the rise of *artificial intelligence*, and especially later on in *artificial life* research (Dyer, 1994). Evolutionary algorithms can be divided into five main implementation techniques (Eiben and Smith, 2003): learning classifier systems, genetic programming, evolutionary programming, genetic algorithms, and evolutionary strategies. Here, we will only consider the latter two because they are the most common techniques for the evolution of behavior in robotic agents. For comprehensive overviews about the entire field of EAs see (Bäck, 1996; Bäck et al., 1997; Eiben and Smith, 2003).

Genetic algorithms (GAs), are probably the most popular technique, especially in the field of *evolutionary robotics*. They became widely recognized by the work of Holland (1975) who used GAs as an optimization method in his studies of cellular automata. In general, a GA needs a form of 'genetic' representation of the solution domain to a particular problem. Usually this representation is an array of bits. Specific parts of these arrays can for instance encode variables of a function which has to be approximated, or synaptic strengths of a neural network. As a second requirement, a fitness function has to be defined, which describes a specific target solution. For instance, for function approximation one would try to minimize the distance of an approximated function to a real data set. Once an appropriate fitness function is designed and a genetic representation defined, the procedure is usually as follows:

- Initialize a population of individuals randomly.
- Evaluate each individual with the fitness function.
- Choose the best individuals ($P(0)$).
- Start with $g = 0$ and repeat:
    1. Variation and reproduction: Create new individuals ($O(g)$) through mutation and cross over among $P(g)$.
    2. Evaluation: Determine fitness of $O(g)$.
    3. Selection: Determine best individuals of $O(g)$ and $P(g)$, which from $P(g{+}1)$.
- until process is stopped.

The process is stopped either at a predefined number of generations g, when the fitness reaches a plateau or when a minimal solution criteria is reached. It can also be stopped manually by the observer who decides through manual inspection of the current solutions. Selection and reproduction operators are usually stochastic (for details see Eiben and Smith, 2003; Holland, 1975).

Rechenberg (1973, 1994) and Schwefel (1995) proposed Evolution Strategies (ESs) as another evolutionary optimization technique (for an overview see also Beyer and Schwefel, 2002). Similar to GAs, ESs operate in a loop of variation, reproduction, evaluation, and selection as described above. In contrast to GAs, ESs use real-vectors as encoding representation and deterministic selection operators. In addition to variations of the coding representation, so called strategy parameters are optimized during the evolutionary process. Strategy parameters concern parameters and probabilities of the variation operators. Thus, evolutionary parameters are evolved in parallel depending on the fitness development of the individuals. In that sense, it might be beneficial to have at the beginning rather large variations to generate a great diversity which explores the fitness landscapes rather quickly. If individuals approach a local optimum in the fitness landscape, it might be helpful to decrease the variation range to ultimately reach the peak of that optimum.

2.5.2 What evolutionary robotics can tell us

The term *evolutionary robotics* (ER) was first mentioned in a publication of Cliff et al. (1993)[6] and is an ever growing research field (for overviews see Harvey et al., 2005; Nolfi and Floreano, 2000; Walker et al., 2003; Husbands et al., 1997). The major motivation of ER is to utilize evolutionary computation techniques to automatically design control architectures in order to realize adaptive behavior in autonomous robots. On the one side, ER promises to develop solutions for robotic tasks where it is tremendously complicated to design their control systems manually. Thus, ER can be seen as an optimization tool for behaviors which are hard to engineer, very similar to the use of EAs to approximate complicated functions.

However, ER is also proposed as an "ideal framework for studying adaptive behavior" (Nolfi and Floreano, 2000) or the emergence of higher level cognition (Parisi, 1997). In some respects we can relate ER to the biorobotics approach discussed earlier. Both methods utilize robots as physical models to study behavior (which they also have in common with some of the early cybernetic studies). However, researchers in biorobotics usually use robots to test their hypotheses about specific behavioral mechanisms in animals, that is, they implement these mechanisms at an abstract level in their robots. The majority of researchers in ER start at a much lower level. Even though they still design their robots[7], they convey the process of control implementation to automated methods, which are inspired by biological evolution. This led Nolfi and Floreano to the claim:

> "Evolutionary robotics and biology share an interest in the following ques-

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[6] Harvey et al. (2005) point out that the earliest use of *evolutionary robotics* actually goes back to the unpublished work of Cariani (1988) presented at the first Artificial Life workshop.

[7] Note that also the evolution of morphologies receives increasing interest. There are already impressive experiments, for instance, by Sims (1994), but most of them are limited to virtual worlds. For real robots, morphological evolution is generally limited to few parameters, such as wheel distances or sensor orientations (for examples see Pfeifer and Bongard, 2006, chap. 6). It is obvious that an unconstrained evolution of morphologies for real robots is rather difficult because it is hard to change the form of sensors, motors, or power supplies like they exist today. Devices for rapid prototyping comparable to 3D printers are going to change this problem (see Lipson and Pollack, 2000), but they are still at the beginning.

> tion: what are the key characteristics of natural evolution that make it so successful in producing the extraordinary variety of highly adapted life forms present on the planet? Producing better answers to this questions may significantly increase both our understanding of biological systems and our ability to design artificial systems."
>
> *Nolfi and Floreano (2000, p. 12-13)*

We fully agree with this statement as long as it concerns the design of artificial systems, or the improvement of machines performance. ER is a powerful tool for developing solutions to hard problems, especially when it comes to adaptive behavior of real robots acting in a noisy and often unpredictable environment. However, one has to be careful since there is still a lot of design effort necessary. Proper fitness functions have to be designed, which can be quite challenging without knowing what the optimal behavior would be for a complex task. And because evolution is a time consuming process relying on many trial-error cycles, simulations of robots are the preferred tool. These simulations have to be designed in a way that the solutions are still applicable to real robots, which we will discuss later on in more detail.

We are more critical with the claim that ER methods may help us to understand better biological systems and their evolution. Even though we believe studying simplified (not idealized!) complete system is clearly a key component for understanding intelligent and adaptive behavior, we have to be careful that we do not simplify at too many levels. ER methods entail simplifications at the agent level (robots vs. animals), at the control level (e.g., artificial vs. biological nervous systems), at the environmental level (controlled laboratory conditions vs. complex ecosystems), and at the level of evolution. The problem is, that for many reasons we are far away from having a complete knowledge at any of these level in their biological counterparts. First of all, there is the overwhelming complexity of biological organisms which becomes unfeasible when leaving the reductionists approach, that is, studying the smallest components into which we can decompose a system, and considering the organism as whole with its nervous system and metabolism embedded in its body that is itself embedded in an environmental context. And when it comes to evolution, we have the problem of time. The generation span of an organism is the limiting factor to study evolution in vivo. And evolution is usually a very slow process which has to be studied over myriads of generations. In this sense, ER provides a big advantage. We have complete systems, robots, which we are usually able to understand in their parts as well as a whole. And we can run evolution on computers which are getting faster with every year. However, the danger is, that because of the strong simplifications we make, we may set up experiments whose results are hard to relate to biological systems because of the great differences.

Harvey et al. (2005) discussed this problem in the context of cognition which we, as said already, try to avoid. However, the points they made about the relation between cognitive science and ER, emphasize much of the motivation that lead us to using ER to study cooperation and communication.

> "These systems, then, will not tell us how real cognitive systems work, but they will do something very useful nonetheless. They provide us the

> proofs of concept and exploratory studies that can challenge existing views and unwritten assumptions in a healthy manner. Additionally, these existence proofs can provide further lessons in that it is possible to manipulate and understand them in dynamical terms to some extent. The potential scientific role of such examples should not be underestimated. They can help us re-organise our conception of a problem (e.g., origin of learning), bring added importance to factors previously considered of little relevance (e.g., neural homeostasis), and explore situations too complex even to start asking the right questions about using traditional tools (e.g., minimal developmental systems)."
>
> *Harvey et al. (2005, p. 95)*

We would extend this view from cognitive systems to biological systems in general. Research in ER entails so many abstractions that it becomes hard to gain any direct insight into the actual physical mechanisms of biological organisms. Nevertheless, ER can generate proof of concepts. Hence ER aims to find the minimal conditions which allow the emergence of phenomena, comparable to those found in nature, it may help us to show what is required for such a phenomena and what can be refuted. However, whether or not these findings can then be easily translated into biological studies is still arguable. The stronger argument is clearly the aim of ER to challenge existing views on unwritten assumptions. In that sense ER continues where cybernetics started. Properly designed ER experiments challenge the perspective issue, they can show us that the mechanisms behind seemingly complex behaviors are often rather trivial. They can do so, because they have the power of dealing with complete systems which are still understandable at every level of detail, and as a whole.

To give some examples, the work of Beer and Gallagher (1992) and von Twickel and Pasemann (2007) has shown that adaptive walking in machines which resemble gait pattern of stick insects can be realized without any form of neural central pattern generators (CPGs), solely relying on sensory-motor feedback loops. Especially Beer (1995) tested the different influence of several control architectures (without CPGs, with CPGs and sensory-motor feedback, solely CPGs) on the adaptivity of walking. These are experiments which can hardly be done with real animals. Removing parts of the neural system in a stick insect or the influence of sensory-motor feedback loops without damaging other vital parts of the organism is almost impossible, whereas with robots such tests are rather easy to conduct so that it allows analysis of the whole system in a behavioral context. Other examples have shown that also for straight two-legged locomotion no CPGs are required (Wischmann and Pasemann, 2004), and that through the passive dynamics of the body, bipedal locomotion can be highly efficient (Collins et al., 2005; Wischmann and Pasemann, 2004). Other examples such as the simple predator-prey experiments of Floreano and Nolfi (Floreano and Nolfi, 1997; Nolfi and Floreano, 1998) showed the development of an evolutionary arms race between co-evolving species of agents where behavioral strategies reoccur in cycles during the evolution over a time span of hundreds of generations.

Intriguingly, ER allows not only a detailed analysis of the behavioral mechanisms, it allows to observe the development and change in behavior on an evolutionary time scale whereas biological studies are often left with relying on fossil records. For instance, the impressive work of Ijspeert et al. (2007) demonstrated with a salamander-like robot that early animals probably did not need to invent completely new neural pathways to change from aquatic to terrestrial locomotion.

In this realm, we see a major motivation for this thesis: Investigating the minimal requirements for the evolution of cooperation and communication in situated and autonomous agents. Of particular interest are the minimal requirements at the neural dynamics level. How complex has an RNN to be to realize efficient communication strategies not only within a group of cooperating agents but also between competing groups? To find this out, we have to minimize our preconceptions about these kind of behaviors and their underlying mechanisms. A first step toward that direction is the method of structural evolution.

2.5.3 Structural evolution

The evolutionary algorithm we will use in this thesis is called ENS^3 (evolution of neural systems by stochastic synthesis). It was originally developed by Dieckmann (1995). Later on, Martin Hülse and Keyan Zahedi further extended the algorithm and embedded it in a software package called *ISEE* (see also Hülse et al., 2006). Through a neural interface, *ISEE* allows a rather uncomplicated interaction of the ENS^3 algorithm with either the physical robots or their respective simulation models.

The technical details of the ENS^3 algorithm are extensively described in (Dieckmann, 1995; Hülse et al., 2004; Hülse, 2007). Here, we only want to mention its salient features.

The ENS^3 algorithm belongs more to the class of ESs than to GAs. However, it differs from most ESs in the respect that it relies on stochastic selection operators, that it has no strategy parameters, and that the dimensions of the parameter space which is to be optimized can vary during the evolutionary process. It brings together combinatorial with real-value parameter optimization. For this reason, RNNs, which are here the subject of evolution, are represented as parameterized graphs were nodes represent neurons and directed edges represent the synapses. The parameters are bias terms (associated with nodes) and synaptic weights (associated with edges); they undergo real-value optimization. Nodes and edges can be added and deleted during an evolutionary process by combinatorial optimization, that is why the dimensions of the parameter space change permanently.

What has to be defined at the beginning of an evolutionary process are the input and output neurons. These are the only elements which are protected from evolutionary deletion. A further restriction is that there are no synapses allowed to project toward the input neurons because input neurons serve as linear buffers and therefore provide the input space of our RNNs as dynamical systems (see Section 2.4.4, p. 49).

Table 2.2 shows the general procedure of the ENS^3 algorithm. A population is divided into parents $\mathcal{P}(g)$ and offspring $\hat{\mathcal{P}}(g)$. The parameter g refers to the generation of the population. All operators, like selection, reproduction, and variation, are stochastic (for a detailed description see Hülse et al., 2004; Hülse, 2007).

The evolutionary process is initialized with an arbitrary number of RNNs which are identical with respect to their input and output neurons and their transfer function. The transfer function and the input-output structure are defined problem specific, according to the task that the neuro-controllers will be evolved for. Initial RNNs can either be ‘empty’ (i.e., they have no internal structure) or they already possess a specific structure which can be different among the initial RNNs. However, initial structures can change during evolution.

Starting with non-empty networks can be useful if one wants to start with individuals which already have a particular behavioral repertoire. This becomes important when agents are confronted with a rather complex environment or are evolved for non-trivial behaviors. Thus, it allows *incremental evolution* which might be necessary for complex tasks because the probability that some individuals of the first generation can accomplish, at least partially, the task is inversely proportional to the complexity of the task itself (Nolfi and Floreano, 2000). Then, chances are high that all individuals in the first generation get zero fitness and, consequently, the selection process can not operate. This is often referred to as the bootstrap problem.

At this point, we have to mention another important difference to general ESs. ESs assume a so called *strong causality* (Rechenberg, 1994; Sendhoff et al., 1997). That is, small changes at the ‘genetic’ level should result on average in small changes of the fitness values (smoothness assumption). In contrast, evolving the topology and parameters of RNNs entails a *weak causality*. For instance, in Section 2.4.3 we have seen that if changes of the input space cross bifurcation points, the dynamics of the system can change dramatically (see also Figure 2.6c, p. 48). Synaptic weights change the influence of the input signals and, thus, a change in synaptic weights might also lead to a dramatic change of the dynamical properties, especially changes close to bifurcation points where very small variations have great effect. Figure 2.8 illustrates the weak causality for structural changes. On the left side we see the network from Figure 2.6 (p. 48) and its corresponding attractor map. The right side shows how the attractor landscape changes significantly for two instances where we only removed a single synapse and all other parameters remained unchanged.

Because the dynamical properties of an RNN are closely connected to the behavior

Table 2.2: **General procedure of the ENS^3 algorithm** (modified from Hülse et al., 2004). Initialization and the reproduction-variation-evaluation-selection cycle (P: parents; $\hat{\mathcal{P}}$: offspring; g: generation)

```
Begin
   $\mathcal{P}(0)$ := set_of_initial_structures;
   $t$ := 0
   Repeat
      $\hat{\mathcal{P}}(g)$ := reproduction($\mathcal{P}(g)$);
      variation($\hat{\mathcal{P}}(g)$);
      evaluate($\mathcal{P}(g) \cup \hat{\mathcal{P}}(g)$);
      $\mathcal{P}(g+1)$:= selection($\mathcal{P}(g) \cup \hat{\mathcal{P}}(g)$);
      $g$ := $g+1$
   Until stop_criterion;
End.
```

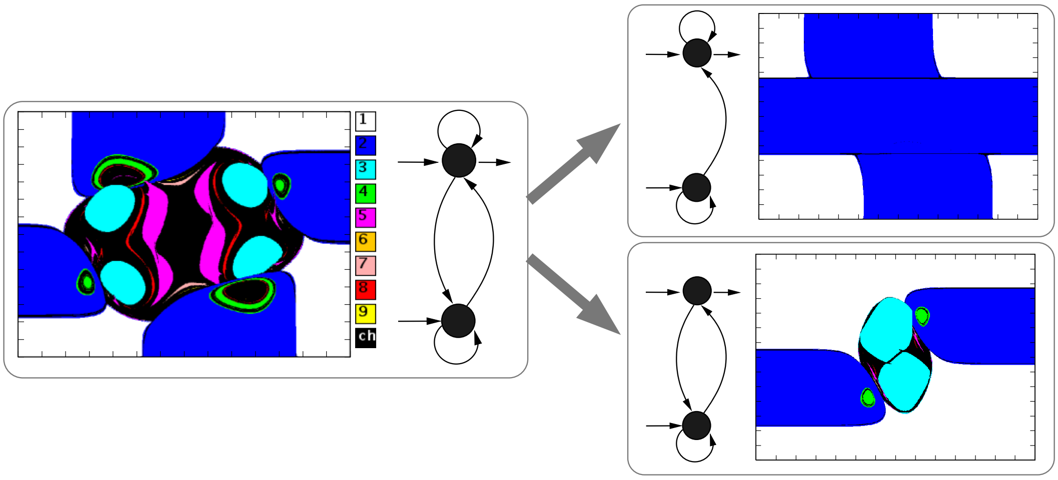

Figure 2.8: **The weak causality of structural evolution.** Left: RNN discussed in Figure 2.6 and its attractor map. Right: The removal of a single synapse significantly changes the attractor landscape.

of an agent, small changes at the neural level can strongly influence their performance. Therefore, it is important that parents and their offspring are evaluated together and undergo the selection process because it may happen that all offspring perform significantly worse than their parents due to the weak causality. However, this also means that the opposite is possible: Small variations may lead to much improved offspring which can then be observed as sudden jumps in the fitness development, as we will see it for instance in Chapter 7 (e.g., Figure 7.12, p. 161). Thus, weak causality may help to escape from local optima, which is rather complicated when strong causality is assumed.

To conclude the discussion about structural evolution, in a first step to minimize our preconceptions about which kind of control architectures and which kind of dynamical properties are required for a particular behavior, we include the evolution of the topologies of RNNs and do not only evolve their parameters, as it is still very common in the field of *evolutionary robotics* (for a few exceptions see, for instance, Nolfi and Parisi, 1995; Harvey et al., 1997). A very pragmatic reason for structural evolution is that we usually do not know beforehand which structure is most suitable for a particular task. That means, if we would evolve only the parameters of our networks, we would be forced to try several configurations. The study of Psujek et al. (2006) showed how exhaustive this configuration space can be. They tested different neural architectures for their evolvability in a simple walking task. In their case there were 64, 4096, and 528,284 possible distinct architectures for a three-, four-, and five-neuron network (without self-connections!), respectively. They could indeed demonstrate that some types of architectures out of this vast pool of possibilities showed a significant higher evolvability, that is, they led to a much better performance than others. Now, it is obvious that oscillatory networks may be required for walking and, therefore, one could choose architectures which allow for oscillations for this particular task. However, usually it is rather complicated to anticipate which dynamics and, therefore, what kind of architectures are needed for certain behaviors. For instance, what is needed for cooperative or competitive behavior, or for communication? To investigate this question with evolutionary methods, an appropriately designed fitness function is required.

2.5.4 Fitness functions

A central problem in ER is the design of fitness functions which determine the performance of the evolving individuals and, thus, their selection criteria. Jin and Branke (2005) identified four major problems which we will put in the context of evolutionary experiments with autonomous robots (see also Hülse, 2007):

1. **Noise**: The sensory-motor system of a robot is always subject to noise. This can lead to different fitness values of several evaluation trials under identical starting conditions and environments.

2. **Robustness**: Perturbations of design variables lead to different fitness values. Such design variable can be varying starting positions of a robot or environmental parameters like position of obstacles or targets within the environment.

3. **Fitness approximation**: The use of meta-models influence the fitness value, like the use of simulations instead of real robots.

4. **Dynamic environments**: The environment may change during the evaluation time and, therefore, the fitness function varies in time.

We will now discuss methods to approach those problems as they are used in this thesis.

Robustness and structural complexity of evolutionary solutions

We have seen that the evolution based on the ENS^3 algorithm proceeds in a repeat-until loop as long as a special stop criterion is not fulfilled. Up to now there is no formal stop criterion implemented. The user has to decide, when to stop the evolution. This is not a lack of implementation, we argue it is necessary. The most obvious criterion to stop an evolutionary process is the development of the fitness values. However, there are two additional demands, robustness and structural simplicity of evolved solutions.

With robustness we mean, that the behavior of evolved individuals should be sufficiently good despite the noise of their sensory-motor system and despite their initial conditions. A good example is the classical light seeking task, where a robot should explore its environment without bumping into obstacles and find a light source as fast as possible. If we would evolve such a task without varying the initial conditions, such as the location of the light source, the starting position of the robot, or the locations of obstacles, it may happen that solutions come up which are specialized for specific configurations of initial conditions, but would fail in other configurations. We call such individuals specialists. Our interest is, however, in generalists which show robust behavior with respect to their sensory-motor noise and varying initial conditions. For this reason initial conditions are varied from generation to generation while a given configuration is equal for all individuals within the same generation.

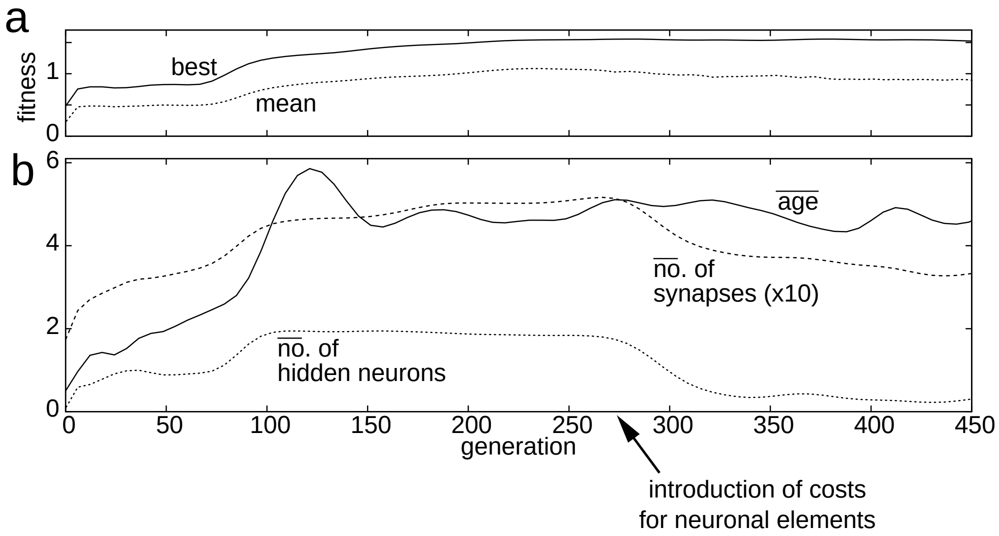

Figure 2.9: **Stop criteria.** Important parameters for determining when to stop an evolutionary process (shown is a smoothened development of parameters from a particular run during the experiments described in Chapter 6). A: Fitness development of the best individual and the average of all individuals. B: Average number of survived generations (age), of synapses, and hidden neurons.

As we said already, parents and offspring form the next generation after a selection process. Therefore, the number of generations a particular individual survives (i.e., it is always selected as a parent) indicates its ability to handle various initial conditions. We call the number of survived generations the 'age' of an individual. Thus, a low age indicates specialists which probably became parents because they could handle a specific initial configuration sufficiently well. The higher the age of parents becomes, the more generalists we expect.

The second criterion, structural simplicity, relates to the size of the evolved neural structures. As we previously emphasized, our main aim is to keep the systems analyzable. It is plausible that smaller RNNs, that is, RNNs with a small number of hidden neurons and synaptic connections, are more feasible from an analytical point of view. Thus, we as the observer prefer small structures of evolved solutions, which does not inevitably imply trivial dynamics (cf. Section 2.4.3).

Figure 2.9 shows the development of the parameters crucial for us to determine when to stop an evolutionary process. The figure illustrates a typical evolutionary run (data taken from the experiments described in Chapter 6). We see the fitness development of the best performing individual and the mean of all individuals in each generation (Figure 2.9a). During the first 250 generations the fitness value develops toward a plateau. At generation 275 we introduced costs for neural elements (hidden neurons and synapses). These costs reduce the fitness value of an individual depending on its number of neural elements. Thus, in the case of similarly well performing individuals, the individual with the smaller RNN has a higher chance to get selected as a parent for the next generation. The influence on the size of evolved solutions is shown in Figure 2.9b. We see how the average number of neurons and synapses decreases after the introduction of costs while the average age and the performance of the best individuals remains at the same level.

Of course, one has to be careful with cost parameters. If they are too high, it may happen that RNNs without any behavioral functions are favored just because of their small size. Thus, cost values depend on the current fitness level and the current average size of the networks. Because fitness level and average size of networks can vary significantly from task to task, and even from one evolutionary run to another with the same task, the user has to change these values on-the-fly. That is also the reason why the user has to stop the evolutionary process when a reasonable fitness is achieved, the behavior is satisfactory, solutions are robust, and RNNs are structurally small. These criteria are hard, if not impossible, to formalize especially because they are highly task-dependent.

To come back to the problem of noise and robustness, we have seen how the number of generations an individual survives, that is, its age, indicates how robust an individual is with respect to noise and varying conditions. Because this thesis deals with groups of cooperating agents, a second method to deal with noise and achieve robust solutions is to consider the performance of the group as the selection criterion instead the individual performance.

Group selection In evolutionary biology, group selection (Wynne-Edwards, 1986) refers to the idea that genes spread in a population because they are beneficial for a group regardless of the individual fitness. As much as there is severe criticism on group selection as a major selection mechanisms (Maynard Smith, 1964; Dawkins, 1976; Dennett, 1994), there is also a rising favor for its general idea, especially for explaining the evolution of altruism. Still insisting on individual selection, Hamilton (1964) approached this problem with taking into account also genetic relatedness among individuals of one species. This led him to his famous postulate which tries to explain altruistic behavior:

$$rb > c, \tag{2.3}$$

where c is the cost for the actor, r the genetic relatedness between actor and recipient, and b is the benefit for the actor. Costs and benefits are measured in reproductive success. Thus, according to Hamilton's rule altruistic behaviors become more probable the closer the actor and the recipient are genetically related (kin selection). Later on, Wilson (2005) modified Hamilton's rule to: $rb_k + b_e > c$, where b_k still refers to kin selection but b_e is the benefit accruing to the whole social group independent of the genetic relatedness. Wilson claims that $b_e >> b_k$ in the present state of evidence from studies of social insects and that, therefore, altruism should be explained more at the colony level than at the level of kin. For criticism see for instance (Foster et al., 2006; West et al., 2007). We will leave the debate at this point with the conclusion that it is still controversial whether group selection is an important factor or whether it can always be explained by kin selection alone.

In this thesis, we take a rather pragmatic approach to group level selection. Except of one occasion all experiments deal with homogeneous groups of agents, that is, agents are identical concerning their morphology as well as their control architectures. During evolution each generation consists of several different RNNs (parents and offspring). For evaluation each RNN is copied and distributed to the agents which form a group.

In this sense all group members are clones, that is, after Equation 2.3 is $r = 1$. The success of a group is measured in terms of fitness values (as opposed to reproductive success in Hamilton's equation), this can be either the collective performance of a group (Chapter 3) or the average performance of all individuals in a group (Chapter 4, 6, and 7). Thus, whatever is a beneficial behavior for the group is automatically beneficial for an individual agent. This simplification enforces the emergence of cooperative behavior, if possible, in groups of interacting agents, and that is what we are aiming at in this thesis.

In both cases, collective performance measurement as well as averaging of individual performances, many individuals contribute to the selection criteria of a single RNN. And especially in the latter case we automatically reduce the perturbations of the fitness function caused by noise or varying conditions because we average the performance of single individuals (which all have different initial conditions) within a group. Thus, we average the performance of a single RNN in one trial instead of averaging it over several evaluation trials which makes the fitness value more reliable and saves a lot of computation time.

Using group level selection with homogeneous agents to facilitate the development of cooperation and communication is supported by the study of Floreano et al. (2007). They tested individual versus colony level selection with either homogeneous or heterogeneous groups of robots. Their results indicated that the evolution of communication is more likely in groups of genetically identical individuals selected at the colony level.

Fitness function approximation

The third issue raised by Jin and Branke (2005) is the problem of fitness function approximation. In the context of ER this becomes relevant when using simulations of robotic systems. Besides the ease of data collection, simulations are usually the preferred tool to apply evolution because evolution with real machines is time expensive and miss-performing solutions may severely damage the physical hardware. On the other hand, when simulations are used it is often difficult to guarantee that evolved solutions perform equally well on the target system, the physical robot. And even if we obtain similar performance, the fitness would always differ between evaluations in simulation and on real robots. That is why simulations as meta-models can only approximate the fitness.

One solution to minimize the resulting approximation error would be to simulate the real system as accurate as possible which entails the risk that simulations loose their advantage of being much faster than evaluation in hardware. The question is, how accurate must a simulation be? Brooks doubted that controllers developed in simulations would be transferable to real robots:

> "There is a real danger (in fact, a near certainty) that programs which work well on simulated robots will completely fail on real robots because of the differences in real world sensing and actuation. [...] sensors [...] simply do not return clean accurate readings. At best they deliver a fuzzy approximation to what they are apparently measuring, and often they return something completely different."
>
> *Brooks (1992, p. 4-5)*

To address this issue Jakobi et al. (1995) (see also Jakobi, 1997) proposed the use of *minimalistic simulations* which include only relevant real world properties, that is, properties relevant for the target behavior. For instance, for a small wheel driven robot gravitational forces or inertia of the body are not as relevant as for a legged robot, whereas friction with the ground is highly relevant for both. Thus, to built a sufficient simulation a collection of empirical data is required which has to be validated for their relevance and then implemented into the simulation model. Comparative tests between the behavior in simulation and the real robot are essential. Special attention should be paid to the inclusion of sensory-motor noise with an appropriate level comparable to the noise level of the real sensors and motors.

To give an example, most of the robotic systems discussed in this thesis rely on infrared sensors to measure the distance to objects. If we would simulate this kind of sensors similar to their real characteristics, that is, emitting infrared radiation and measure the intensity of radiation reflected from objects, the simulation would tremendously slow down because one robot relies on several of these sensors and we want to simulate many robots, up to 150. However, the relevant information is the distance to an object. Therefore, in simulation we would simple attach a ray to the robot with a length resembling the range of the real infrared sensor. Whenever this ray intersects with an object, the depth of this intersection gives us the distance to an object. Finally we would add noise to this virtual sensor which resembles the noise empirically measured with the real sensor.

For simple sensory-motor systems the *minimalistic simulation* approach proved to be successful when it comes to the test on real robots (see, for instance, Jakobi et al., 1995; Hülse et al., 2004; Manoonpong et al., 2007). And in this thesis we will use only robots with simple or, as we prefer to say, minimalistic sensors and actuators. However, we should note that for more complex systems, such as visual information processing of cameras, evolution directly on the real systems should be preferred[8]. First studies with rather simple robots showed possibilities to overcome the difficulties of evolution in the real world, such as continuous power supply, fitness calculation, exchange of genetic material, and so on. This approach is subsumed under the term *embodied evolution* (for examples see Watson et al., 2002; Mondada and Floreano, 1995; Nolfi et al., 1994; Floreano and Mondada, 1996).

2.5.5 Fitness functions for open-ended and creative evolution

As we have seen, one of the most crucial aspects of artificial evolution is the design of fitness functions which rate the performance of an individual with respect to an expected behavior. However, often we do not know exactly how a specific behavior is beneficial for a given problem. In contrast to a pure optimization process, this aspect is not a problem here. It is even desirable, because using exact a priori descriptions of behaviors shall be prevented as much as possible.

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[8] An interesting 'hybrid' approach to this problem is taken by Floreano et al. (2005). They evolved neural networks for an outdoor robot which could navigate by camera vision. The synaptic connections from the visual photo-receptors to hidden neurons could be changed via Hebbian plasticity while the robot was moving around. In this way solutions evolved in simulation performed very robust on the real robot in outdoor environments.

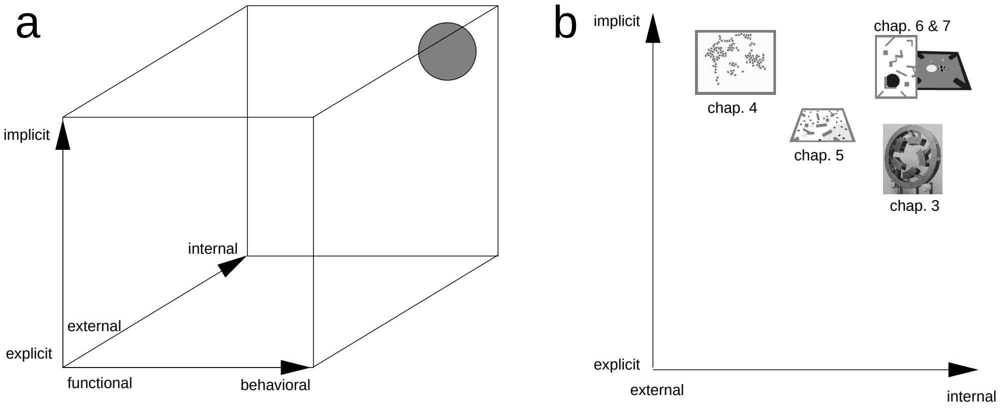

Figure 2.10: **Fitness function design.** A: Space to describe and design fitness functions (adapted from Nolfi and Floreano, 2000). Ideally, fitness functions should be located in the top corner (see text for details). B: Rough classification of the experimental studies discussed in this thesis (fitness functions have exclusively behavioral characteristics).

Nolfi and Floreano (2000)a used three dimensions to describe the fitness space for ER experiments (Figure 2.10). *Functional-behavioral* relates to whether specific functional control aspects are rated or whether the behavioral outcome is rated. Take for instance that task of walking in a multi-legged robot. One can reward specific oscillatory neural activities which are defined beforehand to be beneficial for walking (functional) or one can just rate the distance the robot is traveling (behavioral). *Implicit-explicit* relates to the number of variables and constraints given by the fitness function. For instance, for a foraging task, one can define explicit variables that reflect how well the robot explores the environment, how fast it finds energy sources, etc., or one can simply set the implicit constraint that the robot 'dies' as soon as it runs out of energy. *External-internal* relates whether variables and constraints are used which are also accessible by the agent through its sensors (internal), or whether global variables are used which are hidden for the agent (external).

In this thesis, we completely exclude functional considerations because our motivation is to find out which mechanisms emerge for a specific behavior. Furthermore, because we want to minimize our preconceptions about the target behavior itself, we try to keep our fitness functions as implicit as possible. Considering the frame of reference problem, only internal variables should be used to translate the perspective from the observer to the agent. Thus, in the best case our fitness functions would be placed in top right corner of the fitness space given in Figure 2.10a. Figure 2.10b roughly indicates the location of the experimental studies described in the following chapters. Since our fitness functions are never functional, there are only two dimensions left. As one can see, we try to keep fitness functions as implicit as possible using, if possible, only internal variables. In this manner, we not only reduce our preconceptions but we also give ground for truly open-ended and creative evolution.

In the most reduced case, the fitness function defines solely a general survival criterion of individual agents, such as maintaining its energy level. In order to survive, individuals have to compete for limited resources and are not selected for specific high-level goals. Thus, we abandon extrinsically defined fitness functions that select individuals which are optimized for a specifically given task (Taylor, 2001).

Bianco and Nolfi define open-ended evolution in the context of ER as follows:

> "By open-ended evolution we mean an evolutionary process that leads to a large variety of qualitatively different solutions and to the development of novelties, that is, new traits that tend to be retained for long evolutionary periods and to constitute important building blocks for further evolutionary stages. Examples of major novelties discovered by natural evolution are: multi-cellular individuals, new cell types (e.g. the neural cells) and new organs and systems (e.g. the central nervous system)."
>
> *Bianco and Nolfi (2004, p. 228)*

However, we have to admit that with the current state of the art in evolutionary robotics the evolutionary development of novel components within a robot itself can not be realized. This is one reason why we can not expect cognition as defined by Maturana and Varela (1980) (see discussion in Section 2.3, p. 39). However, even with the systems we have nowadays, as limited and simple they are compared to natural organisms, we can expect the emergence of novel, unexpected, and creative behaviors. Bianco and Nolfi (2004) identified three major factors necessary to promote open-ended evolution:

- **Favorable organization of the evolving individuals.** This point refers to the development of novel phenotypic characteristics not only as a result from the selection criteria but also from the current organization of evolving individuals. As we said, the only structural changes we consider here are changes at the neural level. Thus, we can not expect the emergence of new behaviors which do not exclusively increase the performance of evolving individuals with respect to a given selection criterion. However, as we will see especially in Chapter 6 and 7 novel and unexpected neural mechanisms do emerge.

- **Changing environmental conditions.** This brings us back to the fourth problem Jin and Branke (2005) defined for the evaluation of fitness functions (see Section 2.5.4, p. 59). In the context of open-ended evolution, changing environments are not a problem, actually they are a prerequisite. This distinguishes open-ended evolution from a mere optimization process. In an open-ended scenario individuals will never converge to a specific predefined optimum. In the most desirable case, evolving individuals are part of an ecosystem where their behavior is not only reciprocally coupled with the environment, but also with other evolving individuals or species. We can now return to the concept of structural coupling proposed by Maturana and Varela (1987) (Section 2.3, p. 40). Permanent mutual perturbations between individuals and individuals and their environments trigger structural changes in all interacting systems. Thus, individuals and environments underlie a continuous development which does not converge toward a specific steady state. The only steady state individuals strive toward is the maintenance of their organization which guarantees their survival and reproductive success.

In this thesis, environmental conditions do not change as a consequence of structural coupling. The only way in which environments change is due to us. We will change the environmental conditions when individuals reach a certain level of behavioral complexity. For instance, in Chapter 6 we investigate the evolution of cooperative foraging in a single group of homogeneous agents in an environment with limited resources. Once individuals are successful in surviving in this environment, we introduce another group of agents which now compete for the same limited resource. At the same time we enrich the environment by additional qualities of energy supply. We then focus on how the behavior changes when specific aspects of the environment are changed.

- **Implicit and general selection criteria.** We think that is the most important factor to promote open-ended and creative evolution. That is why it will be a focal point of this thesis (see Figure 2.10b). In fact, the more general and the more implicit fitness functions are designed the more novel and creative behaviors we can expect to emerge from an evolutionary process as we will see in Chapter 6 and 7.

2.6 Summary

At the beginning of this chapter we motivated the experiments of this thesis by biological research on cooperation and communication. We clarified that there is a need for a complementary approach. The unified methodology proposed here aims at investigating cooperative behavior based on communication from three different perspectives: the *cybernetic perspective*, the *dynamical systems perspective*, and the *evolutionary perspective*. The research presented here deals with abstract models of: simple animal-like behaviors, recurrent neural networks, and artificial evolution. The motivation for these abstractions can be summarized as follows:

- Why robots?
  - They keep our focus on complete systems which may be simplified, but not idealized.
  - They allow the exploitation of sensory-motor feedback loops.
  - They are grounded in the real world.
- Why RNNs as dynamical systems?
  - RNNs are composed of simple elements, and the interactions between these elements embedded in a situated body allow the exploitation of a rich dynamical repertoire for adaptive behavior.
  - They reject the need for explicit knowledge about the world.
- Why evolution?
  - Evolution reduces our preconceptions about particular behavioral aspects and their underlying mechanisms.

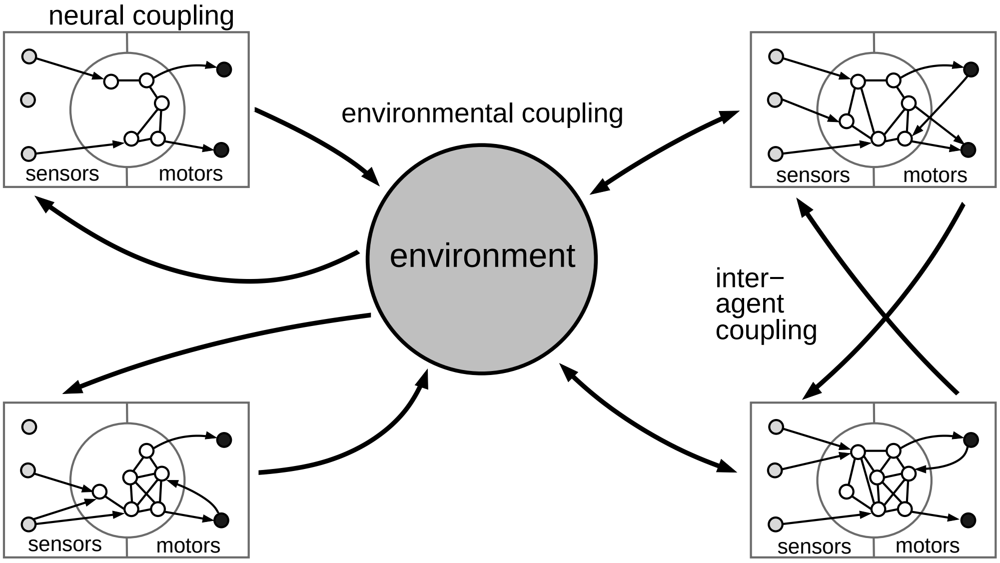

Figure 2.11: **The coupling between an individual, its environment, and other individuals.**

– It allows the emergence of truly novel and creative behavior.

Here, special attention is directed toward the development of open-ended evolutionary scenarios which may generate sophisticated cooperative behavior while transferring the perspective during this developmental process from us, the observer, to groups of autonomous situated agents.

Once such behaviors have evolved, the simplifications or abstractions we made about the complexity of an individual, its nervous system, and its environment, should enable us to investigate the underlying mechanisms and the structural coupling between an individual and its environment, including other individuals. The different levels of coupling we are interested in are illustrated in Figure 2.11.

We are interested in the connection between the dynamical processes, internal to an agent, and the resulting behavior and how this behavior influences the environment with which the agent is reciprocally coupled through the sensory-motor loop. However, agents do not only interact with their environment, they also interact with other individuals, either indirectly through the environment or directly through communication.

At the end of this thesis, we will show how it is possible to generate social behavior, which include aggressive interspecific and cooperative intraspecific signaling, with an rather unconstrained evolutionary process. Even though the behaviors by themselves are still far away from the complexity of natural species, they are, to our knowledge, at the edge of current artificially generated robotic behaviors. And the main contribution of this thesis is that we can explain at every level, from individual neuron dynamics to interactions in robot groups, how and why the social behavior is generated (proximate and ultimate explanations), thus, turning seemingly complex behaviors into complicated and thereby understandable behaviors.

Chapter 3

Cooperation without explicit communication channels

> "Some people say that point attractors are boring and nonbiological; others say that the only biological systems that contain point attractors are dead ones. That is sheer nonsense from a theoretic modeling point of view, as it ignores the crucial issue of what fixed points refer to. When I talk about fixed points [...] it will be in the context of collective variable dynamics of some biological system, not some analogy to mechanical springs or pendula."
>
> *Scott A. Kelso (1995, p. 53)*

3.1 Introduction

Many biological examples, such as ant societies (Wilson, 1971) or schools of fish (Camazine et al., 2001), exhibit complex collective behavior patterns while the behavioral capabilities of each individual seem rather simple, compared to the global behavior of the group. Such societies are highly decentralized and often the rules which determine the interactions among conspecifics are rather simple and locally limited. Especially for insect societies it is well known that communication heavily relies on implicit information sharing: Individuals communicate by modifying their local environment, a mechanisms known as stigmergy (Grassè, 1959; Theraulaz and Bonabeau, 1999). Decentralization and locally limited interactions make such societies highly robust and flexible to disturbances, like predation, individual failures, and environmental changes.

In this chapter we investigate concrete examples which realize a decentralized control approach in the context of evolutionary robotics experiments while fulfilling our methodological demands discussed in Chapter 2. We discuss why and how distributed control facilitates robustness and resilience to individual failures compared to centralized organizations. We see how evolution develops control systems which heavily integrate feedback loops with the environment and how this results in a surprising simplicity at the individual neural control level. Eventually, we discuss how independent autonomous agents interact with each other to cooperatively accomplish a global function even though they lack the ability to directly communicate with each other.

3.2 A minimalistic robot for the study of cooperative behavior

Originally developed by Julius Popp as an art object, the robot *micro.eve* will serve us in the following as a minimalistic physical model to investigate the emergence of cooperation. The robot, shown in Figure 3.1, is a solid metal ring placed on two supporting rollers. Five movable arms are connected to this ring. A servo motor is located in each arm which allows active movements by translating the arm's center of mass. To achieve a steady rotation of the ring a coordinated motion of these five arms is needed.

We might compare this behavior to a mouse jogging in a running wheel. By running in one direction the mouse dynamically translates the overall center of mass of the wheel-mouse-system to one side which keeps the wheel spinning. Similarly, we can consider the ring of the robot as the environment for the five movable arms, our agents in this case. In contrast to the mouse, our robotic arms are physically connected to the ring. Imagine five mice roped, equally distributed, to one running wheel. If they still want to move the wheel in this uncomfortable situation, they have to move their bodies back and forth because they are not able to run anymore. And they have to coordinate these movements to achieve a steady rotation of the ring. Most likely because of the very unnatural experimental setup, you will hardly find such a behavior of mice occurring naturally. But one might train them to do so by providing positive rewards for a steady rotation of the wheel. In our robotic system a specifically designed fitness function will represent such a reward, although, to be correct, we should call it the selection criteria of an evolutionary process.

Why is this rather simple system of interest? First of all, because it is an autonomous robot and, thus, fulfills our demand for a complete system. Second, it is simple and we, therefore, expect that only a structurally small control system is necessary which allows a thorough analysis of the overall system. Third, and that is the main motivation for the following experiments, it is obvious that only a coherent behavior of the subsystems (i.e., individual arm movements) can achieve a functional global behavior (i.e., a steady rotation of the ring). Therefore, this system allows us to study the evolutionary development and behavioral mechanisms of three fundamentally different control approaches.

In the first approach, the rules which determine the interaction between the subsystems emerge from a single RNN, that is, from a *centralized control* which is responsible for realizing the global function of the system by correct associations between the sensor and motor units of the robot. Then, to realize a shared responsibility a *distributed control* approach is pursued. There, each arm is considered as an autonomous agent having its own control system which has only access to local sensor information and which can also act only locally. Such a distributed system is realized in two different ways. We will discuss a *homogeneous system*, that is, every agent has an identical controller, and a *heterogeneous system*, where every agent can have a different controller, which may result in a division of labor.

High fault-tolerance and robustness is an intrinsic property of biological self-organized distributed systems (Camazine et al., 2001; Resnick, 1994). In this context, in our experiments we expect better performance of decentralized systems compared to central-

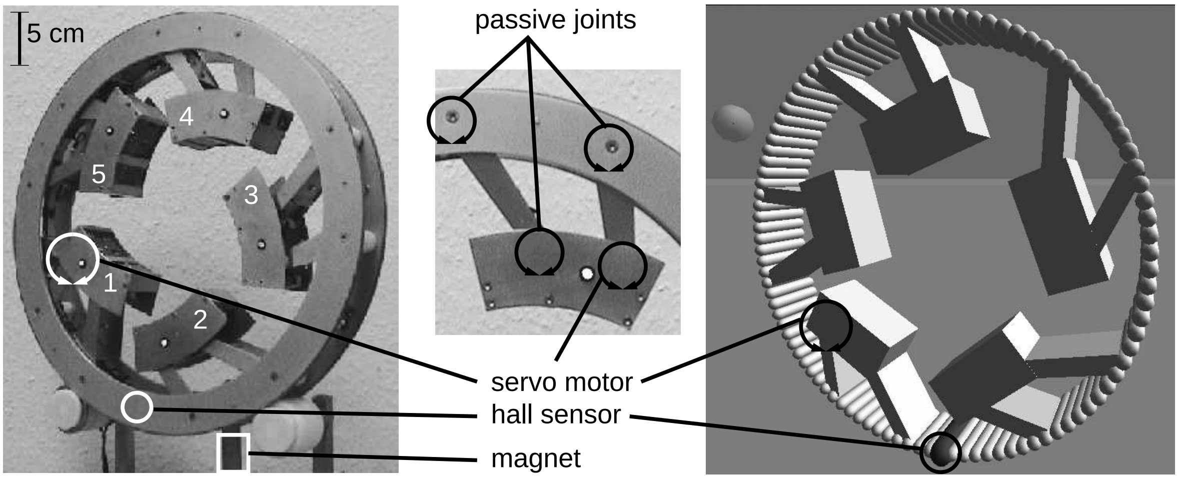

Figure 3.1: **The artbot *micro.eve*.** Left: physical implementation; right: simulated model. Each arm is connected to the main body by four joints, three are passive and one is actuated (shown for a single arm). There are five hall sensors, each located between two consecutive arms (only one is shown), which emit a peak when they pass the magnet at the bottom of the robot.

ized organizations. But do we also find a significant difference between homogeneous and heterogeneous distributed systems? And how is cooperation carried out between autonomous agents in a distributed system? Of special interest is the realization of interaction rules because individual agents in a distributed system can not communicate with each other via dedicated channels. Do homogeneous agents interact differently than heterogeneous agents? If so, are there any differences concerning robustness and resilience?

Thus, even this simple system poses many questions. Their answers will become relevant for the next chapters and might be of general interest for our understanding of collective behavior among autonomous agents. Before we try to answer the questions by concrete examples of evolved control systems, we have to clarify the general experimental setup first.

3.2.1 Sensory-motor system

The sensory-motor system of the robot consists of five actuators, one motor in each arm, five potentiometers which measure the actual position of the motors, five hall sensors, and one gyroscope.

For the following experiments RNNs as described in Section 2.4.1 (p. 43) are used with the transfer function $f(x) = tanh(x)$. Thus, the output of each neuron is $o \in (-1, 1)$. Therefore, motor and sensor signals of the robot are mapped into this interval. Note that Ix, Ox, and Hx refer to input, output, and hidden neurons with index x, respectively; and ix, ox, and hx refer to the corresponding output of these neurons.

Motors

The only actuators of the robot are the five arm motors. From its zero position each motor can rotate about 0.3 radian clockwise and counterclockwise. A clockwise rotation will move the arm closer to the ring periphery (see Figure 3.1). Accordingly, a counterclockwise rotation moves it closer to the center of the ring. For neural processing the working range of each motor is linearly mapped to $[-1, 1]$, where -1 corresponds to a maximal clockwise rotation and $+1$ to a maximal counterclockwise rotation.

Hall sensors

The sensory system consists of potentiometers in each motor, a gyroscope located inside the ring, and five hall sensors equally distributed over the ring. Each hall sensor is located between two arms, respectively. These hall sensors are binary switches emitting a peak if they pass a magnet placed at the bottom of the ring (see Figure 3.1). All five hall sensors are merged to one sensory input relative to the arm index, that is, for each arm the next hall sensor to the right has the index 1. The arm and hall sensor indices are incremented counterclockwise. The mapping (i, s_i), where i denotes the index of the last activated hall sensor and s_i the according sensor value, is as follows: $(0, 0.0); (1, 1.0); (2, 0.66); (3, 0.33); (4, -1.0); (5, -0.33)$. Because the output of the input neuron, which provides the hall sensor information, should be zero if no hall sensor is activated ($i = 0$), the use of this discrete mapping was chosen instead of a monotonic function. Accordingly, within the decentralized control approach each agent which controls a particular arm has it its own sight on the hall sensory information.

To reduce the amount of input neurons for the centralized control structures the sight of the first arm is provided as the only hall sensory input.

Potentiometers and gyroscope

The sensor values of the potentiometers, which provide information about the actual motor position, are linearly mapped to the interval $[-1.0, 1.0]$ according to the mapping of the motor command signals as described above.

The gyroscope values are transformed to an angular velocity of the ring with a maximum at 0.5 rounds per second. For the input of the neural network these values are also mapped to the interval $[-1.0, 1.0]$, where negative values indicate a counterclockwise and positive values a clockwise rotation.

To both sensor modalities Gaussian noise is added with $\sigma^2 = 0.1$ (i.e., 5% noise).

3.2.2 Fitness function

All evolutionary developed RNNs are evaluated on the following fitness function:

$$F \;=\; |\overline{\omega}| \left(1 - \frac{\sum_{t=0}^{n} |\omega(t) - \overline{\omega}|}{2n}\right) \quad \text{with} \quad \omega \in (-1, 1), \tag{3.1}$$

where n is the number of evaluation time steps and ω the angular velocity of the ring represented by the mapped gyroscope sensory input of the RNN. Therefore, fitness values are always between 0.0 and 1.0. The left term ($|\overline{\omega}|$) rewards a high mean velocity and the right term rewards a harmonic rotation.

This is an *implicit fitness function* based on internal variables (recall Section 2.5.5, p. 63), that is, no global knowledge is used. Parameters of the fitness function are solely determined by sensor information that are accessible by the agents. It does define neither how the arms have to move individually nor how they have to interact with each other to coordinate their behavior. Thus the rules which define the interactions between the neural elements at the individual control level and between the arms at the global behavior level are not predefined but they are expected to emerge from an evolutionary process.

To avoid a possible dominance of specialists (refer to Section 2.5.4, p. 59) RNNs are evaluated on 20 trials with different, randomly chosen (uniformly distributed), initial conditions. These are the ring rotation (varied in the full range of $[-\pi, \pi]$) and the motor position of each arm actuator (varied within the complete working range). The resulting fitness value is the mean fitness of these 20 evaluation trials. One evaluation trial lasts $1,200$ time steps (corresponds to 120 seconds of real time).

3.3 One robot, one controller

The most intuitive way to evolve RNNs for the robot *micro.eve* is to use all the provided sensory information and motor control commands as inputs and outputs of a single RNN, respectively. Before we can discuss the advantages of decentralized solutions with respect to robustness, we need to clarify the neural mechanisms of an evolved centralized neural network first (and of decentralized architectures later).

3.3.1 Neural mechanisms

A successfully evolved centralized RNN is shown in Figure 3.2a. Figure 3.2b shows the motor output signals of each motor neuron controlling a particular arm and the input neuron signals of the hall and ring velocity sensors. We identify one motor neuron, $O5$, exhibiting period-2 oscillations. These oscillations are due to an over-critical negative self-connection [1] (Figure 3.2a) and persist for all the time (Figure 3.2b).

$O2$ and $O4$ are mainly controlled by the hall sensory input. A strong synapse projects from $O4$ to $O1$. Thus, $O1$ is indirectly driven by the hall sensor, too. $O3$ gets a strong input from $I3$ which is directly influenced by the output of $O1$. $O3$ is, therefore, also strongly, even though again indirectly, influenced by the hall sensor activation.

What does this mean for the behavior of the robot? At the beginning the hall sensor is inactive. Hence, the signal of the according input neuron is zero. Referring to Figure 3.2b, most of the motor neuron signals ($O1$-4) stay or fluctuate with small amplitudes around an output value according to their bias terms and/or the input of other neurons. Therefore the overall center of mass of the ring is translated once when these motors move away from their initial positions. Thus, the ring may rotate a

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[1] By over-critical we mean a weight configuration leading to dynamics beyond single fixed point attractors (for details see Pasemann, 1995a, 2002).

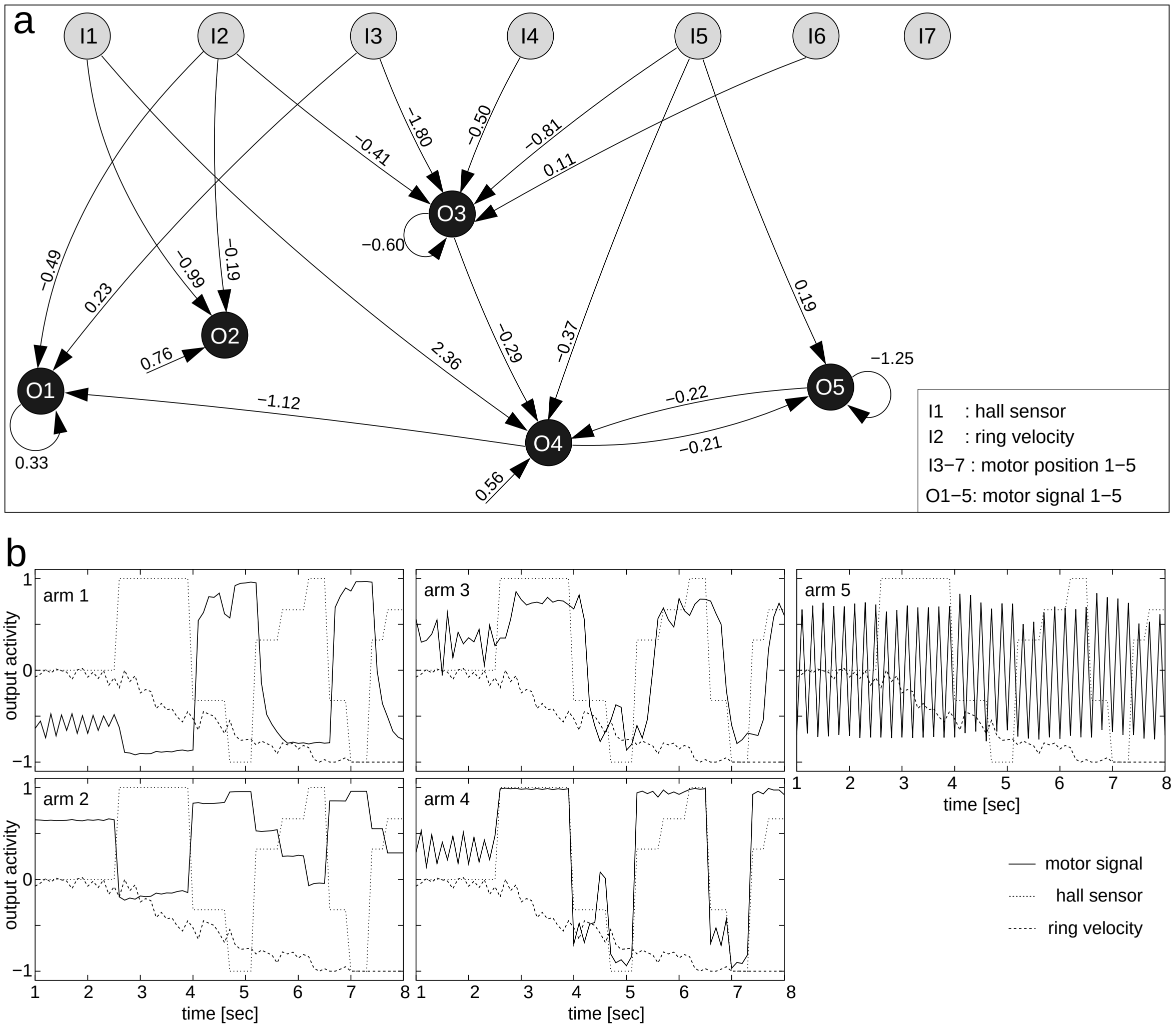

Figure 3.2: **Centralized control.** a: Global RNN controlling the robot *micro.eve* (cf. Figure 3.1). b: Output activity of selected neurons (see text for details).

little depending on the starting conditions. If the initial motor movements are strong enough, the resulting ring rotation may suffice to activate a hall sensor if this is near the magnet (cf. Figure 3.1). If this initial movement is insufficient to trigger one hall sensor, the rotation would stop because most of the motor signals ($O2$ and $O4$ directly, $O1$ and $O3$ indirectly) depend on this input and the according arms would not move anymore (output oscillation with small amplitudes are almost completely compensated by friction and inertia). In this case, due to the period-2 oscillations with a high amplitude of motor neuron $O5$, arm 5 oscillates accordingly, although with a smaller amplitude (because of friction and inertia, see Figure 3.3). This will move the ring very slowly, rather in rapid successive small steps, until the hall sensor becomes activated which changes the output of neurons $O1$-4. Than the rotation starts and is maintained as it can be deduced from Figure 3.2b (compare motor neuron outputs with the development of the ring velocity).

For most of the time, we observe two pairs of output neurons producing opposed

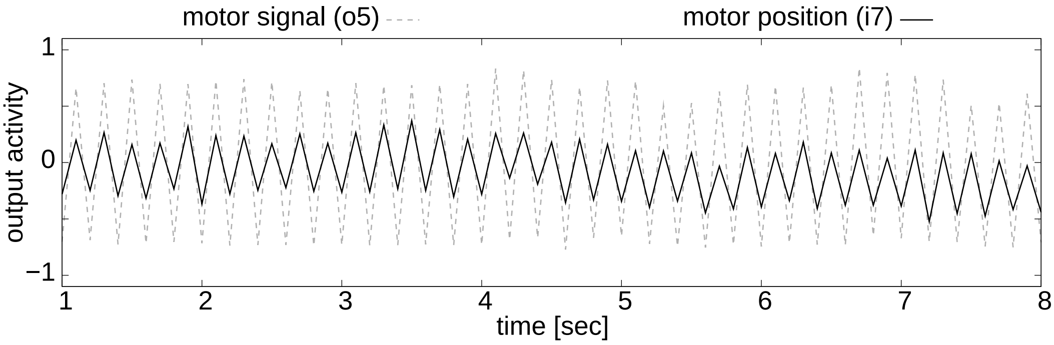

Figure 3.3: **Influence of inertia and friction.** Signal from motor neuron $O5$ (cf. Figure 3.2) and the actual motor position measured by the according potentiometer. Because of inertia and friction, the motor oscillates with a much lower amplitude compared to the according motor neuron output.

signals ($O1$ & $O2$ compared to $O3$ & $O4$) due to positive and negative feedback from the hall sensory input. This means that two arms translate their masses to the center of the ring while, at the same time, two other arms translate their masses to the ring periphery and vice versa. This action maintains the ring rotation by dynamically translating the overall center of mass to one side.

3.3.2 Main characteristics

To this point, we should keep in mind two major characteristics. First, the behavior of each single arm is mainly determined either by *intrinsic dynamical properties* of the neural network or by agent-environment interactions. Second, as a consequence of evolving unconstrained[2] centralized control architectures, we find direct couplings, via synaptic links, between the motor neurons which control the individual arms.

Intrinsic neural dynamics and agent-environment interaction

Two main mechanisms are responsible for two different sub-behaviors, respectively. First, oscillations are important to initialize the rotation. These oscillations are due to intrinsic dynamical properties, such as the period-2 oscillations of $O5$. Second, to maintain a steady rotation of the ring opposing arm movements are necessary as they are caused by the activity of $O1$-4. This behavior results from the interaction with the environment, in particular from a strong feedback of the hall sensor whose changes are, in turn, a result of the coordinated arm movements.

Recalling Section 2.3 (p. 39), we can already find two types of structural coupling in this simple, but *complete* system: The coupling of an agent with its environment, and the coupling intrinsic to an agent's control architecture (i.e., neural coupling).

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[2] By unconstrained we mean here that RNNs are not restricted concerning the evolutionary development of their topology, that is, how neurons are connected with each other.

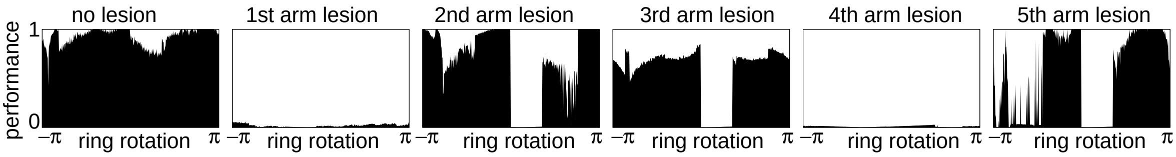

Figure 3.4: **Robustness of centralized control.** A breakdown of each arm was simulated by setting the output of the corresponding motor to zero. X-axes represent different starting conditions (i.e., initial rotation of the ring). Y-axes represent the corresponding performance (see text for details). Basically, black indicates the success of the robot in handling different starting conditions while a particular arm is deactivated.

Direct coupling via synaptic links

To return to our example at the beginning about mice roped to a running wheel, we can think about the centralized RNN in our robotic example as a human operator who controls all muscles of the five mice by observing the reaction of each mouse and the running wheel. In our case the human operator is represented by the centralized control system.

If we recall the structure of the discussed RNN (Figure 3.2a), we see that some motor neurons which control the individual arms are tightly coupled via synaptic links. We find such couplings, for instance, between $O4$ and $O1$ or between $O3$ and $O1$ via $I3$.

Are there any consequences of such a tight coupling with respect to behavioral robustness?

3.3.3 Robustness

To answer the question at the end of the previous section we conducted lesion experiments to test for behavioral robustness. Robustness means the ability to compensate the failure of individual parts which constitute the system. In this case, these parts are the individual arms of the robot. Thus, we lesioned each arm by fixating the output of the corresponding motor neuron to zero simulating a motor break down. We then measured the performance of the lesioned system according to Equation 3.1. Note, it is nearly impossible to reach a maximal fitness value of 1.0 due to the time needed to initiate a rotation. During this initialization the angular velocity cannot be constant. Therefore, the first ten seconds of an evaluation cycle did not contribute to the measured performance.

Performance was measured under different starting conditions. The initial rotation of the ring was varied within $[-\pi, \pi]$ in steps of $1°$. In each step 20 trials, each lasting $1,200$ time steps, were conducted. In each trial the initial motor positions were randomly varied within their complete working range (uniformly distributed). The average performance of these 20 trials is plotted in Figure 3.4 over the initial rotation of the ring.

If the system is not lesioned, we can see that it performs almost perfectly over the whole range. Strikingly, the system fails completely when either arm 1 or arm 4 is lesioned. Why is it such a disaster? The answer lies indeed in the tight synaptic coupling discussed earlier. A lesion of $O1$, the motor neuron which controls the first arm, indirectly also effects $O3$ because $O3$ receives its strongest synaptic input from $I3$, the motor position sensor of arm 1 (cf. Figure 3.2a). Similarly, a lesion of $O4$ has a direct effect on $O1$. In these cases the lesion of one motor neuron also affects the function of an additional motor neuron. At the behavioral level, the failure of two arms can not be compensated by the remaining two motor neurons responsible for maintaining a steady rotation (recall that $O5$ was important to initialize the rotation, but not for maintaining it). The functional loss of only one arm, as it is the case for lesions of motor neuron $O2$ and $O3$, can be compensated much better (see Figure 3.4).

With a lesion of $O5$, the neuron responsible for the initializing movements, about half of the initial conditions can still be handled. As we said previously (Section 3.3.1, p. 73), the oscillations of this neuron are important if the initial movements of all arms are insufficient to activate the hall sensory input. Thus, if a hall sensor is already close to the magnet at the bottom of the ring (recall Figure 3.1), the oscillations of arm 5 may not be needed to initialize a rotation.

It is important to note that these lesions did not occur during the evolutionary development. Of course, to improve the robustness of our system we could include such individual failures in the evolutionary process. However, we have to consider two things. First, it is almost impossible to foresee every possible failure which can occur in a robotic system. Second, even when we try to implement as much failures as we may predict, this will tremendously slow down the evolutionary process because individuals have to be tested under many different conditions.

To summarize this section about centralized control, the lack of behavioral robustness with the presented centralized RNN is mainly due to a tight synaptic coupling within the network. Failure of single neurons may propagate through the network with effects on the function of other neurons. We have seen how small disturbances can have large effects. Lesion of either neuron $O1$ or $O4$ resulted in a total loss of function. However, the same disturbances applied to the other motor neurons resulted only in a partial loss of function. The reason is rather obvious. Even though the elements of the control system, the neurons, are identical, the interactions between distinct neurons by synaptic links are different. Therefore, different motor neurons do not contribute evenly to the global behavioral function and that is why the failure of some neurons causes dramatically more damage than the failure of others.

The use of decentralized, that is, distributed, control architectures omits such a close coupling. The questions are then:

- How can unconnected autonomous systems solve a cooperative task?

- Are such systems more robust to individual failures than centralized control systems?

The next two sections will approach these questions by concrete examples of two different kinds of decentralized control systems which are either homogeneous or heterogeneous.

3.4 Homogeneous decentralized control

As we figured out in the previous section one main characteristic of the centralized control is the synaptic coupling between motor neurons which control different arms of the robot. The main purpose of this section is to show how, instead of evolving one centralized RNN, a distributed homogeneous solution can be developed. Returning to our thought experiment, there is no human operator anymore. Five identical, for instance cloned, mice have to rotate the running wheel by its own. They cannot communicate directly with each other. They even do not have any knowledge that there exist other mice with whom they have to cooperate to fulfill the task. Consequently, each individual can only act on its environment, the running wheel, and can sense changes of this environment which possibly result also from actions of other individuals.

Similar to the cloned mice in our thought experiment, the control systems of the following experiments are homogeneous. All arms are controlled by identical RNNs. However, each arm is an autonomous agent. As we already said, such an agent has only access to local sensor information and no knowledge about the other agents. Given such a system, will we find similar behavioral mechanisms as for the centralized control, in particular oscillations to initialize the rotation and opposed arm movements to maintain the rotation steady? If so, how are they realized even though all five RNNs are identical and not directly connected to each other? In other words, how can these two different functions be executed in a homogeneous distributed system?

3.4.1 Experimental differences

The main difference to the centralized system is that one RNN has only three sensory inputs which are: the current position of the motor it controls, the relative information about the hall sensor state (as described in Section 3.2.1, p. 71), and the angular velocity of the ring to which it is connected.

The evaluation was similar as described before. We used the same fitness function to determine the selection criteria (see Equation 3.1). The only difference was that we copied one RNN from the evolving population five times to control each arm. The connection between these RNNs could be realized through the environment solely, that is, the action caused by one RNN could influence the behavior of the ring which, in turn, could be sensed locally by other RNNs.

3.4.2 Neural mechanisms

Figure 3.5a shows a successfully evolved solution. Strikingly, only the hall sensor information is used. Thus, the whole distributed control system relies only on one sensor modality. Considering the motor output of each module (Figure 3.5c), we indeed find the same two main behavioral mechanisms as discussed for the centralized system. At the beginning, when the hall sensor is inactive, we see period-2 oscillations of each motor output. We find a period-2 attractor in the system which is due to the over-critical negative self-connection at hidden neuron $H1$ (see Figure 3.5a). The output of $H1$ is inverted by the negative connection from $H1$ to $O1$. Note, that in contrast to the centralized control, where only one arm exhibits these initializing oscillations,

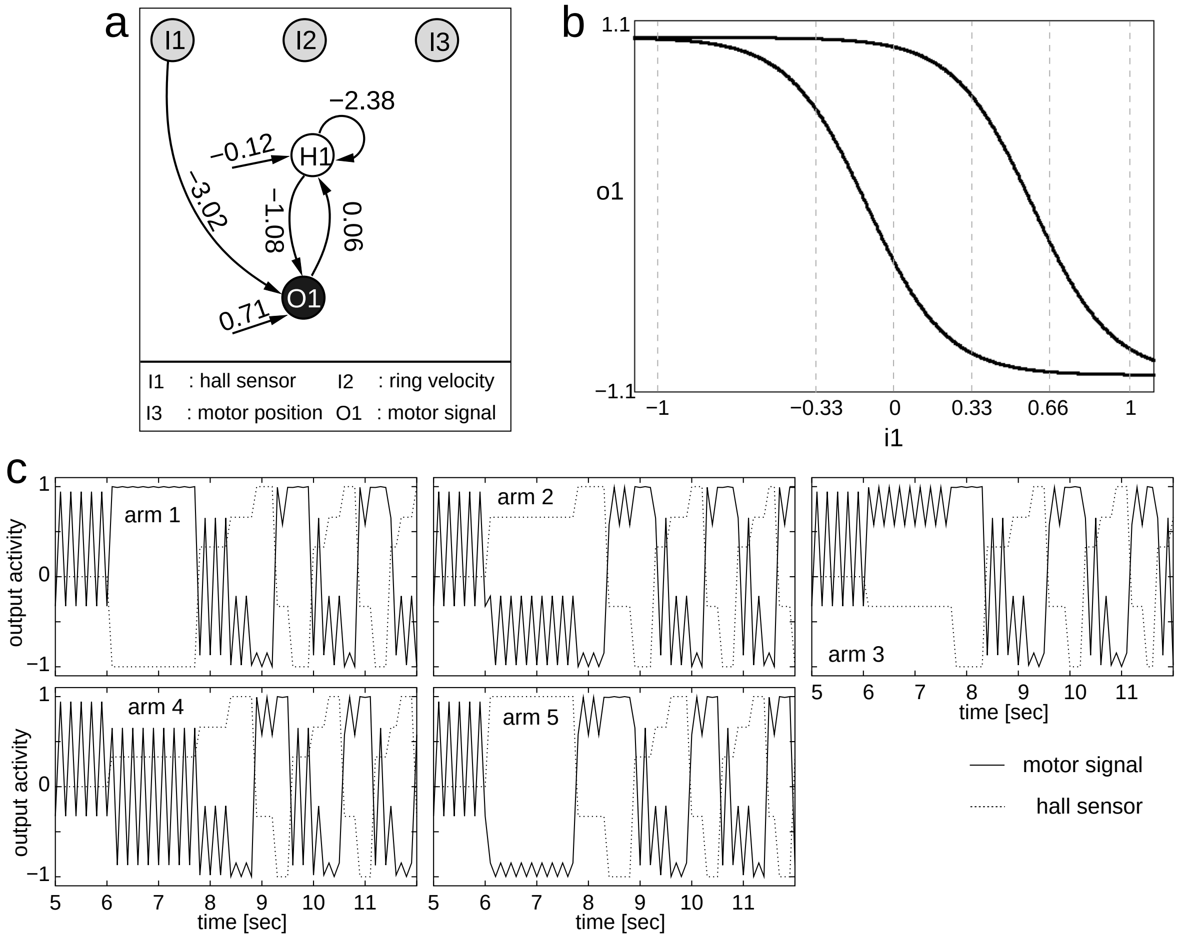

Figure 3.5: **Decentralized homogeneous control.** a: The RNN used for a decentralized homogeneous control of *micro.eve*. b: Bifurcation diagram for $o1$ while varying $i1$. Vertical dashed lines indicate all possible states of $i1$ during robot-environment interaction. c: Neural output of $I1$ and $O1$ when this RNN is applied to each arm (see text for details).

here *each* arm oscillates because the RNNs are identical and receive the same sensory input, at least at the beginning when the hall sensor is still inactive.

As soon as the ring rotates, the hall sensor becomes the main driving force. It modulates the oscillations through the strong positive connection between $I1$ and $O1$. The bifurcation diagram in Figure 3.5b shows how the hall sensory input influences the oscillation at $O1$. The vertical gray lines represent the possible states of $i1$. Comparing Figure 3.5b with the actual neural activity in Figure 3.5c we see that the points of the periodic orbit vary depending on the sensory state of $i1$ which modulates the amplitude and the mean of the oscillation. It is important to note that this behavior results from a *reciprocal coupling with the environment*: $i1$ changes as a result of the oscillation modulation at $O1$ which, in turn, depends on the state of $i1$.

Again, we can identify opposed arm movements (Figure 3.5c) although they are not as clearly distinguishable as in the centralized control. However, we can group arm 1 and 3 together opposed to arm 2, 4, and 5. Here, opposed arm movements result from

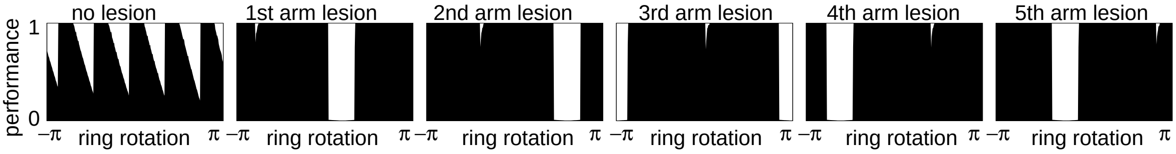

Figure 3.6: **Robustness of decentralized homogeneous control.** A motor breakdown of each arm was simulated and performance over various initial conditions was measured (see also Figure 3.4).

the fact that each arm has its own sight on the hall sensory input (refer to Section 3.2.1, p. 71).

Thus, we identify the same two behavioral mechanisms as in the centralized system: oscillations to initialize a rotation of the ring (caused by intrinsic dynamical properties) and opposed arm movements to maintain a steady rotation (caused by the strong feedback from the hall sensor).

Astonishingly, this very small sized neural network realizes all necessary sub-behaviors if applied to each arm. In contrast to the tight synaptic coupling of the centralized RNN, each arm acts autonomously, there are no links between them. Communication occurs only *indirectly* as a result of the reciprocal coupling with the environment on which each single module acts.

Now that we have answered the question about how unconnected autonomous homogeneous agents can solve a cooperative task, we turn to the question whether such a decentralized system is more robust to failure of individuals than the discussed centralized control architecture.

3.4.3 Robustness

To test the system with respect to its behavioral robustness to failure of single individuals, we conducted the same lesion experiments as described for the centralized control system (refer to Section 3.3.3, p. 76).

The results are shown in Figure 3.6. Without any lesion we can see that in some situations the system does not perform as well as in others. The drop in performance is a regular pattern as can be seen from the saw-tooth shaped performance curve. The problem is the homogeneity of the system. We figured out that at the beginning all arms are oscillating and that these oscillations are important to initialize the rotation by activating the hall sensory input. This process can take a long time if an arm is initially located at the very bottom of the ring, right above the magnet (cf. Figure 3.1). In this position, the oscillatory movements of the two arms on the left side are canceled out by the oscillations of the two arms on the right side. That is, during the initial oscillations, all arms *simultaneously move* their mass either to the center of the ring or to its periphery, because the system is homogeneous. If one arm is located at the bottom, the movements of the right pair and the left pair compensate each other. Thus, the overall center of mass of the whole system is actually not moved along the horizontal axis. Only because the arm at the bottom does not move up and down in a straight line, there is still a little horizontal translation of the overall center of mass and the ring moves in very small successive steps until the hall sensor becomes activated. In this situation the initialization of the rotation takes much longer because the masses of the arms are equally distributed to the left and right side of the ring and one arm is located at the bottom of the ring. This is also the case if one arm is at the top of the ring. However, the latter situation is resolved much faster because it is an unstable situation comparable to an inverted pendulum. Only small disturbances are required to move the system away from this unstable equilibrium.

The symmetry in the mass distribution of all arms explains the regular drop of performance if no lesion is conducted (Figure 3.6). This also explains why the system performs even better if lesions are conducted. It performs better in every situation where one arm is at the bottom, because either on the left or on the right side one arm is not moving due to its lesion. This symmetry breaking facilitates the performance except of the situation where the lesioned arm is located at the bottom of the ring. In this narrow range it fails completely because the arm at the bottom does not move (Figure 3.6). There, the symmetry is even enhanced and the oscillations of the pair of arms on the right side compensate exactly for the oscillations of the arms on the left side.

To this end, it is important to emphasize that it does not matter which part of the homogeneous system is disturbed. Because every part contributes evenly to the global function, the effect is always the same: a loss of function over a narrow, well defined, range of initial conditions. This is fundamentally different to the centralized system, where disturbances applied to different parts effect the overall function quite differently, as we have seen in Section 3.3.3 (p. 76).

Compared to the centralized control architecture, we obtain two major advantages in the homogeneous system. First, the neural networks are surprisingly small and at the same time able to integrate the needed sub-behaviors. Second, the system is much more robust to individual failure because the active parts are not as tightly coupled as it is the case in the centralized RNN. Nevertheless, we also figured out one drawback. Since all RNNs are identical, they act identical given that they receive the same sensory information. Because the robot in itself is symmetric, this symmetric behavior can be disadvantageous for the function of the robot. The next section introduces a heterogeneous system which breaks the symmetry at the control level and, therefore, may perform better.

3.5 Heterogeneity and division of labor

So far, we have seen that the two necessary behavioral mechanisms, oscillations and environmental feedback integration, realized by a centralized control architecture can also be achieved by a decentralized homogeneous control system. There, each control unit is autonomous, that is, they act independent of each other. The only interaction between them can occur through the environment. For the homogeneous system we saw that each autonomous agent responds similar if each gets the same sensory input.

For the following experiment we used a co-evolutionary strategy to evolve heterogeneous control architectures. That is, each of the five modules can evolve independently and may, therefore, develop a different neural structure or even a different function. Recalling the findings of the previous two examples, the most intriguing questions are:

Will division of labor evolve in a heterogeneous group of autonomous agents that have to cooperate? If so, what are the neural differences between agents which may fulfill different functions? And what are the advantages of such a system compared to a centralized system or a decentralized homogeneous system?

3.5.1 Co-evolutionary setup

To be decentralized, each agent (i.e., each arm) is controlled by an autonomous RNN. Similar to the homogeneous control experiments, the sensory input was reduced to one relative hall sensor input (as previously described), the ring velocity, and the arm's potentiometer. Again, a single controller has one output neuron controlling the motor signal of a specific arm.

To develop heterogeneous agents, we applied a rather simple co-evolutionary strategy (Wischmann et al., 2005; Hülse et al., 2004). In contrast to the homogeneous control experiments, where one RNN was copied to each arm, here, every agent was evolved in a separate population. The evolutionary process for a single population was the same as for the evolution of the centralized and distributed homogeneous control structure, that is, every population had its own selection, reproduction, and variation operators (recall Section 2.5.3, p. 56). For the sake of simplicity (and because it turned out to be efficient) we used the same parameter values for all populations. However, RNNs in each population could develop differently due to the stochastic nature of the evolution operators.

In each population individuals were sorted according to their fitness values, starting with the highest. The fitness value determined the number of offspring each individual got. All offspring were appended at the end of the sorted list of parents who got at least one offspring. For evaluation, one agent of each population was selected and applied to the arm which corresponded to its population, that is, a group of five agents, each from a different population, was evaluated together at the same time. The selection of the group members was rank based, related to the fitness value, that is, agents taking the first place in each population were evaluated together, then the agents on the second place and so on. In such a way the evaluation of i populations needs j evaluation cycles, where j is the number of individuals within the largest population.

The fitness function (Equation 3.1) regarded the performance of a group of agents, which had to cooperate. Therefore every agent within one group got the same fitness value, regardless whether it gave the most or even the least contribution to it (see also Section 2.5.4, p. 61).

3.5.2 Structural diversity

Since five agents are needed to control the robot *micro.eve*, we needed five co-evolving populations. Figure 3.7 sketches the fitness development and the structural changes over 25 generations. The right hand pictures show the structure of the best performing individuals of each population at generation 25.

The example shown in Figure 3.7 illustrates how different structures arise during the course of evolution and how the costs for neural elements influence the size of the resulting networks (see also Section 2.5.4, p. 59). As one can see in Figure 3.7a around

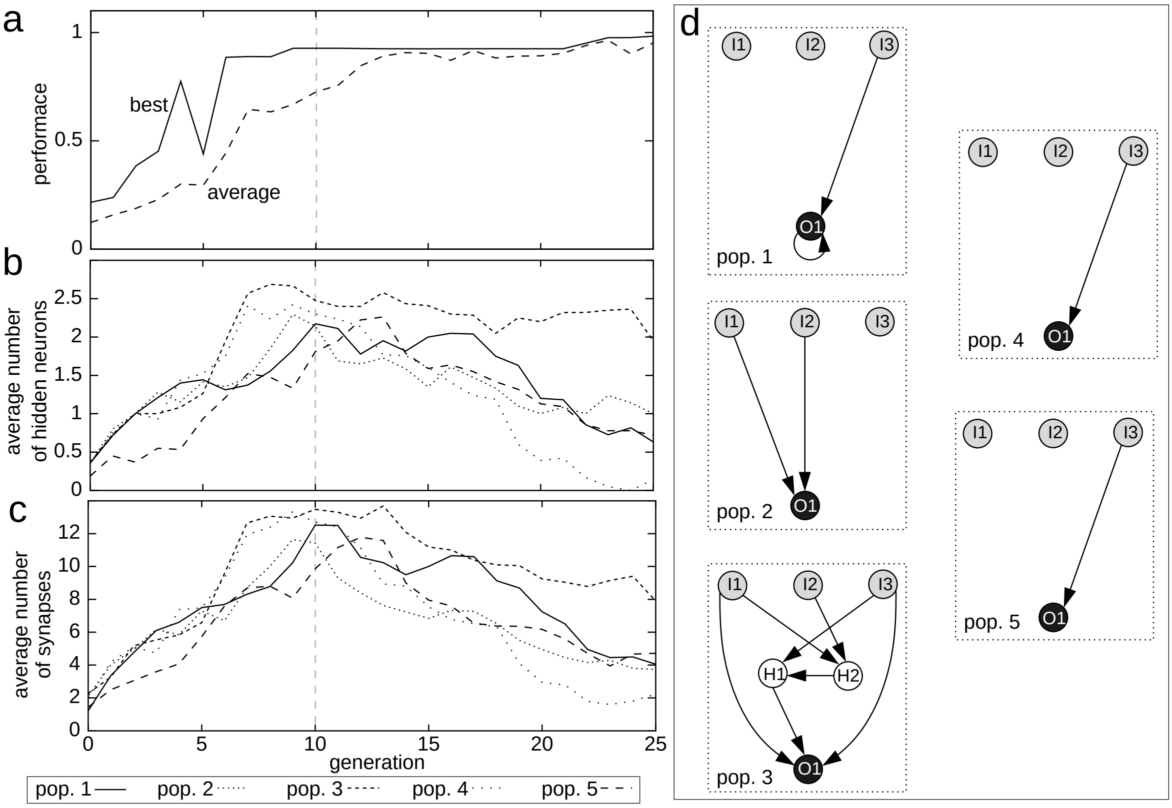

Figure 3.7: **Structural changes within co-evolving populations.** Development of the average fitness (a) and the average number of hidden neurons and synapses of all individuals in each population (b,c). Vertical dashed lines indicate the generation where costs for structural elements were applied. d: Structure of the best performing RNNs from each population at generation 25.

generation ten the maximal fitness level is almost reached by the best performing group. At this point we introduced costs for neurons and synapses. In Figure 3.7b,c the development of the average number of hidden neurons and synapses for all individuals in each population is shown. Compared to Figure 3.7a, we see that a high fitness level can be maintained, while the networks get smaller. Eventually, we get smaller networks with the same performance as larger networks which occur at the beginning where we did not restrict their growth by structural costs. Note, costs were not used right from the beginning to bootstrap the system (recall Section 2.5.4, p. 59).

The introduction of costs leads to a decrease in number of hidden neurons and synapses in each population. We can see that this average decrease is less strong in population 3 compared to the other populations. This trend is also reflected in the different structures of the RNNs with the highest performance taken from generation 25 (Figure 3.7d).

At the behavioral level we already detect a division of labor among the networks shown in Figure 3.7d. The networks from population one and three are important to initialize the rotation of the ring while the other networks maintain a steady rotation. The next section will discuss in detail the neural mechanisms behind such a division

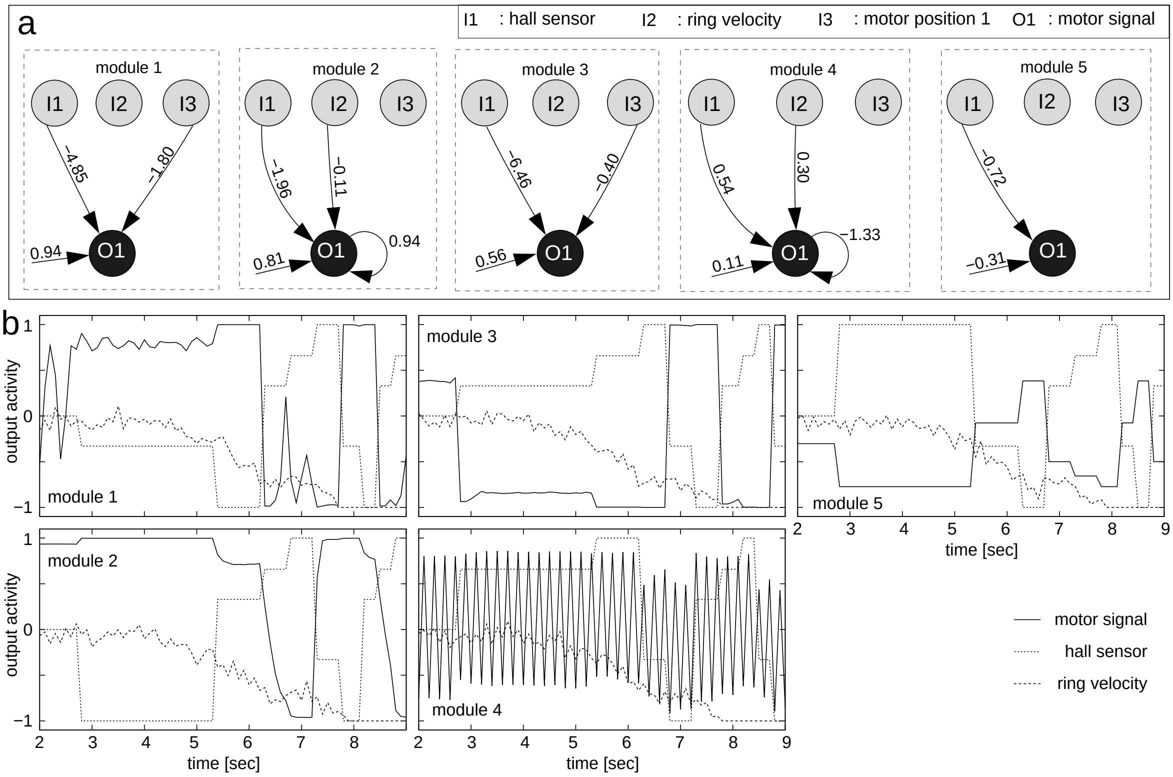

Figure 3.8: **Decentralized heterogeneous control.** a: Group of heterogeneous RNNs controlling the single arms of *micro.eve*. b: Outputs of selected neurons (see text for details).

of labor among even smaller networks.

3.5.3 Neural mechanisms

Figure 3.8a shows a decentralized group of evolved heterogeneous RNNs. If we compare the motor output of each module (Figure 3.8b) with the motor outputs of the centralized RNN (Figure 3.2b), we find surprising similarities. Here, module 4 exhibits period-2 oscillations all the time and, similar to the behavior of a single motor neuron in the centralized RNN (cf. Figure 3.2), this is caused by an over-critical negative self-connection. We also find opposed arm movements between module 1,2 and module 3,5 (Figure 3.8b) caused by the strong influence of the hall sensory input (see also Figure 3.8a). As we pointed out for the centralized and decentralized homogeneous control, these opposed movements are necessary to maintain a steady rotation. And to initialize the rotation, oscillations with high amplitude are important when the hall sensory input is still inactive. Here, we observe such oscillations in module 4 and 1.

Thus, we find the same sub-behaviors as discussed for the other two control systems. However, the different functions are now realized by different networks. That is why we indeed can call this a *division of labor*. The function of module 1-3,5 are important to maintain a steady rotation and the function of module 4 and 1 to initialize this rotation.

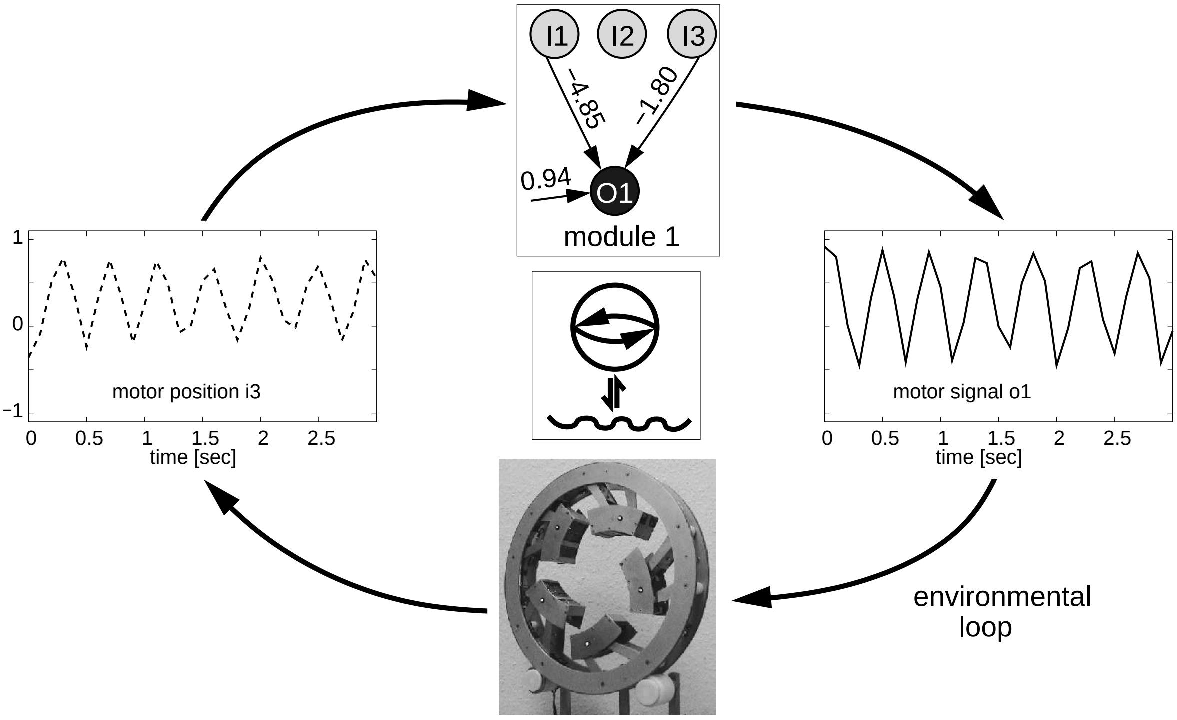

Figure 3.9: **Agent-environment coupling.** Module 1 from Figure 3.8 realizes a reflex oscillator because of the environmental loop and its internal connections (see text for details).

If we now take a closer look at the output of module 1, we observe high amplitude oscillations when the hall sensor is still inactive (Figure 3.8b). However, these oscillations are not caused by the dynamics of the network. There are no recurrent connections which are needed to realize periodic attractors; it is a simple feed forward network (cf. Figure 3.8a). The next section will discuss the cause of these oscillations which, as we will see later, are a key for the behavioral robustness of the overall system.

3.5.4 Agent-environment coupling

In the previous section we have seen that the motor neuron of module 1 oscillates even though there are no internal dynamics which can cause this. Figure 3.9 illustrates the actual mechanism. Oscillations are a result of the loop through the environment. The oscillations become only relevant when the hall sensory input is zero (as discussed in the previous section). In this case, the only sensory input is the potentiometer signal ($i3$ in Figure 3.9) of the motor which is controlled by this module. The output of $O1$ is sent to the servo motor, and due to the motor's inertia and friction the desired position is approached with a certain delay. The current position of the motor is fed back to the network through $I3$ which has a strong negative connection to $O1$. Therefore, $O1$ produces signals with an opposite sign to the current motor position.

A neuro-module with this property is referred as a *neural reflex-oscillator*. These kind of oscillators have also been found to be important for controlling the gait of walking machines where no central pattern generators were required to support periodic

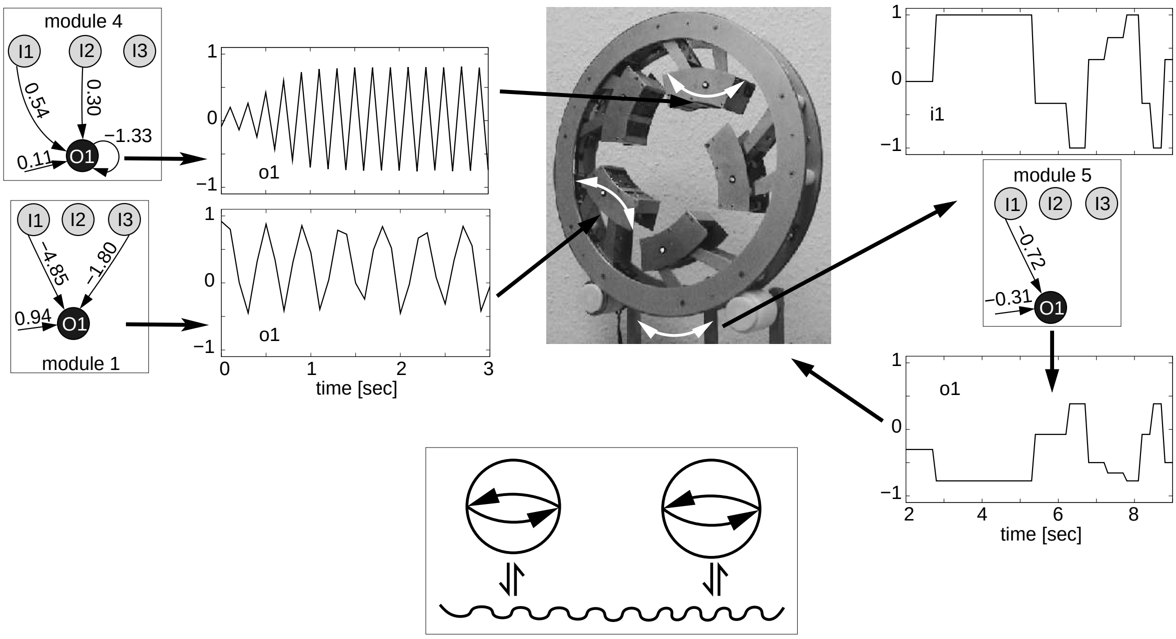

Figure 3.10: **Agent-agent and agent-environment coupling.** Oscillatory outputs of module 1 and 4 (cf. Figure 3.8) initialize movements of the ring. These movements soon lead to the activation of the hall sensor input of module 5 (cf. Figure 3.8), which than changes its motor output and, consequently, supports a steady rotation of the ring, which will than, in turn, influences the oscillatory behavior of module 1 as shown in Figure 3.8b.

single leg motions (von Twickel and Pasemann, 2007).

Thus, oscillations in module 1 are caused by the environmental loop. As soon as the ring starts to rotate, the hall sensor becomes active and due to the much stronger connection from the according input neuron ($I1$), oscillations are suppressed depending on the strength of $i1$ (see Figure 3.8b). Therefore, this single module is functionally similar to the homogeneous RNN discussed in Section 3.4.2 (p. 78). Module 1 exhibits high amplitude oscillation while the hall sensory input, $i1$, is inactive. As soon as $I1$ becomes active the motor output is mainly driven by $i1$ and the module, therefore, contributes to the needed opposed arm movements. The difference to the homogeneous system is that the initializing oscillations are caused by the environmental loop rather than by intrinsic neural dynamics.

This is indeed a rather simple but even though a very vivid example of how the motor actions of an agent can change the state of its sensors which then, in turn, changes its behavior. It is a striking example of an agent reciprocally coupled to its environment. In the next section we will see that identifying such couplings is also important to explain *coordinated behavior* among different agents.

3.5.5 Indirect agent-agent coupling

How do the heterogeneous agents now coordinate their behavior even though there are no direct links between them? The underlying mechanism is a result of the coupling

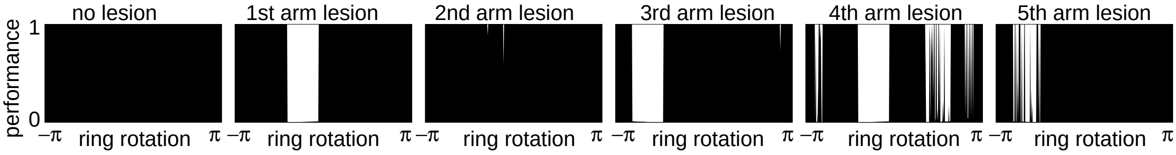

Figure 3.11: **Robustness of decentralized heterogeneous control.** A motor breakdown of each arm was simulated and performance over various initial conditions was measured (cf. Figure 3.4 and 3.6).

between agents through the environment, which we call *indirect coupling*. Figure 3.10 illustrates how it works.

As we now know, oscillations are important to initialize the rotation of the ring at the beginning when the hall sensor is still inactive. As we have already discussed, this is realized by module 1 and 4, as it is shown on the left hand side of Figure 3.10. We see how module 4 exhibits period-2 oscillations after a short transient period at the beginning. And the reflex oscillator of module 1 exhibits oscillations of lower frequency. Both behaviors together move the ring in rapid successive steps until a hall sensor is triggered which changes the sensory input of module 1-3, and 5. The right hand side of Figure 3.10 exemplifies how this change of sensor states changes the motor output of module 5. Due to sensory changes, module 5 starts to contribute to the maintenance of a steady rotation and to a continuous change of the hall sensory signal which in turn drives the behavior of all agents, except of module 4 (cf. Figure 3.8b).

Changing the environment, that is, changing the movement of the ring, is induced by the action of single agents. These environmental changes influence the behavior of other agents. Thus, agents sense the consequences of other agents' actions via an indirect coupling with the environment without having any knowledge about the actual states of the other agents. That is the fundamental mechanism which coordinates the behavior among five heterogeneous autonomous agents in our robotic system which do not have dedicated communication channels.

So far, we have seen three fundamentally different control systems (centralized, and homogeneous and heterogeneous decentralized architectures). At the behavioral level we identified similar principles leading to a coordinated behavior of the five different arms to rotate the ring. Even at the neural level we found similar mechanisms, like the initializing oscillations and the strong influence of the hall sensor. The major difference is that in the centralized control some motor units, responsible for the arm movements, are tightly coupled via synaptic links. Whereas, in the decentralized systems each arm is controlled by an autonomous agent and agents are only indirectly coupled through the environment. For the homogeneous case this led to an improvement in robustness to failures of single individuals. However, we have also seen that homogeneity entails minor drawbacks because of behavioral symmetry as discussed in Section 3.4.3 (p. 80). In the heterogeneous system we do not have such a symmetry. Can this facilitate behavioral robustness?

3.5.6 Robustness

To answer the question at the end of the previous section we again conducted lesion experiments as described in Section 3.3.3 (p. 76). Comparing the results shown in Figure 3.11 with the performance of the centralized system (cf. Figure 3.4) and of the decentralized homogeneous system (cf. Figure 3.6) we see that, if no lesion is applied, the heterogeneous systems slightly outperforms the other systems over the whole range of initial conditions. It also outperforms the other systems when lesions are conducted. For instance, a lesion of arm 2 does not influence the performance at all. The small performance gaps observable for lesions of arm 1, and 3-5 are not as straightforward explainable as the performance gaps observed with the homogeneous system (recall Section 3.4.3, p. 80). Yet, the basic reason is the same. At certain configurations the masses of all arms are equally distributed in a way that the whole system is not sensitive enough to initial disturbances. This prevents the hall sensor from getting activated. As we said, these disturbances are either the initial movements of all arms away from their starting positions or oscillatory movements. Compared to the homogeneous systems (cf. Section 3.4.3), control asymmetry is of minor advantage because different arms fulfill different functions. Consequently we observe no critical initial conditions in the non-lesioned case (compare Figure 3.11 with 3.6).

Unlike in the centralized system, the failure of agents who are responsible for the initializing oscillations has not such a great impact on the performance because here we have two agents with that property, each compensating the failure of the other. And as we found it for the homogeneous control system, the autonomy of the agents is of great advantage. The failure of one agent does not entail a failure of other agents because agents are only indirectly coupled via the environment on which every agent acts.

To summarize the issue of robustness, we have to recall that none of the conducted lesions were part of the evolutionary process. All three control systems perform similar well under the conditions they were faced with during their evolutionary development. Most strikingly, when confronted with individual failure the strong robustness of *decentralized systems* is an *intrinsic property* because of the *autonomy* of their constituent parts and because these parts are only *indirectly coupled* through the environment.

3.6 Discussion

3.6.1 Environmental feedback loops minimize control complexity

The most striking similarity in all three different control approaches presented in this chapter is the strong coupling between neural control and the environment. To maintain a steady rotation all three control types heavily rely on the hall sensory input which changes according to the action applied to the ring by each arm. This is the only sensor modality relevant for the sub-behavior of supporting an already initialized rotation.

We also analyzed other, similar efficient, solutions developed by evolution and we always found the same strong dependence on the hall sensor. Interestingly, from all the available sensor modalities this is the most reliable one. It is based on binary switches which do not have the disadvantage of being noisy like, for instance, the gyroscope which could also be used to measure the ring rotation. We argue that this may be one explanation why evolution always selected solutions which utilize this sensory input the most. Another strong reason is the fact that this sensor actually provides two different types of information. The rate of change encodes roughly the velocity of the ring rotation. Additionally, the sensor value also encodes a rough localization, because the value depends on which of the binary switches was turned on at last.

Thus, the hall sensor information is helpful to decide not only how fast an arm has to change its position, which depends on the ring velocity, but also in which direction it has to move, which depends on the current position of the arm within the ring. In contrast, the gyroscope encodes only information about the velocity of the ring. And because we enforce evolving neural systems to be as less redundant as possible, it is indeed reasonable that evolution tends to exploit the most useful sensor information. Because we will observe this phenomena also in the following chapters, we postpone a discussion about the reduction of redundancy at the neural level to Chapter 8 (Section 8.2.1, p. 174), although we should keep in mind that redundancy is abundant in natural nervous systems. Here, we deliberately enforce such non-redundant neural systems for the sake of analytical feasibility.

By analyzing the systems at every level we also identified a fundamental property of recurrent neural networks to be of high behavioral relevance, the property that they are *parameterized dynamical systems* (see also Section 2.4.4, p. 49). The RNN of the homogeneous system vividly demonstrates how the parameters of the control system, its sensory inputs, modulate the intrinsic dynamics (cf. Figure 3.5 on p. 79). Oscillations caused by a periodic attractor are modulated by the hall sensory input in a way that the very same system can exhibit different dynamics. These dynamics are important for different sub-behaviors, such as high amplitude oscillations to initialize the rotation of the ring as well as a dynamic amplitude and mean modulation of the oscillations to maintain a steady rotation. Thus, the neural system is minimalistic in that it only possesses one kind of periodic attractor which is modulated by the sensory input. Again, this system is driven by the reciprocal sensory-motor coupling of an agent with its environment. Thus, this coupling is an integral part of the control system.

Integrating environmental feedback loops in the control system of an agent can indeed decrease the complexity required at the neural level. A striking example is module 1 of the heterogeneous control system, discussed in Section 3.5.4 (p. 85). We observed oscillations in a simple feed forward network which were not deducible from its intrinsic dynamical properties. They result from the tight sensory-motor coupling of an agent with its environment. Such phenomena are not an superficial artifact of our specific robotic system. They were also found in other robotic experiments (for some examples see Hülse et al., 2007a). In earlier studies we showed how rhythmic motor signals are produced by the sensory-motor loop to support the walking of an under-actuated bipedal walking robot (Wischmann and Pasemann, 2004). More detailed investigations of locomotion in walking machines (von Twickel and Pasemann, 2007; Beer, 1995) demonstrated that sensory-motor feedback loops are a fundamental mechanism to realize rhythmic leg movements. Some studies indeed support the fact that sensory-motor feedback is not only of utmost importance for locomotion in animals, especially in insects (Delcomyn, 1999; Ekeberg et al., 2004), but it is also under discussion to be important for mental actions (Clower, 1998).

Considering these facts and the findings presented here we may return to and emphasize the introductory quote of this chapter taken from Scott Kelso. A control system which has only fixed point attractors is everything but boring or non-biological. Integrated sensory-motor feedback loops can make the behavior of such systems highly dynamic and robust. Environmental feedback loops are not only crucial for the behavior of an individual but also for the coordination of collective behavior as we will discuss in the following section.

3.6.2 Cooperation based on indirect communication

In Section 2.1 and at the beginning of this chapter we introduced the concept of stigmergy (Grassè, 1959; Theraulaz and Bonabeau, 1999). Stigmergy occurs if the action of an individual is determined or influenced by environmental consequences of another individual's action. It is a form of indirect communication which results in coordination and regulation of collective activity among many individuals. Specifically in insect societies many examples are known, where collective behavior results in global patterns whose realization tremendously exceeds the (cognitive) capabilities of a single individual. Such examples are, for instance, the construction of highly sophisticated nest structures in social wasp societies (Theraulaz and Bonabeau, 1995), corps aggregation (Theraulaz et al., 2002) or the optimization of transportation networks in ants (Buhl et al., 2004). All these examples of self-organized collective behavior have in common that coherent global patterns emerge from an indirect interaction between individuals through active modifications of their environment.

In the very same line, we observed that the coordinated behavior of distributed agents in our robotic system also emerges as a result of indirectly coupled environmental feedback loops. The action of one arm changes the state of the environment, the ring. This change is sensed by other individuals who change their behavior too, which then again changes the state of the environment, and so on. Thus, the environment is the crucial link between individuals exhibiting cooperative behavior. It is the medium of communication between the agents. That is why we can consider the coordinated global behavior as a result of *indirect communication*, similar to the stigmergic behavior observed in insect societies.

Therefore, the global behavior, accomplished by our decentralized systems can be described by the term of *indirect emergence*. Indirect emergence captures phenomena which result from the collective activity of either homogeneous or heterogeneous agents and which require that the interactions between the agents are mediated by active environmental structures (Clark, 1996). The role of indirect emergence of collective behavior with respect to flexibility and robustness of an artificial society will be also discussed in more detail in Chapter 6. Here, we focused on behavioral robustness, which means the adaptive response to individual failure, which will be the objective of the following section.

3.6.3 Intrinsic robustness of decentralized systems

A general characteristic of self-organizing systems is that they are robust and resilient. An important reason that such systems can efficiently compensate functional failure of some constituent parts is their redundant and distributed organization (Nicolis and Prigogine, 1989; Heylighen, 2003).

Non-living self-organizing systems generate fascinating phenomena such as the spontaneous formation of Bénard convection rolls (e.g., Getling, 1997), the ripple of sand-dunes (e.g., Nishimori and Ouchi, 1993), or the puzzling patterns in the Belousov-Zhabotinsky reaction (e.g., Petrov et al., 1993). Compared to these systems or compared to living self-organized systems such as insect societies, fish schools (for a review see Camazine et al., 2001), or even the human brain (e.g., Kelso, 1995), the robotic system discussed in this chapter consists of only a very few constituent parts. Nevertheless, we also found an *intrinsic robustness of decentralized systems* compared to a centralized organization.

By testing our different control approaches for robustness to individual failure we figured out that a distributed organization is a key aspect. Both types of decentralized control systems outperform the centralized one. As the main reason we identified the tight synaptic coupling between the motor units if control is evolved with a single RNN. Damage on single motor units entailed damage on other motor units which, in the worst cases, led to a total loss of function.

As we discussed, the coupling between motor units in the distributed organization is realized through the environment. Thus, damage of one agent affects the overall behavior only a little and can be compensated by other agents which act as a response to changes in their environment not as a response to changes in other agents.

However, we also observed an important difference between homogeneous and heterogeneous systems. In the heterogeneous system we saw that a division of labor led to agents with different functionalities. Hence, some agents contribute more to the initialization of a ring rotation, whereas other agents contribute more to maintaining it steady. Even though we recognized that the heterogeneous system performed better over small ranges of initial conditions than the homogeneous system, the performance loss of the homogeneous system, if individuals were damaged, was always the same, whereas it differed in the heterogeneous system. We have also discussed that the major problem of the homogeneous system was indeed the spatial symmetry of the robot. However, because each agent contributes evenly to the global behavior, the consequences of individual damage were minimal and always predictable. This is a property as it is known for self-organizing processes in non-living as well as in biological systems, as discussed at the beginning of this section. That is why, in the following chapters, we will focus on homogeneous decentralized systems. Interestingly, even in such systems we still can expect behavioral heterogeneity, but in contrast to heterogeneous systems, more as a result of different environmental contexts individuals are in, rather than as a result of individual control differences.

3.7 Summary

The main purpose of the experiments presented in this chapter was to study the emergence of cooperation among autonomous agents without explicit communication channels on a minimalistic robotic system. We used an unconventional, yet rather simple, robot. On a first glance, the robotic system may seem to be too simple to be of any serious interest to study cooperative behavior, especially because of its limited behavioral capabilities. Nevertheless, we demonstrated that for the very reason of being rather simple, yet still *complete*, the robotic system allows a comprehensive study of some fundamental properties of decentralized cooperative behavior.

To conclude this chapter we should summarize the main aspects of our discussion:

- *Sensory-motor feedback loops* are heavily exploited by the evolutionary development and are an integral part of control systems.
- The *reciprocal coupling with the environment* minimizes the complexity at the level of required neural dynamics.
- This is, in turn, an important property of RNNs realized as *parameterized dynamical systems.*
- Cooperative behavior and interactions among distributed agents can be effectively realized by using *indirect communication* with the environment as an active medium.
- Decentralized systems possess an *intrinsic robustness* to individual failure and they do not need to be specifically optimized for that.

Stinkingly, we were able to observe and analyze these principles already in such a seemingly simple robotic system as presented in this chapter. Although, they are, each by itself, not a new discovery, we have to emphasize that they were a result of an evolutionary process where we did not explicitly enforce any of these aspects by specific predefined constraints. All we deliberately put into this process was the sensory-motor specification and a fitness function as the selection criteria. Remarkably, this fitness function did not enforce the optimization of any of the resulting properties except that the robot should rotate as harmonically as possible. And the emergence (not the enforcement!) of such fundamental principles of adaptive collective behavior is exactly what we want to achieve by reducing the design bias as much as possible.

Thus, the experiments and results presented in this chapter already emphasize the most important methodological principle of this thesis: The rules which determine the behavior of an individual and the collective behavior resulting from the interaction among autonomous individuals are predefined *neither* at the neural control level *nor* at the level of the interactions between individual agents.

Chapter 4

Aggregation with minimalistic control

Three robots (green) evolved to pursue the red robot which continuously emits an acoustic signal (indicated by the red sphere).

> “[. . .] and the thousands of fishes moved as a huge beast, piercing the water. They appeared united, inexorably bound to a common fate. How comes this unity?”
>
> *Anonymous, 17th century, quoted in (Camazine et al., 2001, p. 167)*

4.1 Introduction

Aggregation is a prevalent pattern found in biological systems. The classical interpretation from an evolutionary perspective is that aggregation gives a group of animals advantages regarding mate choice, collective information sharing, or increased protection from predators[1]. Aggregation can be found on any scale, from unicellular organisms to whales, from small groups to millions of individuals (Allee, 1931).

Observed from an outside perspective the aggregation behavior of, for instance, a swarm of fish seems to resemble the behavior of a super-organism moving in unison while cohesively executing sudden shifts in direction. Probably the most impressive property is the fast information transfer among the individual parts of such a group allowing coherent evasive behaviors when predators approach the school (Partridge, 1982). Interestingly, this self-organized group behavior can be explained by a few, yet simple, local interaction rules which are based on a balance between positive and negative feedback. Mathematical models showed that these feedbacks are basically realized by attraction and repulsion whereby each individual obeys the same rules and

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[1] Protection from predators is classically seen as an important selective advantage because it can, for instance, cause confusion for a predator which is not able to lock on one specific target. However, aggregation can also attract predators. For instance, some marine mammals are strongly attracted by a concentrated occurrence of their prey. This leads to the interesting question about whether aggregation formation of animal groups always serves a specific function or whether it is just a self-organized pattern which is not necessarily evolutionary advantageous (for a deeper discussion see Parrish and Edelstein-Keshet, 1999).

reacts only to the action of its closest neighbors (Aoki, 1982; Huth and Wissel, 1992). And indeed, for the example of fish schools experimental data revealed that the lateral line system of a fish is most important to avoid collisions whereas the visual system is important for maintaining a certain position and angle to neighboring individuals (Partridge and Pitcher, 1980).

Another interesting example of self-organized group behavior is the coordinated motion of locusts, which also lack centralized leadership. With experimental data from field studies Buhl et al. (2006) confirmed the, from theoretical models predicted, existence of a critical density at which a rapid transitions occurs from disordered to ordered movement. They also demonstrated a dynamic instability at typical locust population densities at which the whole group switches direction without external perturbations. Hence each individual interacts only with a very few individuals in its immediate vicinity, information must propagate from the large scale (the whole group up to millions of individuals distributed across tens of kilometers) down to a very small scale (the interaction range of neighbors of about a few centimeters).

Even though mathematical models and tools for analyzing collective phenomena in such large scale biological systems can resemble their underlying general self-organizing properties very well, they are designed from known or presupposed interaction rules and, therefore, do not extract interaction rules from the observed global behavior (Grünbaum, 2006). One central aim of this thesis is to tackle this problem by a synthetic bottom-up approach, where interaction rules emerge from the dynamical properties of individual neural control which in turn result from an evolutionary process with as less preconceptions as possible.

In the previous chapter we approached that problem with a system of very few agents physically connected to their environment. There, we already identified some basic properties of decentralized control, such as robustness to individual failure. And we demonstrated how cooperative behavior can emerge from an indirect coupling between a few agents through their environment. However, the rigid physical connection to the environment, the environmental simplicity, and the small number of interacting agents limits the variety of possible collective behavior patterns. Therefore, in this chapter we want to introduce a robotic system which is a promising platform for experiments aiming at the development of collective behavior in large groups of individuals and which, therefore, will also appear again in the proceeding chapters. Here, we want to investigate (i) how individual behavior can be evolved which shows similar attraction and repulsion properties as discussed above for fish schools and (ii) which collective phenomena can be observed when many individuals interact with each other. Therefore, this chapter is mainly dedicated to the following questions:

- What are the minimal neural mechanisms required to robustly integrate two competing goals, such as positive and negative tropisms?
- Once we achieved such a robust and minimal control, how much do we have to add to achieve a coherent collective behavior among many individuals?

In addition, individual behavior has to be robust because a robot does not act in a static environment, but has to handle, for instance, moving obstacles as well as targets which dynamically change their position.

The experiments presented in this chapter reveal that the integration of two competing behaviors can by realized by a differently weighted influence of different sensor modalities, that is, by a different impact of the changing parameters of an RNN. Interestingly, both behaviors result from the very same neural dynamics on which the different sensor modalities act on. We will see that the neural mechanisms which enable the robot to handle difficult environmental conditions are based on hysteresis effects, caused by bi-stable regions within the control system. We then can use the very same structurally small control system, actually evolved for an individual behavior, to accomplish complicated aggregation patterns, solely based on simple local interactions. All what is needed is making every robot in a large group a potential target for all other robots. That is, the robots by themselves realize the link between individual behaviors (such as avoiding obstacles and approaching a target) and a global coherent pattern, such as aggregation, without the need of centralized or hierarchical control. By this *direct inter-individual coupling* each robot serves as a cue for other robots.

Before we discuss the behavioral mechanisms in detail, we want to introduce the robotic system and explain the experimental setup first.

4.2 Getting strong in number: The swarm robotics approach

Research in collective behavior of large scale distributed robotic systems, how it is pursued for instance in the swarm robotics approach (for an overview see Şahin and Spears, 2004), is mainly motivated by three aspects: robustness, flexibility, and scalability. In general a swarm robotic system can be characterized by *decentralized* control of many *simple* and (quasi) identical autonomous units leading to a high *reliability* because of its intrinsic *redundancy* which makes the whole system robust to disturbances and *flexible* to novel environmental conditions (Beni, 2004). The constituent parts of a swarm system move and interact dynamically. And while these parts are rather simple they coordinate their behavior based on self-organizing principles and local interactions which eventually lead to the emergence of new and complex global patterns. Of course this field of research is heavily inspired by examples of self-organization in groups of biological organisms.

In this chapter we want to focus on one particular aspect of swarm systems, namely patter formation processes by aggregation. For this purpose we conducted basic experiments with the robotic platform *Do:Little* which will also serve us as a testbed in the ongoing chapters where we will turn our focus more to the *evolutionary development* of communication and cooperation (Chapter 6 and 7).

4.2.1 The *Do:Little* robot

The *Do:Little* robot (Figure 4.1) is a prototype still under development which is led by Manfred Hild, now at the Humboldt University of Berlin. This small-sized robot (length: 14.5 cm, width: 11.5 cm) satisfies the basic requirements to study collective behavior in large groups of robots, that is, individual robots should be rather simple by using basic sensors and actuators. The *Do:Little* robot has many basic sensor modal-

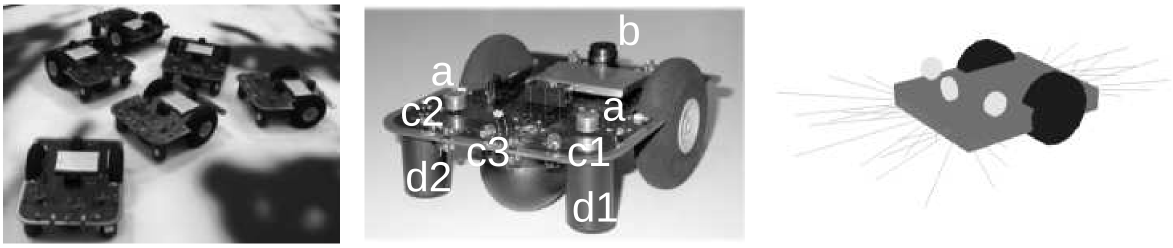

Figure 4.1: **The *Do:Little* robot and its simulated model.** Characters mark sensor positions: (a) stereo microphone; (b) speaker; (c) infrared and light sensors (not shown are two additional infrared sensors at the back of the robot); (d) floor sensors.

ities: infrared sensors to detect obstacles or other robots, light dependent resistors to measure illumination, floor sensors which can can discriminate gray levels of the ground beneath the robot, and internal force and traction sensors. Additionally, the ability to communicate makes this robot especially suitable for experiments as presented in this and the ongoing chapters. The robots can not only interact with each other via simple sound signals, they are also able to exchange energy by physically connecting to each other or to energy sources within the environment (i.e., charging stations). While the ability to collect energy becomes relevant in the next chapters, for the following experiments we only used the infrared and sound sensors of the robot.

4.2.2 Sensory-motor setup

For the following experiments we used RNNs (cf. Section 2.4.1, p. 43) with the standard sigmoid transfer function $f := \sigma$. Thus, the output of each neuron is $o \in (0, 1)$. Therefore, motor and sensor signals of the robot were mapped into this interval. Note that Ix and Ox refer to input and output neurons with index x, respectively; and ix and ox refer to the corresponding output of these neurons.

The only actuators controlled by an RNN are the wheel motors. The angular velocity of a wheel is determined by:

$$\omega_x = c(2 \times ox - 1), \tag{4.1}$$

where ox is the output of the motor neuron controlling either the left ($O1$) or the right wheel ($O2$) and c is a speed factor. Thus, output values $ox \in [0, 0.5]$ correspond to negative wheel speeds, that is, driving backwards. Accordingly, output values $Ox \in [0.5, 1]$ correspond to positive wheel speeds, that is, driving forward.

As sensor modalities we used the infrared sensors (IRs) and the stereo microphone of the robot (cf. Figure 4.1). IRs measure the distance to obstacles. For our experiments we used only two of the five IRs. They are oriented 45° to the left ($I1$) and the right ($I2$) of the robot's heading direction ($I1$ and $I2$ correspond to $c1$ and $c2$ in Figure 4.1, respectively). The values of the IRs were linearly mapped to the range of the transfer function $[0, 1.0]$, where zero represents no obstacle detection and 1.0 the closest measurable distance to an obstacle. Gaussian noise was added with $\sigma^2 = 0.1$ (i.e., 10% noise).

Signals of the stereo microphone are represented by the input neurons $I3$ and $I4$. There outputs are defined by:

$$\begin{aligned} i3 &= 0.5\left[1+sin\left(\alpha\right)\right], \\ i4 &= 0.5\left[1-sin\left(\alpha\right)\right], \end{aligned} \tag{4.2}$$

where α is the angle of a detected sound signal to the heading direction of the robot. Measurements conducted on the real system showed that the stereo microphone of the robot is able to detect sound signals within a range of approximately 1.5 meters and that angle detection is rather noisy. Therefore, we limited the sound detection range of a single robot in simulation to 1.5 meters as well and added Gaussian noise to the signals of the according input neurons with $\sigma^2 = 0.3$ (i.e., 30% noise), which is remarkably high, but we will see that even very small networks can handle such high noise levels. Note, as a constraint of the hardware a robot can only recognize the angle of a sound signal, but not its distance, and a robot does not recognize signals emitted by its own speaker.

Given this minimalistic sensory-motor setup, the next sections will discuss the robustness of an evolved RNN which enables a robot to follow a moving target and how the very same control system enables a large group of interacting robots to exhibit complicated aggregation patterns.

4.3 Chasing behavior with minimalistic control

4.3.1 Evolutionary setup

To evolve a basic chasing behavior we used the *MRC* (minimal recurrent controller) as initial RNN (cf. Figure 4.2a). This RNN, adapted from (Hülse et al., 2004) and originally evolved for the *Khepera* robot (Hülse and Pasemann, 2002), exhibits a highly robust obstacle avoidance and exploration behavior. Thus, we equipped one non-evolving robot with this RNN and let this robot continuously emit a sound signal making it the moving target for the other evolving robots. The task of these robots was to minimize the distance between them and the target. For this purpose we used the following fitness function:

$$F = \frac{1}{n}\sum_{i}^{n}\left(1-\frac{r_i}{1.5}\right), \tag{4.3}$$

where n is the number of robots which have to follow the target and r_i is the distance between robot i and the target. Hence the maximal detection range for sound signals is 1.5 meters, r_i was thresholded to this value. Thus, if r_i is larger than the threshold, robot i does not contribute to the fitness of the group.

The evolutionary strategy is akin to the experiment described in Section 3.4.1 (p. 78). That is, one RNN from the evolving population was copied six times to control each of the six robots which are part of the group. Then the average performance of these six robots was taken to determine the selection criteria for this particular RNN. Note, that this corresponds to an explicit averaging of the fitness function (cf. Section 2.5.4, p. 61).

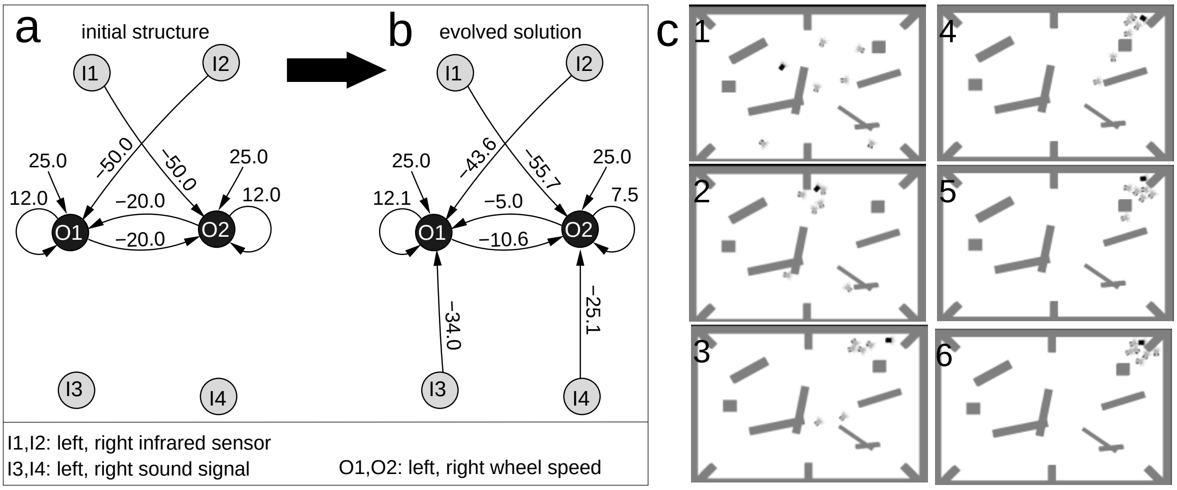

Figure 4.2: **Neural network realizing chasing behavior.** The initial (a) and the resulting evolved RNN (b) which realizes a chasing behavior as indicated in the right panel (c): The black robot (controlled by the initial RNN) continuously emits a sound signal and is, therefore, the moving target for the gray robots (controlled by the evolved RNN). Snapshot 1 shows the starting position of each robot. The interval between subsequent snapshots is 10 seconds of simulated real time (i.e., 100 time steps in simulation).

We have to admit, that this fitness function does not rely on internal variables (cf. Section 2.5.5), because we used global variables which were not accessible by the agents themselves. However, this was done because the sound sensor is not able to measure the intensity of a signal and therefore can not determine the distance to a signal. Nevertheless, the fitness function is still implicit because it does not describe how to solve the required sub-behaviors, such as avoiding obstacles or other robots, and how to approach and follow the moving target.

To bootstrap the system the *MRC* was provided as an initial structure (Figure 4.2a). Then, we used a so called semi-restrictive method (Hülse et al., 2004; Hülse, 2007), that is, already existing structural elements are not allowed to be removed (even though their parameters can change), but new structural elements could be added within the *whole* network which has new, initially unconnected, sensory inputs (the sound sensors in this case).

4.3.2 Neural mechanisms

Figure 4.2b shows a successfully evolved RNN. Compared to the initial structure (Figure 4.2a) we see only minor changes of the original synaptic weights and only two new synaptic connections between the sound detecting input neurons and the motor neurons. This very small module, applied to a group of six robots, realizes a highly robust chasing behavior (Figure 4.2c) which can be described as the integration of two tropisms: a negative one to avoid obstacles and other robots, and a positive one to follow the sound signal.

The most important structural elements of this RNN are the strong positive posi-

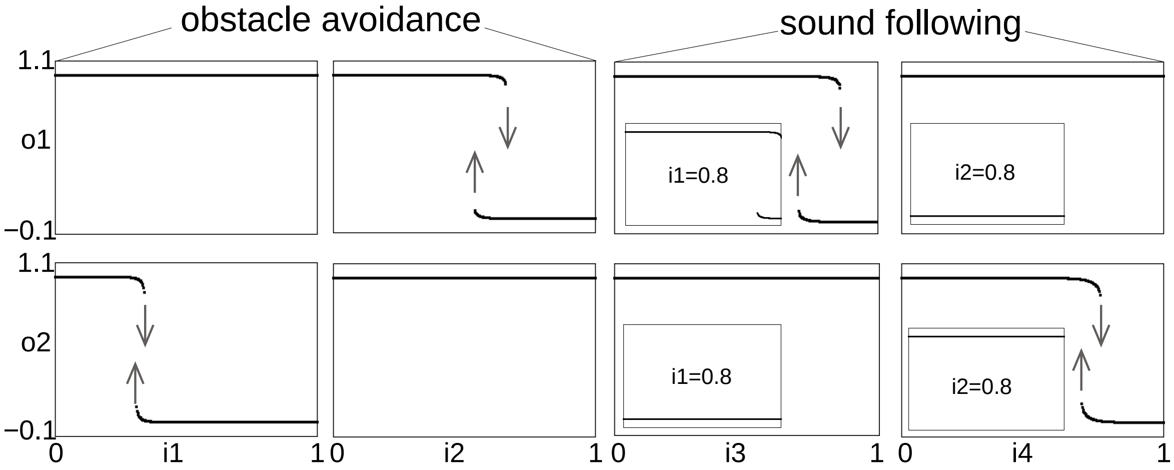

Figure 4.3: **Neural mechanisms of the chasing behavior.** Shown are bifurcation diagrams for the motor neurons $O1$ and $O2$ while varying all sensory inputs (not varied inputs were set to zero, except for the inset diagrams in the right panel, where always one infrared sensor was set to a value different from zero, as indicated).

tive self-connections at $O1$ and $O2$ and the even loop between these two neurons. Such elements can exhibit hysteresis effects as a result of bi-stability (for a profound mathematical discussion see Pasemann, 1997, 2002). How such hysteresis effects realize robust obstacle avoidance behavior is already discussed elsewhere (Hülse and Pasemann, 2002; Hülse et al., 2004; Hülse, 2007). However, we want to briefly summarize the main properties and features because they are fundamental to the behavior in our case as well.

First, we want to explain the obstacle avoidance behavior with the help of the bifurcation diagrams given in the left panel of Figure 4.3. When we vary the input of $I1$ (the left infrared sensor) we see that $o1$, which controls the left wheel, stays in the upper saturation domain of the activation function over the whole input space. Thus, the left wheel rotates forward with maximum speed. Considering $o2$, which controls the speed of the right wheel, we see that that it jumps between the upper and the lower saturation domain at specific input values. We also see that a jump from the upper to the lower domain occurs at a higher input value than the jump back from the lower to the upper domain. Between these two values the system is bi-stable, it ends in either one of two fixed points depending whether the input values are increasing or decreasing. That means the behavior of the system does not only depend on its current state, but also on its history.

To get an impression how this is related to the behavior of a robot, let us suppose a robot is approaching an obstacle to its left side. The closer the robot comes to the obstacle the higher gets $i1$. At a specific value of $i1$, $o2$ jumps from 1.0 to 0.0 leading to a backward rotation of the right wheel which turns the robot away from the obstacle. That in turn decreases $i1$, but $o2$ jumps back from 0.0 to 1.0 at a lower value of $i1$. The width of this hysteresis domain is determined by the strength of the self-connection at $O2$ and the synaptic strength of the even loop between $O1$ and $O2$. The larger the hysteresis domain the larger is the turning angle of the robot away from an obstacle (see Hülse et al., 2004 for a deeper discussion about this correlation). The same can be found when we change $i2$, the right infrared sensor value, but this time we find a bi-stable region for $o1$, resulting in a turn to the left when an obstacle is detected on the right side of the robot.

There are two main properties why this mechanism ensures a robust obstacle avoidance behavior (Hülse et al., 2004):

- Noise is filtered efficiently because small and fast changes of the sensory input do not result in small and fast changes of the output.

- Because the turning still continues although the input value is already lower than the value which initiated the turning, the robot is able to escape even acute angles or dead ends in the environment.

The very same mechanism realizes the tropism toward a target, only that this time the robot is not turning away from the source of sensory changes, but adjusts its heading direction toward it (compare left and right panel of Figure 4.3). The reason for this inverse reaction becomes obvious when we consider the connection between the different sensor modalities (infrared and sound sensors) to the motor neurons (cf. Figure 4.2b).

Thus, two different behaviors are integrated into one control unit where the very same dynamical properties are used to realize either a positive or a negative tropism depending on the coupling between sensory input and motor output.

Which of the competing behaviors becomes apparent is determined by how strong the different sensor modalities are connected to the control system. When the robot is confronted with both, that is, it detects an obstacle and a target signal at the same time and on the same side, the dominant behavior is determined by the strength of the synaptic weights projecting from the different sensor modalities. As we can see in Figure 4.2b the synapses from the infrared sensors are stronger than the synapses from the sound sensors. The insets in the right panel of Figure 4.3 illustrates two occasions of conflict. For instance, when an obstacle on the left side of a robot is detected (high $i1$) and we vary $i3$ (representing sound signals to the left side of a robot), we see that the hysteresis domain of $o1$ is shifted to the right side in a way that $o1$ actually does not jump to the lower saturation domain, at least not in the range of values of $i3$. That means, an orientation to the left is inhibited when, at a same time, the left infrared sensor detects close obstacles, as it is also the case for the other side of the robot (see insets in the right panel of Figure 4.3 for varying $i4$). This means, obstacle avoidance is always the dominant behavior and heading toward a sound signal takes only place when the values of the infrared sensors are below a certain threshold.

Now that we have clarified the neural mechanism of the chasing and obstacle avoidance behavior, the next section will discuss what happens if we add a speaker to all robots (i.e., each robot becomes a potential target) and increase their number. Thus, we change a property of the robot, but we do not change anything concerning the control architecture.

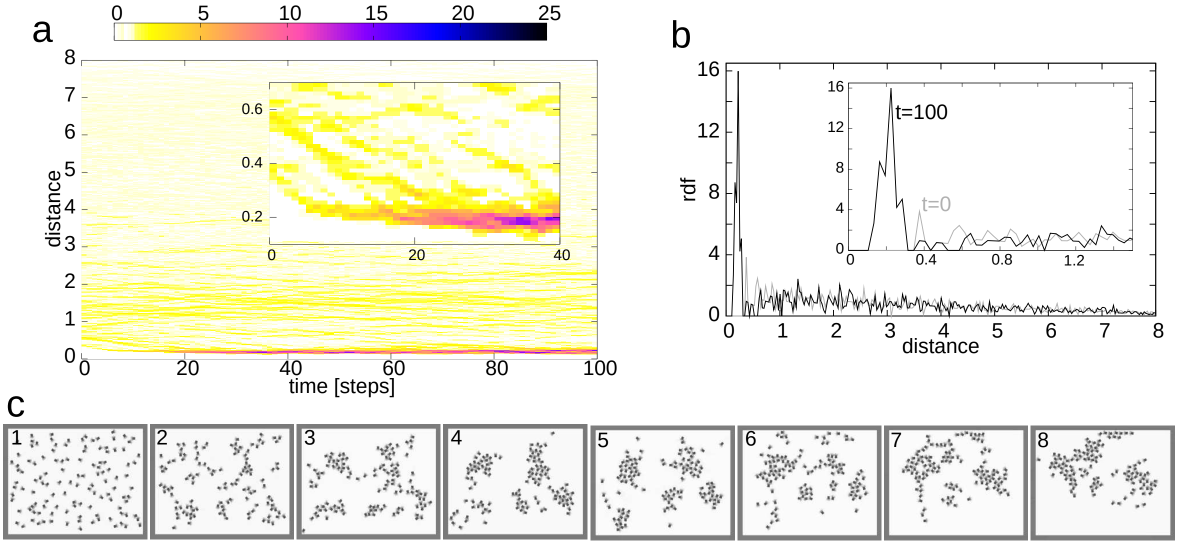

Figure 4.4: **Clustering of 120 robots.** The top panel indicates the average number of neighbors from an individual at specific distances by means of a radial distribution function (see text for details). Shown is its development over time (a) and a snapshot at the beginning and after 100 time steps (b). The bottom panel (c) visualizes the aggregation process. Snapshot 1 shows the initial position of each robot. The interval between subsequent snapshots is ten seconds of simulated real time (i.e., 100 time steps in simulation).

4.4 Self-organized clustering

If we take the RNN that enables a robot to robustly follow a moving sound signal while avoiding obstacles and other robots and apply it to many robots where each individual emits a sound signal, we can observe self-organizing clustering as it is visualized for a group of 120 robots in Figure 4.4c. What happens is that each robot most strongly reacts with a positive tropism toward the sound signal of its closet neighbor, that is, individuals are attracted by each other because each robot is a potential target for every nearby robot. At the same time each robot also represents a moving obstacle. And obstacle avoidance has priority over approaching a target as we have discussed in the previous section. Thus, the observable clustering is based on local attraction and repulsion.

To measure the degree of clustering we used a two-dimensional radial distribution function (RDF):

$$RDF(r) = \frac{1}{n}\sum_{i}^{n}\frac{N_i(r)}{2\pi r\Delta r}, \tag{4.4}$$

where n is the number of all individuals, N_i the number of individuals that are in a ring with a width of Δr at distance r of individual i. Thus, this function gives us an averaged indication of how many neighbors we can expect at a specific distance to an individual. The development of the RDF with time is drawn in Figure 4.4a. At the beginning all individuals are more the less equally distributed, which corresponds to a situation as shown in the first snapshot of Figure 4.4c. Very soon individuals aggregate in rather dense clusters (see also the inset of Figure 4.4a). Figure 4.4b gives the RDF at the beginning and after 100 time steps which corresponds to a situation as shown in the first and second snapshot of Figure 4.4c, respectively. We can see that individuals very quickly start to aggregate and we can also see that a distance of about 0.1 meters is the physical boundary given by the bodies of the robots where individuals cannot further approach each other. However, the distance in which we find the most neighbors around an individual is about 0.2 meters, which reflects the obstacle avoidance response. But robots do not just stay close to each other once they reached a target (i.e., another robot). Because of the repulsion, which is due to the obstacle avoidance behavior, a robot drives away from a nearby robot to which at the same time it is attracted as long as the infrared sensor activation is not too high. When driving away, a robot may become attracted to another robot which is closer then the previous target. Because of these two forces, attraction and repulsion, and because each robot is a potential target for each nearby robot, the size and position of locally formed clusters change dynamically with time as it is illustrated in Figure 4.4c.

4.5 Discussion

The experiments presented in this chapter differ in two aspects from the experiments of the previous chapter. First, communication between agents is a *direct* form of *communication* via acoustic channels and, second, agents are no longer physically connected to the environment. However, there is still no knowledge represented in the individual control about the presence of other agents. Attraction and repulsion, the two driving forces of the aggregation process, are behavioral responses to environmental stimuli. Actually, for the behavior of a single agent it does not matter whether those stimuli come from static objects in the environment or whether their source are other agents. What realizes the global collective clustering is that other agents are dynamically changing environmental cues for an individual. Aggregation emerges from this dynamic interaction among agents. Thus, it is a result of a decentralized self-organizing homogeneous system. With such a system we can answer the questions from the beginning of this chapter.

The first question concerned the minimal requirements of neural mechanisms to robustly integrate two competing behaviors. As we have seen, the robustness to sensor noise and complicated environmental conditions (such as sharp corners) basically results from hysteresis effects which occur because of specific bistable regions within the RNN as a dynamical system. Interestingly, both behaviors operate on the very same dynamics. The difference is how the different sensor modalities, as parameters of the dynamical system, influence the dynamics. The different influence results from how the corresponding input neurons are coupled to the motor neurons. And because the sound sensor is coupled via weaker synapses than the infrared sensors, the presented small network is even able to solve a conflict of simultaneously competing sensor stimulation. In that way a network with very few synapses and no hidden neurons is able to realize robust obstacle avoidance and target chasing behavior. Note, that such a structurally very small solution is efficient to realize behavior switching follows from considering RNNs as *parameterized dynamical system*, a property we already found in the previous chapter where an external input acted on a switchable oscillator (cf. Section 3.4.2, p. 78 and Figure 3.5, p. 79). In the next chapter (Section 5.4, p. 114) we will discuss a slightly different mechanism to switch competing behaviors.

The second question concerned the additional requirements to provoke a coherent collective behavior with this type of neural control. Surprisingly, only a small change was required to achieve dynamic aggregation patterns: We just attached a speaker to every robot without changing its neural control in any way. Making every robot in a large group an environmental cue (i.e., it acts as a moving obstacle and a moving target) linked the individual behavior to the observable global pattern which is a result of mutual attraction and repulsion among interacting agents.

There exists many examples in biology where individuals aggregate and cluster because of local attracting forces, for instance schooling of fish, clustering of penguins for warmth, feeding aggregation of bark beetles, or the initial aggregation of unicellular slime mold bacteria when food sources become rare (for an overview see Allee, 1931; Camazine et al., 2001). Aggregation results not only because individuals respond to environmental cues, such as when flies gather around light sources, but also from attracting inter-individual forces, as it can be found for instance in fish schools as discussed at the beginning of this chapter.

Inspired by such examples of self-organizing biological swarms, a lot of research has been done to convey their underlying general principles to artificial systems. One of the most famous examples is the so called stick pulling experiment (Ijspeert et al., 2001), where only two cooperating robots are able to pull a stick out of the floor. In another example Theraulaz and Bonabeau (1995) evolved agents that collectively built nest structures by depositing bricks. Inspired by the work of Robson and Traniello (1998) who investigated collective transportation of heavy prey items in ants, Kube and Bonabeau (2000) used robots which can recruit other robots to collectively push boxes which are too heavy to be moved by single individuals (see also Kube and Zhang, 1993). Holland and Melhuish (1999) investigated the operation of stigmergy and self-organization in a homogeneous group of physical robots which had to cluster and sort two different types of discs. Even though agents or robots in these examples rely only on local information and communication without any centralized control, their behavior is mainly determined by simple *predefined* behavioral rules, often represented as inter-connected functional blocks.

What we are aiming at is the emergence of individual behavioral rules from the dynamic interaction between simple control elements, such as artificial neurons. Thus not only the global collective behavior should emerge from local interaction among lower level components, but also the individual behavior itself. There is some work investigating the development of collective behavior by utilizing the evolution of artificial neural networks where no such behavioral rules are defined in advance. In that realm very interesting collective behaviors could be demonstrate, such as a variety of different flocking strategies (Baldassarre et al., 2003), or team role allocation in a group of robots which have to move together while relying solely on infrared sensor information (Quinn et al., 2003). However, to our knowledge no work on collective behavior in group of artificial agents which uses RNNs as dynamical system for behavioral control, like for instance (Quinn et al., 2003; Marocco and Nolfi, 2006), revealed how the internal dynamics of the RNNs are actually related to the observable behavior. The focus of attention is, up to now, mainly directed toward an analysis of the behavior from an outside perspective or restricted to analysis of input-output activities of the according RNNs.

At this point we have to be aware of that the collective behavior presented in this chapter is indeed less complex than the behaviors in the studies mentioned above. Nevertheless, by relating the internal dynamics to the individual behavior and then to the global behavior we can explain what we observe by understanding every level, from individual to collective, and how these levels are interconnected. One of the reasons why such a complete analysis is so hard to find in the literature may indeed be the complexity of the behavior which may already require complex internal dynamics which is then too difficult to analyze. We argue, that this does not have to be an inevitable conclusion, as we will see in the following chapters of this thesis, where more complicated collective behaviors will be investigated. In fact, we claim that trying to understand the system as a whole, that is, in all of its constituent parts, as we have done it here for this rather simple behavior, is worth the effort because it may offer new insights about novelty not only of behavior, but also about novelty of its underlying mechanisms, which will become more evident in the examples of the proceeding chapters, especially in Chapter 6 and 7.

Up to this point we should keep in mind that the reason why the mechanisms which lead to the dynamic spatial aggregation pattern, as discussed here, seem to be rather simple and trivial is exactly because we are able to minimize the complexity of individual control, which at the same time allows us to understand the complete system. However, in this sense the experiments presented here are of course not a new discovery. We just have to think about the pioneering work of Gray Walter and Valentino Braitenberg done already almost sixty years ago, which we have discussed in Section 2.2.2 (p. 33). Their work and what originated from it, such as very much of the work presented in this thesis, showed that seemingly complex behavior of a system may be apparently simple because its constituent parts are rather simple, and because we are able to understand how these parts, whether they are neurons or robots, interact with each other. And the clustering (as presented here) based on the interplay between different reflexive behaviors is in fact just the beginning. The next chapters will reveal that this even holds for more sophisticated levels of communication and cooperation which will go beyond the dynamic interaction of simple individual reflexes.

4.6 Summary

In this chapter we demonstrated how competing behaviors can be realized by a very small-sized neural network. We have seen that the same internal dynamics are used for the two behaviors of avoiding obstacles and chasing a target. The required sensor modalities, infrared and sound sensors, are differently coupled to the neural network resulting in a different influence on its internal dynamics. And because the influence of the infrared sensors is stronger than the influence of the sound sensors, obstacle avoidance is the dominant behavior resolving the conflict which can occur when a robot is attracted to a location by sound signals and at the same time repelled from the location by an obstacle.

By using the very same network, actually evolved for this individual behavior, and by making each robot to an environmental cue (attracting and repelling at the same time) for each other robot, we showed how complicated aggregation patterns (cf. Figure 4.4), where individuals interact with each other only locally, are achievable with this structurally very small neural control architecture (cf. Figure 4.2b).

However, even though sub-behaviors like avoiding obstacles and approaching a target were evolved, and therefore not pre-designed in any way, we have to admit two major lacks. First, our fitness function rewarding the chasing behavior relied on external variables and, therefore, the resulting individual behavior was not very surprising. Second, for the transition from individual to collective behavior we decided what to change in the experimental setup, namely making every robot a potential target for any other robot. Thus, even though these experiments completely fulfill four of our demands (completeness, complexity out of simplicity, dynamical systems, and comprehensibility) they lack the demand for a reduction of preconceptions. However, these experiments form the ground for the following chapters, where we first want to increase the behavioral complexity (Chapter 5) and later we will focus more strongly on the emergence of interaction rules and communication systems from a rather *unconstrained* evolutionary process (Chapter 6 and 7). And we will see that this is the key to achieve not only robustness, but also *novelty* and *flexibility* of coordinated behavior in general and of communication mechanisms as the basis of cooperation in particular.

Chapter 5

Behavior coordination and synchronized communication

> "It is then too that one sees the great belt of light, some ten feet wide, formed by thousands upon thousands of fireflies whose green phosphorescence bridges the shoulder-high grass. The fluorescent band composed of these tiny organisms lights up and goes out with a precision that is perfectly synchronized, and one is left wondering what means of communication they possess which enables them to coordinate their shining as though controlled by a mechanical device."
>
> *Joy Adamson (1961), quoted in (Strogatz, 2003, p. 12)*

5.1 Introduction

In 1938 Buck reviewed a number of travel notes by diverse authors about the astonishing phenomena of synchronized flashing of fireflies in different locations around the world (even though most observation were made in Southeast Asia). He started his article with:

> "One of the most interesting and complex types of group behavior in animals is that in which several organisms simultaneously repeat the same activity at regular intervals of time. [...] such behavior [...] involves two distinct factors, synchronism and rhythm."

He also reviewed some theories about the underlying mechanisms which existed at this time. Nowadays, most of them seem rather obscure. They ranged from explaining that the synchronized flashing is caused by accidents, such as the influence of wind, and then maintained by the normal flashing rhythm of the individuals to the so called illusion theory, which holds that the human mind deceives itself into seeing synchrony. Other approaches reviewed by Buck (1938) assumed that fireflies possess a "sense of rhythm" similar to humans, or that there is a leader fly emitting flashes to which the mass of fireflies respond to. However, already at this time Richmond (1930) proposed a theory, which Buck judged to be the most promising explanation of the phenomena. It postulated that all flies flash rhythmically with nearly the same period, by a battery-like discharge and recovery, and that each insect flashes immediately if a neighboring insect flashes at a time close to its own next flash (Richmond, 1930).

Exactly fifty years after his first review, Buck (1988) published a second review where he stated:

> "Fifty years ago [...] it was not surprising [...] that hardly anything could be said about either mechanism or meaning of this remarkable communal behavior. [...] Today [...] the behavior has graduated from enigma to general significance in the fields of coordination physiology, group communication and evolutionary biology. [However,] each step of physiological elucidation has revealed new black boxes and each behavioral insight has left major puzzles yet unsolved."

The early ideas of Richmond (1930) were not that wrong at all. It turned out that the actual mechanism which enables thousands upon thousands of fireflies to flash in synchronized unison is based on resettable oscillators which are coupled through the pulses represented by the flashes of each individual (Buck, 1988). Thus, every individual emits and receives signals, influencing the rhythm of others and be influenced by them; a clearly self-organizing process and as Strogatz (2003, p. 13) expressed it:

> "Sync occurs through mutual cuing, in the same way that an orchestra can keep perfect time without a conductor. What's counterintuitive here is that the insect don't need to be intelligent. They have all the ingredients they need: Each firefly contains an oscillator, a little metronome, whose timing adjust automatically in response of flashes of others. That's it."

Much more could be said not only about synchronized flashing of fireflies, such synchronization mechanisms are prevalent in nature. They can be found in crickets which chirp in synchrony (Walker, 1969), neurons which fire together, and even, indeed more controversially discussed, human female menstrual cycles which get synchronized through pheromones (Stern and McClintock, 1998). For more on this topic we refer to the excellent and exciting books by Winfree (2001) and Strogatz (2003).

For the rest of this chapter we will stick to the general properties summarized in the quote above: Synchronization occurs through mutual cuing of rather simple individuals which contain a resettable oscillator. We want pursue the following question:

- Given our dynamical (neural) system approach, how can we achieve self-organized and coordinated (i.e., synchronized) behavior among autonomous robots with minimized communication efforts?

To do so we discuss an experiment where we increase the behavioral complexity of a robot as compared to the experiments discussed in Chapter 4. Instead of aggregation without function, we now want to achieve a group behavior with a specific purpose. Therefore, we consider a setup where robots have to collect energy (i.e., foraging behavior) in their environment and convey that energy to a base (i.e., homing behavior) where it is stored and constantly consumed. To display one of the both behaviors, either foraging or homing, robots are equipped with a structurally small neural rhythm generator, a resettable oscillator inherent in the robot's neural control which periodically

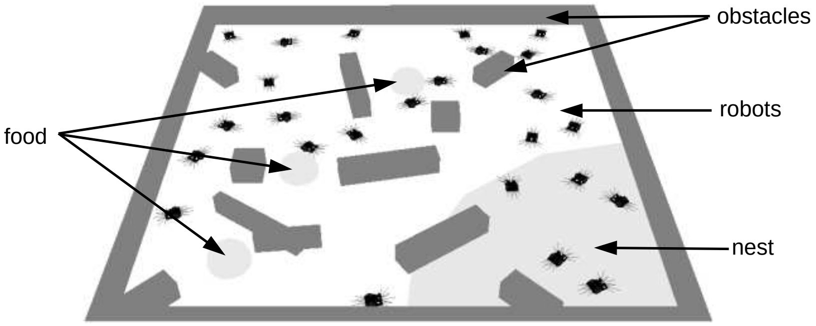

Figure 5.1: **Environment for a foraging and homing task.** Food sources are represented by three light bulbs which are randomly placed in the left half of the environment. The direction to the nest area (gray region in the bottom right) is marked by a acoustic signal continuously emitted from the center of the nest.

inhibits specific sub-behaviors. To coordinate the behavior among many individuals driven by such an internal rhythm, individuals can communicate with each other via simple acoustic signals, reminiscent of the flashes used by fireflies. Communication among the robots links what is internal to them, their rhythm, to what is external to them, their foraging and homing behavior. In that sense we will go a step further to what Parisi (2004) proposed as *internal robotics.* We not only consider the interaction of an internal drive with environmental stimuli which externally drive an individual, we also consider how a whole population coordinate the internal drive of each individual through *local direct couplings* realized by minimalistic acoustic communication. It can be shown that synchronizing behaviors among robots based on this rather simple, yet highly efficient, mechanism is not only scalable but also remarkably robust to the spatial range within individuals can interact with each other.

5.2 Experimental setup

5.2.1 Environmental setup: The foraging habitat

For the following experiments an environment as shown in Figure 5.1 was used (length: 5 meters, width: 5 meters). The large gray circle in the bottom right corner represents the nest that emits a strong periodic sound signal which can be detected within the complete environment. This signal can be used by the robots to find their way home to the nest.

In the left half of the environment three light sources are randomly distributed, which represent food sources. A robot can recharge its own energy level by approaching and finally standing in front of a light source (foraging behavior). The overall task of a robot group is to transfer collected energy to the nest. A single robot can load a maximum of one energy unit. If a robot enters the nest area its energy is continuously transferred to the nest, which has its maximum at 50 energy units. The difficulty for the group is that the nest also looses energy with time (that is, if you like, a simplified analogy of stored food in an ant nest used to feed the brood). The energy amount of the nest is calculated as:

$$E_{nest}(t+1) = E_{nest}(t) - \Delta E_L + n\Delta E_R, \tag{5.1}$$

where $\Delta E_L = 10^{-2}$ is a constant energy leakage, n the number of robots within the nest, and $\Delta E_R = 5 \times 10^{-3}$ the amount of energy a single robot conveys to the nest per time step. Because the time dependent leakage rate of the nest is higher as compared to a possible energy income from a single robot, its energy level cannot be maintained by a single foraging robot (note, that the robot also spends at least half of the time outside the nest to forage). Only the coordinated foraging action of a robot group can yield a maximization of the nest energy.

5.2.2 Sensory-motor system

As agents we used again the *Do:Little* robot, as introduced in the previous chapter (Section 4.2.1, p. 95). Note that Ix, Ox, and Hx refer to input, output, and hidden neurons with index x, respectively; and ix, ox, and hx refer to the corresponding output of these neurons.

The mapping from the motor neurons ($O1$ and $O2$) to the wheel speed and from the sound sensors to the according input neurons ($I7$ and $I8$) as well as the noise levels correspond to the setting given in Section 4.2.2 (p. 96). The same was done for the infrared sensors (IRs), except that we used here not only the left and right IRs ($I4$ and $I5$) but also an IR ($I6$) located at the back of the robot to increase its spatial sensory range of detecting objects (see also Figure 4.1, p. 96). Thus, IRs can be utilized to avoid collisions with other robots and obstacles within the environment. The sound sensor can detect the signal emitted by the nest to guide the robots to it.

To find food sources, robots are additionally equipped with light density resistors (LDRs) which measure illumination. As we said, light sources represent food. Thus, the closer the robot is to a food source the higher the activation of its LDRs. The sensor values of the LDRs were also linearly mapped into the range of the transfer function, that is, $[0, 1]$, where 0 represents darkness and 1 maximal illumination which is the case when the robot stands right in front of a light source. $I4, I5$, and $I6$ represent the left, right, and front LDR sensor, respectively (corresponding to c1, c2, and c3 in Figure 4.1, p. 96). Gaussian noise was added with $\sigma^2 = 0.1$ (i.e., 10% noise). A robot can use food sources to gain energy which then can be transfered to the nest. The energy of a robot is determined by:

$$E_{robot}(t+1) = E_{robot}(t) + \Delta E, \tag{5.2}$$

where $\Delta E = 10^{-2}$ if the robot stands in front of a light source (i.e., if $i6 > 0.8$), $\Delta E = -5 \times 10^{-3}$ if the robot is within the nest (this energy is transfered to the nest, see also Equation 5.1), and else $\Delta E = -5 \times 10^{-4}$ (leakage). E_{robot} is limited to $[0, 1]$. For the sake of simplicity, the energy level of a robot is considered only as 'carrying' energy, that is, the actual amount of energy has no consequences on the robot's behavior (as it would be the case if the battery of a real robot gets discharged).

Furthermore robots are able to communicate with each other by primitive sound signals. One nice feature of the sound processing implementation on the physical robot is that frequency and amplitude filtering is done on-board. Different signals

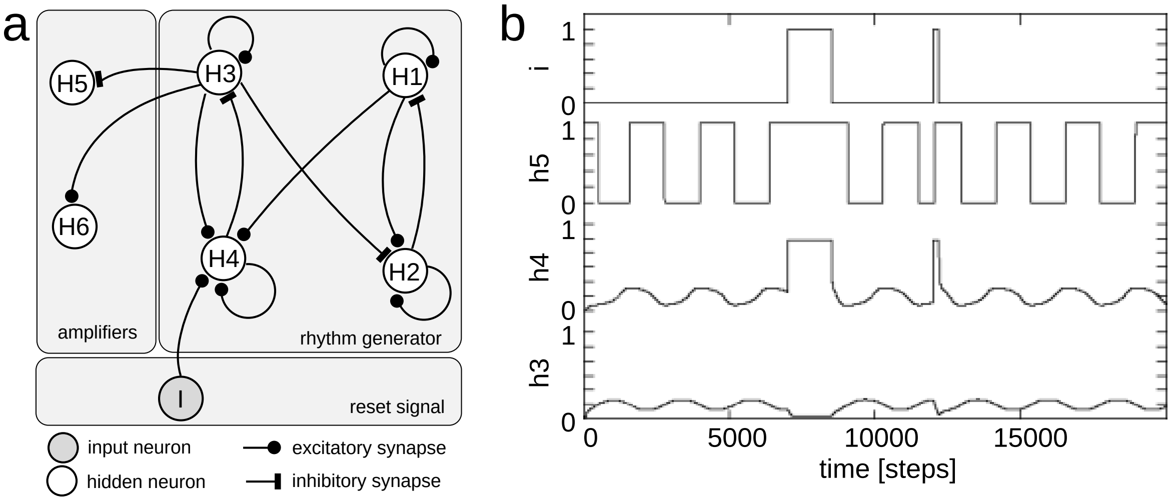

Figure 5.2: **Coupled SO(2)-networks realizing an internal rhythm generator.** The right panel shows how an external signal resets the output oscillations at the hidden neurons (shown only for $h3-5$).

are characterized by different pulse sequences. Hence, the robot can sense and produce different "chirp" signals. As we said, one signal is utilized to indicate the location of the nest. A different signal can be used by the robots for inter-individual communication. To produce a single sound signal the output of the corresponding motor neuron ($O3$) has to cross a certain threshold from below. Here, this threshold was set to 0.7. Other robots can sense the occurrence of this signal, but not its direction, by the activation of input neuron $I9$ which is either 1.0 when there is a signal within a specific range of the robot or 0.0 when there is no signal. In accordance with the hardware the detection range of a signal emitted by a robot was set to 1.5 meters.

5.2.3 Neural model of a resettable inner rhythm

To realize an internal rhythm generator we used a CPG which is composed of so called SO(2)-networks. An SO(2)-network, proposed by Pasemann et al. (2003), is a two neuron network having a weight matrix w which is an element in the special orthogonal group (that is where the name originates from). The weight matrix is associated with a rotation in the plane and is represented by functions of the rotation angle φ. Due to the existence of quasi-periodic attractors, these networks can generate almost sine-shaped waveforms (for details see Pasemann et al., 2003).

Here we used two coupled identical SO(2)-networks (see Figure 5.2a). The coupling of two networks assures stability of very long wave lengths. The frequency can be adjusted by only one parameter, φ. The weight matrix is given by:

$$w = \alpha \cdot \begin{pmatrix} \cos(\varphi) & \sin(\varphi) & 0 & 0 \\ -\sin(\varphi) & \cos(\varphi) & \epsilon & 0 \\ 0 & 0 & \cos(\varphi) & \sin(\varphi) \\ -\epsilon & 0 & -\sin(\varphi) & \cos(\varphi) \end{pmatrix}, \tag{5.3}$$

where $\alpha = 1.05$[1] and $\varphi \in [-\pi, \pi]$. The strength of the coupling and hence amplitude size are given by $\epsilon \neq 0$. All bias terms were set to 0.0 and ϵ to 0.008, and the activation of each neuron was randomly initialized. This weight matrix will work for the activation function $\sigma(x) = \tanh(x)$, but a transformation to a network with the standard sigmoid activation function $\sigma(x) = (1 + e^{-x})^{-1}$, as it will be used in the following experiments, with equivalent dynamics is possible (for details see Pasemann, 2002).

Setting $|\varphi|$ close to zero one can get very long wavelengths, for example using a φ of 10^{-8} yields stable wavelengths of more than three million time steps. For such wavelengths the size of the amplitude becomes very small, so it was useful to add amplifying neurons downstream ($H5$ and $H6$ in Figure 5.2a). Connecting them with a very strong weight to one of the oscillator neurons results in an (inverse) amplified output within the saturation domains of the activation function (see Figure 5.2b).

By giving input on one of the four neurons ($H4$ in Figure 5.2a) one can interrupt the CPG's oscillations. After the input ceases, the CPG will immediately start its oscillations again, thereby causing a phase shift. Depending on which neuron receives this reset signal, the amplified output will be in an "on" or "off" mode while the input is given. The plot in Figure 5.2b shows the reaction of the oscillators after getting a long reset signal starting at time step $7,000$ and a short one at time step $12,000$. Both times the quasi-periodic oscillations will be inhibited at once and the amplified output switches to "on". When the input comes to an end, oscillations restart in a stereotypical way.

5.3 Combining foraging and homing behavior

Three basic behaviors were evolved by a so called restrictive expansion technique (Hülse et al., 2004; Hülse, 2007). First, we evolved an RNN to realize robust obstacle avoidance behavior (OA-module). Second, while keeping the OA-module's structure and its parameters (synaptic weights and bias terms) fixed, a positive photo tropism was additionally evolved (P-module). In the following this photo tropism is considered as foraging behavior because it guides robots to light sources within the environment. Third, in the same way a positive sound tropism was evolved (S-module) that is considered as homing behavior because it guides robots to the nest in the environment.

Up to that point we can combine the same OA-module with either the P- or S-module resulting in two different behaviors. As a result of combining these modules with our pattern generator, as it can be seen in Figure 5.3, an exclusive switching between the evolved foraging and homing behavior can be carried out. The internal rhythm of the pattern generator does not influence the OA-module because the robot should avoid collisions at any time[2]. The sensor input neurons of the P- and S-module project feed forward to a corresponding hidden neuron layer. Only these hidden layers have connections to and from the motor outputs controlling the wheels. The amplifying neurons ($H5, H6$) of the pattern generator inhibit the according hidden layer through

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[1] The value of α has to be larger than 1 to assure quasi-periodic oscillations. For details about the parameters see (Pasemann et al., 2003).

[2] That is, obstacle avoidance is always the dominant behavior. The neural mechanisms to switch between obstacle avoidance and either one of the tropisms is similar to the mechanism described in the previous chapter (Section 4.3.2, p. 98) and is, therefore, not discussed here again.

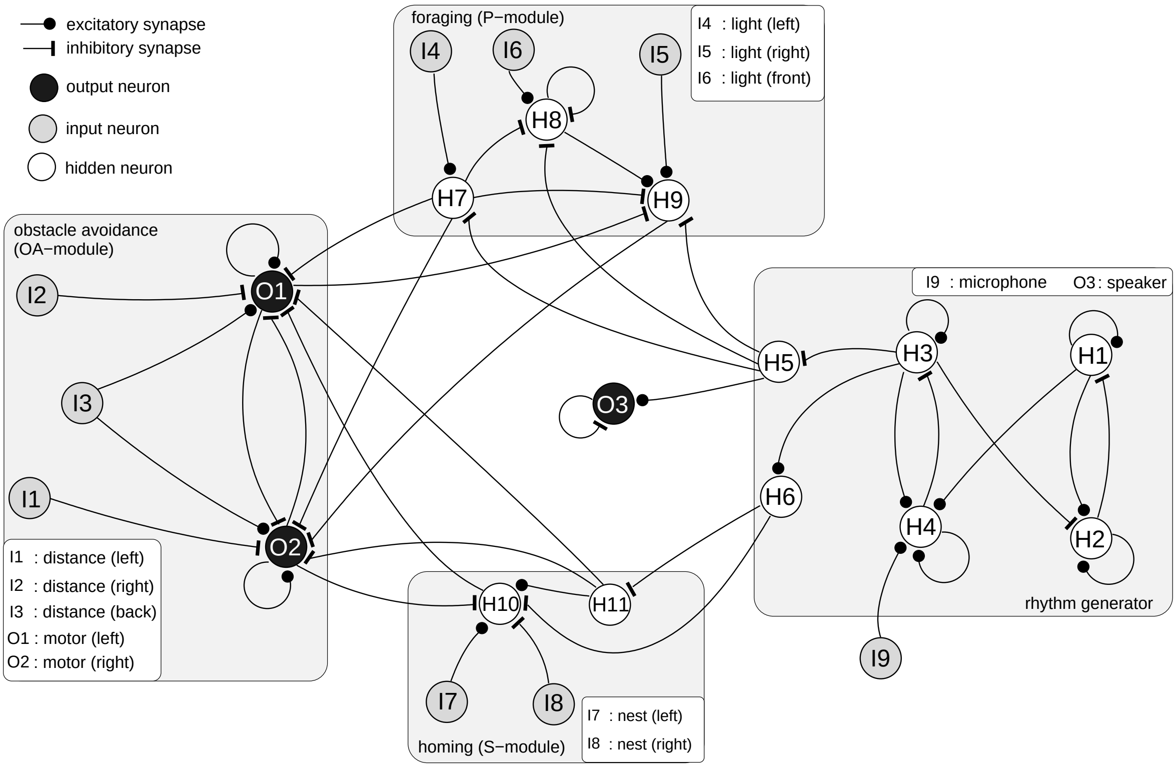

Figure 5.3: **A modular RNN realizing foraging and homing behaviors depending on an internal rhythm generator.** The rhythm is generated by a module based on the coupled SO(2)-module shown in Figure 5.2a. This module periodically inhibits either the foraging or the homing module.

synapses with very strong negative weights (cf. Figure 5.3) . As a result of using the standard sigmoid transfer function for this RNN, the inhibition only proceeds while the output of an amplifying neuron is 1, that is, in the upper saturation of its transfer function. As explained earlier the two amplifying neurons produce opposed signals, that is, whenever the output of one neuron is 1, the output of the other neuron is zero. In this way the robot displays either foraging or homing behavior.

Additionally, one output neuron ($O3$) allows the robot to communicate its behavioral state switches via its speaker. Therefore, this output neuron is excited by one amplifying neuron ($H5$, see Figure 5.3). By setting an appropriate bias and a negative self connection, this neuron integrates the signal of $H5$ and produces the highest peak when the output of $H5$ switches from zero to one, that is, when the robot switches from foraging to homing behavior. This maximal peak is slightly higher than the threshold of 0.7 and, therefore, triggers a sound signal lasting ten time steps which in turn can be detected by nearby robots (range = 1.5 meters) through an input neuron ($I9$, see Figure 5.3). This represents the reset signal for the oscillator as discussed before (see also Figure 5.2).

Each individual within a robot population possesses its own oscillator, that is, the individual inner rhythms vary in their wavelengths. For each experiment the oscillator of a single individual is randomly (uniformly distributed) chosen, the lower wavelength

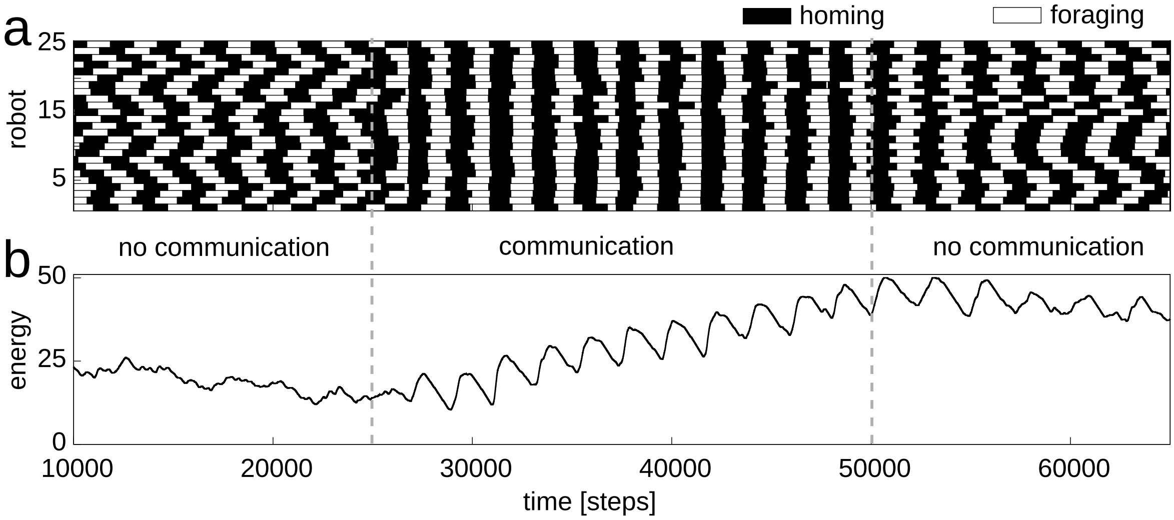

Figure 5.4: **Behavior synchronization in a group of 25 robots.** a: State synchronization among the robots. b: Development of the nest energy. Robots are allowed to communicate between time step 25, 000 and 50, 000, which gives rise to behavior coordination and, therefore, to a periodic increase of energy returned to the nest (see text for details).

bound was 2250 and the upper bound 2600 time steps, that is, the mean wavelength within a population is 2425 ± 175 time steps. We deliberately did not choose the same frequency for each individuals to (a) take into account the imprecision of the physical hardware (rounding errors, etc.) and to (b) to resemble the behavior of biological clocks in animals where it is known that the internal rhythms of individual members of one species can vary significantly (see for instance Winfree, 2001).

5.4 Behavior synchronization through local communication

In Figure 5.4a the behavioral states of 25 robots are drawn with time. From time step 0 to 25, 000, robots were not allowed to communicate (i.e., their speakers were disabled). We can see that each robot switches its behavior according to its inner rhythm. Each robot is starting in a different phase because the pattern generator is always randomly initialized. In this time slot the uncoordinated action of the robots leads to a slight decrease of the nest energy (Figure 5.4b).

The main reason for this decrease is that the robots enormously interfere with each other. What generally happens is, that a subgroup of robots are in the foraging state, that is, they are leaving the nest to search for energy. At the same time another subgroup of robots is in the homing state, that is, they are returning to the nest. If the ways of both groups intersect, for instance at a narrow passage (for example in the center of the environment, see Figure 5.1), they obstruct each other. Over time, while continuously avoiding each other, this conflict will be solved. But this can take so much time that probably no robot will accomplish its current task (either foraging or homing) before its inner rhythm again switches its behavior.

Between time step 25, 000 and 50, 000 robots could communicate their behavioral state switching (i.e., speakers were enabled). Now, each individual is signaling its switch from foraging to homing behavior and hence resets the inner rhythm of all robots which can detect this signal within a range of 1.5 meters. Because of this locally limited interaction, individuals most often synchronize their rhythms when they are gathered around a light source. However, there are three light sources (A,B, and C in the following) distributed within the environment (see Figure 5.1, p. 109). Individuals around light source A probably synchronize their behavior at a different time than individuals around light source B or C. The time when the members of one of these groups become synchronized is determined by the individual which switches its behavior first because it elicits a signal which resets the other's rhythm resulting in the same behavioral switch. This means members of group A may return to the nest earlier than members of group B or C. When an individual returned to the nest after a while it starts to forage again because of its internal rhythm. This behavior is independent of the other individuals. Thus, members of group A can now gather with member of group B around the same light source. Because individuals of group A switch their behavior earlier than members of group B, all individuals in this group become now synchronized to the rhythm of the individuals in group A. This mechanism is so efficient that the whole population becomes synchronized rather quickly within about 3, 000 time steps (cf. Figure 5.4a). Thus, global synchronization is achieved even though only some individuals of the population collectively entrain each other.

The transition from uncoordinated to coordinated group action is reflected in the evolution of the nest energy which now periodically increases (Figure 5.4b) because all robots return to the nest at roughly the same time. This is a characteristic overall behavior independent of the initial conditions, such as starting positions of the robots, initialization of the CPGs, or spatial distribution of the food sources (not shown, but see Wischmann et al., 2006).

From time step 50, 000 on, communication was again inhibited by disabling the speaker of each robot again. As a consequence each robot falls back in its own rhythm of foraging and homing (Figure 5.4a). This leads slowly to a more and more uncoordinated action that in turn provokes a slight decrease of the nest energy (Figure 5.4b).

5.5 Robustness to minimized interaction radius

In order to figure out the limitation of the system with respect to the detection range of the sound signals, we repeated the aforementioned experiment in simulation with different ranges. In Figure 5.5 the relative percentage of robots which simultaneously are in the foraging state is drawn over time. Note, a robot which is not displaying foraging behavior can only be in the homing state because of the rigorous switching between these two behaviors. Perfect synchronization is reached when at any time every robot in the population is in the same behavioral state, that is, every robot switches its state at the same time (which, for instance, is the case at the end of the bottom right diagram in Figure 5.5).

If the robots are not able to detect any sound signal (top left diagram in Figure 5.5), we can see that for most of the time there is no coordination within the population

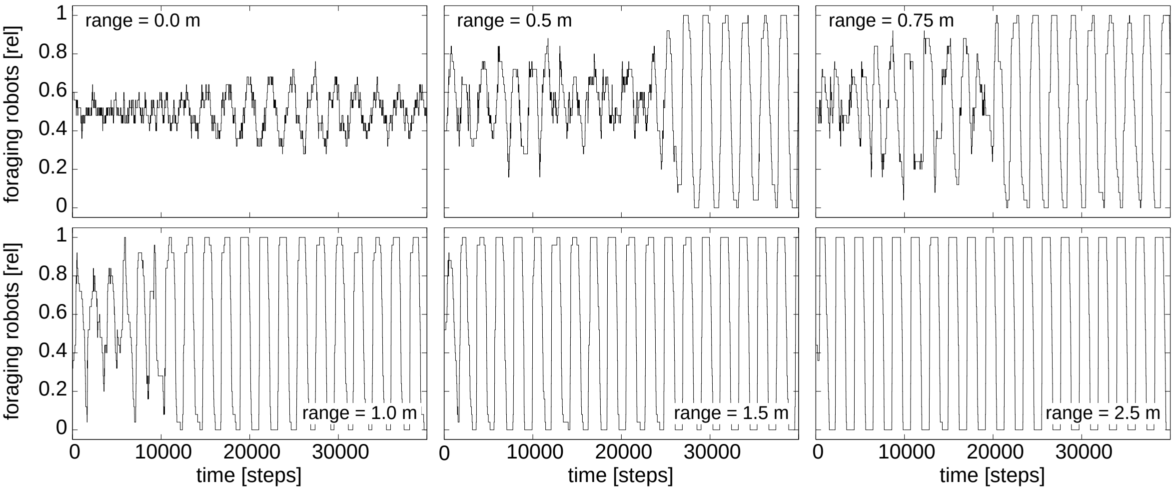

Figure 5.5: **Effects of different sound sensor ranges on the synchronization process.** Shown is the relative percentage of foraging robots in a group of 25 individuals. Increased detection range increases the radius where an individual can entrain other robots. Consequently, the time until the group behavior becomes synchronized decreases.

at all. Roughly half of the population displays foraging and the other half homing behavior. However, after a certain period seems to be a slight development toward synchronization (between time step 15, 000 and 30, 000). That is due to the differing free run periods of the robots' CPGs. After a while a portion of the internal rhythms are almost completely overlapping. But for the same reason, the different free run periods, this effect ceases after a while (between time step 30, 000 and 40, 000).

If we now consider a detection range of 1.5 meters (bottom central diagram in Figure 5.5) as it was set in the previous experiments, which is approximately the detection range of the physical robots, we can see that the system very quickly becomes almost perfectly coordinated (after about 3, 000 time steps). If we now increase the detection range, e.g. to 2.5 meters, the system synchronizes even faster. A decrease of the detection range entails increased time the population needs to become synchronized. That is because a smaller detection range consequently reduces the interaction radius of an individual and, therefore, limits the number of robots which it can entrain simultaneously. Although, for the sake of clarity, Figure 5.5 represents only sample runs, this is an overall characteristic of the system independent of the initial conditions like spatial distribution of the robots and food sources, or the initialization of the internal CPGs. However, there is lower limit of detection range (about 0.3 meters ± 0.1) where no synchronization can be achieved. This limit is approximately the nearest possible distance between two robots because of their reactive obstacle avoidance behavior. It is simply impossible for an individual to receive any sound signal from nearby robots because as soon as a robot detects other robots by its infrared sensors, it always tries to keep a certain distance to them as it also does for static obstacles within the environment.

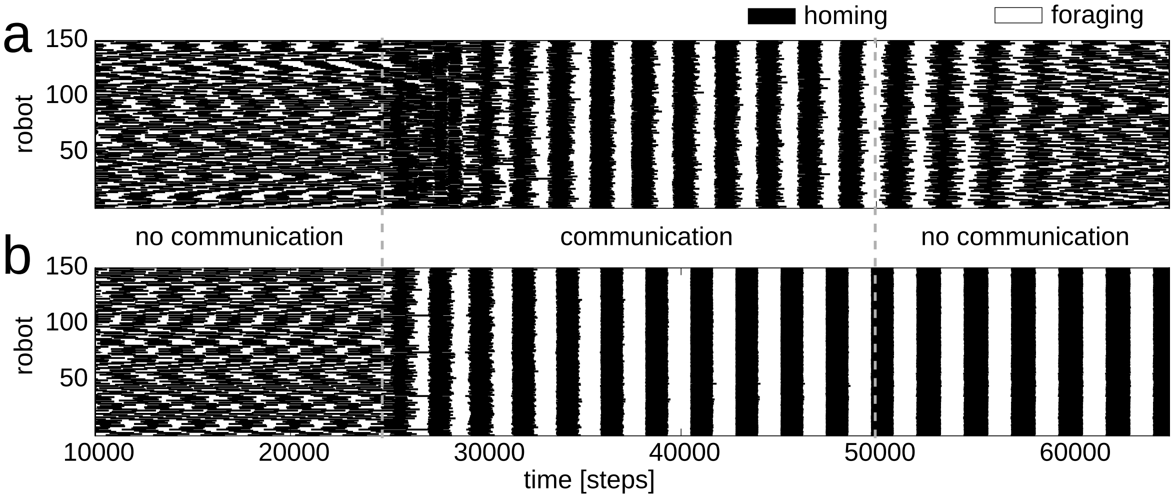

Figure 5.6: **Behavioral state synchronization of 150 robots.** a: Each robot has a slightly different inner rhythm. b: All have identical inner rhythms. Robots were allowed to communicate between time step 25,000 and 50,000.

5.6 Scalability

To demonstrate that the described synchronization process is also stable for larger robot groups we repeated the previous experiment with 150 robots in an enlarged environment (length: 10 meters, width: 10 meters). Figure 5.6a shows the development of the individual behavioral states. Again, individuals were allowed to communicate between time step $25,000$ and $50,000$. We obtain the same synchronizing effect as for the smaller sized population. However, the time needed to reach a stable synchronized state, which in this case is approximately $6,000$ time steps, is about twice as long as for a group of 25 robots.

Figure 5.6b shows the result of the same experiment, but this time the inner rhythms of each individual are identical within the whole population (wavelength $= 2,425$ time steps). We see that the population is perfectly synchronized within $25,000$ time steps, and, as it could be expected, once the behavioral states are synchronized, they remain synchronized although the individuals can not communicate any more (from time step $50,000$ on). The reason is quite obvious. Because there is no mechanism of de-synchronization, there is no need for persisting synchronizing forces once the system is synchronized. However, one can always expect slight differences among (quasi) identical robots, as one find differences in biological clocks (Winfree, 2001). Synchronizing these clocks from time to time helps to adjust individual behavior to achieve coordinated patterns.

5.7 Discussion

In Chapter 4 we discussed how a very small-sized neural network is able to integrate two competing behaviors such as obstacle avoidance and a positive tropism. Here, we increased the complexity of such combined reflex behaviors. A network was presented which combines not only a negative and a positive tropism, namely obstacle avoidance and finding food sources, but also an additional behavior which is in conflict with finding food sources, that is, finding a way back to a nest.

By combining these three behaviors with an internal rhythm a robot spend half its time with the search for food and half of its time with returning the gained energy to its nest[3]. However, a single robot was not able to maximize the energy stored in the nest because the virtual consumption of energy within the nest was much larger then the amount of energy one robot could bring in. Yet, also the collective foraging of many (quasi) identical robots, each acting by its own, was not sufficient to succeed in this task. Only coordinated behavior, that is, when all individuals displayed the same task more the less simultaneously, it was possible for the group to maximize the energy of the nest. To sum up, we observed a synergistic effect of behavior coordination by synchronization: A group of individuals which act independently of each other performed rather weak compared to the same number of individuals which coordinate their behavior. Coordination was achieved through direct, yet rather simple, local communication. By signaling behavioral switches to other individuals the internal rhythms of all individuals participating in this interaction became synchronized. And even though a synchronization process was always locally limited, over time all individuals became synchronized because interaction partners dynamically changed. Thus local communication processes led to a coherent synchronization within the whole group.

We started this chapter with the astonishing example of synchronized flashing among fireflies, and there are indeed some strong analogies to the behavior discussed for our robotic experiments. In both cases synchronization is a result of pulse coupled oscillators with varying frequencies. Individual oscillators have a free run period (firefly: 965 ± 90 ms, *Do:Little* robot: 2425 ± 175 time steps) which can be influenced by an external stimuli presented by neighboring individuals leading to a phase reset. This signal strongly correlates to a certain period the oscillation (firefly: begin of the rising excitation phase; *Do:Little* robot: switch from foraging to homing behavior). Strogatz and Stewart (1993) pointed out that "the behavior of communities of oscillators whose members have differing frequencies depends on the strength of the coupling among them." Future work could investigate the effects of weakening the direct coupling among the individuals, e.g. by introducing uncertainties during sound detection and transmission. In the presented experiments the coupling was strong enough to always achieve synchrony, that is, every detected signal provoked a phase reset.

Because of the great difference in the details of the nervous systems and individual physiology, our experiments may indeed not help us to understand the actual detailed physical mechanisms of a specific biological system which exhibit self-organized collective behavior, such as the synchronized flashing of fireflies. However, we have to consider that these creatures have to struggle with much more than just achieving

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[3] Of course, one could implement a much simpler neural mechanism to realize this kind of behavior switching. For instance, we could utilize the energy level of a robot as a sensory input. If this input is low, the homing behavior could be inhibited and, vice versa, if the robot is fully charged foraging could be suppressed. Using an internal state of a robot, such as its energy level, as a sensory input (i.e., as a parameter of its neural control) can realize action selection processes by highly interesting mechanisms. In (Hülse et al., 2007b) such an example is discussed which demonstrates that whether a robot shows one behavior or another conflicting one, depends on internal attractor switching as well as on fluctuations caused by the sensory-motor loop.

synchronized flashing, whereas our experimental bottom-up approach aims at the artificial generation of comparable self-organizing phenomena which serve as a starting point for investigating not only the minimal individual requirements necessary to bring on collective behavior coordination but also to test the behavior of such a system for stability. In this realm we demonstrated that only very basic communication is required to coordinate the behavior of a group of up to 150 individuals. The mechanism of achieving synchronized behavior by locally limited communication is scalable and does not depend on the number of involved individuals. By testing the system with respect to its robustness to the spatial range of interaction, we showed that even with a very small range it is possible to achieve a coherent synchronized state within the whole group. The range of interaction only influences the time the system needs to become synchronized.

5.8 Summary

The presented experiments demonstrated that highly minimized communication efforts are required to achieve coordination of individual behaviors and that the sophisticated global behavior pattern emerges mainly from the interaction or coupling of simple units at the individual neural level as well as at the robot-robot level. The coherent behavior of the overall system is scalable, regarding the number of interacting individuals, and robust, regarding the range of local interactions.

However, even though we were able to increase the behavioral complexity of single individuals as compared to the experiments discussed in the previous chapter, we still defined the way how individuals communicate. Besides increased behavioral complexity, the main purpose of this chapter was to show how a *functional coordinated behavior* (and that is the great difference, or extension if you like, to the previous chapter because, there, the discussed clustering did not serve a particular function) can be achieved by minimalistic communication. Nevertheless, this was a global function determined by our definition of the task, namely maximize the energy level of the nest. The next two chapters will now tackle the problem of to much design constraints imposed by us. By doing so, communication does emerge from an evolutionary process without any preconceptions about whether individuals have to communicate or if they do, how they should communicate. Surprisingly we will discover the evolutionary development of neural mechanisms of communication which are quite similar to the example discussed in this chapter, even though we will also find completely different and unexpected, that is, truly novel, solutions.

Chapter 6

Emergent communication and signal coordination

> “Unlike engineers, tinkerers who tackle the same problem are likely to end up with different solutions. This also applies to evolution, as exemplified by the variety of eyes found in the living world.”
>
> *François Jacob (1977, p. 1164)*

6.1 Introduction

The above quote is taken from the fascinating article *Evolution and tinkering* by François Jacob (1977). Nowadays considering evolution solely as a tinkering process is often criticized. Many researchers emphasize the importance of self-organizing principles as the main driving force for evolution (Kauffman, 1993; Corning, 1995; Hoelzer et al., 2006). However, Jacob stressed an important aspect of biological evolution, the variety of solutions developed by nature for similar problems. This chapter will discuss the role of evolutionary variety concerning different neural mechanisms that underlie seemingly similar behaviors among cooperating agents. Here, cooperation is based on simple communication forms which are reminiscent of food or alarm calls among animals (Maynard Smith and Harper, 2003).

To understand the evolution of animal communication and the origins of language the simulation of emergent communication and language systems turned out to be a promising research direction (Wagner et al., 2003; Cangelosi and Parisi, 2002; Steels, 2003). Taking into considerations the limitations of experimental investigations into natural systems, such simulations are an encouraging method not only for revealing details of the mechanisms of animal communication, but also for answering questions about its evolutionary origins and the conditions under which communication systems emerge.

Former studies of emergent communication covered systems which used either non-situated or situated agents with a repertoire of either single or a number of unstructured signals or a structured vocabulary composed of multiple signals (for an overview see Wagner et al., 2003). The present chapter concentrates on situated agents using atomic signals. The use of situated agents means that agents also interact in non-communicative ways with entities of their environment or other agents, and agents have outputs that affect the environment or other agents which in turn modify their own inputs and, consequently, internal states of their behavioral mechanisms.

Communication possibly has to be structured in complex environments, whereas unstructured communication is sufficient for basic tasks such as finding food sources or avoiding predators. Studies of situated agents using unstructured communication (for an overview see Wagner et al., 2003; Cangelosi and Parisi, 2002) demonstrated that, for instance, alarm calls evolve most often when population density is high enough and food calls when food sources are rich but rare in number (Reggia et al., 2001). Werner and Dyer (1994) conducted simulations aiming at the evolution of food, alarm, and mating calls. They demonstrated that sometimes signals are not as useful as they might seem from our observational perspective. Other studies revealed that communication can be realized without dedicated communication channels (Quinn, 2001; Wischmann et al., 2005). We already discussed such examples in Chapter 3 where agents lacked the ability to communicate explicitly. Thus, it was enforced that evolution discovers solutions where cooperative behavior among agents relies on implicit information sharing.

As a common principle of the aforementioned studies agents are evaluated on their performance on non-communicative tasks instead on their communication skills. This is essential to support communication as an *emergent* phenomena of an evolutionary process as it is used in the present chapter to develop cooperative foraging behaviors.

Besides the analysis of emergent communication at the behavioral level, the central aim of this chapter is again to investigate in detail the individual neural dynamics, that is, to reveal the link between behavior and the dynamical properties of its underlying neural control structures. Further questions pursued in this chapter are:

- What are the environmental prerequisites to discover the emergence of cooperation and communication in an unconstrained evolutionary process?
- Will explicit information sharing inevitably emerge when agents are able to make use of direct communication channels?
- To which degree do we observe evolutionary variety of solutions to the same problem?
- How important is evolutionary variety for the adaptivity of cooperating agents?

The experiments discussed in this chapter will show that the emergence of cooperative behavior depends heavily on how difficult it is for a single individual to discover a food source. Surprisingly, the easier it is the more likely cooperation emerges. Furthermore, in this chapter we will discuss several different solutions developed by evolution. Although we indeed find a great diversity of neural mechanisms, cooperation is always based on explicit communication, that is, individuals emit food calls when they discover a food source which guides other individuals to this source. However, at the neural level we can identify two distinct mechanisms. *Direct mechanisms* are characterized by a direct correlation between food source sensation and signaling, whereas *indirect mechanisms* are characterized by signaling depending rather on a behavioral context than on a specific sensor activation.

Thus, even though the evolved behaviors are seemingly similar, evolution develops a variety of clearly distinct neural mechanisms which realize these behaviors. And this diversity of mechanisms is in fact important for the flexibility of groups of agents when environmental conditions change because some of them possess an intrinsic robustness to these changes.

6.2 Experimental setup

6.2.1 Individual setup

For the following experiments we used the *Do:Little* robot as we did in the last two chapters. For the RNNs, *tanh* as a transfer function was used (cf. Section 2.4.1, p. 43). Note that Ix, Ox, and Hx refer to input, output, and hidden neurons with index x, respectively; and ix, ox, and hx refer to the corresponding output of these neurons.

Robots were equipped with infrared sensors to detect distances to obstacles, a floor sensor which measures the gray scale of the ground, and two microphones to detect the direction of sound signals. Sensor values were mapped to the activation of the sensory input neurons and appropriate noise was added which was determined by experiments with the real robot. The mapping and noise level of each sensor is given in Table 6.1. All sensor values are linearly mapped to the range of the activation function, except sensor values for detecting the direction of sound signals, in the following referred to as signals of type S_A. The angle α of a detected signal to the heading direction of the robot is represented by:

$$\begin{aligned} i5 &= 0.5 \times (1 + sin(\alpha)), \\ i6 &= 0.5 \times (1 - sin(\alpha)). \end{aligned} \tag{6.1}$$

In simulation the range of S_A signals was locally limited to 1.5 meters which is in accordance with the hardware. Note the high noise level of signal detection (Table 6.1).

The output values of the motor neurons determine the speed of the wheels and when an acoustic signal is triggered by the speaker of the robot. The angular velocities of the left and right wheel are given by:

$$\begin{aligned} \omega_{left} &= c \times (o1 - o2), \\ \omega_{right} &= c \times (o3 - o4), \end{aligned} \tag{6.2}$$

Table 6.1: Mapping from physical sensor values to sensory neuron activation.

sensors	neuron index	mapping [min, max]	simulated noise
IR left, right, back	$I1, I2, I3$	-1 : no obstacle 1 : close obstacle	0.05 (≈ 10%)
floor	$I4$	-1 : white 1 : black	0.05 (≈ 10%)
sound signal S_A, left	$I5$	0 : 90° to the right 1 : 90° to the left	0.3 (≈ 30%)
sound signal S_A, right	$I6$	0 : 90° to the left 1 : 90° to the right	0.3 (≈ 30%)

where c is a speed factor ($c = 2.0$).

The motor neuron $O5$ controls the emission of S_A sound signals. Important for the understanding of the communication systems, described later on, is that a robot emits a single sound signal when $o5$ values switch sign from negative to positive. This is demanded by the physical hardware design.

All of the described sensor and actuator mappings were implemented in a way that RNNs evolved in simulation are easily transferable to the actual hardware without any need of an additional pre- and post-processing of sensor inputs and motor outputs. That was done because we wanted to keep the focus on the evolutionary development of control structures for a given physical body. Although the co-evolution of morphology and control is an additional important aspect of artificial life research (see for instance Pfeifer and Scheier, 1999; Taylor and Massey, 2001), it is not within the scope of this thesis.

6.2.2 Evolutionary setup

To facilitate *emergent* behavior our evolutionary experiments rely on an implicit fitness function (see Section 2.5.5, p. 63), where a robot is evaluated on its efficiency of succeeding in a particular survival criterion instead on explicit descriptions of an expected behavior. For our study this means that during the final experiments the robot was evaluated only on its success of exploiting food sources, marked as black spots on the ground in the environment. Therefore, the fitness of a single robot i was defined as:

$$F(i) = s\frac{k(i)}{T}, \tag{6.3}$$

where T is the number of evaluation time steps, s a scaling factor ($s = 600$), and $k(i) \in N$ counts how often the robot is able to find a food patch. Whenever a robot r finds a food source and stops on it, it recharges its virtual battery, and afterwards it is again replaced randomly within the environment if its energy level is $E_r(t) > 0.95$. This energy level is defined as:

$$E_r(t+1) = \begin{cases} E_r(t) - D_t + I_t & \text{if } i4 > 0.8 \text{ and } |\omega_{left}|, |\omega_{right}| < 0.1, \\ E_r(t) - D_t & \text{else.} \end{cases} \tag{6.4}$$

The first case corresponds to the situation when a robot stops on a food source. D_t is a constant energy loss ($D_t = 0.001$) and I_t is the gained energy ($I_t = 0.006$). $E_r(t)$ is bounded by the interval $[0.0, 1.0]$. Note, for the sake of simplicity an energy value of $E_r = 0$ has no consequences for a robot. However, with low energy levels the time needed by a robot to recharge its battery is larger than with high energy levels. Thus, the faster a robot finds a food source the shorter the time of recharging and, therefore, the higher the performance, which depends on how often a robot is able to find food sources in a given evaluation time.

The evaluation of a particular RNN was done with a homogeneous group of robots (that is, they are identical with respect to their morphology and control). Such selection based on homogeneous groups means that the average fitness of all robots in a group was taken to evaluate the performance of a particular neural network (this corresponds to a fitness averaging as discussed in Section 2.5.4, p. 61). However, a robot was not evaluated on how it solves the several subtasks, such as avoiding obstacles and other individuals, approaching food sources, and, that is particularly important, how to cooperate and communicate with other agents. Thus, not only cooperative behavior can be successful, and communication does not have to inevitably emerge. For instance, even solitary behavior can be efficient if each individual is able to locate food patches reliably without running into obstacles or other robots. However, whether or not cooperative behavior emerges depends also on the given environmental constraints, for instance, on how difficult it is for an individuals to find food sources by random search.

Because agents are evaluated on a non-communicative task, it is ensured that communication is indeed an emergent phenomena of the evolutionary process. Grounded signals[1] can, but they do not have to, emerge during evolution. In our studies only a single signal is available to the agents. This signal can be used directly when related to basic needs such as finding food source. However, grounded signals do not necessarily have to evolve, because there are no initial associations of a signal with particular actions. An evolutionary algorithm is used to probably establish such associations (see Section 2.5.3, p. 56). With this method we can demonstrate how *structural changes* evoke cooperative behavior among communicating robots and adaptation to changing environmental conditions.

6.2.3 Incremental evolution

The difficulty of evolving cooperative foraging behaviors is the implicit existence of several subtasks. In our case the robot has to explore the environment to find food sources while avoiding obstacles, it has to react appropriately once such a source is found which means it has to emit useful signals and it has to react reasonably to signals of other robots. Evolving such a behavior without any bias is nearly impossible (we tried it, it never worked). Therefore, we applied a so called semi-restrictive incremental method (Hülse et al., 2004). In the first evolutionary step a single robot had to explore its environment without running into obstacles. The topology of the neural network was not determined beforehand, only input and output neurons were defined. Structural elements, such as synapses and hidden neurons, could freely emerge in between. The fitness function was still implicit. It demanded only high wheel speeds. For the second evolutionary step we selected several different RNNs which were successful in solving the exploration task as initial structures, and robots should now additionally stay on discovered food patches (fitness function of Eq. 6.3 was used). Already existing structural elements were not allowed to be removed (whereas their parameters could be changed), but new structural elements could be added within the *whole* network which now also had a floor sensory input to detect food sources. Resulting solutions realized the basic solitary foraging behavior whose according RNNs again served as initial structures for the next evolutionary step where robots were able to communicate (again, fitness function of Eq. 6.3 was used).

Consequently, after the first evolutionary step we always put a certain bias in each subsequent step. However, this was only done to provide basic behaviors for the evolu-

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[1] Grounded signals are signals that are related to the agent or its environment, and therefore have a meaning (Harnad, 1990). That is, there is a specific relation between the act of signaling the resulting action of a receiver.

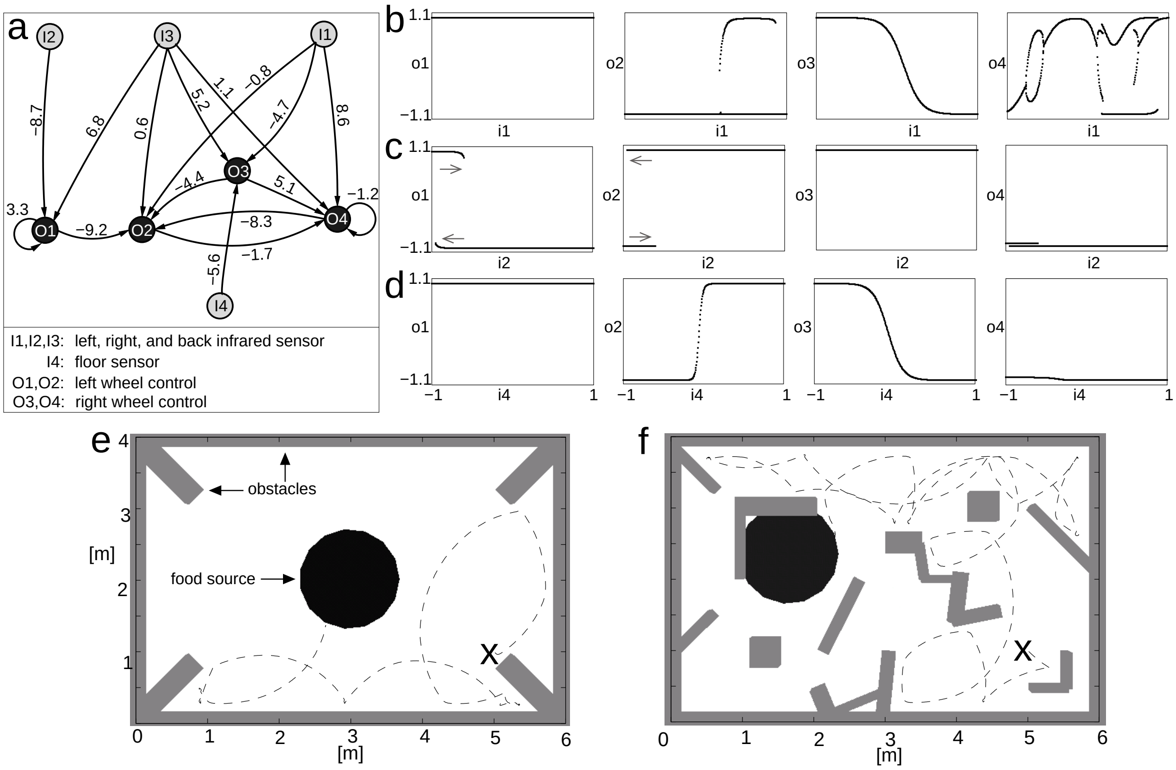

Figure 6.1: **The basic solitary foraging behavior and its neural mechanisms.** a: RNN of $\mathcal{A}_1$ individuals realizing the basic solitary foraging behavior. b-d: Bifurcation diagrams for $o1$-4 by separately varying $i1$, $i2$, and $i4$ (not varied inputs were set to -1.0; gray arrows indicate whether the varied value is increasing or decreasing). e,f: Path (dashed line) of a single robot during a sample run in two different environments starting at x with an initial south-east heading direction away from the food source.

tion of more complex behaviors, for which we never defined how a network eventually should be realized. Therefore, we argue that the emergence of communication during evolution was neither explicitly forced by a given network structure nor by the fitness function.

Solitary foraging

In two subsequent evolutionary steps, as described in the previous section, we evolved the basic foraging behavior which entails three sub-behaviors: exploring the environment, avoiding obstacles, and stopping on a food source. The environment shown in Figure 6.1f was used. During evolution each neural network was evaluated on ten robots in the same environment at the same time (the starting position of each robot was randomly determined within the complete environment excluding the food source). This method promotes more reliable fitness values as compared to single robot evaluation because we took the average of all ten individual fitness values (cf. Eq. 6.3), which is equivalent to averaging the fitness of a single individual over ten trials with different initial conditions, such as the starting position and heading direction (for a discussion about fitness averaging see also Section 2.5.4, p. 59). Furthermore, it facilitates a robust obstacle avoidance behavior because each robot is also challenged with moving barriers (that is, other robots). One resulting network is shown in Figure 6.1a. Individuals equipped with this RNN are in the following called $\mathcal{A}_1$. Such a robot solves all three subtasks not only in the environment where it was evolved (Figure 6.1f), but also in differently structured environments (see for instance Figure 6.1e).

The main neural mechanisms that underlie the observable behavior are summarized in Figure 6.1b-d. Obstacle avoidance is characterized as follows: When the activation of the left infrared sensor ($i1$) increases, the system enters periodic attractors (Figure 6.1b) which leads to an oscillation of $o2$ and $o4$. These oscillations are averaged through the properties of the motors and the robot's body (inertia, friction). Thus only the mean of these oscillations lead to the actual velocity of the wheels. For $o3$ we observe a change of a fixed point from the upper to the lower saturation domain of the activation function, resulting in a turn to the right (cf. Eq. 6.2). A different mechanism is activated when the right infrared sensor input ($i2$) varies. The motor outputs $o1$, $o2$, and $o4$ change their fixed point at different values depending on whether $i2$ increases or decreases (Figure 6.1c). This hysteresis effect is due to the strong positive self-connection at $O1$ and the even loop between $O2$ and $O4$. For a detailed discussion of these mechanisms, oscillation averaging and hysteresis effects, see (Hülse et al., 2005). For the purpose of our study it is sufficient to notice that these mechanisms slow down the corresponding wheels (cf. Eq. 6.2) when an obstacle is detected, and that this evokes an avoidance behavior as shown in Figure 6.1e,f.

Figure 6.1d shows the neural mechanisms that underlie the stopping on a food source. When the robot enters a food source, the activation of the ground sensor ($i4$) changes. In our experimental setup the gray value of food sources was randomly chosen in a range that it always provoked a sensor activation between 0.8 and 1.0 (± sensory noise). For these values the fixed point, important for $o1$ and $o2$, lies in the upper saturation domain, which means the left wheel stops. The same holds for $o3$ and $o4$, only that the according fixed point is within the lower saturation domain. According to Eq. 6.2 this forces the robot to stop.

6.3 Emergent communication in small groups

6.3.1 Required environmental conditions

To evolve cooperative behavior based on emergent communication systems we took RNNs from the previous evolutionary step (including the RNN of $\mathcal{A}_1$), which performed well in the solitary foraging task. Our first intuition was that a complex environment, as shown in Figure 6.1f, would enforce the emergence of cooperation. In this environment it is rather complicated for a solitary individual to quickly find the single food patch. Once an individual finds it perchance, it could use its communication system to guide the others. Thus, cooperating individuals would have a significant higher fitness than solitary individuals. Using a homogeneous group of ten robots we conducted 30 evolutionary trials, each lasting at least for 1000 generations, and with each generation having an average population size of 100 individuals. Communication and cooperation has not evolved in any case. Our explanation is that the performance gap between solitary and cooperative behavior, what we actually thought might facilitate the emergence of communication, is too large (compare the performance of communicating and non-communicating agents in Figure 6.4a). It takes too much time until an individual finds the food patch. And consequently, even when it than starts to call other robots, this would not significantly increase the performance compared to robust solitary behavior because we have to consider that the robots had to learn signaling *and* the appropriate responses to other signals at the same time (and the communication range is spatially limited). And this is very unlikely to happen in a single evolutionary step from one generation to the next. Therefore, a stepwise refinement of the communication system during evolutionary development is actually not possible.

We than decreased the environmental complexity by removing obstacles and placing several food patches in the environment. But even there, no cooperation emerged, which is more easily to explain. Because food sources were many in numbers, there was no need to communicate because solitary individuals needed only a very short time to discover them by chance. Reggia et al. (2001) made more thorough investigations into the environmental conditions which enable the emergence of communication. Their experiments, despite that they were done with grid worlds, convincingly demonstrate that communication most often evolves when food sources are rich but few in number. We did not test for the richness of food sources, but our experiments confirmed that they have to be few in number. However, what seems to be counterintuitive is that only in environments where food sources were easily accessible, cooperative behavior emerged. Intuitively, one might think that the more difficult it is to discover food sources the more likely cooperative behavior would evolve. A thorough investigation of these surprising aspect would be interesting for future research. As discussed above the most likely explanation for this phenomena in our experiments is the increased performance gap between solitary and cooperative foraging behavior in environments where food sources are hard to find.

Finally we used an environment as illustrated in Figure 6.2b where a single food source is rather easy to find by random search. Evolution with this environment gave rise to the emergence of cooperation, as it will be discussed in the following section. It is important to stress that although all RNNs were evolved in this rather simple environment, the resulting cooperative behavior was robust enough that, in the end, we could also observe better performance compared to solitary behavior in the more complicated environment (compare Figure 6.1f with Figure 6.2c), without any additional evolutionary optimization.

6.3.2 Unidirectional broadcasting

The basic foraging behavior (Figure 6.1) is sufficiently good for a solitary individual. If robots get the ability to communicate, the most intuitive improvement would be that a robot as soon as it detects a food source releases a signal to call and to guide other individuals. This is exactly the behavioral strategy realized by the network shown in Figure 6.2a. This RNN was one result of the evolution with a homogeneous group of ten robots capable to communicate. Individuals controlled by this type of RNN are called $\mathcal{B}_1$. When such a robot receives the food call of another individual it follows the signal and finds the food source very quickly while still avoiding obstacles (Figure 6.2b,c). The neural mechanisms of obstacle avoidance and staying on a detected food source are

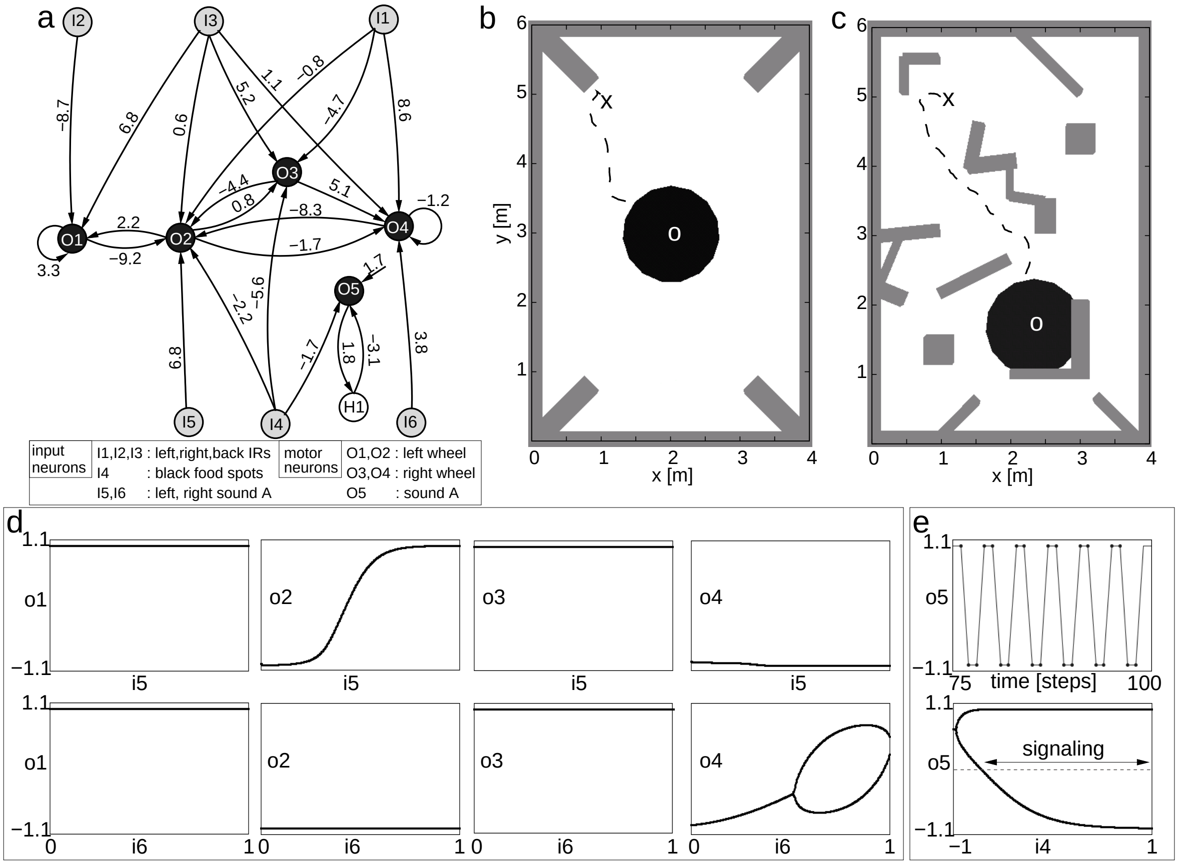

Figure 6.2: **Behavior and neural characteristics of $\mathcal{B}_1$ individuals.** a: RNN of $\mathcal{B}_1$ individuals resulting from the evolution with a group of ten robots capable to communicate ($H1$ is a hidden neuron). b,c: Path of a robot placed at starting position x (cf. Figure 6.1e-f) while another robot on position o emit food calls. d: Bifurcation diagrams for the output neurons which control the wheels while varying the left and the right sound sensor input $i5$ and $i6$, respectively ($i1 = i2 = i3 = i4 = -1.0$; not varied sound sensor was set to 0.0). e: Signals of $O5$ (top) with the robot on a food patch and the bifurcation diagram for $o5$ (bottom) by varying the floor sensor input ($i1 = i2 = i3 = -1.0$; $i5 = i6 = 0.0$).

qualitatively similar to the mechanisms discussed for the basic foraging behavior (see Section 6.2.3). Therefore, in the following we will concentrate on the neural principles of emitting food calls and the behavioral response to such signals.

Figure 6.2d explains the principles of signal following. When a signal on the right side ($i5$ increases) is detected, only the output of $O2$, the neuron to which $I5$ is connected (see Figure 6.2a), changes in a way that the left wheel is slowed down leading to a right turn. If a signal on the left side of a robot occurs, $i6$ increases. This affects only neuron $O4$ leading to period-2 oscillations, which are, as mentioned earlier, averaged by the inertia and friction of the robot's body. The consequential slow down of the right wheel causes a turn to the left.

Figure 6.2e (bottom) illustrates the influence of the ground sensor input neuron $I4$ on the motor neuron $O5$, which is responsible for the sound generation. By means of an odd loop with strong positive and negative weights (for deeper discussions about the dynamics of two neuron networks see Pasemann, 1995b, 2002), $O5$ is connected with the hidden neuron $H1$ (see Figure 6.2a). This loop operates as a switchable oscillator (Pasemann, 2002) depending on $i4$, which is about -1.0 as long as the robot is moving on white ground. As we can see in the bifurcation diagram (Figure 6.2e bottom) the oscillation, caused by a period-4 attractor, is switched on by an increased activation of $I4$. The bifurcation point is very close to $i4 = -1.0$, and therefore, it can already be crossed by the noise of the floor sensor. However, to emit a sound signal there has to be at least one point of the periodic orbit in the negative domain and one point in the positive domain because a signal is only elicited if $o5$ switches its sign from negative to positive. This only holds for $i4 > -0.7$ (never reached by sensor noise itself). Since detected food patches always provoke sensor signals of $I4$ within $[0.8, 1.0]$ the output of $O5$ oscillates as shown in Figure 6.2b (top).

There is a direct correlation between food source sensation and emitting food calls. These signals are grounded because they are elicited under a specific environmental stimulation and they provoke a particular action in their receivers. Other robots use these food indicating signals to enhance their own behavioral performance by directly moving to the food source. Once they arrived, they also immediately start signaling. This kind of communication corresponds to unidirectional broad casting because signals are not send to a specific receiver and the act of signaling changes the behavior of a receiver, but this induced behavioral change does not influence the behavior of the signaler.

6.3.3 Communication based on indirect mechanisms

Another evolutionary solution, from now on called $\mathcal{B}_2$ individuals, is shown in Figure 6.3a. The neural principles of obstacle avoidance, resting on a food source, and following a detected food call are qualitatively similar to those described above. But the mechanisms responsible for the release of food calls are significantly different. As we can see in Figure 6.3a, there is no direct connection from the floor sensor input $I4$ to the output neuron $O5$. Thus the sensation of a food source can not explicitly influence the signaling behavior as it is the case for $\mathcal{B}_1$ individuals. All relevant synaptic inputs to $O5$ are emphasized in Figure 6.3a. When a single robot stays on a food source, the motor outputs are $o1 = o2 = 1.0$ and $o4 = -1.0$ (the mechanism is qualitatively similar as shown in Figure 6.1d). And as long as no other robot is in range, the left infrared sensor is not activated (i.e., $i1 = -1.0$). Correlating these values with the synaptic strength of the connections which project from these neurons to $O5$ would lead to an output of $o5 = -0.1$ as can be seen in Figure 6.3c ($i4 > 0.8$ when the robot is on a food source). This fixed point is now in the linear domain of the activation function, and therefore the output of $O5$ is highly sensitive to the noise of $i1$. Figure 6.3b shows how the noise is amplified at $O5$ due to the strong positive weight of the synapse from $I1$. The output of $O5$ now fluctuates randomly around zero which triggers a food call whenever it crosses the zero line from the negative to the positive domain. Thus, in this example fluctuations in form of sensory noise are the driving force of signaling, which in this example is advantageous as we will see in the next section.

In classical engineering approaches to behavior control of autonomous robots it is

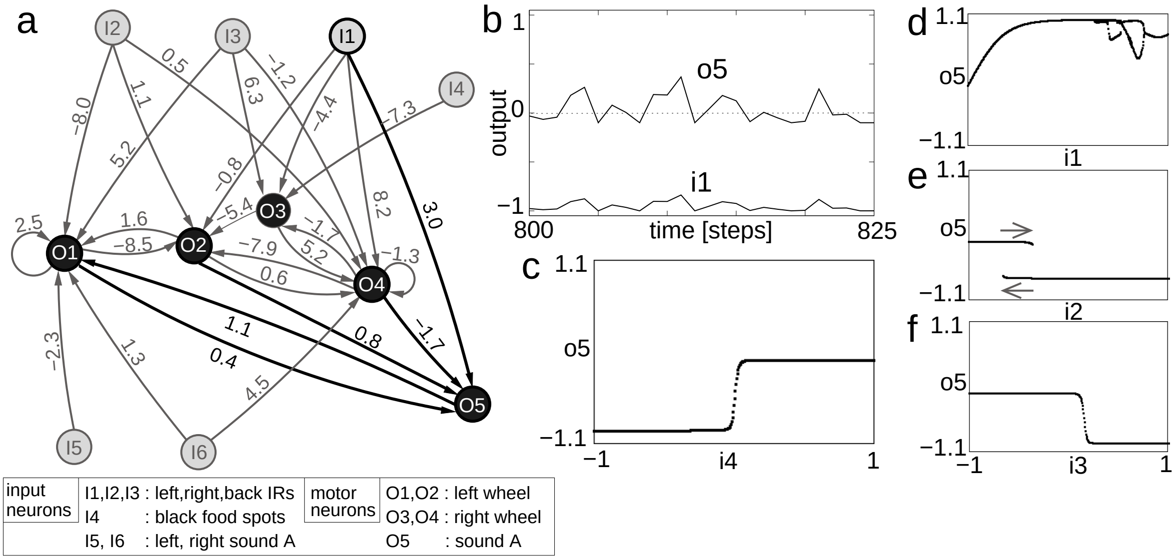

Figure 6.3: **Neural characteristics of $\mathcal{B}_2$ individuals.** a: RNN of $\mathcal{B}_2$ individuals resulting from the evolution with a group of ten robots capable to communicate. b: Signals of $O5$ and $I1$ when a single robot is on a food patch. c: Bifurcation diagram for $o5$ by varying the floor sensor input $i4$ ($i1 = i2 = i3 = -1.0$; $i5 = i6 = 0.0$). c-f: Bifurcation diagram for $o5$ by separately varying the distance sensor inputs $i1$,$i2$, and $i3$ ($i4 = 1.0; i5 = i6 = 0.0$; not varied distance sensor inputs were set to -1.0; gray arrows indicate whether the varied value is increasing or decreasing).

usually tried to prevent or eliminate noise as effective as possible. Contrary, for biological systems it is well known that noise can significantly enhance sensory-motor patterns, for instance by means of a mechanism known as stochastic resonance (Gammaitoni et al., 1998). In our example, utilizing noise is a quite efficient solution to the problem of signaling. Infrared sensors are always noisy, and we tested different noise levels in the simulation environment with the result that the behavior does not qualitatively change if the noise level is varied between 2% and 15% (the noise level of the physical infrared sensors is ≈ 10%).

6.3.4 Performance when environmental conditions change

The major problem, which actually is a constraint of the given physical body, in our experimental setup is that too many signaling robots can produce a continuous signal for a longer time. Then, individuals, still searching for food, are not able to detect reliably the food calls of other robots (note, only signal peaks can be clearly distinguished by the robots). In a group of ten robots such a situation occurs only rarely for $\mathcal{B}_1$ individuals and almost never for $\mathcal{B}_2$ individuals because only a few robots are standing on a food source where they emit food calls. For $\mathcal{B}_1$ individuals at least four agents are needed to produce a continuous signal, and this can happen only if the oscillations of $o5$ are in a different phase for each of the four individuals. The chance that a few individuals produce a continuous signal for a longer time is very low because fluctuations of $o5$ for $\mathcal{B}_2$ are driven by sensory noise and hence rather random.

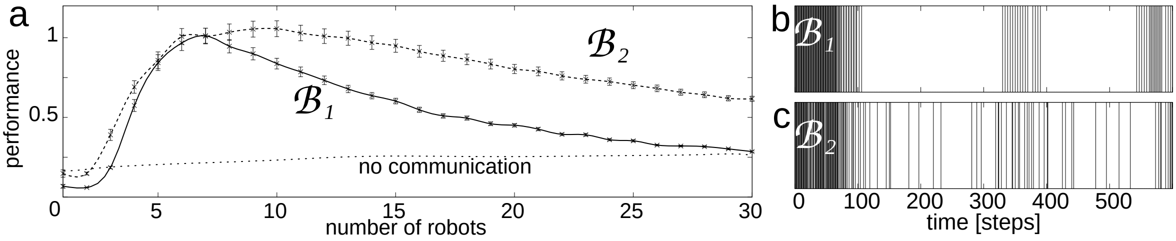

Figure 6.4: **Performance and signaling behavior comparison for $\mathcal{B}_1$ and $\mathcal{B}_2$ individuals.** a: Performance of $\mathcal{B}_1$ and $\mathcal{B}_2$ individuals depending on group size. For each group size 25 simulation runs were performed, each lasting 18,000 time steps. The mean performance of $\mathcal{B}_1$ and $\mathcal{B}_2$ individuals with deactivated communication systems (disabled microphone and speaker) is drawn as a reference. Performance was calculated according to Eq. 6.3. b,c: Black regions indicate the periods where *no* robot within a group of 30 individuals emits a sound signal (see text for details). Measurements were conducted in the environment shown in Figure 6.2b.

And indeed, if we compare the performance of these two RNNs at a group size of ten individuals, we see that they both perform sufficiently well (Figure 6.4a). If we increase the group size, the performance of $\mathcal{B}_1$ drops rapidly, which is due to the overlapping period-4 signals of too many robots signaling simultaneously. The more individuals signal at the same time, the higher the probability that their signals will sum up to a continuous signal. Remember, already four individuals of $\mathcal{B}_1$ can produce a continuous signal when they are all signaling with different phases[2]. This problem becomes even more evident if we look at the signaling behavior in a group of 30 robots.

The black regions in Figure 6.4b indicate the time intervals when no signal is present from any $\mathcal{B}_1$ individual, whereas white regions represent the presence of at least one signal. At the beginning no robot emits a food call because the food source is not discovered yet. But as soon as one robot starts to emit food calls, this attracts other robots which then also start signaling as soon as they arrive at the food patch. This leads very quickly to a long period of overlapping signals (time steps 100-330) where no robot, which is still searching for food, can recognize the food calls. For a short time this conflict is solved (time steps 330-380) because most of the robots on the food patch have recharged their energy level and are replaced randomly in the environment.

In contrast, $\mathcal{B}_2$ individuals perform much better in larger groups (Figure 6.4a). At the behavioral level this can be explained by the signaling behavior of a group with 30 individuals as it is illustrated in Figure 6.4c. One reason for the robustness to increased group size is indeed that signals are released randomly rather than with short periods which decreases the probability that single signals sum up to a continuous signal for a longer time. But there is an additional, more subtle, mechanism. The more robots share an environment the more crowded the food patch becomes and the closer is the distance between the robots on it. If a robot is so close that it activates the infrared sensors of another signaling robot, the fixed point of $O5$ is shifted

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[2] This is not simply an artifact of the simulation. Experiments with physical robots have also shown that the maximal frequency, where two subsequent signals can be distinguished, is $5Hz$. It does not matter from which direction the sound signal comes.

away as shown in Figure 6.3d-f. The influence of increased activation at $I1$ is rather direct because of the strong synaptic connection to $O5$ (see Figure 6.3a), whereas the influence of $I2$ and $I3$ is rather indirect. An activation of these sensors triggers an obstacle avoidance response which is characterized by a change of the activation at the motor neurons which drive the wheels ($O1$-4). This change disturbs the balanced synaptic input of $O5$, and hence, signaling also ceases (see Figure 6.3e,f). Thus, the number of signalers does not necessarily increase with the number of robots which are on the food patch because more robots cause more disturbances which automatically reduces the number of signalers. In addition to the random emission of signals, this self-organized regulation of signaling is the second reason for the intrinsic robustness to increased group size. This means that signaling can not longer be described as unidirectional. The induced behavioral change in receiving robots can also change the signaling behavior of a transmitter as soon as the receiver reaches it, which leads to a coordination of signaling.

What is important to stress is that the signal itself is not relevant for the signal coordination process. Coordination results from activation of infrared sensors which measure the distance to obstacles. A robot can not distinguish between static obstacles in the environment or other robots, both just increase the infrared sensor activation when they are close by and as a consequence a robot would try to avoid that obstacle. This change in behavior, caused by a change of the corresponding motor neurons which control the wheels, causes the signal coordination among many robots trying to exploit the same food source. And in that sense this coordination relies on *implicit* information sharing because there is no need to explicitly coordinate the signaling. It is implicit because information of how many robots are already signaling is not transmitted directly.

6.4 Evolutionary adaptations in larger groups

In the next setup of our experiments we wanted to figure out how evolution as an adaptation process refines solutions which turned out to perform rather weak when confronted with more complicated environmental conditions such as an increased number of interacting robots. Thus, we took the RNN of $\mathcal{B}_1$ individuals (Figure 6.2a), which realized communication by a switchable period-4 oscillator, as the initial structure for the evolution on the same task but we increased the group size to 25 individuals. Again, we allowed parameter changes of the initial RNN as well as the emergence of new structural elements.

6.4.1 Synchronized quasi-periodic oscillators

One of the refined solutions is shown in Figure 6.5a. Individuals controlled by this RNN are called $\mathcal{C}_1$ individuals. When we compare the structural elements responsible for the communication system with the initial RNN of $\mathcal{B}_1$ (Figure 6.2a), we notice the same odd loop between $H1$ and $O5$ with over-critical synaptic weights[3]. In addition, we

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[3] By over-critical we mean here a weight configuration leading to non-trivial dynamics, which are determined by periodic, quasi-periodic, chaotic, or co-existing attractor domains rather than by single fixed point attractors. For a deeper and mathematically thorough discussion see (Pasemann, 2002).

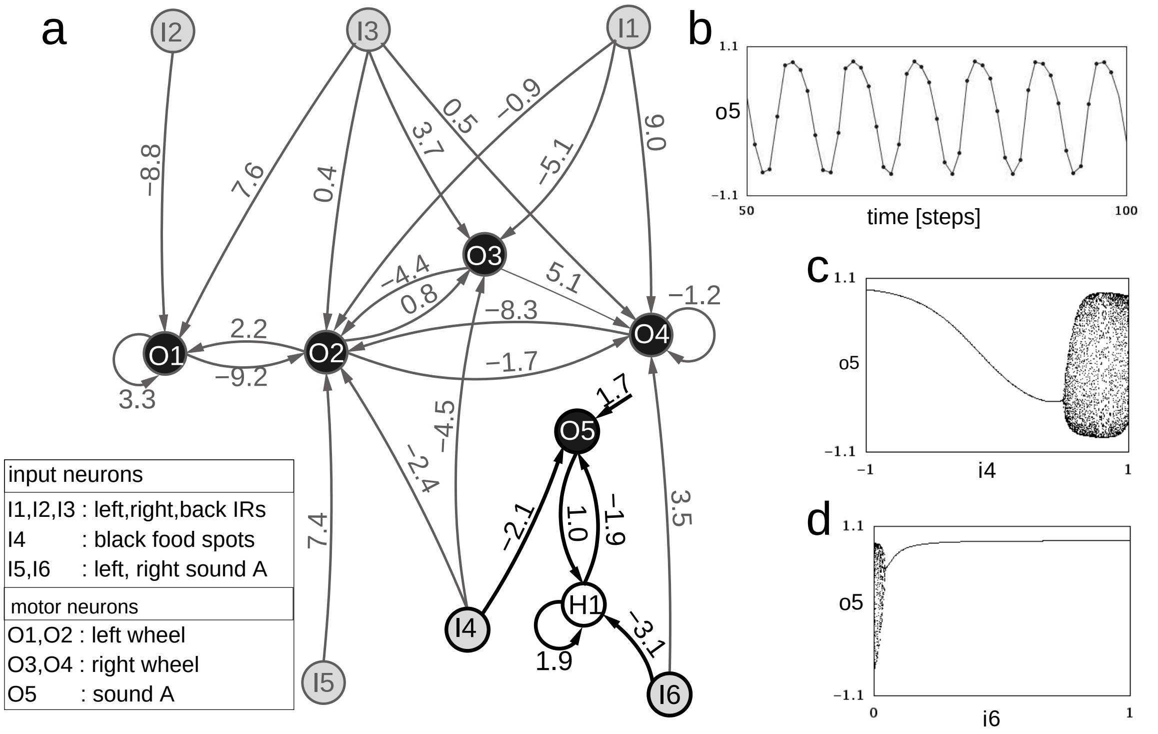

Figure 6.5: **Neural characteristics of $\mathcal{C}_1$ individuals.** a: RNN of $\mathcal{C}_1$ individuals resulting from evolution with a group of 25 robots capable to communicate. b: Signals of $O5$ when a single robot stays on a food patch. c: Bifurcation diagram for $o5$ by varying $i4$ ($i1 = i2 = i3 = -1.0$; $i5 = i6 = 0.0$). d: Bifurcation diagram for $o5$ by varying $i6$ ($i1 = i2 = i3 = -1.0; i4 = 1.0; i5 = 0.0$).

find an over-critical self-connection at $H1$. With this weight configuration the module exhibits quasi-periodic oscillations (Figure 6.5b) which are switched on by an increased activation of the floor sensor $I4$ (Figure 6.5c). We applied a power spectrum analysis to the time series in Figure 6.5b and found a mean period length of about 8.7 time steps. The time between emitting two subsequent sound signals is now almost twice as long as in $\mathcal{B}_1$. Although this is presumably a coincidence, the correlation is interesting because the group size used in evolution of $\mathcal{C}_1$ is also almost twice as large as it was used for the evolution of $\mathcal{B}_1$.

Another new structural element is the connection between the left microphone input $I6$ and the hidden neuron $H1$. Whenever a robot is staying on a food patch, and therefore $i4 > 0.8$, the described quasi-periodic oscillation (see Fig. 6.5b,c) is responsible for sound emission. As soon as another nearby robot also starts signaling, $I6$ becomes activated (even when the other robot is to the most right side, which is due to the high noise, approx. 30%, of the sound direction detection). Then, as we can see in the bifurcation diagram of Fig. 6.5d, the quasi-periodic attractor switches to a fixed point and, therefore, the oscillation will cease. Because the sound signal of signaling robots lasts only one time step, these oscillations immediately start again in the next time step ($i6 = 0$). This reset mechanism will lead to a synchronization of the signaling among robots which stay together on the food patch (a mechanism very similar to the

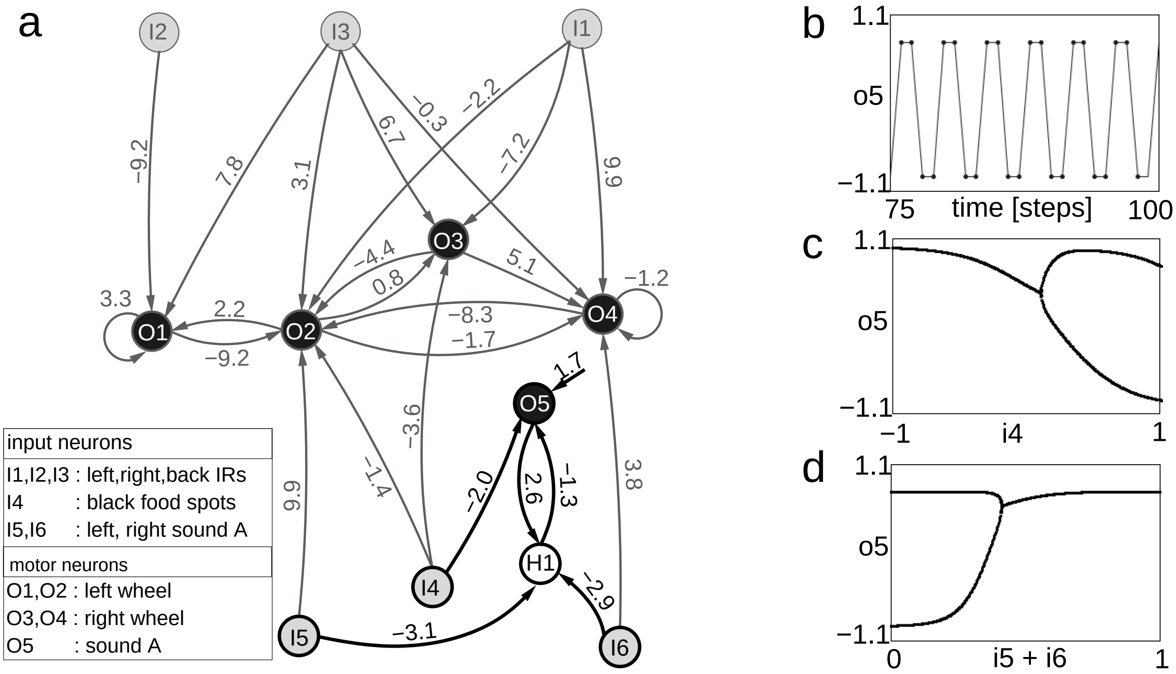

Figure 6.6: **Neural characteristics of $\mathcal{C}_2$ individuals.** a: RNN of $\mathcal{C}_2$ individuals resulting from evolution with a group of 25 robots capable to communicate. b: Signals of $O5$ when a single robot stays on a food patch. c: Bifurcation diagram for $o5$ by varying $i4$ ($i1 = i2 = i3 = -1.0$; $i5 = i6 = 0.0$). d: Bifurcation diagram for $o5$ by varying $i5 + i6$ ($i1 = i2 = i3 = -1.0; i4 = 1.0$).

synchronization of internal neural rhythms described in Chapter 5). That means, if there are many robots on a food patch, they will not produce a continuous sound signal as, in contrast, do $\mathcal{B}_1$ individuals. This leads to a striking performance improvement with respect to $\mathcal{B}_1$ (see also Figure 6.4a and 6.7a). However, the performance of $\mathcal{C}_1$ is not significantly higher compared to $\mathcal{B}_2$, although $\mathcal{B}_2$ was evolved with a population size of ten. This is due to the intrinsic robustness to environmental changes as discussed in the previous section.

6.4.2 Synchronized periodic oscillators

Another evolutionary solution is shown in Figure 6.6a. Individuals controlled by this RNN are called $\mathcal{C}_2$ individuals. The communication system ($O5 - H1$ loop) looks very similar to $\mathcal{B}_1$ (compare to Figure 6.2a). And indeed, if we compare Figure 6.6b,c with Figure 6.2e, we find the same period-4 oscillation which is switched on when the activation of $I4$, the floor sensor input, leads the system to cross a bifurcation point (which is slightly different between these two controllers but this has no significant influence on the signaling behavior). The striking structural differences are the new connections from the sound sensor inputs $I5$ and $I6$ to the hidden neuron $H1$. Figure 6.5d shows how the summed activation of these neurons leads to a switch from the periodic attractor to a fixed point. Consequently, the oscillation is reset whenever a signaling robot

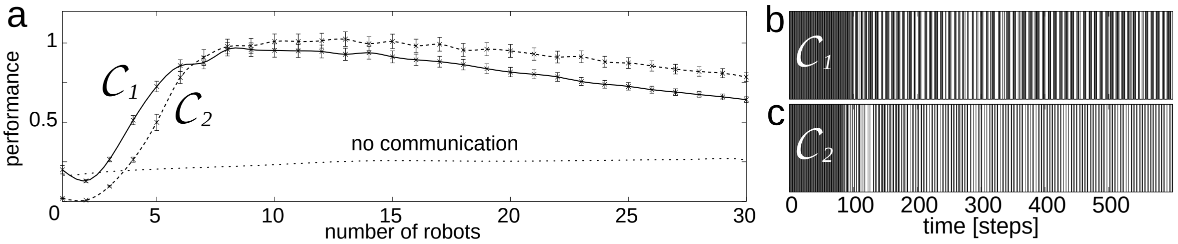

Figure 6.7: **Performance and signaling behavior comparison for $\mathcal{C}_1$ and $\mathcal{C}_2$ individuals.** a: Performance of $\mathcal{C}_1$ and $\mathcal{C}_2$ individuals depending on group size. For each group size 25 simulation runs were performed, each lasting 18,000 time steps. The mean performance of $\mathcal{C}_1$ and $\mathcal{C}_2$ individuals with deactivated communication systems (disabled microphone and speaker) is drawn as a reference. Performance was calculated according to Eq. 6.3. b,c: Black regions indicate the periods where no robot within a group of 30 individuals emits a sound signal (see text for details). Measurements were conducted in the environment shown in Figure 6.2b.

receives sound signals of nearby robots[4]. This gives rise to signal coordination by a synchronization mechanism among robots gathered on the same food patch. Such synchronization among pulse coupled oscillators in a group of acoustically communicating robots is scalable and robust even with very short local interaction ranges. This was already demonstrated in Chapter 5.

6.4.3 Evolutionary adaptation vs. diversity of solutions

The behavior of signaling in synchrony with a period of 4 time steps outperforms not only $\mathcal{B}_1$ individuals with the initial structure but also $\mathcal{B}_2$ individuals with the noise driven mechanism (compare Figure 6.4a and Figure 6.7a). The reason becomes obvious when we compare the occurrences of signal pauses and emitted signals of all three solutions. We see the already discussed long periods of continuous signals for the $\mathcal{B}_1$ individuals (Figure 6.4b, p. 132). During this time no robot is able to detect the food calls of other individuals. Considering the behavior of $\mathcal{B}_2$ individuals (Figure 6.4c, p. 132) we see that there are much more breaks in the signaling behavior which is due to the described noise driven mechanism and the suppression of signaling when food spots become crowded. For $\mathcal{C}_2$ individuals we see a rapid succession of signal emission and breaks (Figure 6.7c) since already two signaling individuals synchronize their food calls. In that sense the alternation of black and white regions in Figure 6.4b,c and Figure 6.7b,c indicates how often robots, which still search for food, can adjust their heading direction toward the food source. This explains why $\mathcal{C}_2$ individuals outperform the other two solutions evolved with a smaller group size. It also explains the slightly better performance compared to $\mathcal{C}_1$, because $\mathcal{C}_2$ individuals can update their heading direction toward a food call more often than $\mathcal{C}_1$ individuals (see Figure 6.7b,c). A high update rate of the orientation toward food calls is of great advantage, especially if we consider the high noise of the sound direction detection ($\approx 30\%$) and the

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[4] Note, whenever the robot receives a signal, then $i5 + i6 = 1.0$ independent of the direction of the sensed signal (cf. Eq. 6.1). Therefore, sound reception will always lead to a reset of the oscillator.

increased interference among moving robots in larger groups. The high performance of $\mathcal{C}_2$ individuals is a result of the interconnection between the dynamics at the neural level (oscillations with a short period) and the interactions among individuals within a group at the behavioral level (synchronization of signaling behavior).

Thus, we have seen how evolution effectively improves a solution (i.e., $\mathcal{B}_1$) which performed rather weak when the number of interacting individuals became larger than the group size with which it was originally evolved. Intriguingly, $\mathcal{B}_2$, which was evolved under the very same conditions as $\mathcal{B}_1$, already possessed the ability to cope with this increased number of interacting individuals, namely the ability to coordinate the signaling behavior. This leads us to conclude that evolutionary variety provides at least some solutions with an intrinsic robustness to environmental changes where no further evolutionary refinement is necessary.

6.5 Discussion

We will now discuss the questions given in the introduction of this chapter. Points of interest are the environmental constraints which give rise to the emergence of communication, the role of explicit communication and indirect neural mechanisms, and the importance of evolutionary variety of developed solutions to the same problem.

6.5.1 Environmental conditions

Even though it was not the central focus of this chapter, our results of evolved emergent communication systems in groups of situated artificial agents confirm and bring together several findings of related studies. Our experiments confirm the findings of Reggia et al. (2001) that food calls evolve most often when food sources are few in number.

Wagner et al. (2003) argue that there is still a need to investigate when communication will *not* emerge. The surprising observation in our experiments was that communication emerged only when the environment was not too difficult. With difficult we mean how easy it is for a single agent to discover a food source. It seems counterintuitive, but cooperation emerged only when the chances of finding a food source by random search were rather high. One might expect that cooperation would be favored by evolution the more difficult it is to access food without the help of other individuals. The only explanation we can give at this point is that the performance gap is simply to large between solitary and cooperative behavior, such that a stepwise refinement of the initial behavior was not possible. At least it was not possible during the limited evaluation time in which the performance of a group of robots was measured.

Two issues are intriguing for future research. First, it would be necessary to conduct more extensive studies on the correlation between evaluation time, environmental complexity, and the emergence of communication to find out under which conditions communication will not emerge. However, the more important aspect clearly is the existence of only one niche in the environment. Robots either develop skills to exploit this niche or not. There is no possibility to survive without this particular niche. Thus, another aspect for future research would be to consider an environment which offers many different niches. Possible niches should provide more profit with increasing difficulty of exploiting them. In that way, individuals are not doomed to develop skills for one single particular niche.

Providing multiple niches is an important aspect of the next chapter and we will see that this indeed facilitates transitional evolutionary adaption. That is, individuals develop more complex behaviors in successive steps when confronted with more than one possible environmental niche.

6.5.2 Explicit communication and indirect mechanisms

Former studies demonstrated how cooperation among situated agents can evolve without using dedicated communication channels. For instance, Quinn (2001) evolved agents on a group movement task. By using their infrared sensors individuals were able to keep a close distance to each other without using direct communication. In Chapter 3 we discussed different distributed control architectures which cooperatively solved a task without the ability to communicate explicitly. In both of these examples there was no other choice than cooperating without communication because (a) cooperation was either needed to fulfill the task (Chapter 3) or explicitly encoded in the fitness function (Quinn, 2001) and (b) agents lacked the physical ability to communicate directly.

In this chapter we wanted to figure out whether agents will always make use of the provided possibility to communicate directly. In every discussed evolved solution they did. In principle, cooperative behavior was always based on the same communicative strategy. Whenever an agent discovered a food source, it emitted food calls which attracted other agents. On the one hand, we have to admit, that there was no other way to transmit the information about food sources within a group of agents. Agents lacked the ability to modify their environment, as for instance ants do when they establish trails to food sources by segregating pheromones on their way which can be sensed by other ants (a mechanisms called stigmergy, see also discussion in Section 2.1 on p. 27 and Section 3.6.2 on p. 90).

Thus, it is not surprising that all successful solutions made use of the only way individuals had to communicate. However, at this point we should distinguish between communication how it can be observed at the behavioral level and the neural mechanisms of communication. At the behavioral level we always observed the same: food calls of individuals on the food sources, and a positive tropisms of individuals which are searching for food toward these signals. At the neural level we identified two clearly separate mechanisms.

On the one hand, a direct neural mechanisms could be found in $\mathcal{B}_1$, $\mathcal{C}_1$, and $\mathcal{C}_2$ individuals. In all three neural structures a switchable oscillator was responsible for periodic signal emission. Oscillations are either switched on or off depending on whether the food source sensor was active or not, respectively. Thus, signaling was directly correlated with sensing the presence of a food source or not.

On the other hand, the neural mechanisms that underlie the signaling behavior of $\mathcal{B}_2$ individuals are rather indirect. As we have seen there is no direct connection from the food source sensor to the motor neuron responsible for signaling. Signaling rather results from a behavioral context. Sensing the presence of a food source causes a robot to stop on it. This stop is realized by changing the activity of the motor neurons which control the wheels. In this situation the motor neuron responsible for signal emission becomes sensitive to the noise of one infrared sensor. These fluctuations in form of sensory noise are the driving force behind the signaling behavior. The evolution of such a mechanism is not as rare as one might assume at this point. In the next chapter we will see a further example of how fluctuations are utilized for communication. It has to be emphasized that even though one may intuitively expect the evolution of direct signaling, our reduced preconceptions with respect to the design of fitness functions or the topology of neural networks enabled the emergence of significantly different mechanisms under the very same conditions, as was exemplified for $\mathcal{B}_1$ and $\mathcal{B}_2$ individuals.

We argue, only by analyzing the intrinsic dynamics of evolved RNNs and relating them to the observable behavior, such fundamental differences of mechanisms behind seemingly similar behaviors can be identified. So, what? Once such different mechanisms are identified, one is able to explain not only the observable behavior at every level of description, but one is also able to explain the reason why some of seemingly identical solutions perform better when environmental conditions change.

One may now argue that signal coordination is an inevitable advantage for our specific robotic system because the hardware is designed in a way that only signal peaks can be recognized and no continuous signals. However, just remember the example of synchronized flashing among male fireflies introduced in Chapter 5; what is more attractive to females? A single bright flash from the crowd or a clutter of dim individual flashes? Or, how much do you understand from a heated discussion with many people where every one speaks at the same time? If our robot would be part of this discussion, it would just 'hear' nothing in this case, but it would be able to 'understand' if every one would 'speak' consecutively. In this sense what we, admittedly, have preconceived through our hardware choice is the selective mechanism of sensing, but what has evolved is the ability to emit signals in a reasonable manner.

6.5.3 Evolutionary variability as the source of flexibility

Our results of evolved communication systems in small groups of robots demonstrated that evolutionary strategies do not converge to one optimal solution. Instead, a variety of different mechanisms can arise which lead to comparable behavioral performance. By analyzing the link between observable behavior and individual neural dynamics, we presented two neural networks ($\mathcal{B}_1$ and $\mathcal{B}_2$) in detail with significantly different mechanisms of utilizing the ability to communicate for solving a cooperative foraging task. In both cases signals are grounded because signaling is the consequence of detecting food sources and receiving agents react specifically to these signals by heading toward the food source.

However, in the first case ($\mathcal{B}_1$) signaling is mainly characterized by the intrinsic dynamical properties of the neural network, namely by a switchable oscillator which is switched on with increased activity of the sensor which detects food. Thus, signaling is directly coupled to the discovery of a food source. In the second case ($\mathcal{B}_2$) signaling is driven by the noise of the infrared sensors due to a balanced synaptic input from the motor neurons, responsible for the speed of the wheels, and one infrared sensor.

There is no direct correlation between the floor sensor input activation and the act of signaling. It is a consequence of stopping on a food source as soon as it is detected. We argue that the occurrence of such completely different mechanisms with similar behavioral performance as a result of evolutionary trials with identical initial conditions and constraints is mainly accounted to the decreased prior assumptions, such as constraints implied by the fitness function design or limitations given by predefined network topologies.

Studies of activity pattern in biological neural networks revealed that even within individuals of the same species there exist a huge variety of different mechanisms leading to the same performance at the behavioral level (for an excellent review see Marder and Goaillard, 2006). This variety gives species not only robustness and flexibility in their behavior but increases also their resistance against mutations and entails the evolutionary potential to exploit different solutions when environmental conditions change. Our results imply that the same holds true for the evolution of artificial situated agents. In particular, we demonstrated that two solutions ($\mathcal{B}_1$ and $\mathcal{B}_2$) performed well in environmental conditions under which they were evolved (group size of ten). However, faced with more complicated conditions (increased group size) individuals with the noise driven communication system outperformed the other solution significantly, although the individuals were never confronted with these conditions during their evolutionary development. This adaptation and robustness is an *intrinsic* property of a particular neural mechanism realizing communication as the foundation for cooperative behavior. Our results imply that, as it is known from natural evolution, also in artificial life experiments evolution can bring up a variety of solutions where, concerning behavioral performance, some of them show only little advantage under the current conditions, but possess the potential to handle also significant environmental changes. We argue, to discover such solutions it is necessary to reduce the prior assumptions made about expected behaviors and their underlying control architectures as much as possible.

Identifying such significantly different mechanisms, which lead to similar observable behavior, presupposes a thorough analysis and understanding of the dynamics at the neural level which than has to be linked to the observable behavioral level. Such an approach becomes unfeasible when our main priority would be to increase the complexity of experiments with simulated agents toward behaviors which imitate more closely the actual intricacy of animal behavior. Therefore we argue, it seems reasonable to initially focus on minimized models of emergent communication systems which are *functionally equivalent* to animal communication, and increase their complexity without loosing the feasibility of understanding not only every detail of such systems, but also the system as a *whole* where all the single parts fit together, which is, as we think, the actual strength of the artificial life approach.

6.5.4 Direct and indirect signal coordination

There are two reasons for the intrinsic robustness of $\mathcal{B}_2$ to an increased number of interacting individuals. Compared to $\mathcal{B}_1$, $\mathcal{B}_2$ individuals release food calls rather randomly instead of in fixed short periodic intervals. This decreases the probability of generating too many interfering signals for a longer time. The second reason is the indirect signal coordination mechanisms. Again, when we talk about signal coordination we have to distinguish between indirect and direct mechanisms.

The neural mechanisms that underlie signal coordination among $\mathcal{B}_2$ individuals are indirect because the signal itself is not relevant for that process. Coordination results from the activation of infrared sensors which measure the distance to obstacles. A robot can not distinguish between static obstacles in the environment or other robots, both just increase the infrared sensor activation when they are close by and as a consequence a robot would try to avoid that obstacle. This change in behavior, caused by a change of the corresponding motor neurons which control the wheels, causes the signal coordination among many robots trying to exploit the same food source. The more individuals gather on a food source, the closer they come together. Hence, some individuals activate the infrared sensors of other individuals which, in turn, deactivates their signaling. There is no need to explicitly coordinate the signaling. This coordination is an emergent property of the interaction among embodied and situated agents and the neural mechanisms that underlie their communication systems.

In contrast, signal coordination among $\mathcal{C}_1$ and $\mathcal{C}_2$ individuals is based on direct neural mechanisms. Evolution as an adaptation process, refined a solution ($\mathcal{B}_1$) which did not possess such an implicit and subtle signal coordination mechanism as discussed for $\mathcal{B}_2$ and, therefore, performed rather weak when faced with more complicated environmental conditions. Evolution was able to improve the behavioral performance by *small structural changes*. A very few additional synapses were sufficient to adapt the initial communication system efficiently. $\mathcal{C}_1$ and $\mathcal{C}_2$ individuals still use a switchable oscillator to signal the discovery of food sources to other individuals. The problem of producing a continuous signal by too many signalers is solved through a synchronization of signaling among food call emitting individuals. And because synchronization is achieved by the signals themselves, we describe this mechanism as direct, in contrast to the indirect mechanism found in $\mathcal{B}_2$ individuals.

Interestingly, here coordinating communication by pulse coupled oscillators is a result of an unconstrained evolutionary process. This is interesting in so far as we explicitly designed it for the experiments discussed in Chapter 5. Such a mechanism is also known from biological examples, for instance the synchronized flashing of fireflies during mating (Strogatz and Stewart, 1993; Camazine et al., 2001). Although the actual mechanisms are now well understood, the evolutionary reason why thousand of fireflies synchronize their flashing behavior can only be assumed. One possible explanation is that females are stronger attracted by sudden bright pulses than by a clutter of single flashes. The mechanisms that underlie behavioral synchronization of signaling in our robotic experiments are indeed not as complex as in fireflies, but the resulting behavior can be seen as functionally equivalent, at least in the sense of synchronized signaling based on pulse coupled oscillators. In our experiments we can not only explain the environmental reasons of the evolutionary transition from uncoordinated to coordinated communication, but we are also able to reveal the evolutionary change in the neural dynamics that underlie the observable behavior patterns.

6.6 Summary

In this chapter we investigated how communication and cooperative behavior emerges from evolution where we reduced our design constraints as much as possible.

The experiments and results indicated that an evolutionary transition from solitary to cooperative behavior in a foraging task depends on how difficult it is for an individual to find food sources by random search. Surprisingly, cooperation and communication evolved only in environments where food sources are rather easy to discover.

All resulting cooperative behaviors were based on explicit signaling. That is, food calls were emitted once individuals found a food source. And other individuals react to these signals by heading toward them. However, we found a great variety of the neural mechanisms that underlie this signaling behavior. We distinguished these mechanisms to be either direct or indirect. In the first case signaling is directly coupled to discovery of food sources. With indirect neural mechanisms we mean that signaling is coupled to a behavioral context and heavily depends on fluctuations in form of sensory noise.

Such a variety of mechanisms turned out to be important when agents were confronted with altered environmental conditions such as an increased number of interacting individuals. The results imply that, as it is known from natural evolution (Kauffman, 1993; Marder and Goaillard, 2006), also in artificial life experiments evolution can bring up a variety of solutions where, concerning behavioral performance, some of them show only little advantage under the current conditions but exhibit the potential to handle also further significant environmental changes. Interestingly, especially individuals which utilized rather indirect mechanisms of signaling turned out to possess an intrinsic robustness to environmental changes.

However, faced with more challenging environmental conditions evolution was able to refine solutions which performed rather weak under more complicated conditions. There, the major behavioral transition, which we observed when we increased the number of interacting individuals, was the emergence of signal coordination which is based on synchronizing resettable oscillators. Interestingly, signal coordination was already realized under less complicated conditions. However, in this case signal coordination again relied on a rather indirect mechanism where the signal itself plays no role for the coordination process.

Revealing such a diversity of mechanisms behind seemingly different behaviors presupposes a thorough analysis of the intrinsic neural dynamics and a clarification of how they are related to the observable behavior.

Chapter 7

Intraspecific cooperation and interspecific competition

> "[...] why, if species have descended from other species by insensibly fine gradations, do we not everywhere see innumerable transitional forms? Why is not all nature in confusion instead of the species being, as we see them, well defined?"
>
> *Charles R. Darwin (1859, p. 171)*

7.1 Introduction

In his famous book *On the origin of species* Charles Darwin raised the above questions to emphasize one of the difficulties with his theory about descent with modification, the difficulty of missing transitional varieties of species. One of the explanations he gave was that natural selection and extinction go hand in hand. New forms might take the same niche as their parents. And if they show profitable modifications, they will exterminate their less improved parents or other less favored forms (Darwin, 1859, p. 172).

Darwin also cataloged the diversity of beak sizes of the probably most fascinating birds for evolutionary biologists, the Galápagos finches. Very recently Grant and Grant (2006) published an impressive study about competition between two finch species. Medium ground finches were living on the island rather by themselves and ate whatever size seeds suited them most until a competitor, the large ground finch, moved in. Its presence forced the medium ground finch to change its diet and only the individuals who preferably ate small sized seeds survived. Within only one year their beak adapted to this new diet by decreasing significantly in size. This competitor driven shift in beak size is a prior example of what evolutionary biologist call character displacement, a term coined by Brown and Wilson (1956). This example demonstrates the interplay between population number and environmental factors. It occurred only because there were enough competing individuals and large seeds were scarce enough to cause a problem (Pennisi, 2006).

The work of Grant and Grant (2006) demonstrates how two species which initially exhibited similar feeding behaviors became distinct enough in their diet and morphological properties that both survived the initial competition for the same type of food.

Scheffer and van Nes (2006) investigated competition of species with a classical Lotka-Volterra simulation model. The most interesting result of their study is that for many species there are two ways to survive. Species are either sufficiently different or sufficiently similar. They showed that even in the absence of environmental discontinuities species self-organize into clumps of species with very similar niches within a clump and large gaps between clumps. One explanation for these patterns is that if for instance two species are within two distinct niches and a third species would take a niche in between, which overlaps with the niche of the other two species, this third species would compete against two species. If the third species would take a location close to one of the both initial species, it has to compete only against one other species.

The simulation experiments of Scheffer and van Nes (2006) also revealed that the coexistence of clumps of species is a transient phenomena, even though they can exist for thousands of generations. That is, on a long timescale each clump will be thinned out to one species in one niche. These findings support the explanation given by Darwin for the sometimes missing transitional varieties of species. The most striking result of Scheffer and van Nes (2006) clearly is the transient occurrence of clumps of species instead of a uniform distribution along a niche axis which is then thinned out with time.

The studies of Grant and Grant (2006), Scheffer and van Nes (2006), and the intriguing questions about missing transitional varieties raised by Darwin (1859) inspired the experiments we will discuss in this chapter. They seamlessly follow the experiments presented in the previous chapter. In fact, we stick to a very similar experimental setup. However, we will enrich the environment and the number of populations.

There are *two* populations whose members are identical at the beginning of an evolutionary process (all are $\mathcal{C}_2$ individuals, discussed in Section 6.4.2, p. 135). Because they are identical, both populations take the same niche, that is, they forage for the same type of food sources within a common environment. And because they are identical all individuals cooperate with conspecifics as well as with members of the other population. However, placed together in the same environment individuals of each population gain less energy as they would when there is only one population. To create an interplay between population number and environmental factors the environment offers a new niche, characterized by a different type of food which initially is unexploited by neither of the two populations. One of the populations undergoes evolutionary development and might therefore increase its performance by adapting to the environment and to the behavior of the other non-evolving population. For the sake of clarity we will refer to the non-evolving population as the parent species and to the evolving population as the new species.

The questions pursued in this chapter are:

- Will the new species specialize for the new niche?
    - If so, how does the communication system change in order to avoid interference with the parent species?
- Will the new species still benefit from the original cooperative behavior among all members of both species and thus maintain interspecific cooperation?
    - If so, will it then develop additional skills to benefit also from the new niche?

- Does interspecific competition occur?
  - If so, how does the evolution of the new species affect the performance of the parent species?
- What are the major neural changes during evolution?

The following pages discuss examples of how very small sized neural networks facilitate robots to display rather sophisticated behaviors. Evolution generates neural structures which enable robots to forage for different types of food, to coordinate beneficial intraspecific communication and to utilize aggressive interspecific communication.

At the neurodynamics level different aspects of communication are realized either by switching between several attractor domains of neural submodules or by taking advantage of fluctuations in form of sensory noise.

At the evolutionary level the new species effectively adapt to a new environmental niche. Surprisingly, to further increase its performance it also shapes its niche actively by changing and disturbing the behavior of the parent species. This two-folded adaption occurs in a transient evolutionary development of different types of beneficial behavior.

7.2 Experimental setup

The experimental setup is very similar to the experiments described in the previous chapter (see also Section 6.2, p. 123). However, this time two populations were used. At the beginning of the evolutionary process members of both populations are identical and controlled by the $\mathcal{C}_2$ RNN discussed in Section 6.4.2 (p. 135). That is, individuals of both populations cooperate in foraging for black food sources. One population, the new species, is allowed to evolve, whereas the other population, the parent species, does not evolve. This is indeed far from biological reality where entities in an ecosystem of course co-evolve. However, it was done here to eliminate the Red Queen effect where the fitness landscape of a species permanently changes because of co-evolving competitors(van Valen, 1973).

7.2.1 Two types of food

In contrast to the experiments of the previous chapter the environment was set up slightly different (compare environment shown in Figure 6.1e and in Figure 7.1a). First, we decreased the radius of the black colored food patch from 0.7 meters to 0.3 meters which increased the competition between individuals of both species for this type of food because it did not provide enough space for all individuals to gain energy from it (see Figure 7.1b). As a second difference a white colored food source was added (radius = 0.4 meters) from which individuals could gain the same amount of energy with time as they can get from black food sources (see Section 6.2.2, p. 124).

Encoding different types of food with a different gray value was chosen because it is easily reproducible with the real robots. Their floor sensor is able to measure 256 different intensities of gray ranging from white to black. Thus, we took the first 128 intensities to realize a white food sensor and the rest to realize a black food sensor. The

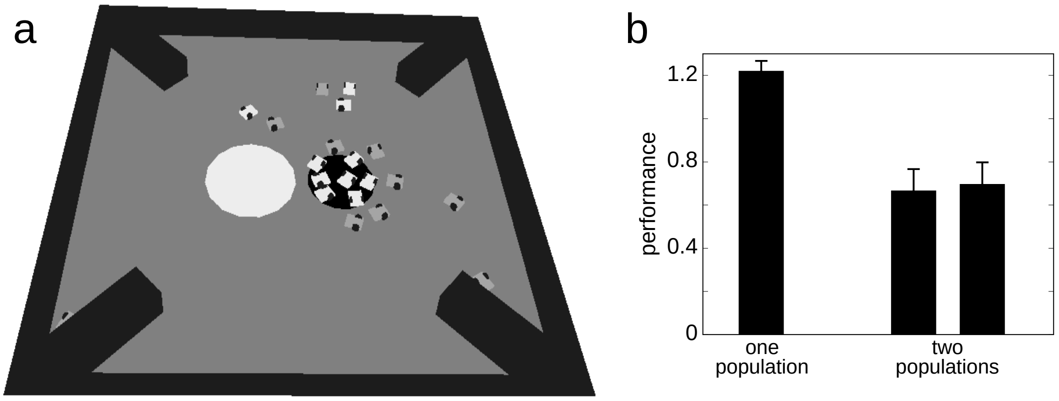

Figure 7.1: **Two populations competing for the same food source.** a: Both populations (indicated by light and dark gray colored robots), equipped with the same RNN (shown in Figure 6.6A), compete for the same food source (black spot). The food source is too small to provide all members of both populations enough space to gain energy from it. However, there is an additional food source (white spot) provided which can be exploited during evolutionary development by one of the two populations (see text for details). b: Performance when a single population of ten individuals is placed in the environment compared to the performance of two populations with ten individuals each. Given is the average performance and standard deviation of 25 simulation runs. Each run lasted 18,000 time steps (performance of each population was calculated according to Eq. 6.3, p. 124).

ground of the environment which represents no food sources had a gray color exactly in the middle between white and black (see Figure 7.1a).

7.2.2 Evolving individuals

Individuals of the parent species could not evolve and were controlled by the $\mathcal{C}_2$ RNN (discussed in Section 6.4.2). For the evolution of the new species the $\mathcal{C}_2$ RNN was taken as initial structure. Individuals of the new species got additional sensors and motors (see Table 7.1). In addition to the sensors which the parent species possessed, individuals of the new species got a new sensor to detect white food sources (represented by $I7$). The intensity of white food sources, equivalent to black food sources, was randomly chosen in a range that it provokes sensor values between $[0.8, 1.0]$ ± sensory noise.

Furthermore, individuals of the new species were able to utilize two sound signals for communication. Similar to the S_A signals they now could also use S_B signals. On the real hardware two distinct signals are differentiated by distinct types of pulses (see Section 5.2.2, p. 110). In simulation the emission and detection of S_B signals were implemented in a similar way as it was done for S_A signals (described in Section 6.2, p. 123). Input neurons which measure the direction of S_B signals are $I8$ and $I9$ (see Table 7.1), and the output neuron responsible for triggering S_B signals is $O6$ (the mapping corresponds to the mapping applied for S_A signals, see also Section 6.2, p. 123).

Individuals of the new species possessed the $\mathcal{C}_2$ RNN with the aforementioned new

Table 7.1: Mapping from physical sensor values to sensory neuron activation for the new species (mapping for the parent species: see Table 6.1, p. 6.1).

sensors	neuron index	mapping [min, max]	simulated noise
IR left, right, back	$I1, I2, I3$	-1 : no obstacle 1 : close obstacle	0.05 (≈ 10%)
floor (black food)	$I4$	-1 : gray 1 : black	0.05 (≈ 10%)
floor (white food)	$I7$	-1 : gray 1 : white	0.05 (≈ 10%)
signal S_A / S_B, left	$I5$ / $I8$	0 : 90° to the right 1 : 90° to the left	0.3 (≈ 30%)
signal S_A / S_B, right	$I6$ / $I9$	0 : 90° to the left 1 : 90° to the right	0.3 (≈ 30%)

input and output neurons which initially were unconnected to the RNN. For the evolutionary process we neither restricted parameter nor topological changes. That is, all parameters could change and structural elements (such as synapses and hidden neurons) could be added or removed without any restrictions.

Nothing else was changed compared to the evolutionary setup of the previous experiments, especially the fitness function was still the same, it rewarded the group for how often its individual members recharged their virtual battery (see Equation 6.3, p. 124).

7.3 Structurally small networks and complex behavior

The evolutionary solution we are going to discuss in the following is shown in Figure 7.2 and called $\mathcal{D}_1$. At first glance this RNN seems to possess a complicated structure but it actually does not. There are no hidden neurons and considering the amount of input and output neurons the network is rather sparsely connected (for instance $I5$ and $I6$ are completely unconnected). However, individuals controlled by this small-sized network exhibit a remarkably sophisticated behavior. They exploit two different qualities of food and utilize communication for *intraspecific cooperation* and *interspecific competition*. These behaviors are based on very subtle neural mechanisms. Revealing the link between neural dynamics and observable behavior is the main subject of the next two sections. Note that Ix and Ox refer to input and output neurons with index x, respectively; and ix and ox refer to the corresponding output of these neurons.

7.3.1 Exploiting two qualities of food

Interestingly, $\mathcal{D}_1$ individuals maintained the ability to stay on black food patches during the course of evolution, even though the actual problem was that initially both species

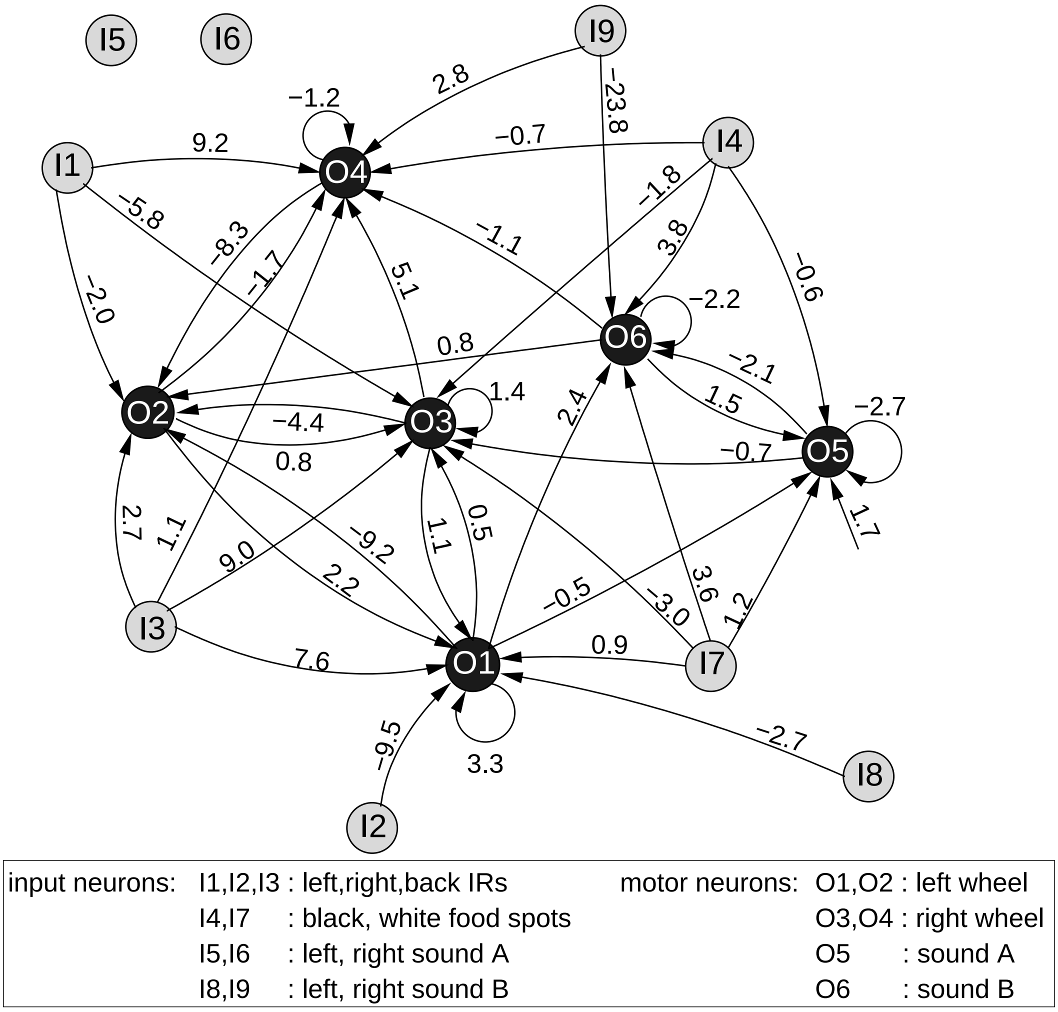

Figure 7.2: **Neural network of $\mathcal{D}_1$ individuals.** See text for details.

foraged for the same quality of food. In Figure 7.3a we see that the neural mechanisms that underlie the behavior of exploiting black food sources are similar to the foraging behavior discussed in Section 6.2.3 (p. 126). When no food source is detected ($i4 \approx -1.0$), $O1$ and $O2$ generate opposed signals as do $O3$ and $O4$ which drives the robot forward (cf. Equation 6.2, p. 123). Note that $o4$ is not exactly -1.0, it rather oscillates with a small amplitude around -0.8. That is, the right wheel drives forward, but not with maximum speed as the left wheel does. Thus, the robot explores the environment rather in large circles than in straight lines.

What seems to be interesting from the bifurcation diagrams in Figure 7.3a, the large quasi-periodic domains around $i4 \approx 0.0$, is actually irrelevant for the foraging behavior because sensor values are either $i4 \approx -1.0$ or $0.8 < i4 < 1.0$ depending on whether a black food patch is detected or not.

In addition to the capability of staying on black food patches, $\mathcal{D}_1$ individuals are also able to stay on white food patches which is a newly developed behavioral quality as compared to the initial RNN. The neural mechanisms, indicated in Figure 7.3b, are similar to the mechanisms discussed above for staying on black food patches. And

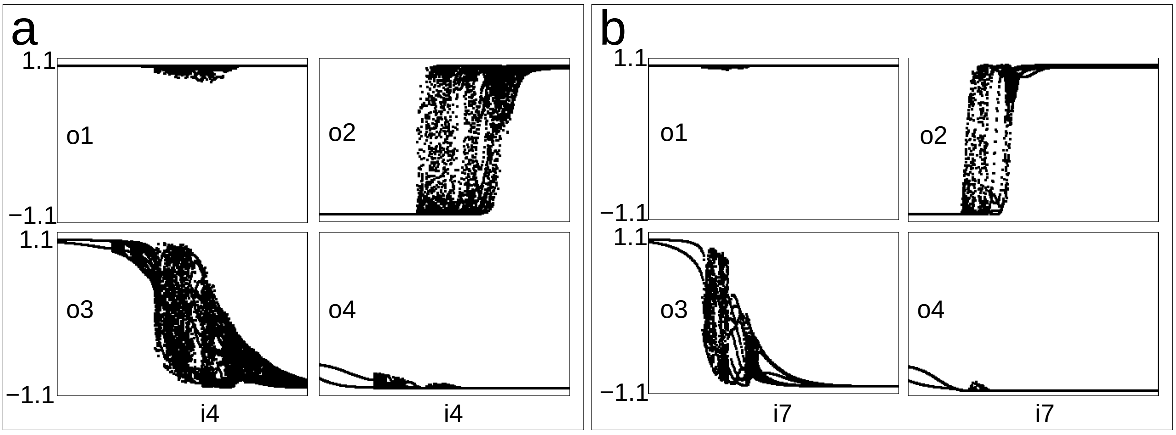

Figure 7.3: **Neural dynamics of foraging behavior.** Dynamics of the RNN shown in Figure 7.2 ($\mathcal{D}_1$ individuals). Given are bifurcation diagrams for the motor neurons which control the wheels while varying the sensor input which measures the presence of black (a) and white food patches (b).

indeed, if we consider the structure of the RNN (Figure 7.2), we see that $I4$ and $I7$ have a similar strong influence on $O3$ via a negative synapse which explains the change of $o3$ when we vary either $i4$ or $i7$ (see Figure 7.3a,b). Via a strong negative connection from $O3$ to $O2$ the change of $o2$ is indirectly caused by a change of $i4$ and $i7$.

Thus, $\mathcal{D}_1$ individuals are able to exploit two different qualities of food. This is a further example how different behaviors are realized by different sensor modalities acting on the very same neural dynamics. We discussed other examples of such *multimodality* already in Chapter 3 and 4 and will return to this important concept in the discussion chapter of this thesis. Here, multimodality of specific neural dynamics is also relevant for the communication system as we will discuss in the next section.

7.3.2 Beneficial and selfish communication

What is most intriguing if we compare $\mathcal{D}_1$ (Figure 7.2) with $\mathcal{C}_2$, the RNN from which $\mathcal{D}_1$ originates (Figure 6.6a, p. 135), is that all synaptic connections from the sensory neurons $I5$ and $I6$, which measure the occurrence and direction of S_A sound signals, disappeared. In the first place this means that $\mathcal{D}_1$ individuals now ignore the guiding signals emitted by the parent species. Thus, $\mathcal{D}_1$ individuals do not take advantage of the cooperative behavior of the parent species. However, as we will see shortly, $\mathcal{D}_1$ individuals still emit S_A signals even though they are of no direct use to them. Before we start to discuss the direct or indirect utility of the different signals for the fitness of the $\mathcal{D}_1$ population, we want to analyze the signaling behavior itself in more detail.

Signaling depending on the type of detected food

We now focus on the neural mechanisms of signaling when a robot discovers a black food patch (left panel in Figure 7.4). Figure 7.4a shows the motor neuron outputs $o5$ and $o6$ (which control the emission of S_A and S_B signals, respectively) when $i4$, representing

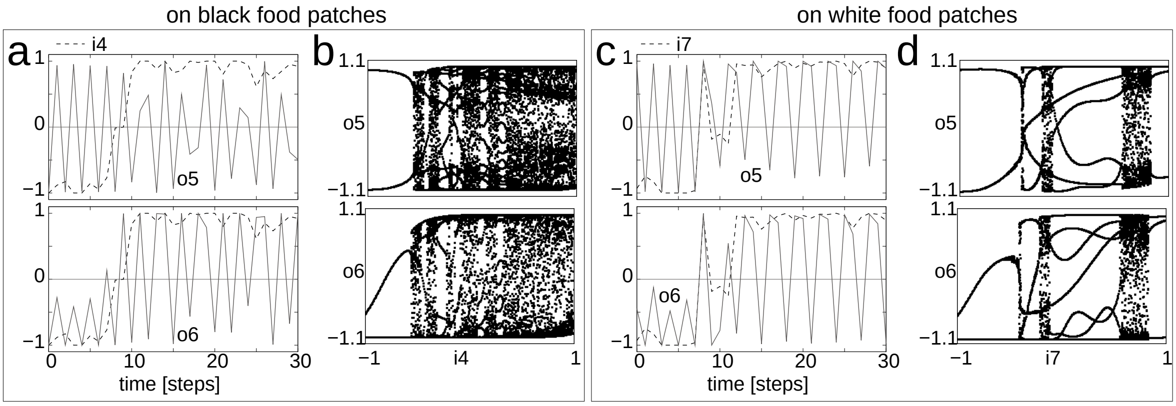

Figure 7.4: **Neural mechanisms of signaling of $\mathcal{D}_1$ individuals on food patches.** a: Signal changes when a robot enters a black food patch (i.e., $i4$ increases). b: Bifurcation diagrams for $o5$ and $o6$ while varying $i4$. c,d: Correspond to a,b. However, here the robot enters a white food patch ($i7$ changes).

the black food patch sensor, increases. Regarding $o5$ we see period-2 oscillations when $i4$ is low. That is, the robot emits S_A signals every second time step when it is not on a black food patch. As soon as it enters such a food source, $o5$ becomes less regular but is still periodically oscillating around zero (note, a sound signal is triggered whenever $o5$ crosses zero from below). What we observe is a transition from periodic to quasi-periodic oscillations with increasing $i4$ as indicated in the bifurcation diagram in Figure 7.4b (top). While the robot is exploring the environment ($i4 \approx -1.0$) we find period-2 oscillation and when the robot stays on a black food patch ($0.8 < i4 < 1.0$), we find quasi-periodic oscillations. Thus, the robot is always periodically emitting S_A signals whether it is on a black food patch or not.

A slightly different behavior can be observed for S_B signals. When $i4$ is low, $o6$ also oscillates with a period of two but with an amplitude always below zero (Figure 7.4a, bottom). Thus, no signal is emitted as long as the robot is not on a black food patch. That changes when it enters such a food source, that is, when $i4$ increases. Oscillations of $o6$ become less regular and oscillate around zero. Again, this is a transition from period-2 to quasi-periodic oscillations as indicated in Figure 7.4b (bottom). In contrast to $o5$ the period-2 oscillations of $o6$ cross zero only when the robot is on a black food patch ($0.8 < i4 < 1.0$). That is, $\mathcal{D}_1$ individuals elicit S_B signals only when they discover black food sources and the corresponding sensor value changes accordingly.

Interestingly, we find a very similar signaling behavior when the robot discovers a white food patch (right panel in Figure 7.4). As long as the robot is not on a white food patch ($i7 \approx -1.0$) the signaling of S_A and S_B corresponds to the behavior described above. When the robot enters a white food patch ($0.8 < i7 < 1.0$) $o5$ and $o6$ switch to period-3 oscillations and trigger a periodic emission of S_A and S_B signals (cf. Figure 7.4c,d).

So far, we figured out that a single $\mathcal{D}_1$ individual emits S_B signals depending on the discovery of a black or white food patch and S_A signals independent of it. However, robots were evolved in a group of ten individuals which interact (i.e., communicate) with each other. As it is clear from the structure of the RNN, S_A signals do not

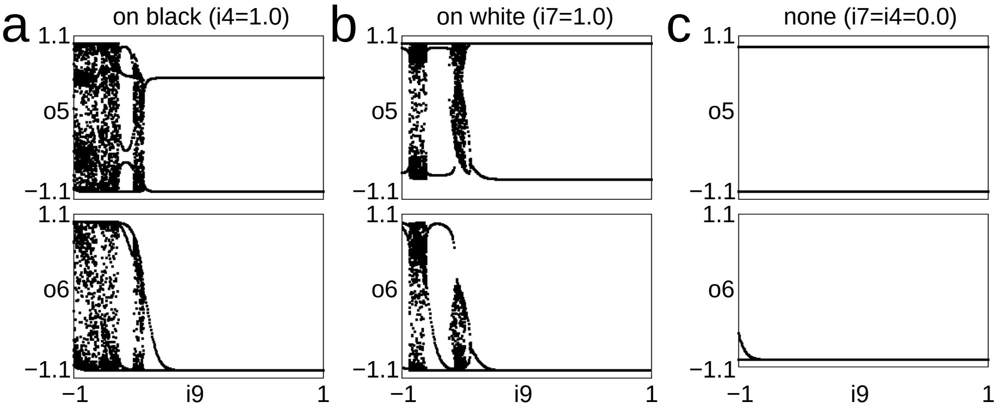

Figure 7.5: **Neural mechanisms of signal synchronization among $\mathcal{D}_1$ individuals.** Given are bifurcation diagrams for $o5$ and $o6$ while varying $i9$ (representing the right direction sensor for sound signals S_B) in three different situations: when the robot stays on a black food patch (a), when it stays on a white food patch (b), and when it is not on any food patch, that is, exploring the environment (c).

influence the behavior of $\mathcal{D}_1$ individuals because the according sensor neurons $I5$ and $I6$ are not connected to the network (cf. Figure 7.2). However, it is different for S_B signals. In Figure 7.2 we see a very strong negative synapse projecting from $I9$ to $O6$ which strongly affects the signaling behavior of interacting $\mathcal{D}_1$ individuals as we will see in the next section.

Signal synchronization

Figure 7.5a shows bifurcation diagrams for $o5$ and $o6$ while varying $i9$ (representing the right direction sensor for S_B signals) when a robot stays on a black food patch. For $o5$ we see a transition from quasi-periodic oscillations to period-2 oscillations. However, $o5$ always oscillates around zero. Thus, S_A signals are periodically triggered rather independent of $i9$. This is also the case when the robot stays on white food patches or explores the environment (see Figure 7.5b,c).

For $o6$ we observe a different behavior. When the robot stays either on a black or a white food patch $o6$ does not oscillate around zero when $i9 > 0.3$ (Figure 7.5a,b) and, therefore, S_B signaling ceases. This means, as soon as another nearby robot also starts signaling, $I9$ becomes activated (even when the other robot is to the most left side, which is due to the high noise, approx. 30%, of the sound direction detection). The quasi-periodic oscillations immediately start again in the next time step because sound signals of other robots last only one time step. This reset mechanism will lead to a synchronization of the S_B signaling among robots which stay together on the same food patch.

Interestingly, this signal coordination mechanism is very similar to the synchronization of internal neural rhythms described in Chapter 5 and the signal synchronization described in Section 6.4 (p. 133). However, all $\mathcal{D}_1$ individuals which detect a S_B signal from another individual still continue to emit S_A signals, whether they are themselves on a food patch or not (Figure 7.5). This plays a role for the group performance of

$\mathcal{D}_1$ individuals because it influences the behavior of the parent species in a way that it dramatically disadvantages them and at the same time profits $\mathcal{D}_1$ individuals only a little. That is why we call this kind of S_A signaling *interspecific selfish communication.* And we call the S_B signaling *intraspecific beneficial communication* because it mutually excels the performance of $\mathcal{D}_1$ individuals.

Before we elaborate the discussion about the effects on the performance of both populations, we firstly examine the dynamics of the communication mechanism in more detail because it is a further, yet highly subtle, example of how different behaviors can be exhibited by the very same neural dynamics realized by the very same structural elements of a small sized RNN.

7.3.3 Change in communication via attractor switching

We have seen that communication of $\mathcal{D}_1$ is mainly characterized by the existence of periodic and quasi-periodic attractors. To get a better picture of these attractors we decoupled the communication module, which is basically the two-neuron ring of $O5$ and $O6$ within the RNN (see Figure 7.2). We can now simulate all inputs to these neurons by varying their bias terms because the activity of a neuron is characterized by the sum of all its inputs (see Section 2.4.1, p. 43). we let the system evolve with time for each bias parameter set, and determined in which kind of attractor the system ends. The resulting map, a so called iso-periodic plot, gives us the attractor landscape of the system.

The attractor map of our two neuron system is given in Figure 7.6. In the given parameter space there exist several domains of different periodic (color coded) and quasi-periodic attractors (indicated by black color). We can now identify the attractors which are relevant for specific behavioral situation of a robot controlled by $\mathcal{D}_1$. The corresponding bias values are given in Table 7.2. If we now look up each pair of bias values in the attractor map of Figure 7.6, we see that the change of the signaling behavior is in fact due to attractor switching. During exploration behavior we find period-2 attractors which corresponds to the oscillations of $o5$ and $o6$ when no food source is discovered (i.e., $i4, i5 \approx -1.0$, see also Figure 7.4a,b). Increasing $i4$, that is, the sensor detecting black food sources, increases the bias term of $O6$ and decreases it for $O5$ because of the positive and negative connection from $I4$, respectively (see Figure 7.2). In Figure 7.6 we see how that moves the system away from the domain of period-2 attractors and eventually reaches a domain of quasi-periodic attractors for high values of $i4$. This corresponds to the change of the periodic oscillations observable for $o5$ and $o6$ with increasing $i4$ (see also Figure 7.4a,b).

On the other hand, when the robot discovers a white food source the bias values of $O5$ and $O6$ increase because of the positive connections from $I7$ (see Figure 7.2). In Figure 7.6 we see how that moves the system from the domain of period-2 attractors to a domain of period-3 attractors which explains the signaling behavior on white food sources (see also Figure 7.4c,d).

In both cases, signaling on black or white food sources, if the robot detects a S_B signal of another individual, the bias term of $O6$ decreases drastically because of the strong negative connection from $I9$ (see Figure 7.2). This decrease moves the system now back into the domain of period-2 attractors (see Figure 7.6). But it immediately

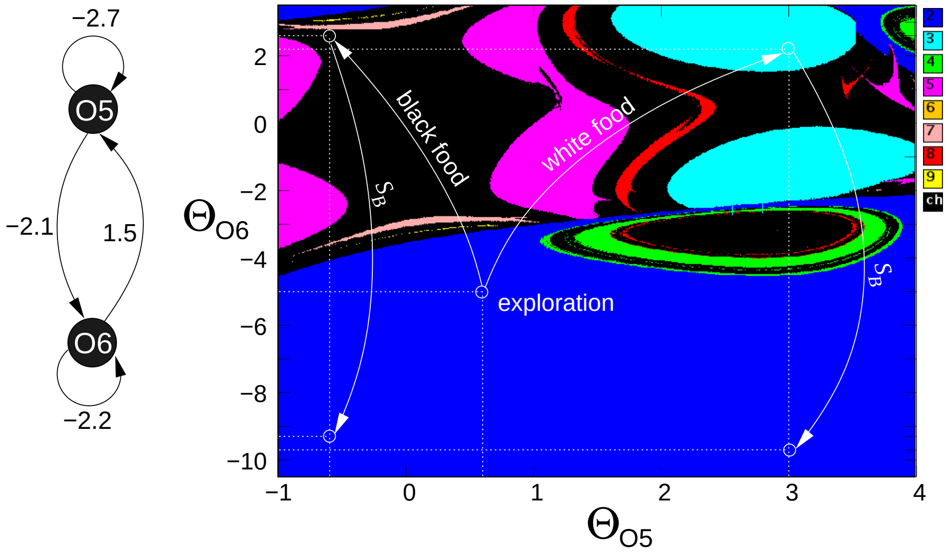

Figure 7.6: **Dynamics of the decoupled communication module.** The $O5 - O6$ ring (left) from the RNN shown in Figure 7.2 without any synaptic input. The map on the right side shows the existence of different attractor domains depending on the bias value of both neurons. Different colors encode domains of attractors with different periodicities (black indicates attractors with a period higher than 9 or the existence of quasi-periodicity). It shows how the system enters specific attractor domains depending on specific behavioral states (i.e., exploration, discovering black or white food patches, and detecting S_B sound signals, see also Table 7.2).

jumps back to either the quasi-periodic or period-3 attractor in the next step when the S_B signal ceases. This, basically, is the synchronization mechanism as discussed in the previous section (see also Figure 7.5).

Analysis of the attractor map tell us further that the synchronization of $o6$ oscillations among many individuals is not achieved by a transition from quasi-periodic to fixed point attractors as we might conclude from Figure 7.5a,b (p. 151). Instead it is a transition from a quasi-periodic attractor to a period-2 attractor. However, the

Table 7.2: Output values of relevant neurons in specific behavioral situations and the resulting bias terms for the two neuron module given in Figure 7.6. Bias terms (Θ_{O5} and Θ_{O6}) are calculated according to the strength of incoming synapses which connect relevant neurons to $O5$ and $O6$, and the static input to $O5$ as given in Figure 7.2.

behavioral situation	$i4$	$i7$	$i9$	$o1$	Θ_{O5}	Θ_{O6}
exploration	−1.0	−1.0	0.0	1.0	0.6	−5.0
on a black food source	1.0	−1.0	0.0	1.0	−0.6	2.6
on a white food source	−1.0	1.0	0.0	1.0	3.0	2.2
on a black food source, perceiving S_B	1.0	−1.0	≈ 0.5	1.0	−0.6	−9.3
on a white food source, perceiving S_B	−1.0	1.0	≈ 0.5	1.0	3.0	−9.7

amplitude of the oscillation caused at high $i9$ is very small. For instance, when the robot stays on black food patches the difference between maximum and minimum for $i9 = 1.0$ is 5×10^{-15}. And in fact, whether the system switches its attractor domain from quasi-periodic to fixed points or to another periodic attractor does not matter for the synchronization of S_B signals. Important is, on the one hand, that signal emission is suppressed when another signal is detected, which is the case for period-2 oscillations with small amplitude in the negative domain. And that, on the other hand, after a signal is detected the system moves again in the quasi-periodic domain leading to a restart of the oscillation of $o6$ which triggers S_B signals.

So far we have demonstrated that the communication system mainly relies on attractor switching which is realized by a very small neural sub-module with rich intrinsic dynamical properties. What does the now explainable signaling behavior mean for the performance of the competing species?

7.3.4 Performance

To sum up the main communication characteristics so far, we have seen that $\mathcal{D}_1$ individuals emit S_A signals all the time independent of detecting a food source, whereas S_B signals are only emitted when a robot stays on a food patch (either black or white), and signals of many robots become synchronized. Hence other $\mathcal{D}_1$ individuals which detect S_B signals react with a positive tropism toward these signals (as described in Appendix A.1, p. 181). Thus, S_B signals function in a similar way as the guiding S_A signal utilized by the parent species (as discussed in Section 6.4.2, p. 135).

There are two advantages $\mathcal{D}_1$ individuals possess by using S_B signals compared to the parent species: (a) They cooperatively exploit two qualities of food instead of only one as the parent species does and (b) using a different signal prevents attracting also individuals of the parent species which makes the food sources less crowded. The advantage of always emitting S_A signals is rather subtle. By releasing as many S_A signals as possible makes the parent species deaf to its own guiding signals. Individuals of the parent species are no longer able to detect the signals released by their conspecifics who discovered a food source. This in turn makes the black food spot less crowded offering more space for $\mathcal{D}_1$ individuals.

How the subtle communication system of $\mathcal{D}_1$ affects the performance of both species is shown in Figure 7.7. We disturbed the communication system of $\mathcal{D}_1$ individuals in several ways, but first we want to discuss the undisturbed case (Figure 7.7a). When no $\mathcal{D}_1$ individual is present, the parent species shows its normal foraging behavior resulting in a relatively high performance (compare with the performance of a single population shown in Figure 7.1b). But as soon as one $\mathcal{D}_1$ individual is present, the performance of the parent species drops significantly. The reason is the S_A signal emitted by $\mathcal{D}_1$. Individuals of the parent species are attracted by this signal and consequently follow $\mathcal{D}_1$ which explores the environment rather randomly and finds a food source mere by chance. This results in a similar performance of both species. Thus, the parent species heavily relies on the ability of $\mathcal{D}_1$ to find food sources. The performance of the parent species gets even worse when two $\mathcal{D}_1$ individuals are present because even when one of the two finds a food source, some individuals of the parent species still follow the other $\mathcal{D}_1$ individual until it also enters the food source guided by the S_B signal of the first

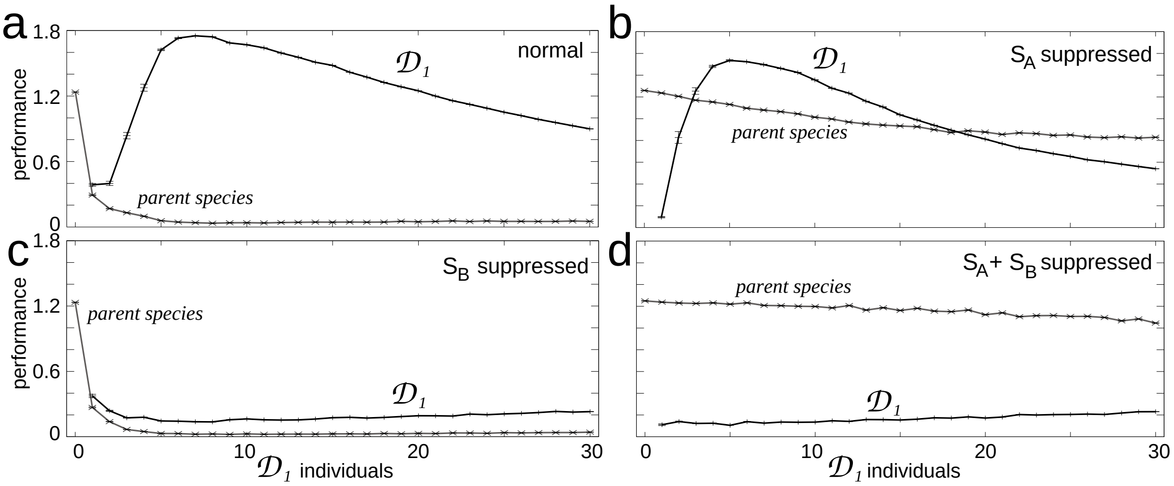

Figure 7.7: **Performance of the interacting $\mathcal{D}_1$ and parent species.** Group size was varied for $\mathcal{D}_1$ and set to ten individuals for the parent species. The average performance of 25 simulation runs is drawn versus the group size (a). Experiments were repeated while suppressing either the emission of S_A (b) or S_B sound signals (c), and both signals (d) for $\mathcal{D}_1$ individuals (each simulation run lasted 18,000 time steps; performance was calculated according to Eq. 6.3, p. 124).

individual. In this case performance of the parent species drops because its members follow one of the $\mathcal{D}_1$ individuals instead of searching for food by themselves.

The more $\mathcal{D}_1$ individuals are present the worse gets the performance of the parent species (Figure 7.7a). However, the reason for this bad performance is now a different one. Because many individuals of the $\mathcal{D}_1$ population are now emitting S_A signals with a period of two, these signals sum up to a continuous signal which can not be detected by other individuals anymore[1]. Most $\mathcal{D}_1$ individuals are gathered around food sources because they guide each other to them via S_B signals. This means even though the range of the sound signals is locally limited, they produce continuous S_A signals in the vicinity of food sources with drastic consequences for the behavior of the parent species. Its cooperative communication mechanism, which relies on S_A signals, fails. That is, even if one individual of the parent species finds the black food source, it is unable to attract other conspecifics.

If we suppress the emission of S_A signals for all $\mathcal{D}_1$ individuals, we see in Figure 7.7b that the performance of the parent species, whose communication system now works normally, drops only slightly with an increasing number of $\mathcal{D}_1$ individuals. This slight decrease is due to the competition for the black food source between the two species which also explains the slightly lower performance of $\mathcal{D}_1$ individuals compared to the normal case. Suppressing S_B signals for all $\mathcal{D}_1$ individuals leads to a very weak performance of the $\mathcal{D}_1$ species because this signal is essential for its cooperative behavior (see Figure 7.7c). On the other hand this also shows us the significant impact of the still activated S_A signaling on the parent species which now performs as bad as in the

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[1] Note, that individuals can only sense signal peaks and no continuous sound signals. However, we argue this is only a minor constraint (see discussion in Section 6.5.2 on p. 139)

case of normal $\mathcal{D}_1$ individuals (cf. Figure 7.7c,a).

Thus, considering our discussion about the neural mechanisms and performance of $\mathcal{D}_1$ individuals, the S_B signaling mechanism is essential for their cooperative success. Utilizing S_A signals to actually eliminate the cooperative behavior of the parent species increases the performance of $\mathcal{D}_1$ only slightly (i.e., about 0.1 for the case of ten $\mathcal{D}_1$ individuals as used for evolution; cf. Figure 7.7a,b).

This behavior is especially intriguing because at the beginning of the evolutionary process both species were identical. And instead of a refinement of the already established mechanism a *novel behavior* emerged which destroyed the cooperative behavior of the parent species completely instead of utilizing it.

One can think about a possible refinement mechanism for instance that individuals of the evolving population maintain their initial behavior, exploiting cooperatively and together with members of the parent species the black food source, and develop the additional skill to stay on white food sources and call conspecifics by S_B signals. In that way they would still benefit from the behavior of the parent species, but would also improve their own performance by using signals not detectable by the parent species. And indeed, this kind of behavior developed but only as a transient evolutionary state as we will discuss later in Section 7.5.

Strikingly, the behavior of disturbing the communication system of the parent species and therefore eliminating its cooperative function resulted from every conducted evolutionary run (altogether 50 trials were performed, each lasting $1,000$ generations) and we will discuss another example in the next section which is also of special interest because fluctuations in the form of sensory noise are again a relevant mechanism as we discovered already in Section 6.3.3 (p. 130).

7.4 The role of fluctuations, again

The RNN shown in Figure 7.8 is another evolutionary solution (called $\mathcal{D}_2$ in the following) with an interesting communication mechanism which relies on sensory noise. Regarding foraging, individuals with this network behave quite similar to $\mathcal{D}_1$ individuals. They conserved the capability of staying on black food patches and possess the newly developed additional skill of exploiting white food sources, too (for details see Appendix A.2, p. 181). However the neural mechanisms of communication are different and, therefore, will be discussed in more detail.

7.4.1 Communication and sensory noise

The signaling behavior of $\mathcal{D}_2$ individuals when they discover a black food patch is illustrated in Figure 7.9. While a robot is exploring the environment it continuously emits S_A signals which ceases with increased $i4$ (see Figure 7.9a,c). Considering the structure of the RNN (Figure 7.8), we see that $O5$ is a switchable oscillator. Because of its negative self-connection, it exhibits either period-2 oscillations or a constant output depending on its input. Interestingly, there is no direct connection from $I4$ to $O5$ (Figure 7.8). The switch from periodic oscillations to a constant output is caused by the activity of $O3$, the motor neuron which controls, together with $O4$, the left wheel. When the robot discovers a black food patch it stops its exploration behavior and stays

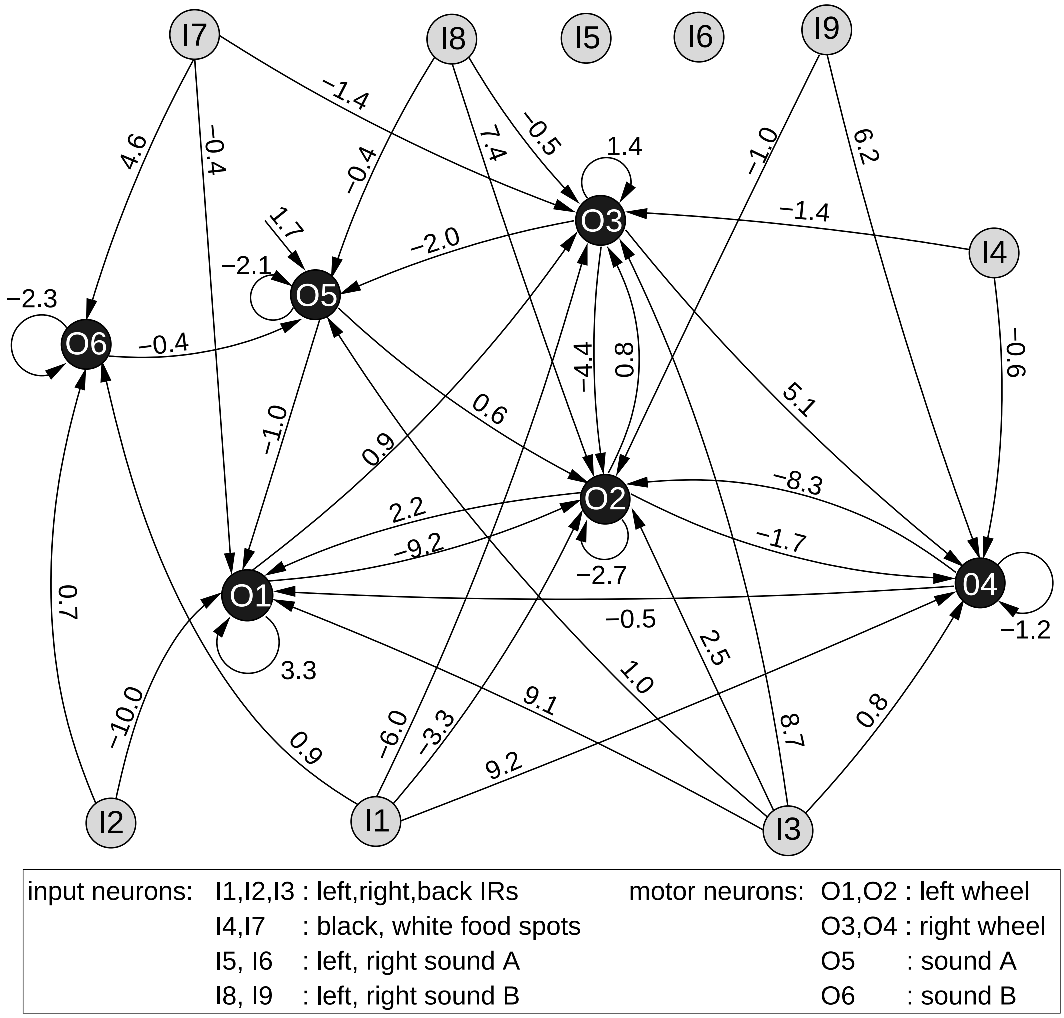

Figure 7.8: **Neural network of $\mathcal{D}_2$ individuals.** See text for details.

on the food source. To do so, $O3$ changes its output from 1.0 to −1.0 (for details see Appendix A.2, p. 181). Thus, the change in S_A signaling depends only indirectly on the activity of the food sensor. It rather depends on the behavioral context of staying on black food patches.

Interestingly, S_B signals are not utilized when $\mathcal{D}_2$ individuals discover black food patches (see Figure 7.9b). Thus, the discovery of black food sources does not change the behavior of other $\mathcal{D}_2$ individuals since the only change in communication concerns the emission of S_A signals, and the sensory neurons which detects this type of signals are not connected to the network (see Figure 7.8).

If a $\mathcal{D}_2$ individual detects a white food source, it again ceases S_A signaling. As we can see from Figure 7.10a (left), $o5$ exhibits always period-2 oscillations independent of $i7$. However, with increased $i7$ these oscillations are shifted into the positive domain, that is, $o5$ is always larger than zero (see also top diagrams in Figure 7.10b) and, therefore, no S_A signals are triggered on white food patches ($0.8 < i7 < 1.0$). In contrast to the behavior on black food patches, this behavior is not only controlled by the change of $o3$. Period-2 oscillations of $o5$ are still present with large $i7$ because of the

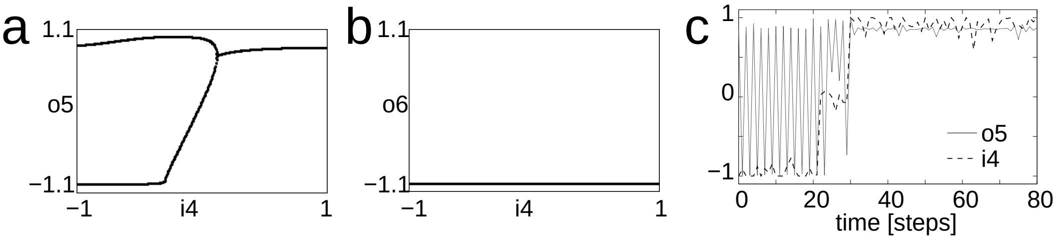

Figure 7.9: **Signaling behavior on black food patches.** Bifurcation diagrams for the two motor neurons responsible for signaling (a,b). Period-2 signaling caused by $o5$ ceases as soon as the robot detects a food patch (a,c) while $o6$ is not influenced by $i4$ (b).

synaptic connection from $O6$ (see Figure 7.8), which starts oscillating with increased $i7$ as we will see in the following.

Concerning $o6$, responsible for S_B signal emission, we see in Figure 7.10a (bottom) that for small $i7$, $o6$ stays in the lower saturation domain. When $i7 > -0.25$, $o6$ enters a domain of period-2 oscillations. Considering the structure of the RNN (Figure 7.8) we have here again a switchable oscillator. Oscillations of $o6$ occur due to the negative self-connection of $O6$ and can be switched on or off depending on $i7$ because of the strong positive connection from $I7$ to $O6$. However, for $i7 > 0.8$ these oscillations only occur within the positive domain, which by itself would not lead to S_B signal emission when a robot discovers a white food source ($0.8 < i7 < 1.0$). In this case, due the noise of the floor sensor, $i7$ randomly gets lower than 0.8 which then leads to period-2 oscillations of $o6$ which cross zero from below leading to signal emissions. As we said, the gray color intensity of food sources is determined randomly at the beginning of each experiment and, therefore, provokes sensor values between 0.8 and 1.0. In Figure 7.10b the signaling behavior on white food sources with different intensities is shown. For high intensities, S_B signals are released less often than for lower intensities. For high $i7$ higher fluctuations (as caused by the sensory noise) are needed to push the oscillations of $o6$ in a domain where it takes positive and negative values and, therefore, to trigger S_B signals.

A further interesting mechanism of S_B signaling on white food patches is that individuals which are close to each other do also coordinate their signaling. In contrast to $\mathcal{D}_1$, this is not realized via a synchronization mechanism as described before. Here, signal coordination is in fact independent of the signal itself. As we can see in Figure 7.10c, when either the infrared sensor on the left or right side of a robot (represented by $I1$ and $I2$) becomes activated while a robot stays on a white food source (e.g., $i7 \approx 0.8$), oscillations of $o6$ are shifted again in the positive domain until they cease completely for high $i1$ or $i2$ values. The influence of the infrared sensors on $O6$ is due to positive connections from $I1$ and $I2$ to $O6$ (see Figure 7.8). We discovered such a subtle signal coordination mechanism already in Section 6.3.3 (p. 130) for $\mathcal{B}_2$ individuals. However, here it is a completely new development because $\mathcal{D}_2$ originates from $\mathcal{C}_2$ which coordinates their signaling by synchronization.

From an observer perspective, the behavior of $\mathcal{D}_1$ and $\mathcal{D}_2$ actually differ only in two aspects. First, $\mathcal{D}_1$ individuals emit S_B signals on both types of food sources whereas

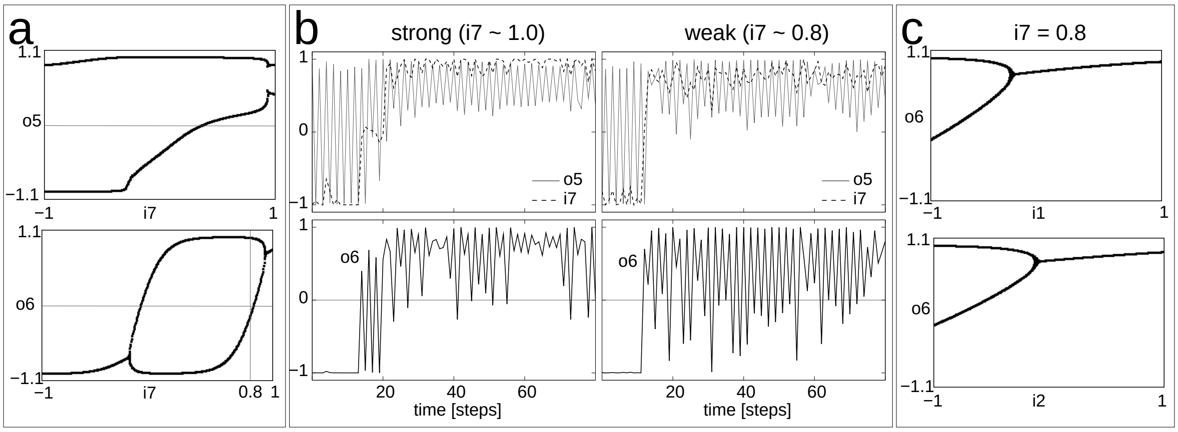

Figure 7.10: **Signaling behavior on white food patches.** a,b: Bifurcation diagram for the two motor neurons $O5$,$O6$ responsible for signaling. Emission of S_A sound signals (controlled by $O5$) ceases as soon as the robot detects a white food patch, in contrast S_B sound signals (controlled by $O6$) are triggered (see text for details). c: With increased infrared sensor activation ($i1, 2$) oscillations of $o6$ are inhibited and, therefore, S_B signaling stops.

$\mathcal{D}_2$ only on white food sources. $\mathcal{D}_1$ individuals emit S_A signals all the time whereas $\mathcal{D}_2$ individuals cease it when entering either one type of food sources. However, by thoroughly analyzing both control architectures we revealed significant differences of, from an observer perspective, seemingly identical communication behavior, such as S_B calls to guide conspecifics to discovered food sources, or the coordination of signaling among population members. Do $\mathcal{D}_2$ individuals also perform differently compared to $\mathcal{D}_1$ individuals?

7.4.2 Performance

To test the performance of $\mathcal{D}_2$ individuals we conducted the same measurements as discussed for $\mathcal{D}_1$ individuals (see also Figure 7.7). The results are shown in Figure 7.11. When we do not disturb the communication system, we observe a similar performance development depending on group size. That is, we observe a drastic performance loss for the parent species because its communication system is heavily disturbed by the S_A signals of $\mathcal{D}_2$. And the performance of $\mathcal{D}_2$ increases with group size because they guide each other to discovered food sources. Hence, the guiding signal S_B is only elicited on white food patches and the performance with smaller group sizes (around ten individuals) is a bit lower than for $\mathcal{D}_1$ individuals which trigger these signals also on black food patches (compare Figure 7.7a with Figure 7.11a). However, the larger the group gets the higher the probability that some individuals always stay on a white food patch. That is why the performance of $\mathcal{D}_1$ and $\mathcal{D}_2$ become similar with increased group size.

If we suppress the S_A signaling of $\mathcal{D}_2$ individuals (Figure 7.11b), the performance of the parent species decreases only slightly because of the competition with $\mathcal{D}_2$ individuals for black food sources. For the same reason the performance of $\mathcal{D}_2$ individuals

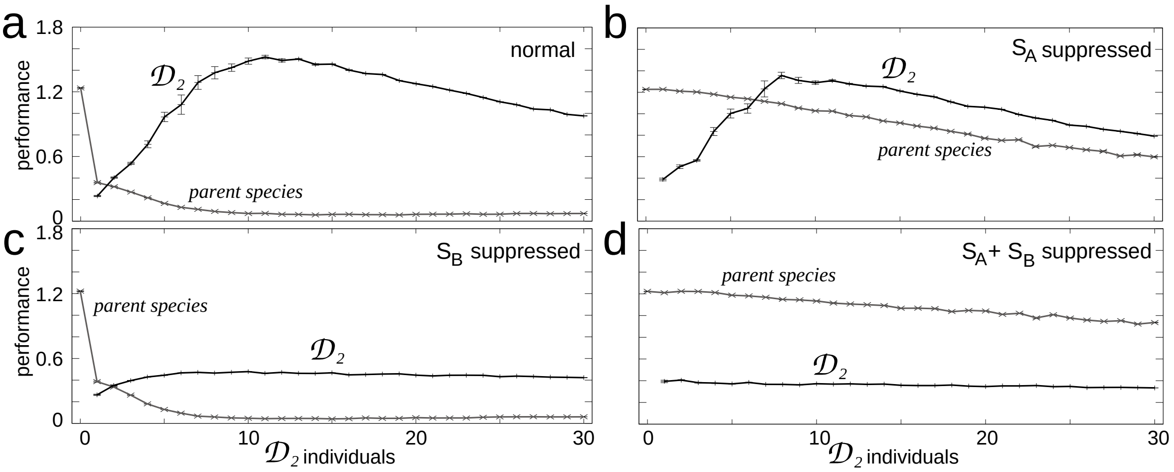

Figure 7.11: **Performance of the interacting $\mathcal{D}_2$ and parent species.** Group size was varied for $\mathcal{D}_2$ and set to ten individuals for the parent species. The average performance of 25 simulation runs is drawn versus the group size (a). Experiments were repeated while suppressing either the emission of S_A (b) or S_B sound signals (c), and both signals (d) for $\mathcal{D}_2$ individuals (each simulation run lasted 18,000 time steps; performance was calculated according to Eq. 6.3, p. 124).

is slightly lower than in the normal case (see Figure 7.11a,b).

Suppressing S_B signaling leads to a rather bad performance for both species (Figure 7.11c) because the communication system of the parent species is disturbed by the S_A signaling of $\mathcal{D}_2$ individuals which need the S_B signal to cooperate. And if both signals of $\mathcal{D}_2$ individuals are suppressed (Figure 7.11d), we observe, as expected, bad performance for $\mathcal{D}_2$ and good performance for the parent species.

From our performance analysis we can conclude that even though $\mathcal{D}_2$ individuals emit S_A signals only when they explore the environment and not, as $\mathcal{D}_1$ individuals do, when they stay on food sources, the impact of S_A signals elicited by $\mathcal{D}_2$ individuals on the performance of the parent species is also quite dramatic. The reason is that there are always some $\mathcal{D}_2$ individuals which explore the environment or are on their way to another calling conspecific. And whether they are enough to generate a continuous S_A signal or not is actually not so important. Members of the parent species get distracted all the time, either because they can not hear their own signals anymore or because they blindly follow the S_A signal of a single $\mathcal{D}_2$ individual which explores the environment.

Thus, even though the mechanisms that underlie the communication system of $\mathcal{D}_2$ are significantly different compared to the communication system of $\mathcal{D}_1$, both solutions show a comparable performance which always entails a loss of the cooperative function in the parent species. We also analyzed further evolutionary solutions and, interestingly, disturbing the communication system of the parent species was always observed. In no case its behavior of discovering and signaling black food patches was utilized anymore even though individuals of both species were identical at the beginning of the evolutionary process. However, there were transients in the change of behavior during the evolutionary development as we will discuss in the following section.

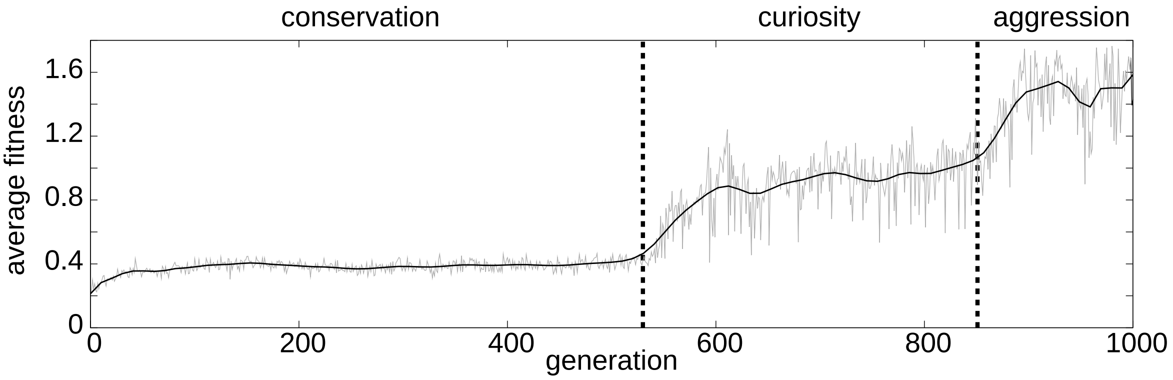

Figure 7.12: **Performance development during evolution.** Drawn is the average fitness of all individual networks in each generation (the black line is a spline of the real data represented by the gray line). Two main behavioral transitions gave rise to the fitness jumps which occurred about generation 600 and 900. First, the ability to exploit the new food source without emitting signals which may also attract members of the parent species. And second, the development of beneficial intraspecific communication and selfish aggressive interspecific communication.

7.5 Conservation, curiosity, and aggression: Transitional niche adaptation

The fitness development of the evolutionary run from which we took the previously discussed $\mathcal{D}_2$ individuals is shown in Figure 7.12. Two main characteristics can be identified. First, it is not a smooth gradual increase of fitness. Performance increase occurs rather in sudden jumps within only a few generations. The second intriguing aspect is the long period at the beginning without any significant change. The performance remains about the same level for more than 500 generations.

The latter aspect might be explained by the behavior which individuals possessed already at the beginning of the evolution. Remember that individuals already foraged for black food sources, generated cooperative signals, and coordinated their signaling effectively. These behaviors resulted from a network which was already evolved in a single population world. A refinement of the given behaviors was almost impossible because they were already very efficient as we have seen in the discussion of Section 6.4.2 (p. 135). Thus, the difficulty was to generate neural variations which realize new behavioral skill which at the same time had to be more efficient than the already established capabilities. This is completely different to the case of starting with nothing where, at the beginning, the performance can get only better by structural changes but not worse. We discussed such an example in Section 3.5.2 (p. 82) where five autonomous agents must cooperate to control the robot *micro.eve*. Here, the initial behavior was already quite sophisticated and efficient. Thus, the chance, that random neural variations lead to a performance improvement, was much lower than in the case of evolving RNNs to control *micro.eve* where the required behavior was rather trivial as compared to the scenario which we discussed in this chapter.

The difficulty of generating new behavioral skills by random variations of the neural structure without getting worse than the already established sophisticated behavior might also explain the sudden jumps in the fitness development which we can see in Figure 7.12 about generation 600 and 900. In fact, the reason of these jumps were two major behavioral transitions. That is the reason why we will divide the evolutionary process into three main epochs: the epoch of *conversation* ranging from the beginning until about generation 530, the epoch of *curiosity* between about generation 530 and 850, and the final epoch of *aggression*.

We analyzed the behavior of the best performing neural networks between generation 500 and 510 for the epoch of conservation, between generation 600 and 610 for the epoch of curiosity, and between generation 990 and 1000 for the epoch of aggression (including the discussed $\mathcal{D}_2$ individual).

Conservative individuals showed behaviors almost identical to the parent species, that is, they foraged for black food sources and used synchronized S_A signals. That means, there was no significant change in behavior for about 500 generations. This suddenly changed in the following epoch. Curios individuals still foraged for black food sources and used S_A signals to guide other individuals to them. In addition, they also exploited white food sources to gain energy from them too. However, they did not emit S_A signals while staying on white food patches. Thus, they acquired the new behavioral skill of resting on white food sources which they discovered by chance, but the white food source is close to the black one (see Figure 7.1a, p. 146) and, therefore, the chances of crossing the white food source on the way to the black one are fairly high. Not using S_A signals while staying on a white food source is rather cunning. In this way individuals of the parent species are not attracted to it and thus it is not as crowded as the black food source. As a second new behavior we observed for three of the ten analyzed networks that individuals also periodically emit S_B signals while resting on white food sources, but other individuals of the same population showed no tropism toward these signals.

All analyzed individuals of the final epoch showed a behavior similar to the behavior discussed for $\mathcal{D}_2$ individuals in the previous section. That is, they exploit white food sources as well as black sources, but they reacted now to the S_B signals emitted by individuals resting on white food sources. They coordinated their S_B signaling, and what makes them aggressive, they emit S_A signals with high frequency all the time which eliminates the communication mechanisms of the parent species.

Thus, for this evolutionary run we indeed observe a transitional niche adaption. After a long period of conservation where both species compete for the same environmental niche (the black food source), curios individuals developed the ability to exploit the new environmental niche (the white food source) while still benefiting from the signaling behavior of the parent species. In the final developmental step, curios individuals were replaced by aggressive individuals which developed their own beneficial intraspecific communication system, the coordinated S_B signaling, to exploit white food sources better than curios individuals did. In addition, they actively extended their niche by selfish interspecific communication, the high frequent S_A signaling, which destroyed the cooperative behavior of the parent species with the result that more space on black food sources was available for their own use.

7.6 Discussion

The examples of this chapter demonstrated several important aspects. On the one hand, they further hint us to the *ubiquity of multimodality* in recurrent neural networks with respect to the variety of possible behaviors, and they showed again that *noise-driven communication* mechanisms are highly efficient for cooperative behavior. On the other hand, they demonstrated how *novel and creative behaviors* can emerge from an unconstrained evolutionary process, and how *transitional niche adaptation* gives rise to *competitive exclusion* between different populations. In the following we discuss each of these aspects in more detail.

7.6.1 Multimodality of dynamical systems

Through the experiments described in this thesis we repeatedly found multimodality of neural structures. Remember the switchable oscillators within the control units of *micro.eve* (Chapter 3), the hysteresis elements controlling aggregation patterns (Chapter 4), the SO(2)-networks realizing internal neural rhythms which determine different behaviors and can be synchronized among many individuals (Chapter 5), and the neural modules responsible for coordinated signaling in a single foraging population (Chapter 6).

In this chapter, especially the neural structure of $\mathcal{D}_1$ individuals hints us further to the ubiquity of multimodality in evolved RNNs as *parameterized dynamical systems.* As discussed in Section 7.3.3 (p. 152), the submodule responsible for the communication system realizes different aspects of communication by different domains of attractors. Which attractor domain becomes apparent heavily depends on the sensory experience of an agent and its interaction with other agents. Attractor domains are switched when an agent discovers food sources which leads to the emission of S_B signals which excels the performance of other $\mathcal{D}_1$ individuals by guiding them to the food source. Once more than one individual arrived at a food source, the detection of signals emitted by other individuals switches the attractor domain again which eventually synchronizes signaling among many individuals. At the same time, attractor switching maintains the interspecific selfish S_A signaling which significantly disadvantages the competing parent species and, therefore, increases the performance of $\mathcal{D}_1$ individuals even further.

Thus, this submodule, which only consists of two reciprocally coupled neurons, enables robots to display a remarkable variety of signaling behaviors. The activation of each of them depends on the sensory experience which in turn changes as a result of individual actions. Therefore, the multimodality of RNNs results from a strong interconnection between dynamical properties of the control system and the sensory-motor loop. Pinpointing the relation between these two components presupposes thorough analysis of the control system as well as the behavior of an individual and its interactions with other components of its environment, a principle which we already summarized as *comprehensibility* (see Chapter 1).

Even though a few studies already demonstrated how the interconnection between neural dynamics and the sensory-motor loop give rise to multimodality of evolved RNNs of non-communicative agents (e.g., Hülse et al., 2004, 2007b; von Twickel and Pasemann, 2007; Wischmann and Pasemann, 2004; Manoonpong et al., 2007; Beer, 2003b) to our best knowledge the experiments discussed in this and the preceding chapters are the first in the literature which demonstrate this principle for communicating agents which display intraspecific cooperation or interspecific competition.

7.6.2 Fluctuations and indirect mechanisms

The role of fluctuations in form of sensory noise for the collective behavior of a group of agents first appeared in this thesis in Section 6.3.3 (p. 130) where we showed that the signaling behavior of an agent resulted from the noise of its infrared sensors. There, the RNN, as a dynamical system, possessed in this behavioral state only fixed point attractors which by themselves could not enable the robot to exhibit periodic signals.

A slightly different, but closely related, example appeared again in this chapter: the mechanisms behind S_B signaling of $\mathcal{D}_2$ individuals discussed in Section 7.4 (p. 156). We have seen that a domain of periodic attractors was responsible for periodic signal emission. However, this domain could only be reached by the noise of the floor sensor which detects white food sources. Thus, the evolution of such noise driven communication mechanisms seems to be not as rare as one might expect. The example discussed in this chapter is especially intriguing because it resulted from a neural structure where communication initially was fully independent of sensory noise. Even though there exist many studies about the evolution of communication among situated agents (for an overview see for instance Wagner et al., 2003; Cangelosi and Parisi, 2002), to our knowledge the emergence of noise-driven communication systems has not been reported so far.

A further similarity to the experiments discussed in Section 6.3.3 (p. 130) is the indirect mechanism of signal coordination. In contrast to the examples given in Section 6.4 (p. 133), Chapter 5, and Section 7.3 (p. 147), the signals which become coordinated are irrelevant for the coordination process. The actual mechanism depends on the infrared sensor activity which in turn depends on the presence of other individuals. Whenever a food spot becomes crowded and, thus, signal coordination becomes necessary, the sensory detection of other agents drives the domains of attraction of the control system into a region which is insensitive to sensory noise (cf. Figure 7.10c, p. 159).

The robot cannot differentiate between other robots or obstacles in the environment. Therefore, utilizing infrared sensors for signal coordination where the signals themselves are irrelevant is indeed a rather indirect, yet highly efficient, mechanism.

One of the main challenges for engineers of robotic systems is to extract real changes in sensory signals and to distinguish them from fluctuations which occur on several system components. Intriguingly, here, and in the example discussed in Section 6.3.3 (p. 130), fluctuations are the driving force of signaling, a control mechanism which engineers probably would never implement. However, for biological systems it is known that fluctuations in form of sensory or neural noise can play an important role, for instance, to detect weak signals (for an overview see Wiesenfeld and Moss, 1995). This mechanisms, called stochastic resonance (Gammaitoni et al., 1998), could be demonstrated to be crucial for the function of the mechanoreceptor cells of crayfish (Douglass et al., 1993), for neural encoding in the cercal sensory system of crickets (Levin and Miller, 1996), or for visual perception in humans (Simonotto et al., 1997).

7.6.3 Niche adaptation and competitive exclusion

At this point we should return to the questions of Darwin, quoted at the beginning of this chapter, the questions about missing transitional varieties. He explained this phenomena as follows:

> "As natural selection acts solely by the preservation of profitable modifications, each new form will tend in a fully-stocked country to take the place of, and finally to exterminate, its own less improved parent or other less-favoured forms with which it comes into competition. Thus extinction and natural selection will, as we have seen, go hand in hand. Hence, if we look at each species as descended from some other unknown form, both the parent and all the transitional varieties will generally have been exterminated by the very process of formation and perfection of the new form."
>
> *Darwin (1859, p. 172)*

This quote perfectly describes what we discussed in Section 7.5 (p. 161) for the evolution of $\mathcal{D}_2$ individuals. While in competition for the same food sources, for a very long time both species took the same niche, exploiting black food patches, a behavior we called conservative. Then two major behavioral transitions occurred. As a result of the first transition $\mathcal{D}_2$ individuals started to exploit also white food sources, but without interfering with the behavior of the parent species, a behavior we called curious. Thus, both species still took the same niche and $\mathcal{D}_2$ gained a bit more profit by individually taking advantage from another environmental niche. During this first transition conservative individuals were replaced by curios individuals because of their increased performance. However, the peaceful coexistence of the parent and $\mathcal{D}_2$ species changed dramatically after the second major transition. $\mathcal{D}_2$ did not only develop its own communication system to excel its own collective foraging for white food sources, they also developed a mechanism to completely exclude the parent species from the previously shared environmental niche. Thus, $\mathcal{D}_2$ individuals did not only take a new niche they also actively eliminated the cooperative foraging behavior of the parent species, a behavior we called aggressive. Thus, we indeed observed a transitional development, from conservative to curious to aggressive individuals.

Interestingly enough, this transitional niche adaptation is in accordance with the findings of Scheffer and van Nes (2006). They conducted extensive simulation experiments with a Lotka-Volterra model of many competing species. They found that species evolve in clumps, where individuals in a clump take very similar niches, and clumps of species organize in regular patterns with large gaps between the clumps. However, this was a transient effect, which yet can be very long lasting. With time, clumps thinned out to a single species taking one particular niche. Even though we considered only one evolving species, we showed that it took the same niche as the parent species for several hundreds of generations before it started to exploit a new environmental niche and finally developed aggressive behavior resulting in a total performance loss of the parent species. Thus, the new species excluded the parent species by aggressive competition after a long time of peaceful co-existence.

Already in 1934 Gause confirmed competitive exclusion among protozoa. He did experiments with two species of *Paramecium.* Both grew well by themselves, but

P. aurelia out competed *P. caudium* when both were grown together (Gause, 1934). Repeated experiments showed that one species was always entirely replaced by the other. This is exactly what we observed in every conducted evolutionary trial. The new species always showed aggressive signaling behavior with fatal consequences for the parent species as we discussed for two examples in Section 7.3.4 (p. 154) and in Section 7.4.2 (p. 159).

Scheutz and Schermerhorn (2004) investigated how the level of aggression influences the benefit of individuals in two populations competing for food sources in an embedded two-player stopping game. Agents possessed certain predefined actions, such as 'fight' or 'retreat'. In addition agents were able to discriminate between agents of their own kind and other agents. Scheutz and Schermerhorn (2004) investigated the utility of agents with different levels of aggression and depending on whether they are able to discriminate between 'own' and 'others'. Their results demonstrated that agents with the highest level of aggression against 'others' outperform all other types of discriminating or non-discriminating agents.

The experiments described in this chapter indicate similar results. As we said, we always observed the development of aggressive signaling behavior in each conducted evolutionary trial. Interestingly, here agents do not possess the ability to explicitly discriminate between 'own' and 'others'. Instead, beneficial intraspecific cooperation and interspecific aggression resulted from the newly developed communication system. Showing aggressive signaling behavior affects the parent species because it disrupts its communication system which is essential for its intraspecific cooperative behavior. And the neural system of the new species was changed by evolution in a way that these aggressive signals do not affect its own intraspecific cooperation (remember the total loss of connections coming from the according sensory neurons). On the other hand, intraspecific cooperation was facilitated by the development of a new communication system relying on using a different type of signals which was of not useful for the parent species.

By evolving aggressive behavior the new species actually removed an initial selection pressure, the interspecific competition about the same niche. That is, the new species generated a feedback in their evolution, a phenomena also known as *counteractive niche construction* (Odling-Smee et al., 2003).

Investigating transitional niche adaptation and competitive exclusion in form of niche construction is not within the main scope of this thesis. However, the experiments presented in this chapter indicate that unconstrained evolution of situated agents might also be a suitable tool to study this phenomena and, therefore, complement research in evolutionary biology which focuses more on theoretical models.

7.6.4 Evolutionary creativity and novelty of behavior

Evolutionary creativity, as it is used here, is understood as the emergence of fundamentally new, or novel, behavior during an evolutionary process which aims at open-endedness. Bianco and Nolfi (2004) defined three major factors that promote open-ended evolution: (a) implicit and general selection criteria; (b) favorable organization of the evolving individuals; and (c) changing environmental conditions. The experiments presented in this and the previous chapter fulfill the first criterion quite well. Maintaining energy is probably the best implicit selection criterion for the evolution of autonomous robots as long as they are not able to reproduce themselves, at least not yet.

The second factor, favorable organization of evolving individuals, emphasizes that new behavioral abilities and solutions which contribute to better individual performance may most likely arise from simpler individuals. That is, individuals descended from their more primitive predecessors might develop new ways of locomotion or exploit new sources of energy and environmental niches (Bianco and Nolfi, 2004). This is exactly what we discovered in this chapter. We have seen how the new species developed more sophisticated forms of communication as compared to their predecessors. Furthermore, it exploited new food sources, took a new environmental niche, and actively changed the old niche to its advantage by displaying aggressive behavior toward individuals of the parent species.

Therefore, the aggressive behavior led also to a change of environmental conditions. Because it exterminated the cooperative behavior among individuals of the parent species, it resulted in more profitable conditions for the new species. Thus, a dynamic change of the environment resulted from altered interactions between individuals of two competing populations. However, we still have to consider that other environmental aspects did not change during the course of evolution. Such aspects could be for instance the depletion of food sources or a change in the number of individuals within the competing populations depending on their success in exploiting food sources. Despite of the importance of these aspects, they were deliberately excluded in our experiments for the sake of comprehensibility. However, taking that into account has to be obviously included in future research.

We might now agree that the experiments presented in this chapter fulfill most of the factors which are required for an open-ended evolutionary process. Such processes promise, but do not inevitably lead to, the emergence of fundamentally new behaviors. It is hard to define precisely what is fundamentally new. A good approximation is given by Taylor (2001):

> "[...] the ability of individuals to interact with their [...] environment with few restrictions, and to evolve mechanisms for sensing new aspects of this environment and for interacting with it in new ways. This includes the ability of individuals to utilise new physical modalities (e.g. sound, light, electrical conductance) which they previously did not use, to develop new functional relationships with their environment [...] and also for the very notion of individuality to change in radical ways (e.g. the evolution of multicellular organisms from unicellular ones). It is these sorts of evolutionary innovations which I am labelling creative. Creativity is therefore distinct from open-endedness; a system capable of open-ended evolution is not necessarily creative."

Agreeing with this line of argumentation, we first have to admit that here evolving individuals did not change in the radical ways which Taylor had in mind. This is a direct consequence of a further simplification we made, namely not allowing morphological changes of evolving individuals. However, we can ascribe a certain degree of creativity to the evolutionary experiments discussed in this chapter. Evolving individuals utilized new sensor and motor modalities to develop a new communication system for intraspecific cooperative communication while they changed the 'old' system to aggressive interspecific communication. And they utilized new sensors to exploit a new environmental niche. Thus, they changed their functional relationship with respect to food sources only slightly, but with respect to the individuals of another competing population they changed their relationship significantly through their newly developed aggressive behavior.

7.7 Summary

In this chapter we discussed the evolutionary development of a new species which competed with another non-evolving population, the parent species, for the same food sources. Initially, individuals of both species were identical in their sensory-motor system as well as in their neural control. This allowed us to carefully analyze how evolution induced structural changes into the neural networks, how these changes affect the dynamical properties, and how that affects the behavior of the new species.

We demonstrated how the new species developed a new way of intraspecific communication which benefits cooperation among individuals of their own kind. In addition they changed the initial communication system in a way that it led to aggressive behavior against individuals of the parent species. This resulted in a competitive exclusion of the parent species from the initially shared environmental niche. Besides a more proficient communication system, the new species also acquired additional behavioral skills to exploit a new environmental niche while still taking advantage of the initial niche. These *new* behaviors emerged from a rather unconstrained evolutionary process. Neither the topology of the networks nor the possible individual behaviors, nor the way how individuals interact with each other were restricted in any way. Thus, we further approached an *open-ended* evolutionary scenario and demonstrated how that can indeed give rise to evolutionary *creativity*.

Two evolutionary solutions were thoroughly analyzed with respect to their internal dynamical properties and how those affect the behavior of situated agents in the sensory-motor loop. We demonstrated that, for instance, different aspects of communication such as aggressive interspecific and cooperative intraspecific signaling were realized by a simple two-neuron loop. Depending on the sensory activation, this neural submodule showed different domains of attractors. Switching between these different domains gave rise to different signaling strategies depending on the environmental context of an agent. The second discussed example illustrated again how the interplay between internal neural dynamics and fluctuations in form of sensory noise realizes highly efficient communication strategies.

Analyzing in which way RNNs were modified during the evolution of new behaviors revealed that a sophistication in behavior does not inevitably entails the development of more complicated network structures. The resulting RNNs were still rather small sized. Versatile behavior can again be mainly attributed to *multimodality of intrinsic neural dynamical properties.*

Chapter 8

Discussion

> "When we analyse a system we tend to overestimate its complexity."
>
> *Valentino Braitenberg (1984, p. 20)*

Each preceding chapter contained its own extensive discussion. Here, we briefly review what has been achieved, highlight some general findings emerging from the experiments presented in the previous chapters, and conclude this thesis.

8.1 Summary of contributions

Chapter 3 – Cooperation without explicit communication channels

Chapter 3 was devoted to the evolution of cooperative behavior without explicit communication in a minimalistic robotic system. The robot was composed of five individual subsystems. To control these subsystems, we considered three different approaches: centralized and decentralized control, where the latter was further distinguished in heterogeneous and homogeneous distributed control architectures.

From an evolutionary perspective, all three approaches performed similarly well under the conditions they were evolved. However, compared to the centralized system, both decentralized architectures showed a much higher robustness to failure of individual subsystems. Intriguingly, failure of individual components was not included the process of evolution. Thus, the robustness of the decentralized systems did not result from evolutionary adaptation, that is, these systems were not selected for this property. *Robustness is an intrinsic property of the distributed organization* as it can be vastly found in self-organizing biological systems as well (Resnick, 1994; Camazine et al., 2001). Thus, distributed non-hierarchical system should be preferred whenever possible because they are likely to provide robustness to individual failure for free.

From a mechanistic perspective, decentralization led also to the evolution of very small individual neural structures, easing the analysis of the relationship between neural dynamics and observable behavior. Analytical investigations demonstrated that sensory-motor feedback loops were an integral and utmost important part of the individual control systems. We have further seen that this led to a reciprocal coupling of an agent with its environment which minimized the required neural mechanisms. This was demonstrated by the mechanisms of context-related switching between two different behaviors (Section 3.4.2), by the environmentally induced reflex-oscillations in simple feed-forward structures (Section 3.5.4), and the perpetual influence of one agent's action to another agent's action through local environmental changes (Section 3.5.5).

Chapter 3 showed that cooperation is possible without dedicated communication channels (see also Quinn, 2001; Wischmann et al., 2005). That is, no signals were required (recall Section 2.1.1) and cooperation, therefore, relied on cues in form of environmental changes caused by local actions of individual agents.

Chapter 4 – Aggregation with minimalistic control

In Chapter 4 we discussed the minimal required neural mechanisms to achieve coherent global collective behavior of numerous robotic agents resembling spatial aggregation patterns found in animals (Allee, 1931; Camazine et al., 2001).

Again, very small-scale RNNs consisting only of two output neurons were evolved with which individual robots were able to integrate two competing behaviors, namely obstacle avoidance and chasing a moving target. The moving target was another robot with an attached speaker continuously emitting an acoustic signal which could be sensed by other robots within a limited range. With this setup a group of robots successfully caught the target as expected from the given fitness function (Section 4.3). An interesting behavioral transition occurred when a speaker was attached to every chasing robot. Through this slight morphological change sophisticated dynamic aggregation patterns emerged solely based on local individual attraction and repulsion behaviors (Section 4.4). Most notably, these two competing behaviors were realized by the very same internal dynamics, namely the hysteresis behavior of the very same neurons. At the mechanistic level these two behaviors differed only in the coupling of the respective sensory stimuli to the dynamical neural system.

The experiments of Chapter 4, as simple as they are, hint us further to two major aspects:

- Coherent collective behavior can emerge from simple local interactions among agents with very basic behavioral skills.
- Completely different behaviors can be realized by the versatile dynamical properties of small-scale neural structures.

The latter finding indicated already that more sophisticated behaviors do not necessarily require more complex neural structures, a principle which became more evident in the proceeding chapters (especially in Chapter 6 and 7).

Chapter 5 – Behavior coordination through synchronized communication

Although the experiments of Chapter 4 demonstrated the emergence of collective behavior from very simple, locally interacting, agents, the achieved global behavior lacked a particular function. In Chapter 5 we added functionalities to the behavior of single agents, that is, collecting energy in the environment and transferring it to a common nest. The question of interest was how to coordinate the foraging and homing behavior of many individuals with as minimal communication as possible. We took inspiration from the synchronized flashing of fireflies (Buck, 1988), where single individuals periodically release flashes determined by the frequency of an internal neural oscillatory circuit. These internal oscillations are disturbed when flashes of close-by fireflies are sensed. Thus, thousands of individuals form a net of locally coupled resettable oscillators where individual rhythms become quickly synchronized until the whole group flashes in unison.

In our experiments, we designed a small neural circuit to realize such internal rhythms for our robotic agents. Driven by this rhythm individual agents either foraged for energy or headed toward their nest. However, if each agent acted just according to its own inner rhythm the foraging of many individuals was not very efficient. Again, just very small structural changes altered the group behavior tremendously resulting in an enormous increase of foraging efficiency. We added one output neuron which triggered an acoustic signal whenever the internal rhythm of an individual fulfilled one cycle. In addition a sensory neuron reset the rhythm as a response to acoustic signals of other individuals. Equipped with this new sensor and motor capacity, individuals quickly synchronized their internal rhythms and showed coherent foraging and homing behavior, thereby avoiding the ‘chaotic’ interferences and obstructions which occurred when every individual acted by its own. Interestingly, this coordination mechanism turned out to be highly robust and scalable. It was robust, because even if individuals could only sense signals of their closest neighbors, sync occurred even though the time span until it spread through the whole colony increased with decreasing local interaction range (Section 5.5). Scalability was demonstrated by increasing colony size from 25 to 150 individuals and still achieving sync in a rather short time span (Section 5.6).

Here, we deliberately set up the mechanism of resettable oscillators, expecting robust and scalable behavior in groups of robots based on locally coupled simple units. Strinkingly, we also found these mechanisms for signal coordination in later experiments emerging from evolutionary processes even though we did not bias their development. Thus, rhythm synchronization between locally and temporally coupled entities seems to be an efficient coordination mechanism not only in biological organisms (see Winfree, 2001; Strogatz, 2003), but also in evolved artificial societies as they are considered here.

Chapter 6 – Emergent communication and signal coordination

The first realization of an evolutionary process with open-ended characteristics (see discussion in Section 2.5.5 and 7.6.4) was shown in Chapter 6. The fitness function rewarded homogeneous groups of robots for how often their individuals were able to fully recharge their batteries by exploiting environmental energy sources. One can think of it as how often an agent is able to reproduce, which depends on its energy level. In this sense, the fitness function was as internal and as implicit as possible (see Section 2.5.5).

Interesting from an evolutionary perspective was the development of completely different solutions. Even though these solutions were quite similar regarding the observable behavior, they differed significantly in the underlying neural mechanisms. It turned out that specific solutions showed an increase robustness to environmental changes that did not occur during their evolutionary development, namely an increase of interacting individuals. This leads us to the conclusion that open-ended evolution experiments with artificial societies can give rise to a *mechanistic diversity of solutions* to the same problem. This diversity entails the potential that at least some solutions are *robust to unanticipated future changes of the environment.* Thus, we could resemble, without biasing it, a phenomenon also found in biological organisms (Marder and Goaillard, 2006).

From a mechanistic perspective the development of signal coordination revealed two different underlying mechanisms. First, individuals coordinated their food calls indirectly (see Section 6.3.3) via their infrared sensors. Indirect communication was first discussed in Chapter 3 where it was evolutionary enforced because individuals lacked the ability to communicate directly. In Chapter 6 individuals could communicate directly and they made use of this ability to release food calls and guide other individuals to energy sources rather efficiently. The elicitation of food calls was driven by the subtle interplay between intrinsic neural dynamics and sensory noise (see Section 6.3.3). The coordination of these food calls was realized by an indirect mechanism, and this mechanism actually evolved to avoid obstacles. Thus, in this case signal coordination relies on cues not on signals (see definitions in Section 2.1.1). Interestingly, this behavior evolved under conditions where signal coordination was not necessarily required to increase the fitness of the group, but it turned out to be of advantage when environmental conditions changed (see Section 6.3.4).

The second interesting mechanism evolved in a further set of experiments. Solutions which lacked to ability of signal coordinate were evolved under conditions where this led to poor performance. In this case we only changed the environmental conditions, that is, we increased the number of interacting individuals; the fitness function remained the same. We then observed the development of very small changes in the neural structure which led to signal coordination by a mechanism very reminiscent of the experiments presented in Chapter 5. Here, food calls were coordinated by the synchronization of internal oscillators through locally limited agent-agent interactions (see Section 6.4). While we designed such a robust and flexible mechanism in Chapter 5 with purpose, here it emerged from an unconstrained evolutionary process. This indicates that *local synchronization of resettable oscillators* is a highly efficient solution to coordinate the behavior of large groups of interacting individuals, very much as it is known from biological organisms (see for instance Strogatz, 2003).

Chapter 7 – Intraspecific cooperation and interspecific competition

In Chapter 7 we extended the experiments of the preceding chapter. Starting with the same setup we added a new quality of food sources to the environment, then we took a good performing evolutionary solution from the previous experiments and distributed it into two separate species. Thus, initially both species were in competition for the same type of food. One of the species was allowed to evolve, being further equipped with a sensor for the new type of food and the possibility to utilize an additional acoustic signal for communication, but no new neural structures were added to connect these new sensors and actuators to the initial control structure. The other species remained unchanged to circumvent the Red Queen effect, that is, an evolutionary arms race between the two species.

We showed the evolutionary development of transitional niche adaptation in form of punctuated equilibrium (Eldredge and Gould, 1972) where long periods of stasis were followed by rather rapid changes. In two major transitions the evolving (new) species first adapted its behavior to exploit the new environmental niche while later it weakened competition for its original niche by actively suppressing competitors, disrupting their intraspecific communication (see Section 7.5 and 7.6.3). The resulting change of selection pressure generated a feedback in the evolutionary process and can, in this context, be interpreted as the first evidence for counteractive niche construction (Odling-Smee et al., 2003) based on communication. This originated from the unexpected development of aggressive inter-species signaling and emphasizes the important role of changing interactions among competing species in the process of niche construction.

That aggressive behavior evolved in our experiments can mainly be ascribed to the inclusion of real world characteristics in simulation. We expected that evolved communication solutions would try to prevent the interference problem of acoustic communication among too many signalers, as we found it for the intraspecific synchronized cooperative signaling in Chapter 6. However, we never expected that the new species will make use of this problem for their own good by evolving aggressive interspecific communication. To our knowledge this is the first time that counteractive niche construction is observed in evolutionary robotics experiments.

The ability to trace back behavioral changes during the evolution of cooperation and competition is one major strength of the unified approach utilized here. As we stressed several times, similar important is the ability to clarify the exact neural causes of the evolved behavior. Remarkably, we could reveal that sophisticated communication abilities, such as signal coordination, cooperative intraspecific communication, and aggressive interspecific signaling was actually realized by the dynamics of a two-neuron subnetwork (Section 7.3.3). The reciprocal coupling of an agent with its environment via its sensory-motor system realized transitions between these different sub-behaviors through switching between different domains of periodic and quasi-periodic attractors within the neural system that controls the agent. Thus, we showed that quite advanced forms of communication can emerge from the versatile dynamics of very small-scale neural networks embedded in sensory-motor feedback loops.

8.2 General findings

To this end we have seen and discussed many experiments with sometimes expected, but often also surprising, results. However, we already noted that we are still dealing with robotic agents which are highly simplified compared to biological organisms (see discussion in Section 2.2 and 2.3). Thus, one might ask: What can experiments as presented in this thesis tell us about evolutionary and mechanistic processes of cooperative behavior in general?

Before discussing the possible biological relevance behind this study, we want to place our findings within the current stream of research with respect to what is called the *synthetic ecology* approach of artificial life experiments (MacLennan, 1991).

8.2.1 Disentangling the mechanisms that underlie evolved social behavior

From our discussion about early cybernetic research (Section 2.2.2) and behavior-based robotics (Section 2.2.4) we know already how relatively simple control systems can exhibit sophisticated behavior patterns when taking sensory-motor feedback loops into account. While cyberneticians, such as Grey Walter, or behavior-based roboticists, such as Rodney Brooks, deliberately integrated feedback loops in their control architectures, we showed that evolution exploits them heavily without being biased toward it (as especially shown in Chapters 3, 6, and 7). Thus, just the mere fact that robots are embodied and situated leads almost inevitably to the integration of sensory-motor feedbacks in the control system which may reduce the dynamical complexity of neural systems.

However, even though we did not enforce these phenomena explicitly, there may by an implicit bias in our experiments. A major focus of this thesis was to keep evolving systems analytically tractable which required the development of rather small neural structures (as discussed in Section 2.5.4). The enforcement of small structures may facilitate evolution to exploit the sensory-motor loop. A good example is the implicit signal coordination mechanism discussed in Section 6.3.3. There, signaling among interacting agents was realized by the neural mechanism actually evolved for obstacle avoidance making additional structural elements unnecessary. However, we have to keep in mind that there is no strong causality between structural complexity and the complexity of internal neurodynamics (see also Section 2.5.3).

That the enforcement of small neural structures does not inevitable entail less intrinsic dynamical complexity was conclusively shown in Section 7.3 by a two-neuron submodule which enabled an agent to show several distinct communication strategies such as signal coordination and aggressive and cooperative signaling. Clearly, the sensory-motor interactions of an agent with its environment and other agents was an important underlying component of its behavior, but only their link to a rich internal dynamical repertoire by means of several distinct attractor domains gave rise to the observed sophisticated behavior. In other words, the behavior resulted from the interplay between subtle internal and external mechanisms.

The fact that sensory-motor feedback loops are heavily exploited by the evolutionary development of neural networks for behavior control is supported by an increasing number of related studies (see, for instance, Nolfi and Floreano, 2000; Harvey et al., 2005; Pfeifer and Bongard, 2006). However, one major challenge remains: Clarifying which aspects of evolved behavior can be ascribed to internal neural mechanisms and which to agent-environment interactions. Though this might be relatively easy to answer when using feed-forward structures with trivial dynamics, it becomes rather complicated when using recurrent neural networks with complex dynamics. There exist only a few studies with regard to the latter problem (see, for instance, Beer, 2003b; Hülse et al., 2007a), but, to our best knowledge, in the context of the evolution of social behavior this problem is still largely neglected.

For instance, Floreano et al. (2007) presented evolved social behavior of comparable sophistication as presented in Chapter 7. The work of Floreano et al. focused on the evolutionary perspective and aimed at clarifying the role of different forms of kin selection; however, the used control structures were feed-forward networks with predefined topologies. Thus, even though they demonstrated rather advanced behaviors, the emergence of non-trivial neurodynamics could not be investigated within their experimental framework.

Marocco and Nolfi (2006) evolved the weights of recurrent neural networks with a predefined architecture for social behaviors comparable to the cooperative foraging discussed in Chapter 6, but an analysis of the neural dynamical properties and how they are connected to the sensory-motor interaction of an agent is still missing.

For a group of three robots, Quinn et al. (2003) evolved behaviors which entailed formation movement and role allocation. The experiments of Quinn et al. are interesting with respect to our studies for two reasons. First, it is one of the few studies that also consider structural evolution instead of a pure parameter optimization. Second, the resulting cooperative behaviors are intriguing because they are carried out even though the robots could not communicate explicitly with each other - very much like the behaviors discussed in Chapter 3. However, the study of Quinn et al. also misses an analysis of the detailed neural mechanisms that underlie the described behavior.

The novel contribution of this thesis is the possibility to clarify the connection between non-trivial intrinsic dynamics and the sensory-motor interactions of an agent during the evolutionary development of social behaviors. With this method, we discovered at least two mechanisms which, to our knowledge, have not been shown so far:

- The utilization of sensory noise for efficient communication strategies (Section 6.3.3 and 7.4).
- The repeated emergence of synchronization of internal rhythms based on local interactions (Section 6.4 and 7.3).

8.2.2 The artificial-reality gap

The intricacy of nature

In the previous section we argued that the possibility of disentangling the interconnection between internal neural mechanisms and the sensory-motor interaction of an agent is the major strength of the unified methodology pursued in this thesis. And even though we are still far away from the behavioral and mechanistic complexity of even the simplest biological creatures, the way of carefully increasing the complexity of individual agents, their synthetic nervous systems, and the artificial ecosystems in which they are embedded promises to complement research of behavioral neuroscience.

Understanding the detailed mechanistic nature of high level behaviors is still a huge challenge for biologists as, for instance, stated by Buzsáki in the context of consciousness:

> “One of the greatest challenges left for systems neuroscience is to understand the normal and dysfunctional operations of the cerebral cortex by relating local and global patterns of activity at timescales relevant for behaviour. This will require monitoring methods that can survey a sufficiently large neuronal space at the resolution of single neurons, and computational solutions that can make sense of complex interactions.”

(Buzsáki, 2007, p. 267)

What challenges research of higher cognitive functions, also challenges complementary research at a much lower behavioral level, as it becomes evident, for instance, in research of social behavior among microorganisms (West et al., 2006b). The experiments presented in this thesis are in fact closer related to the latter aspect and we hope we could convincingly show that they resemble to some extend similar aspects, as, for instance, inter-species competition for limited environmental resources. And even though they still entail many simplifications which makes a direct comparison with biological ecosystems rather difficult, especially those simplifications provided us with the advantage of understanding social systems from an evolutionary perspective down to the level of individual neurodynamics.

This leaves us with a severe question: Why can we expect to gain new insights from systems which seem so simple compared to their biological counterparts? Let us start with reviewing the relations we have drawn from our experiments. We related the cooperative behavior based on indirect communication (i.e., through the environment) discussed in Chapter 3 to stigmergic behaviors observed among social insects, such as ants or termites, the aggregation patterns in Chapter 4 to formation movements in fish schools, the rhythm synchronization in Chapter 5 to the flashing of fireflies, the cooperative signaling in Chapter 6 to the evolution of food or alarm calls, and the niche adaptation in Chapter 7 to competitive exclusion among protozoa. This leads us to a further question. Is it reasonable to resemble the behavior of animals which are usually considered as being rather primitive compared to what is thought to be highly elaborated social species such as primates or humans? We purposely left out almost every part which is traditionally considered as being essential for high-level intelligent, adaptive, and cognitive behavior, like language, grammar, sophisticated motor and sensory skills, or the ability of planning.

Starting with last aspect we want to mention a few studies which already began to 'demystify' the still vastly found anthropocentric view of cognitive and adaptive behavior. Planning for the future is widely assumed to be one of the cognitive skills which distinguishes humans, or at least primates, from the rest of the animal kingdom. However, recent findings contradict this view. For instance, Raby et al. (2007) showed that even birds, as the western scrub-jay, can plan for the future in a non instinctive way: they hide food for the next day to prevent starvation when food supplies are scarce over a longer period. Bshary et al. (2002) reviewed many experimental studies which show that cognitive skills and traits usually associated with primates can also be found in fish species, like social learning, social strategies, co-operative hunting, tool use, cognitive maps, memory, anti-predator behavior, or manipulations of the environment. Short-term memory can already be found in bacteria moving along chemical gradients (see, for instance, Staddon, 2001, 2003, and references within). Fruit flies show selective attention to novel objects when confronted with simultaneously competing stimuli (van Swinderen, 2007). Even the phenomenon of metacognition, the ability to think about your own thinking, can no longer be solely ascribed to primates as shown by the rat experiments of Foote and Crystal (2007).

All these studies, and we most certainly have not considered all, indicate that brain size or the organizational complexity of a species seem not to be the most crucial ingredients for cognitive or intelligent behavior. Yet, even the 'simplest' organisms, such as bacteria, puzzle us with their intricate mechanistic complexity (West et al., 2006b). They are so difficult to understand because even a single cell constitutes a web of complex networks involved in physiological responses to external and internal stimuli, and these networks are constituted by non-linear dynamical processes (for a review see Tyson et al., 2003). The most common answer to this daunting complexity is the reductionist approach: studying the smallest possible components of a system and then trying to draw general conclusions about the whole system by putting the parts together again.

A major problem with the reductionist approach is the pervasiveness of emergent properties in biological systems; interacting components behave completely different as it can be deduced from the behavior of the single parts (Haken, 2004; Kauffman, 1993; Eigen and Schuster, 1979; Prigogine and Stengers, 1984). For instance, the recent study of Wolfart et al. (2005) showed that thalamocortical neurons embedded in an active network show only an unimodal firing response, either bursting or spiking. This contradicted the traditional view, developed from experiments on isolated neurons, that these neurons switch between the two modes as a response to changes in the neuro-modulatory environment (McCormick and Huguenard, 1992).

A further problem is the vast diversity and variability of biological organisms. For instance, knowing the ion channel dynamics of specific cortical neurons in one individual may not be valid for the very same type of neurons in another individual of the same species (for a review see Marder and Goaillard, 2006).

The compelling nature of the artificial

From the discussion above it would now be rather convenient to say: Let us create artificial systems resembling biological behavior and study those, much simpler and, therefore, more understandable, systems to find some general underlying principles of adaptive behavior. Of course this is a big step, and it would be rather naive to claim that systems as presented in this thesis directly improve our understanding of biological organisms' behavior.

Major criticism on artificial life research concerns the level of complexity which is far beneath that of nature. With the current state of the art there clearly exists no argument against this statement. Gross simplifications are being made at the level of artificial evolution, individuals, ecosystems, and nervous systems. And as we discussed in Chapter 2, this thesis is full of such simplifications. However, a major challenge in this thesis was to deliberately avoid too much complexity with the aim to always keep the systems tractable. We claim, that based on the presented findings we can now start to build systems with more sophisticated mechanisms. For instance, in a first study we started to integrate aspects which were left out here (Wischmann et al., 2007c). These aspects include asynchronous distributed evolution which is more biological plausible than the generation based evaluation method employed here. Furthermore, we started to include life-time learning and the evolution of an individual's morphology, and we continued were we stopped in Chapter 7, by considering the co-evolution of different competing species. We argue, it is highly reasonable to start "with the simplest possible models and then incrementally complicating them as our understanding improves" (Beer, 2003a), else we would risk to "replace a world we do not understand by a model of the world we do not understand" (Maynard Smith, 1992). In other words, climbing up the complexity ladder blindly is “not the most practical answer . . . [because]. . . seeking such complexity blindly, by typically restricting the search to achieving more complex behaviors, does not accomplish much” (Di Paolo, 2003).

We argue the methodology proposed here gives promising ground to complement biological research. Despite the comprehensibility, the most important aspects which have been unified are:

- **The cybernetics perspective**. As discussed in Section 8.2.1 this perspective integrates the important aspect of *sensory-motor feedback-loops* in *complete systems* to understand the underlying mechanisms of adaptive behavior, an perspective gaining increasing attention also in modern behavioral neuroscience (e.g., Cisek, 1999)
- **The dynamical systems perspective**. As discussed above even the behavior of a single cell in a biological organism is heavily ruled by non-linear dynamical processes (see also discussion in Section 2.4). Here, we have discussed the interconnection between intrinsic non-linear neural dynamics and the sensory-motor interaction of situated artificial agents.
- **Unconstrained evolution.** It is clear that natural evolution does not optimize biological systems toward specific functions; natural selection solely acts on survivability and reproducibility. Here, we accounted for that in laying the ground for open-ended evolutionary scenarios involving artificial species who, ultimately, were solely selected for their ability to maintain their energy level.

Still, the scenarios discussed here are rather simple, but there are at least two highly novel findings with respect to the evolution of social behaviors:

- **The ubiquity of multimodality.** Throughout all experiments we found a diversity of small but multimodal neural networks. The same structure can realize completely different behaviors, which is a direct consequence of considering neural networks as parameterized dynamical systems (Pasemann, 1996). For instance, to our knowledge, the results of Chapter 7 demonstrated for the first time, how the rich dynamical properties of very small neural structures can realize different sophisticated communication strategies.
- **Aggressive niche adaptation.** Through the complementary nature of our study we were able to trace back the evolutionary development of a species and to analyze not only their change in behavior but also their neural changes. With this method, the results of Chapter 7 are the first “in silico” evidence of niche construction by developing aggressive communication and, therefore, eliminating the competition with another species about limited environmental resources. That is, the behavioral change in the evolving species generated an evolutionary feedback which decreased its own selection pressure (see also Wischmann et al., 2007a)

Both aspects are extremely difficult to study in biological systems, the first because of the discussed complexity and diversity among natural organisms, and the second because *in vivo* experiments are limited by the generation span of biological organisms.

8.3 Concluding remarks

Now that we reached the end of this thesis, we should recall our first main objective. We tried to turn complex systems into complicated systems, where the latter is more understandable than the former. The complex subject matter was the evolution of social behaviors, or, more concrete, the evolution of cooperation and communication. While traditional methods in evolutionary biology are mostly based on game-theoretic approaches which often assume a fixed and limited set of rules and actions that agents can choose of, and consider agents in rather abstract terms, we proposed a completely different approach. By merging the cybernetic ideas about sensory-motor feedbacks of complete, situated, and embodied agents with the dynamical systems perspective on adaptive behavior, we clearly simplified evolutionary scenarios compared to the daunting complexity of nature. Even though we considered simplified models, we tried to avoid idealization, which was possible in particular by using open-ended evolution, a method from Evolutionary Robotics.

The second main objective comes naturally along with such a unified method. It concerns the complementary perspective on the evolution of cooperation, that is, trying to explain not only the evolutionary causes, but also identifying the detailed mechanisms that underlie evolved behaviors. In an abstract sense we tried to account for the notion of Theodosius Dobzhansky (1973) that "nothing in biology makes sense except in the light of evolution" with the statement of J. Scott Turner (2007) that "no attribute of life, including its evolution, really makes sense unless we view it through a physiological lens" (see also Wedekind, 2007).

We started with probably the simplest robotic system to investigate the evolution of cooperative behavior without communication, followed by experiments with individuals just possessing a positive and a negative tropism, but developing fascinating spatial aggregation patterns in groups of many locally interacting individuals. We then added functionality to the behavior of single individuals and demonstrated how simple entrainment mechanisms gave rise to a robust and scalable coherent behavior coordination. Finally, we investigated the evolutionary emergence of communication without biasing it, and investigated how communication changes when confronted with inter-species competition. Following this path, we increased the organizational complexity of individual agents and simultaneously decreased our assumptions and predefined constraints about the expected evolutionary development of behaviors and their underlying neural mechanisms.

Even though the presented experiments are in fact too simple to ground them directly in evolutionary biology, they revealed novel findings which can hardly be expected to emerge from traditional approaches. Such findings, include the important role of sensory-motor feedbacks for the social behavior of interacting individuals and the ubiquity of small-scale neural networks exhibiting versatile dynamics which, in interaction with the former aspect, enable individuals to display sophisticated behaviors, which include several distinct communication strategies. Furthermore, with the method employed here it becomes possible to investigate not only the actual neural mechanisms that underlie behavior, but also its history in form of structural changes occurring during the course of evolution. That this can be highly useful, became evident in the case of counteractive niche construction through the development of aggressive signaling which has, to our knowledge, not been shown so far.

The results in this thesis should not be seen as a ‘better approach’ to comprehend the evolution of cooperation and communication than traditional ones. In fact, it can not be considered in this way, because we omit several similarly important aspects, such as the cost of signals, the role of kin selection, etc. However, experiments as discussed here may provide a new, and probably more concrete, perspective on the evolution of cooperation, because they deal with aspects largely neglected in traditional approaches, aspects such as embodiment and situatedness, or the dynamical nature of the underlying mechanisms of behavior. Thus, both approaches simplify the real world at different levels, and seeing them as sources of mutual inspiration and complementation should further enhance our understanding of the evolution and mechanisms of social behaviors.

Appendix A

A.1 Signal orientation of $\mathcal{D}_1$ individuals

Figure A.1 illustrates the positive sound tropism of $\mathcal{D}_1$ individuals toward detected S_B signals. If a signal is detected to the left of the robot's heading direction, $i8$ increases, and if it is detected on the right side, $i9$ increases (see also Table 7.1, p. 147). If no signal is detected, $i8$ and $i9$ are equal zero. In this situation the robot drives straight forward since $o1$ is about its maximal and $o2$ about its minimal value, resulting in high forward speed of the left wheel (cf. wheel speed calculation given in Equation 6.2, p. 123). The same holds for the right wheel, controlled by $o3$ and $o4$. If a signal on the left side of the robot is detected, $i8$ increases and consequentially $o1$ and $o2$ enter domains of periodic and quasi-periodic oscillations (Figure A.1a). The output of those neurons oscillates always around 0.0. These oscillations are averaged through the properties of the motors and the robot's body (inertia, friction). Thus only the mean of these oscillations lead to the actual velocity of the wheels, in this case zero (cf. Equation 6.2, p. 123). This results in a turn the left because the left wheel stops while the right wheel remains at high speed because $o3$ and $o4$ do not change significantly with increased $i8$ (Figure A.1a). In contrast if a signal to the right is detected, $i9$ increases. This does not change $o1$ and $o2$ and, therefore, the left wheel speed, but slows down the right wheel because the mean of $o4$ increases and approaches $o3$. The consequence is a turn to the right.

A.2 Collective foraging of $\mathcal{D}_2$ individuals

Foraging for black and white food sources

When a $\mathcal{D}_2$ individual enters a black food patch the according sensor input value $i4$ is always between 0.8 and 1.0 (± sensor noise). For this domain we see in Figure A.2a that the values of $o1$ and $o2$ are equal as well for $o3$ and $o4$. According to Equation 6.2 (p. 123) this forces the robot to stop. So far it is a similar behavior as already discussed for the initial structure (compare to Figure 6.1d, p. 126). The periodic domains of $o2$ and $o3$ are not relevant for the behavior because $0.8 < i4 < 1.0$ if a black food patch is detected or $i4 \approx -1.0$ if not. Thus the capability to stay on black food patches was conserved during the course of evolution.

In addition to conserving an already existing behavioral capability, the RNN also enables the robot to exploit the newly introduced white food patch. As we can see in

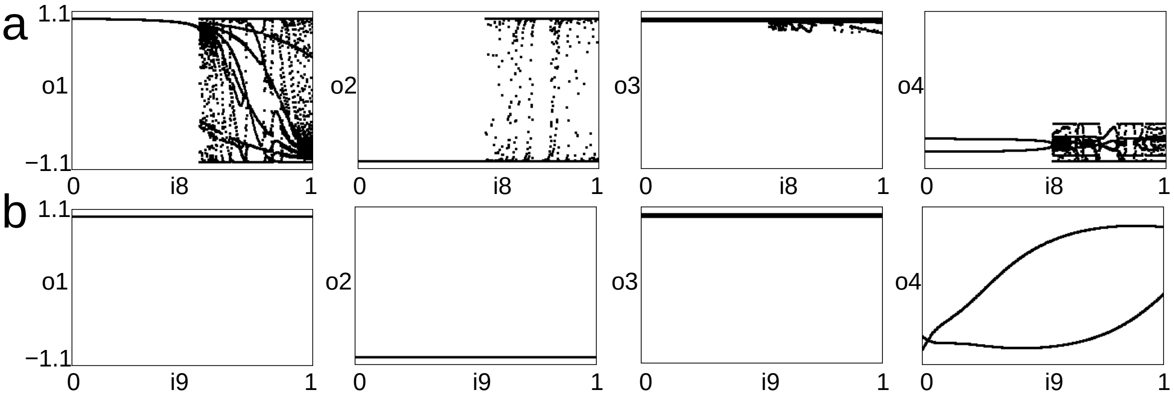

Figure A.1: **Sound signal tropism of $\mathcal{D}_1$ individuals.** Bifurcations diagrams for $o1, 2$ and $o3, 4$, steering the left and right wheel, respectively, while varying $i8$ and $i9$, the left and right sound sensor input for detected S_B sound signals (the corresponding network is given in Figure 7.2, p. 148).

Figure A.2b, the dynamics, we observe by varying $i7$, the black food sensor, are quite similar to the dynamics when we vary $i4$. And indeed both input neurons influence the dynamics in a similar way. If we consider the structure and parameters of the RNN, as given in Figure 7.8 (p. 157), we see the neurons $I4$ and $I7$ have an equally strong connection to $O3$ which explains the similarities in the bifurcation diagrams (compare $o3$ in Figure A.2a and A.2b). Both sensory inputs, $i4$ and $i7$, also effect $o2$ similarly (compare Figure A.2a and A.2b). However, none of these sensory neurons is connected to $O2$ directly. That $O2$ switches to a fixed point in the upper saturation domain of the transfer function is a result of the coupling with $O3$ (see Figure 7.8, p. 157). $O3$ projects to $O2$ with a strong negative synapses, and that is why we observe an inverse reaction of $o2$ at increased values of $i4$ and $i7$. Thus, the acquisition of the new behavior is actually a result of one single new synapse projecting from $I7$ to $O3$. $I7$, the sensor for white food patches, influences the dynamics of the RNN now in a similar way as $I4$, which was already given by the initial structure.

This is a prior example how new behaviors, which are similar to already existing behaviors, can be acquired during the course of evolution by very small structural changes. We discovered another example in Chapter 6, where we have seen how the addition of a two new synapses changed the communication system from uni-directional broadcasting to highly efficient synchronized signaling (see Section 6.4, p. 133).

Sound tropism toward S_B sound signals

The mechanisms behind the positive sound tropism of $\mathcal{D}_2$ individuals toward detected S_B signals are very similar to the mechanism discussed for $\mathcal{D}_1$ individuals in Section A.1. Figure A.2c illustrates the behavior of $o1, 2$ and $o3, 4$, controlling the left and right wheel, respectively, while varying $i8$ which increases the more a detected S_B signal is on the left side of the robot. As we can see, only $o2$ changes significantly, entering a domain of periodic oscillations. Again, these oscillations are averaged through the properties of the motors and the robot's body (inertia, friction) and only the mean

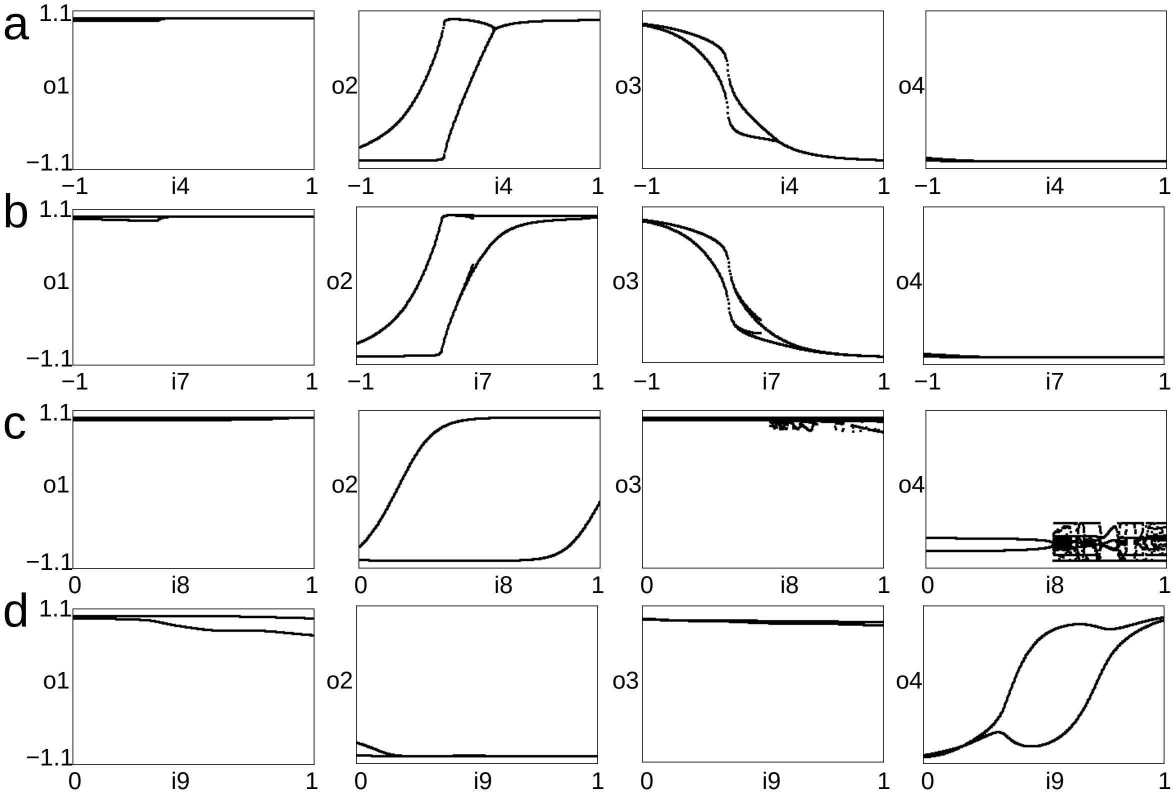

Figure A.2: **Neural dynamics of foraging behavior of $\mathcal{D}_2$ individuals.** Dynamics of the RNN shown in Figure 7.8 (p. 157). Given are bifurcation diagrams of the motor neurons $o1, 2$ and $o3, 4$ which control the left and right wheel, respectively, while varying the sensor input for detecting black food patches, $i4$ (a), for detecting white food patches $i7$ (b), and for detecting S_B sound signals, $i8$ and $i9$, on the left (c) and right side (d) of the robot's heading direction, respectively (the corresponding network is given in Figure 7.8, p. 157).

of these oscillations lead to the actual velocity of the wheel. According to Equation 6.2 (p. 123), this slows down the left wheel while the right wheel remains at high speed, resulting in a turn to the left. Similarly, if a signal is detected on the right side, $i9$ increases and only $o4$ changes significantly (Figure A.2d), slowing down the right wheel (cf. Equation 6.2, p. 123) and, therefore, leading to a right turn.

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