Cooperation and competition: Neural mechanisms of evolved communication systems [⋆]

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Abstract. Combining mechanistic and evolutionary perspectives to understand the emergence of communication is still a major challenge in evolutionary biology. Regarding this challenge, we discuss experiments which unify the ideas of evolutionary robotics with the dynamical systems approach to adaptive behavior. Here, we investigate how already evolved communicative behavior changes during further evolution when a population is confronted with competition about limited environmental resources. A thorough analysis at the neural level reveals changes of the mechanisms that underlie behavior, which eventually lead to the emergence of signal coordination, intraspecific cooperative, and interspecific aggressive signaling. Further, we 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. Our findings strongly support the complementary nature of robotic experiments to study the evolution of communication.

1 Introduction

There is still an ongoing debate about whether or not robotic models are useful to study particular aspects of animal behavior or its evolution [1]. The strong simplification of robots with respect to the opaque complexity of biological organisms is probably the most often raised argument against the usefulness of this approach. However, we argue that for studying the evolution and mechanisms of basic communication forms, a robot does not necessarily have to be as complex as a social insect [2], not even as complex as a bacterium [3]. In contrast, the strength of the robotic approach is that it deals with rather simple, yet *complete*, systems [4] facing similar real world problems as animals do, such as sensory noise or dynamically changing environments. These systems allow us to study communication not only from an evolutionary, but also from a mechanistic perspective.

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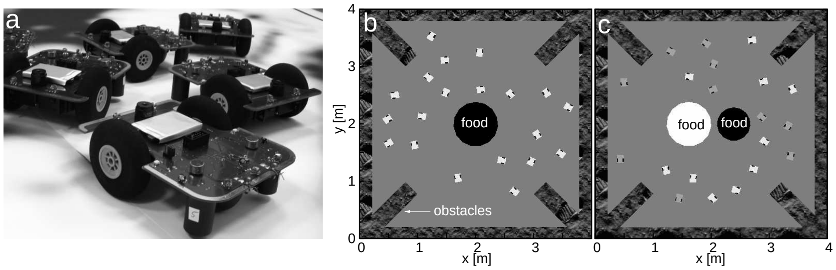

Fig. 1. The physical *Do:Little* robots (a) and their simulated models in the environment used for single population (b) and competitive (c) evolution.

Even though there exists a growing body of research related to communication and cooperation in artificial systems [5, 6], there is still a lack in the literature of investigations concerning the link between observable behavior and the dynamical mechanisms that underlie individual behavior. Revealing this link is inevitable to gain new insights about the underlying mechanisms of evolved *complete* brain-body-environment system [7].

This paper briefly discusses the evolutionary development and neural mechanisms of cooperative foraging involving food calls as an efficient communication strategy. Then, we focus on how such established communication mechanisms change under interspecies competition for limited environmental resources.

From a mechanistic perspective our results demonstrate that sensory noise can be an integrative aspect for cooperative communication strategies. Further, we can show that rather sophisticated communicative abilities do not necessarily require complex neural structures. Instead, we can show how signal coordination, cooperative intraspecific communication, and, most intriguingly, aggressive interspecific signaling can emerge from the versatile dynamics of very small-scale neural networks embedded in sensorimotor feedback loops. From an evolutionary perspective, modifications of communication strategies are observed which generate an evolutionary feedback resulting in an active reduction of selection pressure caused by the behavioral change of an evolving population.

2 Methods

Following the dynamical systems approach to adaptive behavior [7], our robots are controlled by parameterized discrete-time recurrent neural networks (RNNs). A network with n units is defined as:

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

Table 1. Noise ratio and mapping from physical sensor values to sensory neuron activation (sound sensor inputs are mapped to the angle α, β of a received sound signal $S_{A,B}$ to the heading direction of the robot; all other sensor values are linearly mapped into the given min/max).

sensors	neuron index	mapping [min, max]	simulated noise
infrared left, right, back	$I_{il,ir,ib}$	-1 : no obstacle 1 : close obstacle	0.05 ($\widehat{=}$ 10%)
floor intensity (black food)	I_{fb}	-1 : gray 1 : black	0.05 ($\widehat{=}$ 10%)
floor intensity (white food)	I_{fw}	-1 : gray 1 : white	0.05 ($\widehat{=}$ 10%)
sound signals			
$S_{A,B}$ (left)	$I_{al,bl}$	$0.5(1 + sin(\alpha, \beta))$	0.3 ($\widehat{=}$ 30%)
$S_{A,B}$ (right)	$I_{ar,br}$	$0.5(1 - sin(\alpha, \beta))$	0.3 ($\widehat{=}$ 30%)

where $a_i \in \mathbf{R}$ denotes the activity of neuron i, w_{ij} the synaptic strength of the connection from neuron j to neuron i, and θ_i its fixed bias term [8]. The output $o(i) = f(a_i)$ of a unit i is given by a sigmoidal transfer function, here by $f := tanh$ (i.e., $o(i) \in (-1, 1)$). Details about the complex dynamics of small neural modules of this type can be found in [8].

As agents we utilized a physically realistic, simulated model of the *Do:Little* robot (see Fig. 1a) which we already employed successfully in previous studies [9, 10]. All used sensors as well as their mapping to neural activity and their noise ratios are given in Tab. 1 (deduced from experiments with the physical hardware).

On the actuator side four output neurons control the angular velocity of the two wheels which is given by: $\omega_{left,right} = c((O_1, O_3) - (O_2, O_4))$, where c is a speed factor (here, $c = 2.0$). Further, robots can elicit two distinct sound signals $S_{A,B}$ (for details about the acoustic communication system see [9, 10]). Sound emission is controlled by the output neurons $O_{A,B}$; whenever the output of these neurons switches sign from positive to negative, the according sound signal is triggered and lasts for one time step (one time step corresponds to 0.1 s of real-time).

For evolution we applied the ENS^3 algorithm [11], which evolves not only the parameters of an RNN, but also its structure, that is, the number of hidden neurons and the connectivity (for details and applications see [12, 13]).

We conducted two different sets of experiments, which will be described in more details below. In general, we evolved a population of homogeneous robots (i.e., all individuals are equivalent with respect to morphology and control) on a cooperative foraging task (for details see [10]). Therefore, for evaluation an RNN was distributed in a group of robots placed in an environment as shown in Fig. 1b,c. Each robot possesses an internal virtual battery. It looses energy with time and through driving around. However, it can recharge its energy by stopping on a food source marked as a black or white spot on the ground (see Fig. 1b,c). Whenever a robot fully recharged its energy, it was replaced randomly in the environment with half of its energy. The fitness function simply rewarded how often, on average, individuals of a population were able to recharge their batteries per minute in a given evaluation time (for parameter details of the energy discharge/charge see [10]). Using a joint fitness for evaluating a particular solution by the average performance of a whole group indeed facilitates the emergence of cooperative behavior [14]. However, robots were neither evaluated on how they solve the several subtasks, such as avoiding obstacles and other individuals and approaching food sources, nor, and that is particularly important, how to cooperate and communicate with other agents. Thus, even though the evolutionary development of cooperation and communication is rather likely to occur within our experimental framework, we may yet discover unexpected signaling strategies and underlying mechanisms.

3 Results

In a first set of experiments we evolved a population of twenty homogeneous robots in the environment shown in Fig. 1b. There was no competition with another population and only one food source was available (the black spot in Fig. 1b). Thus, the sensor input I_{fw} was not utilized. Further, robots could only sense and emit S_A sound signals by $I_{al,ar}$ and O_A, respectively (i.e., $I_{bl,br}$ and O_B were also omitted).

Fig. 2a shows one resulting network (called $\mathcal{A}_\mathcal{S}$) of the single population evolution. In this paper we want to focus only on the signaling mechanisms (the relevant neural elements are highlighted in Fig. 2a). However, the evolved RNN entails also a behavioral response to these signals which will be specified, but not discussed at the neural level (nevertheless, the RNN shown in Fig. 2a realizes the complete behavioral repertoire of the robots).

As described in the methods section, a robot emits a sound signal only when the output of the according motor neuron switches its sign from negative to positive. Fig. 2b illustrates the influence of the floor sensor input neuron I_{fb} on O_A. By means of an odd loop with strong positive and negative weights, O_A is connected with the hidden neuron H_1 (see [8] for deeper discussions about the dynamics of two neuron networks). This loop operates as a switchable oscillator depending on the value of I_{fb}. I_{fb} is approximately -1 as long as the robot explores the environment. The bifurcation diagram in Fig. 2b shows that oscillations of O_A, caused by a period-4 attractor, are switched on by an increased activation of I_{fb}. To emit a sound signal at least two points of the periodic orbit have to be in the negative and in the positive domain. This only holds for $I_{fb} > 0.3$. Since detected food patches always provoke sensor signals of I_{fb} within $[0.8, 1.0]$, the output of O_A oscillates as shown in Fig. 2d. Thus, there is a direct link between food source discovery and food call emission.

Further important structural elements are the synaptic connections from the sound sensor inputs $I_{al,ar}$ to the hidden neuron H_1. Fig. 2c shows how the

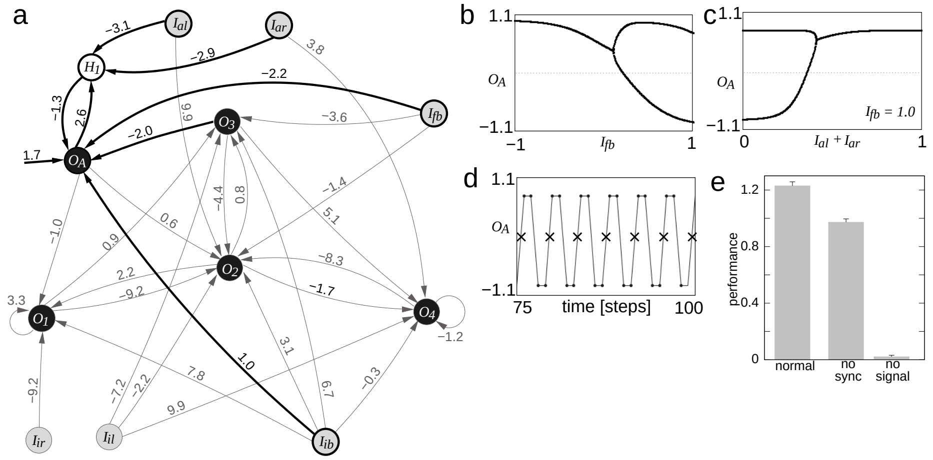

Fig. 2. a: RNN of $\mathcal{A}_\mathcal{S}$ individuals resulting from single population evolution. b,c: Bifurcation diagrams for O_A by varying the floor sensor input I_{fb} and the sound signal input $I_{al} + I_{ar}$ (if not indicated otherwise, all not varied input neurons are set to their minimum (cf. Tab. 1); this holds for all bifurcation diagrams in this paper). d: Output of O_A when the robot stays on a food patch (i.e., $I_{fb} > 0.8$); × marks S_A sound signal elicitation. e: Performance of $\mathcal{A}_\mathcal{S}$ (average and standard deviation of 25 simulation runs with randomized initial conditions; each simulation run lasted 18,000 time steps; no sync: synapses between $H1$ and $I_{al,ar}$ were set to zero; no signal: speaker on the robot was deactivated).

summed activation of these neurons leads to a switch from the periodic attractor to a fixed point. Consequently, the oscillation of O_A is reset whenever a signaling robot receives sound signals of nearby robots. This gives rise to signal coordination by a synchronization mechanism among robots gathered on the same food patch. That such synchronization among pulse coupled oscillators in a group of acoustically communicating robots is scalable and robust even with very short local interaction ranges is demonstrated in [9].

What does the food calling and its coordination mean for the performance of the group? $\mathcal{A}_\mathcal{S}$ individuals react to food calls of other individuals by a positive tropism towards these signals if they are in sensor range (in accordance with the real robots, the radius of sound signal perception was limited to $1.5m$ [9]). This behavior allows the group to forage efficiently for the food source which otherwise could only be sensed if a robot enters it by chance. The influence of cooperative food calls becomes clear if we compare the high performance of $\mathcal{A}_\mathcal{S}$ with normal signaling to the low performance when the speaker is deactivated (cf. Fig. 2e). Deactivating only the synchronization mechanisms leads to a performance loss of about 20% (Fig. 2e). The reason for better performance with

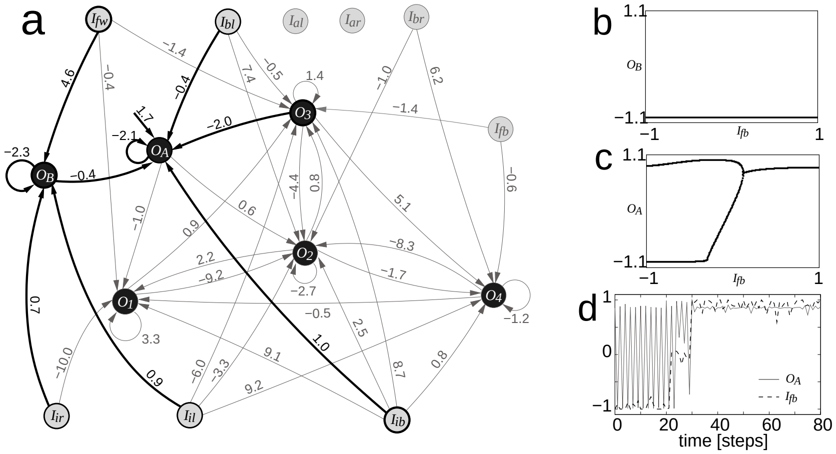

Fig. 3. a: RNN of $\mathcal{B}_{\mathcal{N}}$ individuals resulting from evolution under competition. b,c: Bifurcation diagrams for O_A and O_B by varying the floor sensor input I_{fb}. d: Period-2 oscillations of O_A cease as soon as the robot enters a black food patch (indicated by increasing I_{fb}).

signal synchronization is that if too many individuals simultaneously emit frequent and uncoordinated food calls, individual sound signals interfere with each other too much and, therefore, can hardly be located correctly [10].

In a second set of experiments we took the $\mathcal{A}_{\mathcal{S}}$ RNN and applied it to two populations, our two artificial 'species'. For the following experiments we placed both species with ten individuals each into the environment shown in Fig. 1c. We equipped one species (the new species) with new sensors and effectors and let it evolve. Individual members of the new species could now sense a new type of food (white patches) and utilize an additional sound signal (S_B). Note, initially these were just new sensor and motor neurons unconnected to the initial structure (even though the $\mathcal{A}_{\mathcal{S}}$ RNN was provided as initialization, its topology and parameters were free to change during evolution). To investigate how the new species might now change their behavior because of the high competition for the black food source, we did not evolve the other species. 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 [15].

A representative evolutionary solution ($\mathcal{B}_{\mathcal{N}}$) is shown in Fig. 3a. The signaling behavior of $\mathcal{B}_{\mathcal{N}}$ individuals when they discover a black food patch is illustrated in Fig. 3b-d. While a robot is exploring the environment, it continuously emits S_A signals which ceases with increased I_{fb} (see Fig 3c). Considering the structure of the RNN, we see that O_A is a switchable oscillator. Because of its negative self-

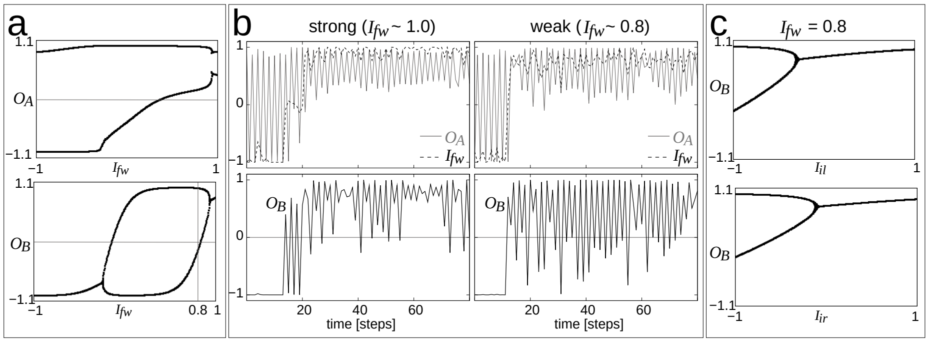

Fig. 4. Signaling behavior on white food patches. a: Bifurcation diagram for the two motor neurons $O_{A,B}$ while varying I_{fw}. b: Emission of S_A sound signals (controlled by O_A) ceases as soon as the robot detects a white food patch whereas S_B sound signals (controlled by O_B) are triggered (see text for details). c: With increased infrared sensor activation ($I_{il,ir}$), oscillations of O_B are inhibited and, therefore, S_B signaling stops.

connection, it exhibits either period-2 oscillations or a constant output depending on its input. Interestingly, there is no direct connection from I_{fb} to O_A (see Fig. 3a). Signal suppression is caused by the activity of O_3, the motor neuron which controls, together with O_4, the right wheel. When the robot discovers a black food patch, it stops its exploration behavior and stays on the food source. To do so, O_3 changes its output from 1.0 to -1.0. 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 $\mathcal{B}_{\mathcal{N}}$ individuals discover black food patches (cf. Fig. 3b). The only change in communication concerns the emission of S_A signals which does not affect the behavior of the receiving $\mathcal{B}_{\mathcal{N}}$ individuals since the according sensory neurons $I_{al,ar}$ lost their connections to the network (cf. Fig. 3a).

If a $\mathcal{B}_{\mathcal{N}}$ individual detects a white food source, it again ceases S_A signaling. O_A exhibits always period-2 oscillations independent of I_{fw} (Fig. 4a, top). However, with increased I_{fw} these oscillations are shifted into the positive domain, that is, O_A is always larger than zero and, therefore, no S_A signals are triggered on white food patches ($0.8 < I_{fw} < 1.0$). In contrast to the behavior on black food patches, this behavior is not only controlled by the change of O_3. Period-2 oscillations of O_A are still present with large I_{fw} because of the synaptic connection from O_B (cf. Fig. 3a) which starts oscillating with increased I_{fw} (cf. Fig. 4a, bottom). If $I_{fw} > -0.25$, O_B enters a domain of period-2 oscillations. Considering the structure of the RNN (Fig. 3a), we have here again a switchable oscillator. Oscillations occur due to the negative self-connection of O_B and can be switched on or off depending on I_{fw} because of the strong positive connection from I_{fw} to O_B. However, for $I_{fw} > 0.8$ 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 ($0.8 < I_{fw} < 1.0$). In this case, due to the noise of the floor sensor, I_{fw} randomly gets lower than 0.8 which then leads to period-2 oscillations of O_B which cross zero from below resulting in according signal emissions. 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 (not considering noise). Fig. 4b shows the signaling behavior on white food sources with different intensities. For high intensities, S_B signals are released less often than for lower intensities. For high I_{fw}, higher fluctuations (as caused by the sensory noise) are needed to push the oscillations of O_B into a domain where it takes positive and negative values and, therefore, to trigger S_B signals. Because of the dependence on noise, S_B signals are released rather randomly which entails less interference compared to more frequent emissions as observed for $\mathcal{A}_\mathcal{S}$ with deactivated synchronization mechanism.

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 $\mathcal{A}_\mathcal{S}$, this is not realized via a synchronization mechanism as described above. Here, signal coordination is in fact independent of the signal itself. As we can see in Fig. 4c, when either the infrared sensor on the left or right side of a robot (represented by I_{il} and I_{ir}) becomes activated while a robot stays on a white food source (e.g., $I_{fw} \approx 0.8$), oscillations of O_B are shifted again into the positive domain until they cease completely for high I_{il} or I_{ir} values. Infrared sensors influence O_B through the positive connections from I_{il} and I_{ir} to O_B (cf. Fig. 3a). We discovered such a subtle signal coordination mechanism already in a previous study [10]. However, here it is a completely new development because $\mathcal{B}_\mathcal{N}$ originates from $\mathcal{A}_\mathcal{S}$ which coordinated its signaling by synchronization. Note that this is an indirect mechanisms. The more robots are attracted by the food calls of others, 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 O_B oscillations cease as indicated in Fig. 4c.

Considering the consequences of these communication strategies for the performance of the $\mathcal{A}_\mathcal{S}$ and $\mathcal{B}_\mathcal{N}$ species, we observe a drastic performance loss for $\mathcal{A}_\mathcal{S}$ individuals (Fig. 5a). The S_A signaling of $\mathcal{B}_\mathcal{N}$ outside the food sources distracts $\mathcal{A}_\mathcal{S}$ individuals from the food and interferes and, therefore, disturbs their cooperative signaling. Thus, the $\mathcal{B}_\mathcal{N}$ population increased its initial fitness not only by exploiting a new niche (the white food source). Much more intriguingly, by permanently emitting S_A signals, $\mathcal{B}_\mathcal{N}$ eliminated $\mathcal{A}_\mathcal{S}$ individuals from the original niche (the black food source). Therefore, S_A signaling can be interpreted as aggressive interspecific communication. By evolving aggressive behavior the new species actively removed one initial selection pressure, the interspecific competition about the same niche. That is, the new species generated a feedback in their evolution, a phenomena known as counteractive niche construction [16].

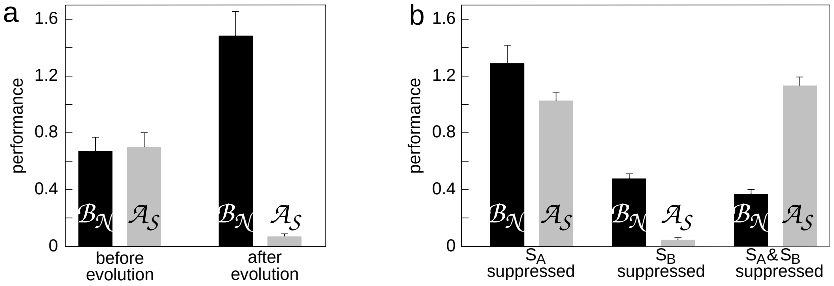

Fig. 5. a: Performance of the $\mathcal{A}_\mathcal{S}$ and $\mathcal{B}_\mathcal{N}$ population, with ten individuals each, competing for food in the environment shown in Fig. 1c (same measurement as for Fig. 2e). b: Suppressing the elicitation of specific sound signals in $\mathcal{B}_\mathcal{N}$ individuals reveals the influence of their cooperative intraspecific S_B and their aggressive interspecific S_A signaling.

Interestingly, if we suppress the S_A signaling in $\mathcal{B}_\mathcal{N}$ individuals (Fig. 5b), the performance of $\mathcal{A}_\mathcal{S}$ is even slightly higher compared to the initial condition (Fig. 5a). On the one hand, $\mathcal{B}_\mathcal{N}$ does not disturb the communication of $\mathcal{A}_\mathcal{S}$ and, on the other, $\mathcal{B}_\mathcal{N}$ forages not only for black, but also for white food sources which, therefore, lowers the competition about the original niche. Suppressing S_B signaling in $\mathcal{B}_\mathcal{N}$ leads to a rather low performance for both species (Fig. 5b) because the communication system of $\mathcal{A}_\mathcal{S}$ is still disturbed by the S_A signaling of $\mathcal{B}_\mathcal{N}$ which, on the other hand, depends on the S_B signal to cooperate. If both signals of $\mathcal{B}_\mathcal{N}$ individuals are suppressed (Fig. 5b), we observe low performance for $\mathcal{B}_\mathcal{N}$ and high performance for $\mathcal{A}_\mathcal{S}$ because $\mathcal{B}_\mathcal{N}$ individuals cannot cooperate anymore and they do not disturb the communication of $\mathcal{A}_\mathcal{S}$.

4 Discussion

Most closely related to the experiments presented here is the recent study of Floreano et al. [14] who studied the evolution of communication in groups of robots with a cooperative foraging task. By investigating different levels of selection they found that cooperation and communication evolved more likely if selection acts on the colony level. As convincing as their experiments are, they do not provide a clear picture about the underlying neural mechanisms of evolved communication strategies and how they change during the course of evolution.

Even though there exists a considerable number of further research studies employing situated artificial agents to study communication and cooperation (for overviews see [5, 6]), only a part considers situated and embodied agents, as for instance robotic systems. Even less involves dynamical systems, as for instance recurrent neural networks, for behavior control. To our knowledge, the experiments presented here and in [10] are among the first which entail thorough analysis of the dynamical mechanisms underlying evolved communicative behavior. This clarifies the relation between intrinsic neurodynamics and observable agent-environment interactions. This was done before only by a few studies considering the behavior of single agents (e.g., [7,13]). Thus, one contribution of this paper is to add an actual example of thoroughly analyzing the dynamical mechanisms underlying communicating agents which interact not only with their environment, but also with other individuals of their own kind and competitors. An example as it, to our knowledge, has not been reported so far for social behavior of situated agents.

Here, we were able to clarify which behavioral aspects of socially interacting agents can be accounted to *internal neural mechanisms* and to *sensorimotor interactions* between an agent and entities of its environment, respectively; of course both are heavily intertwined. As a particularly novel contribution we demonstrated how sensory noise can be an integrative part of communication mechanisms. Many former studies already insisted on the importance of including noise in evolutionary robotics experiments (e.g. [17,18]) and it is currently an essential part of most related research. Commonly, noise is often included to develop solutions which are robust to variabilities in sensorimotor systems or to environmental uncertainties. However, Di Paolo and Harvey [19] pointed out that *all* cognitive systems have to deal with noise and uncertainties which “may also provide positive mechanisms for producing robust and adaptive behavior”. This is certainly true and already well known for biological systems (e.g., signal enhancing mechanisms based on stochastic resonance [20]). However, in artificial systems, noise is usually not integrated into the actual control system, but rather something to which developed solutions have to show a certain robustness. Besides the results presented here, we already demonstrated that the evolution of noise driven communication is not as rare as one might expect. In fact, using noise as an essential element of behavior control can also entail an intrinsic robustness to unanticipated environmental changes (see [10]).

A further intriguing finding of our experiments is the difference between the signal coordination strategies of the two discussed networks, especially the mechanism of $\mathcal{B}_{\mathcal{N}}$. There, the signal which has to be coordinated is itself not involved in the coordination process. This is in so far interesting, as individuals have no direct ‘clue’ about other individuals or signals and they actually do not ‘know’ the difference between obstacles and conspecifics. This is different from the coordination process of $\mathcal{A}_{\mathcal{S}}$ individuals, which shows how two very divergent mechanisms can realize a similar observable behavior. A discovery which may be missed if we would concentrate only on a description of the evolved behavior in form of input-output signals.

There still remains the concern about how general the mechanisms discussed here really are. We do not claim that the presented neural networks resemble in any way actual nervous systems of animals. They have, however, similarities with communication mechanisms of biological organisms. Supporting examples are the synchronized flashing of fireflies based on pulse coupled oscillators [21,22] or bird songs whose emergence could be modeled in form of attractor landscapes of dynamical systems (e.g., [23]). That is where we see the conjunction with mechanisms of animal behavior, behavior whose mechanisms are based on the intricate dynamics resulting from non-linear interactions of rather simple basic elements. And that mechanisms which evolved for a particular robotic system are also generally applicable to completely different systems is shown in [13].

Besides this mechanistic perspective, we investigated how communication strategies and neural mechanisms change during evolution when a population is confronted with competition for the same limited resources. The results presented here are, to our knowledge, the first in the literature which demonstrate counteractive niche construction [16] based on an evolutionary change of communication. This and our other main finding, the utilization of sensory noise, emphasize the strong potential of robotic experiments to complement the study of communication and cooperation not only from an evolutionary, but also from a mechanistic perspective.

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