Synchronization of Internal Neural Rhythms in Multi-Robotic Systems[*]

Synchronization of Internal Neural Rhythms

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Abstract

This paper introduces a method for the coordination of individual action within a group of robots that have to accomplish a common task, gathering energy in a dynamic environment and transferring this energy to a nest. Each individual behavioral pattern is driven by an internal neural rhythm generator exhibiting quasi-periodic oscillations. The paper describes the implementation of this generator, its influence on the dynamics of artificial recurrent neural networks controlling the robots, and the synchronization of internal rhythms with differing frequencies in a group of situated and embodied robots. Synchronization is achieved either by environmental stimuli or even by self-organizing processes solely based on local interactions within a robot population of up to 150 robots. The proposed experimental methodology is used as a bottom-up approach and starting point for answering the question about the complexity required at the individual level to generate sophisticated behavioral patterns at the group level.

1   Introduction

Using artificial recurrent neural networks (RNNs) for autonomous robot control has become a common method in the field of Artificial Life (AL) and Evolutionary Robotics (ER) (Harvey, Di Paolo, Wood, Quinn, & Tuci, 2005; Nolfi & Floreano, 2000; Walker, Garrett, & Wilson, 2003; Hülse, Wischmann, & Pasemann, 2004). Considering a robot and its control architecture as a dynamical system (DS), questions arise about the coupling to other DSs such as dynamic environments (Beer, 1995) or other robots (Baldassarre, Nolfi, & Parisi, 2003; Di Paolo, 2000).

We agree with (Beer, 2003) in that while concrete dynamical models of cognitive phenomena are still under construction "one powerful way to improve our intuitions, clarify the key issues and sharpen the debate is through a careful study of simpler idealized models of *minimally cognitive behavior*, the simplest behavior that raises issues of genuine cognitive interest". We consider minimal cognition as metabolism-independent sensori-motor behavior and presuppose that cognitive behavior generally results from perception-action couplings (see (Duijn, Keijzer, & Franken, 2006), same issue, for a deeper discussion).

Here, we will describe a system of artificial agents interacting in a shared environment. Within the system we find three types of structural coupling (Maturana & Varela, 1992). The first type of coupling refers to the interactions between the elements, e.g. neurons, of the artificial nervous system internal to the agent. Secondly, we have to consider the interaction between the agent and its environment. And Third-order couplings are characterized by social interaction between individuals.

We will present an experimental setup where individual robots possess evolved basic behaviors which are heavily coupled to sensory stimuli coming from the environment (second-order coupling). We will call these behaviors reactive behaviors. Additionally, we realize an example of so called "internal robotics" (Parisi, 2004). Therefore, a minimal neural rhythm generator

inherent in the robot's neural control is introduced which periodically inhibits certain basic behaviors (first-order coupling). In this way the robot changes its behavior depending on the state of its internal rhythm which is reminiscent of circadian clocks found in biological systems (Winfree, 2001), such as the day-night cycle of humans.

Because several robots acting in the same environment we find rather indirect interactions between robots; e.g., robots represent moving obstacles for other robots. In this case, from the individual agent's point of view other agents are seen as perturbations from the environment as they can occur from any other obstacle. But when individuals are able to communicate more direct interactions become possible. Such third-order couplings can, for instance, be found in insects which share locations of food through physically excreting chemicals (Maturana & Varela, 1992).

A major question within the research on self-organizing collective behavior in biological systems is about how much complexity at the individual level is required to generate the observed complexity and sophisticated pattern at the group level (Camazine et al., 2001). Because even the simplest biological units are rather complex a detailed and deep analysis of individual properties during its interaction within its natural environment becomes almost impossible. To get this problem more tractable one can investigate the individual under rather synthetic but well controllable conditions or build up still understandable theoretical models. We propose to complement these approaches by trying to generate similar global phenomena with artificial agents which at the end have to be embodied and situated in the real world to meet the demands for building complete brain-body-environment systems (Brooks, 1999; Beer, 2003). Such complete systems are necessary because often individual control mechanisms can be surprisingly simple when the interaction with the environment is taken into account appropriately (Pfeifer & Scheier, 1999). Reduced complexity at the individual level, concerning morphology, control, and communication effort, is of great advantage for robust and efficient behavior coordination

in large robot groups or swarms.

For our experiments we use a robot especially designed for experiments with large robot groups, i.e. it is of low-price and easily replaceable. Therefore we are challenged by the difficulty of dealing with two constraints: homogeneity and minimal sensors and actuators (Quinn, Smith, Mayley, & Husbands, 2003). Homogeneity can also be found on the control level. We will use one of the simplest neuron model possible having only two parameters, bias terms and synaptic self-weights, and a sigmoid transfer function (Pasemann, 1993). Although the physical setup, the communication capabilities, and the control elements are minimal, it is possible to generate sophisticated global behaviors, such as the synchronization of internal neural rhythms in order to achieve coordination of conflicting behaviors in large robot groups, which is mainly a result of the dynamic interaction between these single units.

2 Methods

2.1 Neural model of an inner rhythm

Biological systems exhibit periodic behaviors on various time scales, and it is known that at least some of them are controlled by so called central pattern generators (CPGs) internal to the nervous system (Kelso, 1995). In the following, we propose a CPG which consists of two coupled SO(2)-networks (Pasemann, Hild, & Zahedi, 2003). This model's frequency can be adjusted by only one parameter and it is stable even for very long wavelengths. Standard discrete-time recurrent neural networks with a sigmoid activation function (Pasemann, 1993) are used.

2.1.1 Coupled oscillator architecture

SO(2)-networks, described in (Pasemann et al., 2003), have weight matrices based on elements of the special orthogonal group of the same name. Their weight matrices are associated with

rotations in the plane and are represented by functions of the rotation angle φ. Due to the existence of quasi-periodic attractors they generate sine-shaped waveforms.

— Figure 1 about here. —

Our oscillator, shown in Figure 1 (A), is based on a coupling of two identical SO(2)-networks. Accordingly, wavelengths depend only on one parameter, as can be seen from their weight matrix

$$
\begin{pmatrix}
\cos(\varphi) & \sin(\varphi) & 0 & 0 \\
-\sin(\varphi) & \cos(\varphi) & \epsilon & 0 \\
0 & 0 & \cos(\varphi) & \sin(\varphi) \\
-\epsilon & 0 & -\sin(\varphi) & \cos(\varphi)
\end{pmatrix}, \tag{1}
$$

where $\varphi \in \{-\pi, \pi\}$. The strength of 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 (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 (H_5 and H_6 in Figure 1 (A)). 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.

2.1.2 Resetting oscillations

By giving input on one of the four neurons (H_4 in Figure 1 (A)) 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 1 (B) shows the reaction of the oscillators after getting a long reset signal starting at time step 7000 and a short one at time step 12000. 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.

2.2 Experimental setup

— Figure 2 about here. —

2.2.1 Individual setup

Figure 2 shows a prototype of the fully autonomous robot *Do:Little* (A) and its simulated model (B). For many reasons this small size (length: 14.5 cm, width: 11.5 cm) robot is a promising platform for large scale distributed robotic system experiments since on the one hand it shall be reasonably priced and provides, on the other hand, rich sensoric and motoric equipments. Despite active infrared, light density, gray scale, energy, and motor shunt sensors, the striking features of the robot are the abilities to exchange electric energy with other robots and to communicate through simple acoustic signals. To keep the communication effort as minimal as possible frequency and amplitude filtering is done by the physical hardware. Different signals are characterized by different pulse sequences. Hence, the robot can perceive and produce different "chirp" signals. Additionally the robot is able to detect the direction of a perceived signal, which is represented by two sensor inputs (left and right) for each signal. In conformity with the physical hardware the simulation is updated with 10 Hz. We also applied noise to the sensors and actuators comparable to the noise level of the real hardware, i.e. 6% for infrared and light sensors, 25% for the sound-direction detection, 2.5% for the motor signals (all are normally

distributed).

2.2.2 Behavioral setup

— Figure 3 about here. —

Three basic behaviors were evolved by the so called restrictive expansion technique (Hülse et al., 2004). Firstly, we evolved a robust obstacle avoidance behavior (OA-module). Secondly, while keeping the OA-module's structure fixed a positive photo tropism was additionally evolved (P-module). In the following this photo tropism is considered as foraging behavior. Thirdly, in the same way a positive sound tropism was evolved (S-module) that is considered as homing behavior. Up to that point we can combine the same OA-module with either the P- or S-module resulting in two different robot behaviors. As a result of combining these modules with our pattern generator, as it can be seen in Figure 3, an exclusive switching between 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. 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. As it can be seen the amplifying neurons (H_{10}, H_{11}) of the pattern generator inhibit the according hidden layer through synapses with very strong negative weights. 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, i.e. in the upper saturation of its transfer function. Additionally, one output neuron (Sp) allows the robot to communicate its behavioral state switches. Therefore, this output neuron is excited by one amplifying neuron (H_{10}, see Figure 3). By setting an appropriate bias and a negative self connection this neuron integrates the signal of H_{10} and produces the highest peak when the output of H_{10} switches from zero to one, i.e. when the robot switches from foraging to homing behavior. This peak triggers a sound signal lasting

10 time steps which in turn can be perceived by nearby robots (range = 1.5 m) through an input neuron (Mic, see Figure 3). This represents the reset signal for the oscillator as discussed before (see also Figure 1).

Each individual within a robot population possesses its "own" oscillator, i.e. 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 bound was 2250 and the upper bound 2600 time steps, i.e. the mean wavelength within a population is 2425 ± 175 time steps.

2.2.3 Environmental setup

For the following experiments an environment as shown in Figure 2 (C) was used (length: 5 m, width: 5 m). The gray circle in the bottom right corner represents the nest that emits a strong periodic sound signal. This signal, which is different to the signal that can be emitted by the robots, is strong enough to be perceived within the complete environment. By using the S-module the robot is able to robustly find a way to the nest while avoiding obstacles (homing behavior). In the left half of the environment three light sources are randomly distributed. The P-module enables a robot to recharge its own energy level by approaching and finally standing in front of a light source (foraging behavior). Robot's energy has a weak leakage with time and a stronger leakage depending on its motor activity. The overall task of a robot group is to transfer collected energy to the nest. A single robot can load a maximum of 1 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. Because the time dependent leakage rate of the nest is 50 times higher compared to a single robot, its energy level cannot be maintained by a single robot. The parameters for the energy in- and outflow of the robot and the nest are chosen in a way that only coordinated, i.e. synchronized, action of a robot group can yield a maximization of the nest energy amount.

The described experimental setup should demonstrate the application of an internal neural rhythm and introduce a method of how to synchronize individual rhythms within a robot group to achieve coordinated action. The following experiments show how to reach coordination by environmental stimuli as well as by solely local interactions even if the individual rhythms slightly vary in their length. For local communication we will furthermore investigate the effects of perception range and group size on the synchronization process. And at the end we shortly compare the main difference between the synchronization of homogeneous and heterogeneous oscillators in very large robot groups.

3   Results

3.1   Synchronization through environmental stimuli

— Figure 4 about here. —

As a result of disabling the speaker output neuron (Sp, Figure 3) robots are not able to communicate their behavioral state switches. Instead we replaced this signal by a global signal that can be perceived within the complete environment. In Figure 4 (A) the behavioral states of 25 robots is drawn with time. From time step 0 to 25000 no signals are presented and we can see each robot is switching 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.

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, i.e. they are leaving the nest to search for energy. At the same time another subgroup of robots is in the homing state, i.e. they are returning to the nest. If the ways of both groups intersect, for instance at a narrow passage, 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 (foraging / homing) before its inner rhythm again switches its behavior.

To achieve coordination a global acoustic signal is presented between time step 25000 and 50000. The signal appears every 2425 time steps (mean wavelength of the inner rhythms within the population) for 10 time steps. Each robot can receive this signal and its pattern generator is reset as described before. The uncoordinated action very quickly becomes coordinated during the time period of signal perception because the rhythm of each robot is reset at the same time. Now, the coordinated action of the group leads to a periodic increase of the nest energy. From time step 50000 the global signaling is stopped and we can see that each robot falls back in its own rhythm of foraging and homing. This leads slowly to a more and more uncoordinated action that in turn provokes a slight decrease of the nest energy level. Figure 4 (B) shows that this is a characteristic overall behavior for the described experiment. The mean nest energy level is drawn with time for 100 runs with randomized initial activations of the pattern generators and random locations of the three light sources. We see the result of presenting no signal in comparison to where the signal is presented during the complete evaluation time, and how the overall behavior switches between these two results when the signal is presented only for a certain period of time like it is described for a sample run above.

3.2   Synchronization through local interactions

— Figure 5 about here. —

Instead of using a global "leader" signal, like in the previous experiment, the robots are now able to communicate their behavioral state switches through emitting a sound signal (Sp, Figure 3). Despite of the short range (1.5 m) it is the same signal that was used for the global synchronization process. If more than one signal is emitted at the same time within

the perception range of a robot, the robot is able to recognize only the closest one. This simplification reflects the behavior of the physical hardware, as far as it is tested on the first prototype.

Figure 5 shows the behavioral state evolution of each single robot as well as the evolution of the nest energy. Communication was allowed only between time step 25000 and 50000. Again, we can see the phase shifts of the individual behavioral states at the beginning. The uncoordinated action of the individuals leads to a decrease of the nest energy due to the previously described interference of uncoordinated robots. From time step 25000 on every individual is signaling its switch from foraging to homing behavior and hence resets the inner rhythm of all perceiving robots within a range of 1.5 m. This switch mostly occurs when a robot is close to a light source. Although the light sources are randomly distributed, the population becomes very quickly synchronized within about 3000 time steps.

The transition from uncoordinated to coordinated group action can be seen in the evolution of the nest energy which now periodically increases as we have seen it in the experiment before. Once again, this is a characteristic overall behavior independent of the initial conditions (not shown).

3.2.1 Effects of reduced interaction radius

— Figure 6 about here. —

In order to figure out the limitation of the system with respect to the perception range of the sound signals we repeated the aforementioned experiment in simulation with different perception ranges for the sound signals. In Figure 6 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, i.e. every robot switches its state at the same time (e.g. at the end of the bottom right diagram in Figure 6).

If the robots are not able to perceive any sound signal (top left diagram in Figure 6) we can see that for most of the time there is no coordination within the population at all, but we see that after a certain period of time there seems to be a slight development towards synchronization (between time step 15000 and 30000). That is due to the differing free run periods of the robots. After a while a portion of the internal rhythms are almost completely overlapping. But for the same reason this effect ceases after a while (between time step 30000 and 40000).

If we now consider the perception range of 1.5 m (bottom central diagram in Figure 6) as it was set in the previous experiments, which is approximately the perception range of the physical robots, we can see that the system very quickly becomes almost perfectly coordinated (after about 3000 time steps). If we now increase the perception range, e.g. to 2.5 m, the system synchronizes even faster. A decrease of the perception range entails a longer time period the system needs to become synchronized. That is due to the fact that a smaller perception 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 6 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 rhythms. But there is lower limit of perception range which is about 0.3 m $\pm$ 0.1 m where no synchronization is achieved by the system. 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 of 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 (second-order coupling).

3.2.2 Synchronization in larger groups

— Figure 7 about here. —

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 m, width: 10 m). Figure 7 (A) shows the development of the individual behavioral states. Again, individuals were allowed to communicate between time step 25000 and 50000. We obtained the same synchronizing effect as for the smaller sized population except of the time period needed to reach a stable synchronized state which in this case is ca. 6000 time steps, i.e. about twice as long as for a group of 25 robots.

Figure 7 (B) shows the result of the same experiment but this time the inner rhythms of every individual are identical within the population (wavelength = 2425 time steps). We see that the population is almost perfectly synchronized within 25000 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. 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.

4 Conclusions

In this paper we presented an implementation of a general neural pattern generator that can be used for flexible inner rhythms in autonomous robot control. It is general in the sense that it can be integrated in any kind of RNNs using the standard additive neuron type with discrete-time dynamics. It is flexible because a very broad range of wavelengths can be utilized by changing only one parameter, and it is adaptive to external stimuli, like in the presented phase resetting behavior. This resettable neural oscillator was used to realize a periodic internal drive that

determines the activity of intrinsic behavioral patterns.

In particular, we presented an application addressing a major issue in the control of distributed robotic systems, i.e. the coordination of individual behavior (Baldassarre et al., 2003; Ijspeert, Martinoli, Billard, & Gambardella, 2001; Quinn et al., 2003). It was possible to synchronize behavioral states, which were initially completely out of phase, through global environmental signals. Especially, we have also shown how to synchronize large robot groups through self-organizing processes, i.e. by using only local interactions among individuals. For several reasons the proposed framework is of interest from an engineering point of view. It has been shown that the synchronization mechanism is stable and robust concerning the group size and the effective radius of possible robot-robot interactions. Coordination of conflicting behavior can be achieved by using a minimal physical setup. We argue that especially the minimal character of the communication which is required to achieve coordination contributes much to the robustness and stability of the synchronization mechanism. A system where robots emit and receive only simple undirected sound signals is indeed less error-prone than for instance a radio based communication system, especially if one increases the number of interacting robots in dynamic or rough environments.

The control structure, which is also robust against sensor noise or robot-robot interferences, consists of simple artificial neurons with only two parameters. Hence only very low computational power is required. The modular design of the control structure makes it easy to replace certain neuro-modules if other basic behaviors are required. Because of the simplicity and generality of the sensors and actuators the proposed architecture should be easily applicable to other robotic systems. Additionally there may be more possibilities which can be facilitated for behavior control. For instance, instead of using the internal rhythm for the rigorous "on-or-off" switching between behavioral patterns, it should also be possible to realize smooth transitions. Furthermore the capability of adapting the internal rhythm smoothly to an external rhythm

by environmental stimuli was not utilized so far. And finally, one can also use other neurons of internal rhythm generator to coordinate other non-conflicting behaviors with certain phase shifts.

On the other hand, our experiments were inspired by a well known biological example, the flashing among fireflies during mating (Camazine et al., 2001). Although our model of internal oscillators differs from models of the biological ones, there are some similar principles. Each individual oscillator has 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 of time within the oscillation (firefly: begin of the rising excitation phase; *Do:Little* robot: switch from foraging to homing behavior). In (Strogatz & Stewart, 1993) it was pointed out that "the behavior of communities of oscillators whose members have differing frequencies depends on the strength of the coupling among them." Further work will investigate the effects of weakening the direct, third-order, coupling among the individuals, e.g. by introducing uncertainties during sound perception and transmission. In the presented experiments the coupling is strong enough to always achieve synchrony, i.e. every perceived signal provokes 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 in understanding the actual detailed physical mechanisms of biological systems which exhibit self-organized collective behavior, such as the synchronized flashing of fireflies. But we have to consider that these creatures have to struggle with much more than just achieving 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 when disturbances are introduced. Our proposed setup is a complete brain-body-

environment system, and we have shown that only minimal communication efforts are needed, and that the sophisticated global behavioral pattern emerges mainly from the interaction or coupling of simple units on the individual neural level as well as on the robot-robot and robot-environment level.

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Figure Captions

Figure 1: Coupled oscillator, (A) architecture with optional amplifying neurons and reset control, (B) neuron outputs of a coupled oscillator with a wavelength of ca. 2400 time steps.

Figure 2: The prototype of the *Do:Little* robot (A), its simulated model (B), and the simulation environment (C).

Figure 3: Neural network architecture (see text for details).

Figure 4: Synchronization through environmental stimuli. A: Sample run with a partly synchronized group. B: Mean nest energy of 100 runs with three differently synchronized groups.

Figure 5: Synchronization through local interactions. A sample run of 25 robots population and the evolution of the nest energy.

Figure 6: Effects of different sound perception ranges on the synchronization process, shown by the relative percentage of foraging robots, in a group of 25 individuals. By increasing the perception range the radius where an individual is able to entrain other robots is increased and consequently the time period until the system becomes synchronized decreases.

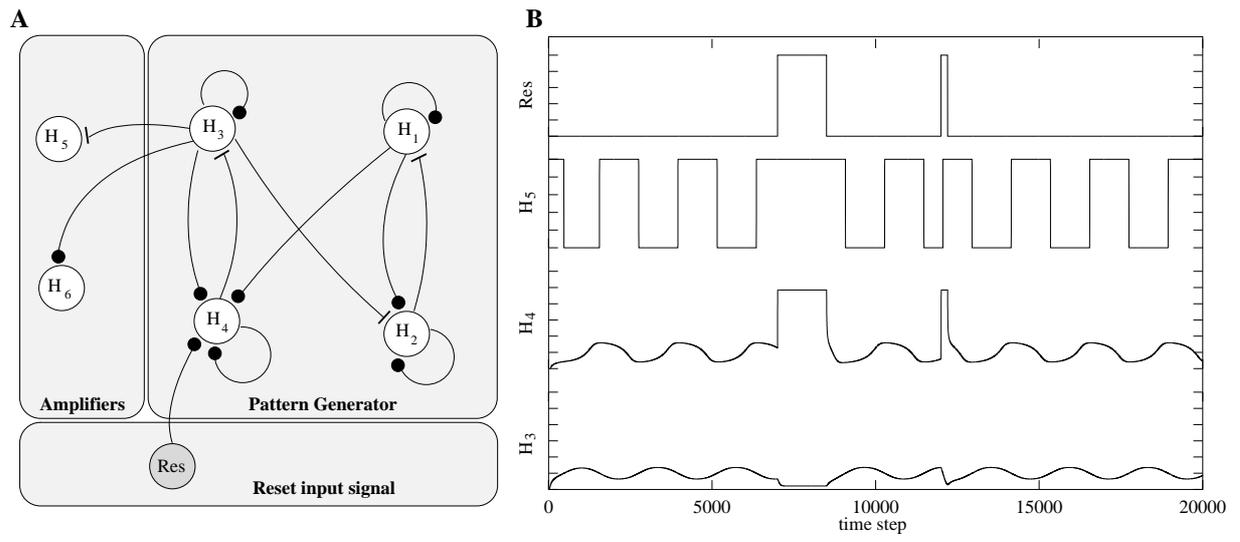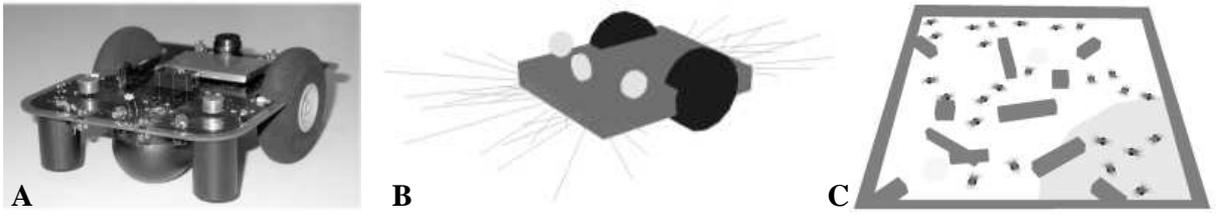**Figure 7:** Behavioral state synchronization of 150 robots with (A) different inner rhythms and (B) identical inner rhythms.
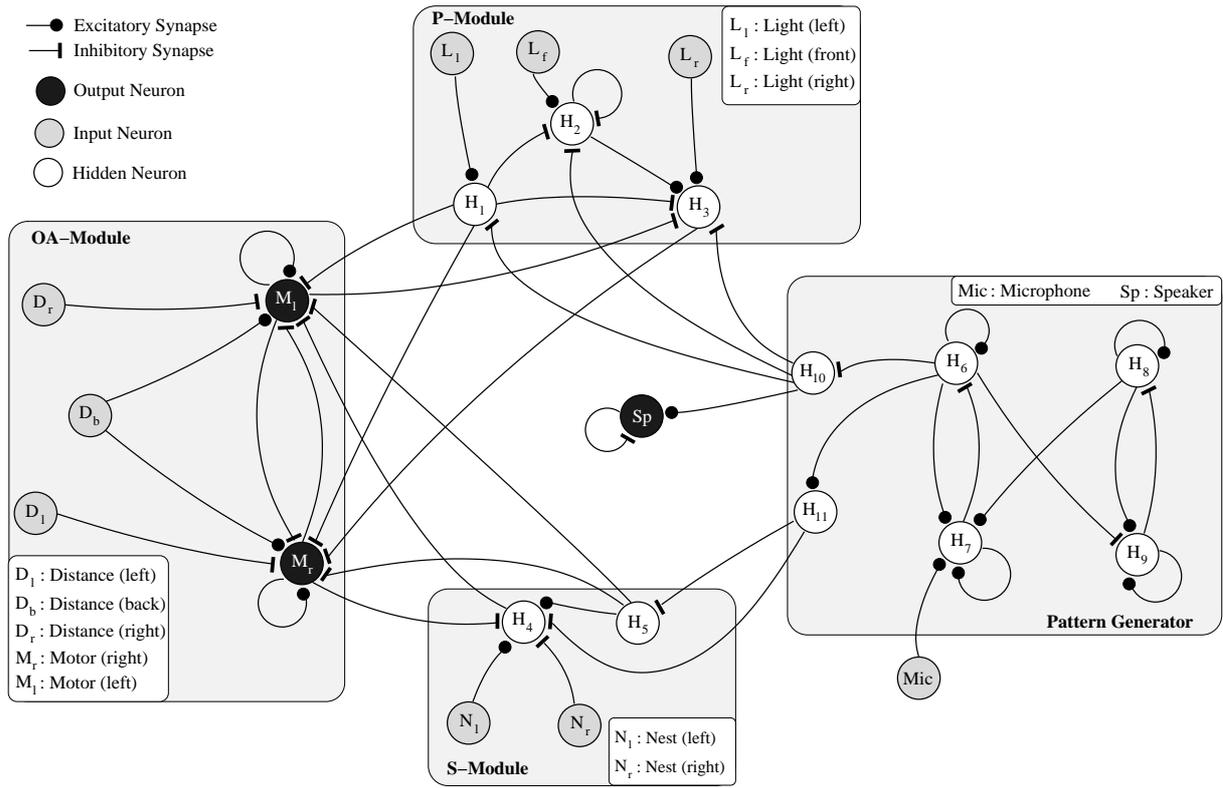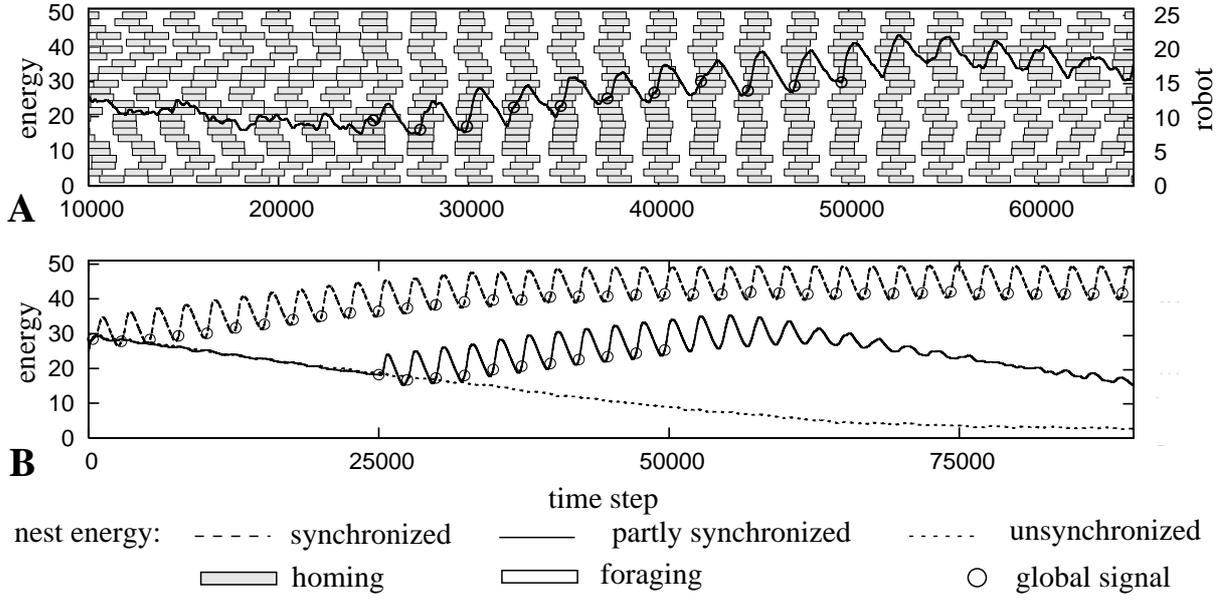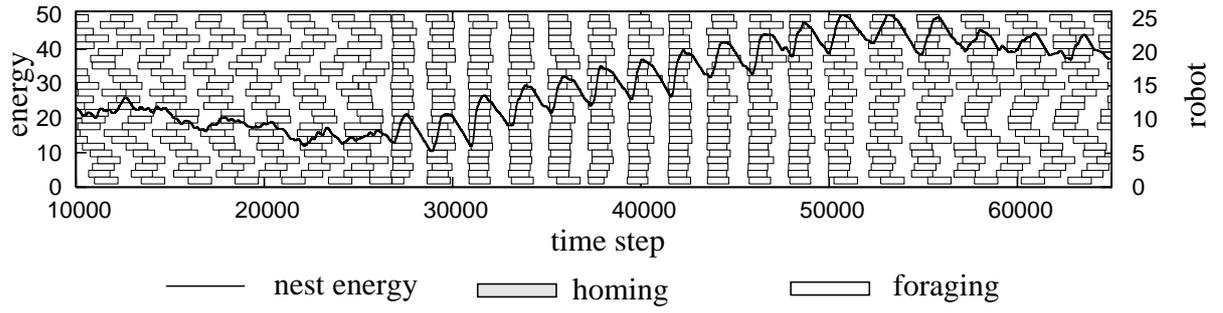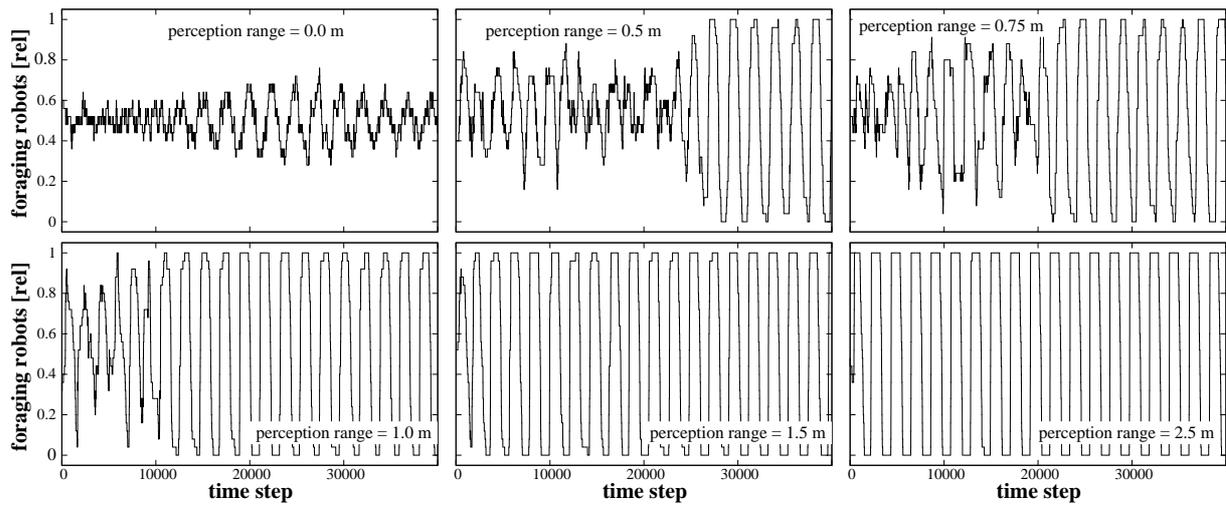
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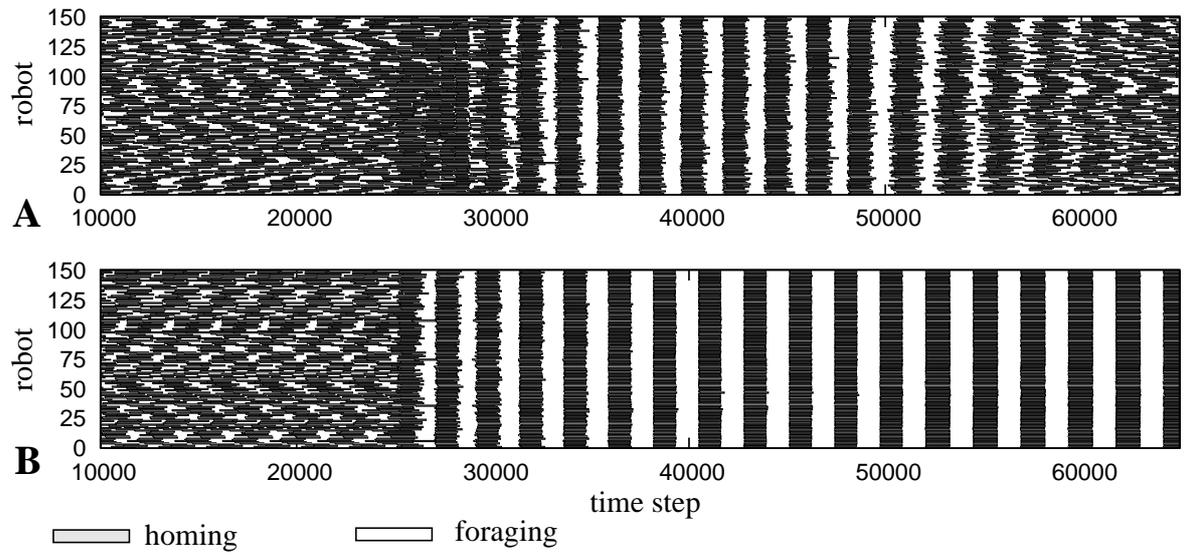
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Figure 7:

Authors

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