Synchronization of Internal Neural Rhythms in Multi-Robotic Systems

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Abstract. This paper shows how to coordinate 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 up to 150 robots. Synchronization is achieved either by environmental stimuli or even by self-organizing processes based on solely local interactions within a robot population.

1 Introduction

Using artificial recurrent neural networks (RNN) for autonomous robot control has become a common method in the field of Artificial Life (AL) and Evolutionary Robotics (ER) [6, 7, 11, 17]. Considering a robot and its control architecture as a dynamical system (DS) questions arise about the coupling to other DSs such as dynamic environments [2] or other robots [1, 5, 15]. In this paper we will describe three types of structural coupling [10]. We will show the coupling (i) between an adaptive internal rhythm and three basic behaviors in one neural architecture, which can (ii) be influenced by environmental stimuli as well as (iii) by local interactions with other robots.

While pursuing more complex behavior the following issue becomes more and more important. Suppose, a single agent possesses a pool of different behaviors, one might ask how the agent decides to activate a certain behavior at a certain time [3]. In biological systems many examples are know where such decisions are made unconsciously by internal clocks [18]. Nowadays such internal clocks are also under consideration for systems within the field of AL and ER. For instance, in [12] a thought experiment is given where a robot gathers food at day and rests at night. When the food gathering behavior becomes active only during the presence of daylight the robot will starve after accidentally entering a cave where no light can be perceived. To solve this conflict, an internal clock was introduced into the neural control structure, which controls the food gathering behavior and can be influenced by ambient light. Here, we want to apply the idea of an internal

clock [12, 18] to the problem of behavior coordination in cooperating distributed robotic systems [1, 8, 15] acting in a dynamic environment.

We will describe how to couple oscillating neural networks to reach very low frequent quasi-periodic oscillations modelling an internal rhythm, how such an internal rhythm, realized as a resettable oscillator, can be influenced by sensoric stimuli, and how to apply this mechanism to typical tasks in distributed robotics, foraging and homing. Even if individual behaviors within a robot population are completely out of phase and individual rhythms follow different frequencies we will see that it is possible to synchronize these rhythms by either environmental stimuli or even by purely local interactions among the individuals. The latter synchronization mechanism can be seen as a self-organizing process, which is, to some extend, inspired by the synchronized flashing behavior among fireflies during mating ([4] and references within it). Here, similar principles are applied to embedded and situated individuals in a dynamic environment, where synchronization is an emergent property of the overall system based on very simple local interactions among a group containing up to 150 artificial agents controlled by RNNs.

2 Methods

2.1 Neural model of an inner rhythm

Biological systems exhibit periodic behavior on various time scales, and it is assumed that at least some of it are controlled by so called central pattern generators (CPG) internal to the nervous system [9]. In the following, we propose a CPG which consists of two coupled SO(2) networks [14]. 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 sigmoidal activation function are used.

Coupled oscillator architecture. SO(2) networks, described in [14], 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 sinus-shaped waveforms.

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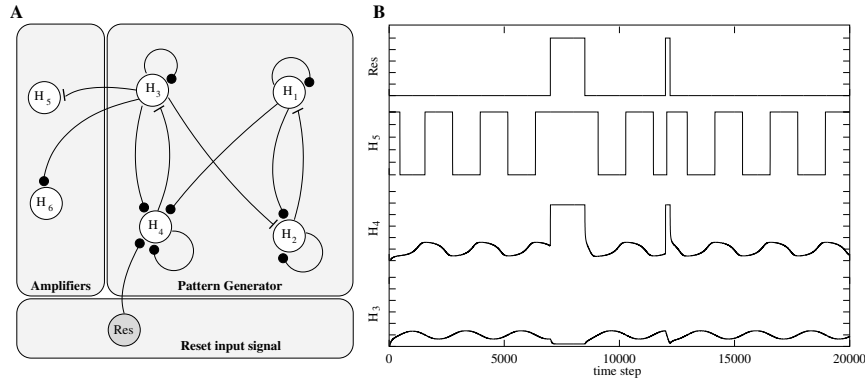
Fig. 1. Coupled oscillator, (A) architecture with optional amplifying neurons and reset control, (B) neuron outputs of a coupled oscillator with a wavelength of ca. 2400 time steps.

activation function $\sigma(x) = \tanh(x)$, but a transformation to a network with the standard sigmoidal activation function $\sigma(x) = (1 + e^{-x})^{-1}$, as it will be used in the following experiments, with equivalent dynamics is possible (see [13]).

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.

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 stops 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 oscillators reaction 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 stop at once and the amplified output switches to "on". When the input comes to an end oscillations restart in a stereotypic way.

2.2 Experimental setup

Individual setup. Figure 3 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
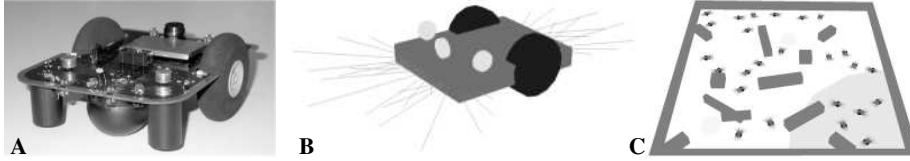
Fig. 2. The prototype of the *Do:Little* robot (A), its simulated model (B), and the simulation environment (C).

distributed robotic system experiments since on the one hand it shall be reasonably priced and provides, on the other hand, rich sensoric and motoric equipment. Despite active infrared, light density, grey 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 communicational 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.

Behavioral setup. Three basic behaviors were evolved by a so called restrictive expansion technique [7]. 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 could combine the same OA-module with either the P- or S-module resulting in two different robot behaviors. As a result of the combination of these modules and our pattern generator, as it can been 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 been 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 sigmoidal transfer function for this RNN, the inhibition only proceeds while the output of an amplifying neuron is 1. Additionally, one output neuron (Sp) allows the robot to communicate its behavioral state switches. Therefore, this motor 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}
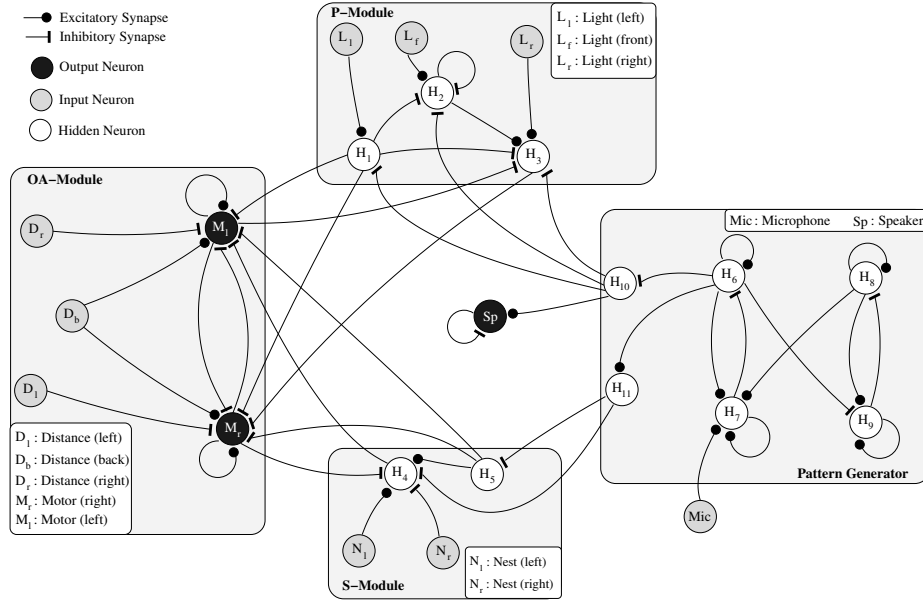
Fig. 3. Neural network architecture (see text for details).

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 m) through an input neuron (Mic, see figure 3). This represents the reset signal as discussed in section 2.1.

Each individual within a robot population possesses its "own" oscillator, i.e. the wavelengths of each individual inner rhythm slightly differ. 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.

Environmental setup. For the following experiments an environment as shown in figure 2 (C) was used (length: 5 m, width: 5 m). The grey 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, can 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
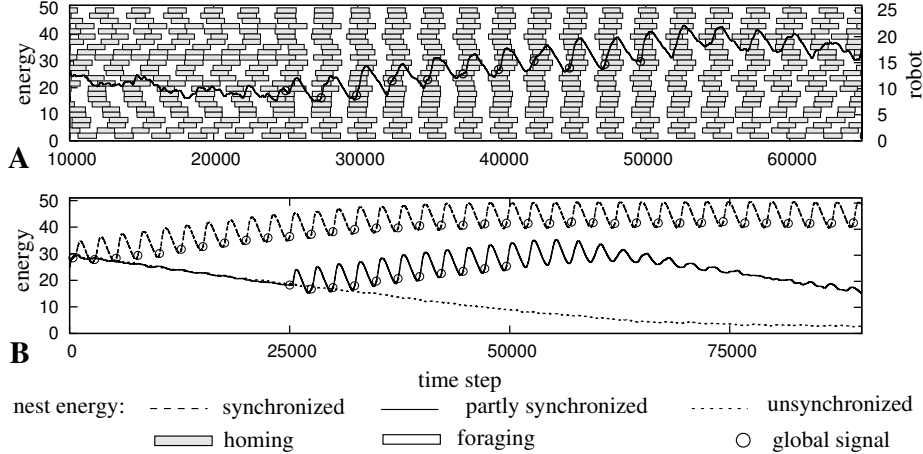
Fig. 4. Synchronization through environmental stimuli. A: Sample run with a partly synchronized group. B: Mean nest energy of 100 runs with three differently synchronized groups.

a robot enters the nest area its energy is continuously transfered 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, as described in section 2.1, and how to synchronize individual rhythms within a robot group to achieve coordinated action. The following experiments show how to reach coordination by (i) environmental stimuli and (ii) solely local interactions even if the length of the individual rhythms slightly differ, and (iii) a comparison of synchronization effects within homogeneous and heterogeneous oscillators of a very large robot group at a macroscopic level.

3 Results

Synchronization through environmental stimuli. 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 could 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 be-
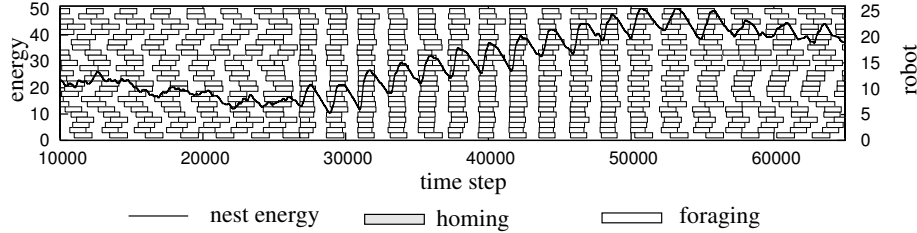
Fig. 5. Synchronization through local interactions. A sample run of a 25 robots containing population and the evolution of the nest energy

cause 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 reseted as we described in section 2.1. What happens is that the uncoordinated action very quickly becomes coordinated during the time period of signal perception because the rhythm of each robot is reseted at the same time. Now, the coordinated action of the group leads to an periodic increase of the nest energy. From time step 50000 the global signalling 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 at a certain period of time like it is described for a sample run above.

Synchronization through local interactions. 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
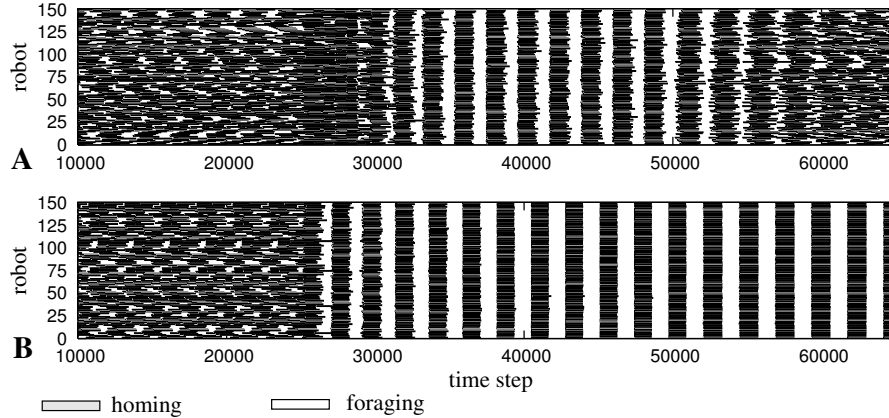
Fig. 6. Behavioral state synchronization of 150 robots with (A) different inner rhythms and (B) identical inner rhythms.

(*Sp*, figure 3). Despite of the short range (1 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 perceiving 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 could be tested on the first prototype.

Figure 5 (A) 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 signalling its switch from foraging to homing behavior and hence resets the inner rhythm of all perceiving robots within a range of 1 meter. 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 5000 time steps.

The transition from uncoordinated to coordinated group action can been 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 from the initial conditions (not shown).

Synchronization of heterogeneous and homogeneous oscillators. To demonstrate that the described synchronization process is stable for larger robot groups we repeated the previous experiment with 150 robots. Figure 6 (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. Figure 6 (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 could 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 terms of 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 the presented phase reseting behavior. This resettable neural oscillator was used to realize a periodic internal drive that determines the activity of innate behavioral patterns.

In particular we presented an application addressing a major issue in control of distributed robotic systems, the coordination of individual behavior [1, 8, 15]. It was possible to synchronize prior completely out of phase behavioral states through global environmental signals. Especially, we could also show how to synchronize up to 150 robots through self-organizing processes, i.e. by solely local interactions among individuals. As we mentioned in the introduction this experiment was inspired by a well known biological example, the flashing among fireflies during mating ([4] and references within it). 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 [16] 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." In our presented experiments the coupling was strong enough to achieve synchrony, i.e. every perceived signal provokes a phase reset. For further work it would be interesting to investigate the effect of weakening the coupling among the individuals. Nevertheless we want to emphasize that we presented synchronization of inner neural rhythms through self-organizing processes for embedded and situated agents acting in a dynamic environment, and that this synchronization based on very simple local interactions, such as emitting and detecting a single acoustic signal.

The presented architecture of an internal rhythm is a versatile framework for experiments and applications in the field of AL and ER. Here, it was applied

to synchronize two innate behavioral patterns within a group of robots. But the architecture offers many more possibilities for behavior control. For instance, instead of using the internal rhythm for an "on-or-off" switching it should be possible to reach smooth transitions between behavioral patterns. Furthermore the capability of adapting the internal rhythm smoothly to an external rhythm was not utilized so far, but it promises many interesting applications for robot control.

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