Adaptive Neural Oscillator with Synaptic Plasticity Enabling Fast Resonance Tuning

Timo Nachstedt, Florentin Wörgötter, and Poramate Manoonpong

Bernstein Center for Computational Neuroscience, The Third Institute of Physics, University of Göttingen, Göttingen, 37077, Germany
{nachstedt,worgott,poramate}@physik3.gwdg.de

Abstract. Rhythmic neural circuits play an important role in biological systems in particular in motion generation. They can be entrained by sensory feedback to induce rhythmic motion at a natural frequency, leading to energy-efficient motion. In addition, such circuits can even store the entrained rhythmical patterns through connection weights. Inspired by this, we introduce an adaptive discrete-time neural oscillator system with synaptic plasticity. The system consists of only three neurons and uses adaptive mechanisms based on frequency adaptation and Hebbian-type learning rules. As a result, it autonomously generates periodic patterns and can be entrained by sensory feedback to memorize a pattern. Using numerical simulations we show that this neural system possesses fast and precise convergence behaviour within a wide target frequency range. We use resonant tuning of a pendulum as a simple system for demonstrating possible applications of the adaptive oscillator network.

1 Introduction

Rhythmic neural activity is very important in the function of animal organisms including locomotion. Neurophysiological studies suggest that the periodic neural activity patterns are generated by central pattern generators (CPGs) [3,5]. CPGs are neural circuits that are capable of producing basic periodic outputs without any rhythmic inputs or sensory feedback. Nevertheless, sensory feedback to CPGs is critical for ensuring their coordination to appropriately control periodic motion of limbs or limbless bodies [3]. Besides the coordination, another role of sensory feedback is for the adaptation and entrainment of the CPGs such that they can produce motion at a natural frequency.

There is a wide variety of different CPG models available ranging from detailed biophysical models to pure mathematical oscillator models [2,3,6]. They can be classified as purely reactive or adaptive oscillators. Only adaptive ones show the ability to memorize the influence of an external perturbation. According to this, Righetti et al. developed a frequency adaptation rule for a general time-continuous oscillatory system [11]. This adaptation rule enables the system to adapt to the frequency of any periodic input signal. It has been applied to automatically tune or generate robot motion to a resonant frequency [1]. However, the mechanism suffers from a long adaptation time typically longer than hundred periods of the goal frequency.

A.E.P. Villa et al. (Eds.): ICANN 2012, Part I, LNCS 7552, pp. 451–458, 2012.

In this contribution we propose for the first time an adaptive neural oscillator with synaptic plasticity which requires only a short time to adapt towards a given goal frequency. It is based on a discrete-time SO(2)-network with recurrent connections [10]. Discrete-time recurrent neural networks reflect properties and phenomena that are also observable in continuous-time recurrent neural networks [10]. At the same time they are easier to study and easier to implement on robots as they are in many cases computationally less expensive. We apply a modified version of the adaptation mechanism developed by Righetti et al. [11] to the SO(2) oscillator. By introducing an additional neuron and three plastic synapses we obtain an adaptive neural oscillator system that is able to operate using the same parameter configuration within a wide frequency range. The weights of the plastic synapses are governed by a Hebbian type learning rule in combination with a relaxation term resulting in short-term plasticity behaviour.

In the following, first, we present the SO(2) network which is the base of our adaptive system. Afterwards, we show that an implementation of the general adaptation mechanism [11] on the SO(2) network does not offer good adaptation behaviour over a wide frequency range. Thus, we modify the adaptation mechanism and introduce an additional neuron together with plastic synapses to the network leading to the complete adaptive neural oscillator system. Finally, we apply this oscillator as a CPG to drive a simple dynamical system and show the ability of the network to adapt to the resonant frequency of the system within few periods.

2 The SO(2) Network

We use standard additive time-discrete neurons H_i, $i \in \{0, \dots, N-1\}$ where N is the number of neurons. The weight of the synapse from neuron H_j to neuron H_i is w_{ij}. There are no biases to neurons, the activity a_i at neuron H_i and time $t+1$ is given by the sum of all products of incoming synaptic weight w_{ij} and pre-synaptic output o_j at time t:

$$a_i(t+1) := \sum_{j=0}^{N-1} w_{ij} o_j(t), \quad i = 0, \dots, N-1 \ . \tag{1}$$

The output o_i of neuron i is given by a sigmoidal transfer function of the activity a_i which in this contribution is always chosen to be the tangens hyperbolicus:

$$o_i(t) = \tanh(a_i(t)) \ . \tag{2}$$

The SO(2) network consists of two mutually and self-connected neurons H_0 and H_1 as shown in Fig. 1a. As proven in [10] the network produces quasi-periodic output when the weights are chosen according to

$$\begin{pmatrix} w_{00} & w_{01} \\ w_{10} & w_{11} \end{pmatrix} = \alpha \cdot \begin{pmatrix} \cos(\varphi) & \sin(\varphi) \\ -\sin(\varphi) & \cos(\varphi) \end{pmatrix} \tag{3}$$

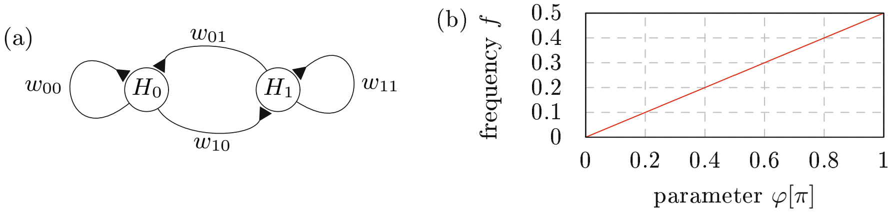

Fig. 1. (a) General two-neuron oscillator network. (b) Relation between the parameter φ and the resulting frequency f of the SO(2) network for $\alpha = 1.01$.

with $-\pi < \varphi < \pi$ and $\alpha > 1$. $o_0(t)$ and $o_1(t)$ have a phase delay of $\pi/2$ where $o_1(t)$ is in front for $\varphi > 0$. For $\alpha = 1 + \epsilon$ and $\epsilon \ll 1$ both $o_0(t)$ and $o_1(t)$ have a small amplitude and are almost sine-shaped [10]. The parameter φ determines the frequency of the oscillation. In this work we always choose $\alpha = 1.01$ which gives a nearly proportional relationship between φ and f and an amplitude of approximately 0.2. Figure 1b shows the relation between the parameter φ and the frequency f of the neural oscillator.

3 Direct Transfer of the Adaptation Mechanism

Applying the general frequency adaptation rule (compare [11]) to the SO(2)-network we additionally introduce a learning rate μ to decouple the coupling strength from the learning speed. The dynamics of the discrete-time adaptive SO(2)-oscillator is therefore given by the following set of equations:

$$o_0(t+1) = \tanh(w_{00}(t)o_0(t) + w_{01}(t)o_1(t) + \epsilon P(t)) \ , \tag{4}$$

$$o_1(t+1) = \tanh(w_{10}(t)o_0(t) + w_{11}(t)o_1(t)) \ , \tag{5}$$

$$\varphi(t+1) = \varphi(t) + \mu\epsilon P(t)o_1(t)\left(o_0^2(t) + o_1^2(t)\right)^{-1/2} \ . \tag{6}$$

The optimal values for ϵ and μ highly depend on the given initial and external frequency. We define the final deviation δ, the final frequency amplitude u, the convergence time t_c and the respective relative values $\hat{\delta} = \delta/f_g$, $\hat{u} = u/f_g$ and $\hat{t}_c = t_c \cdot f_g$ as shown in Fig. 2a. Figure 2b shows the regions in the (ϵ, μ) parameter space which enable a satisfying adaptation behaviour for two different frequency settings. There is no value-pair satisfying the demands for both configurations.

4 Adaptive Neural Oscillator with Synaptic Plasticity

To obtain a less specific adaptive frequency oscillator an additional neuron H_2 is introduced. The output of neuron H_0 is fed back to H_2 where it is subtracted from the perturbation P. This is inspired by the feedback structure used e.g. in [12]. Figure 3 shows the extended neural network.

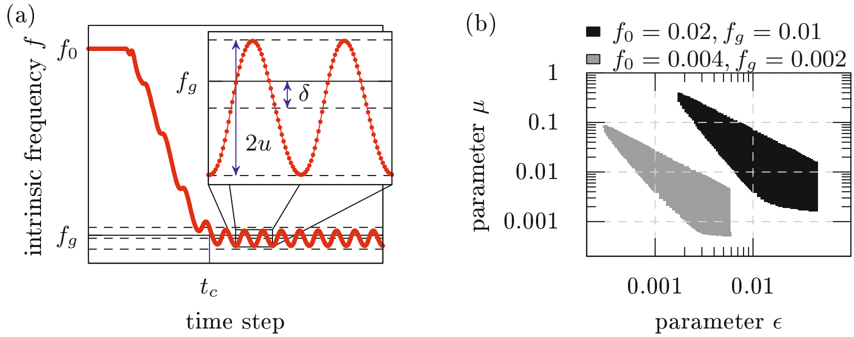

Fig. 2. (a) Definition of the final frequency amplitude u and the final frequency deviation δ for an adaptation process with initial frequency f_0 and goal frequency f_g as given by the external perturbation. The convergence time t_c is the time step at which the intrinsic frequency for the last time deviates more than 5% from the final average. (b) Parameter regions that allow an adaptation with $\hat{t}_c < 50$, $\hat{u} < 0.05$ and $|\hat{\delta}| < 0.05$ for two different frequency configurations. The external perturbation is always sine-shaped with an amplitude of 1.0.

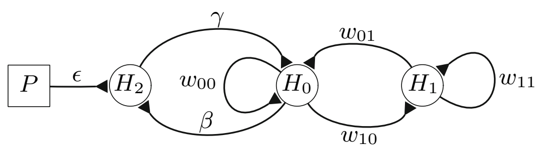

Fig. 3. Struture of the adaptive neural oscillator with synaptic plasticity

The weights of the three additional synapses β, γ and ϵ are governed by a Hebbian-type learning rule based on correlation and a relaxation term driving them exponentially towards predefined relaxation values β_0, γ_0 or ϵ_0. This synaptic plasticity can be considered as short-term synaptic plasticity [14]. The parameters $A, B > 0$ determine the influence of the different plastic terms:

$$\beta(t+1) = \beta(t) - A \cdot o_0(t) \cdot o_2(t) - B \cdot (\beta(t) - \beta_0) \ , \tag{7}$$

$$\gamma(t+1) = \gamma(t) - A \cdot o_2(t) \cdot o_0(t) - B \cdot (\gamma(t) - \gamma_0) \ , \tag{8}$$

$$\epsilon(t+1) = \epsilon(t) + A \cdot P(t) \cdot o_2(t) - B \cdot (\epsilon(t) - \epsilon_0) \ . \tag{9}$$

As the radius $\sqrt{o_0^2 + o_1^2}$ of the limit cycle of the SO(2) oscillator is approximately constant, we omit the corresponding factor in (6). The factor $\epsilon P(t)$ is replaced by the signal arriving at H_0 from H_2. The output of neuron H_1 is multiplied by w_{01}. The altered frequency adaptation rule is given by:

$$\varphi(t+1) = \varphi(t) + \mu \cdot \gamma(t) \cdot o_2(t) \cdot w_{01}(t) \cdot o_1(t) \ . \tag{10}$$

The modulation of φ influences the four synapses of the SO(2) oscillator (w_{00}, w_{01}, w_{10}, w_{11}) in a long-term synaptic plasticity fashion.

If the perturbation $P(t)$ and the output $o_0(t)$ differ the weights β and γ decay towards their relaxation values and $P(t)$ dominates the output of H_2. As

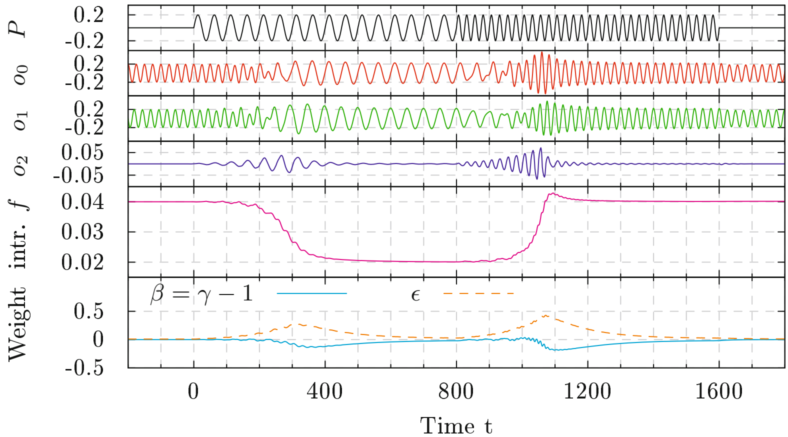

Fig. 4. Adaptation of the neural oscillator with an initial intrinsic frequency of $f_0 = 0.04$ to an external frequency $f_g = 0.02$ and the reversed process. At time step $t = 1600$ the external perturbation is switched off. The intrinsic frequency is calculated out of φ according to the relation in Fig. 1b. The parameters are $A = 1.0$, $B = 0.01$, $\beta_0 = 0$, $\gamma_0 = 1.0$, $\epsilon_0 = 0.01$ and $\mu = 1.0$.

a consequence ϵ gets enhanced. As soon as the oscillator has adapted to the external frequency the outputs of H_0 and H_2 are positively correlated. That makes γ shrink and β grow (according to amount) until the feedback signal from H_0 to H_2 almost fully compensates the external perturbation. This makes ϵ and, as a consequence, also β and γ decay towards their relaxation values.

We use a perturbation with the same amplitude as the oscillator output, namely 0.2, and choose $A = 1.0$, $B = 0.01$, $\beta_0 = 0$, $\gamma_0 = 1.0$ and $\epsilon_0 = 0.01$. The value for the learning rate μ is over a wide range uncritical. We choose $\mu = 1.0$.

Figure 4 shows an example configuration with two adaptation processes. In both cases the systems adapts within 15 periods of the external frequency. Only very small deviations of the goal frequency and small final frequency amplitudes are observed. Removing the signal P at $t = 1600$ demonstrates that the system is independent of the perturbation once the synapses relaxed. Figure 5 shows the relative convergence time $\hat{t}_c$ for all pairs of initial frequency f_0 and goal frequency f_g for which the conditions $\hat{t}_c < 50$, $\hat{u} < 0.05$ and $\hat{\delta} < 0.05$ hold.

5 Resonant Tuning of a Pendulum

Driving a dynamic system at its resonant frequency enables the controller to drive the system in an energy-efficient manner. Applications of this resonant tuning to the locomotion of robots have been described e.g. by Buchli et al.[1] and Ronsse et al.[12]. We use a mathematical pendulum as a closed-loop test control system. The dynamics of a pendulum with length l and mass m within

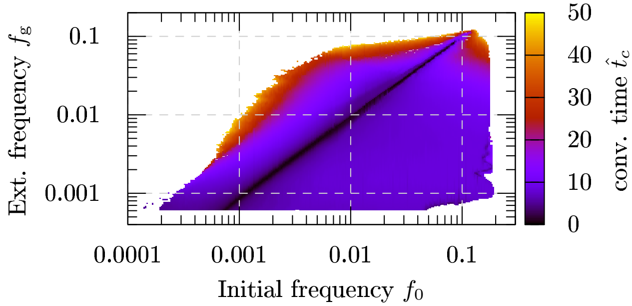

Fig. 5. Relative convergence time $\hat{t}_c = t_c \cdot f_g$ in dependence of the frequency pair (f_0, f_g). The parameters are the same as in Fig. 4. Shown are only those points for which $\hat{t}_c < 50$, $\hat{u} < 0.05$ and $\hat{\delta} < 0.05$ hold.

a gravity field with acceleration g is given by the Newtonian equation of motion for the angular displacement θ:

$$\frac{\mathrm{d}^2\theta}{\mathrm{d}t^2} = -\frac{g}{l}\sin\theta - \frac{D}{ml}\dot{\theta} + \frac{M_{\mathrm{ext}}}{ml^2} \tag{11}$$

where D is a damping constant and M_{ext} an external torque that is here controlled by the adaptive oscillator network as a CPG.

The current value of θ is used as a feedback signal for the controller. When M_{ext} is periodic the pendulum will eventually follow the external frequency. In case of resonance a phase difference of $\pi/2$ evolves between the angular displacement θ and M_{ext} where M_{ext} is in front. It is therefore advantageous to use the output o_1 of neuron H_1 to control M_{ext}. This way the feedback signal θ and the output o_0 are in phase when the system is driven at its resonant frequency. Figure 6 shows the control schema.

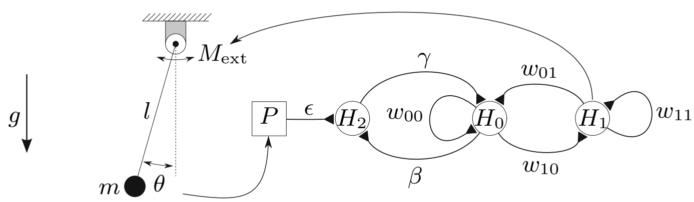

Fig. 6. Control principle of the CPG driven pendulum

The torque applied to the pendulum is given by $M_{\mathrm{ext}} = M_0 \cdot \tanh(7\,o_1)$. The feedback from the pendulum to the neural oscillator is $P = 0.2 \cdot \tanh(20\,\theta)$. For large amplitudes of the pendulum this produces a rectangle-shaped signal P. With a slight parameter adaptation ($B = 0.02$) the network can adapt to this signal as well. The network is updated with a frequency of 25 Hz. Figure 7 shows the time series of the pendulum being driven by the adaptive neural oscillator.

At the beginning the intrinsic frequency of the CPG is $0.032 \cdot 25\,\mathrm{Hz} = 0.8\,\mathrm{Hz}$ which is below the eigenfrequency of the pendulum system. After few periods

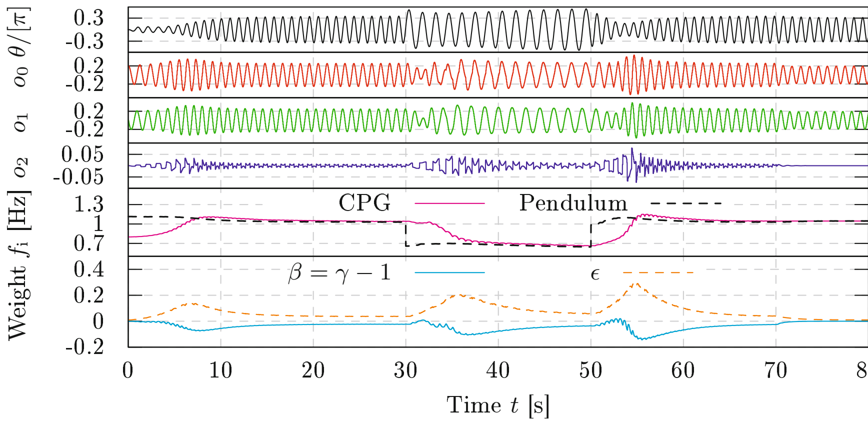

Fig. 7. Pendulum controlled by the adaptive neural oscillator: Shown are the angular displacement θ, the outputs o_i of the three neurons, the intrinsic frequency f_i of the network and the pendulum [8] and the synaptic weights β and ϵ. The parameters are $m = 200\,\mathrm{g}$, $l = 20\,\mathrm{cm}$, $D = 0.005\,\mathrm{Nms}$, $g = 9.81\,\mathrm{m/s}^2$, $M_0 = 0.03\,\mathrm{Nm}$. At $t = 30\,\mathrm{s}$ we set $l = 40$ cm, at $t = 50\,\mathrm{s}$ again $l = 20\,\mathrm{cm}$. At $t = 70\,\mathrm{s}$ the feedback is removed.

the CPG adapts to the eigenfrequency of the pendulum. Changing the pendulum length l influences the eigenfrequency of the system. In both shown cases the CPG adapts within approximately ten periods of the new goal frequency. Finally, the feedback connection is cut by setting $P = 0$. Once the synapses have converged to their relaxation values, feedback is no longer necessary.

6 Conclusion

We developed a discrete-time three-neuron adaptive oscillator network with synaptic plasticity. Compared to other recurrent neural networks that could potentially solve the same task, like e. g. echo state networks [9], the proposed network has a minimal structure which consists of only three neurons and is therefore computationally much more efficient. Furthermore, our network has the ability for faster and still precise frequency adaptation and memorization within a wider frequency range compared to existing solutions [1]. This is achieved by a new short-term plasticity mechanism composed of a Hebbian-type learning rule and a relaxation term controlling three synapses of the network. The other four synapses are governed by a long-term synaptic plasticity rule based on the modified frequency adaptation. In fact, the interplay of long-term and short-term synaptic plasticity seems to also play an important role in biological motor control, especially in fast network reconfigurations [7].

As shown here, the presented oscillator network can be used for fast resonant tuning of the pendulum. Real world applications include generation of rhythmic motion at a natural frequency of mechanical devices and adaptive locomotion of multilegged robots in different terrains and situations[4].

Acknowledgements. This research was supported by Emmy Noether grant MA4464/3-1 of the Deutsche Forschungsgemeinschaft and Bernstein Center for Computational Neuroscience II Göttingen (BCCN grant 01GQ1005A, proj. D1).

References

1. Buchli, J., Iida, F., Ijspeert, A.J.: Finding Resonance: Adaptive Frequency Oscillators for Dynamic Legged Locomotion. In: IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 3903–3909. IEEE (2006)
2. Hellgren, J., Grillner, S., Lansner, A.: Computer simulation of the segmental neural network generating locomotion in lamprey by using populations of network interneurons. Biol. Cybernetics 68, 1–13 (1992)
3. Ijspeert, A.J.: Central pattern generators for locomotion control in animals and robots: A review. Neural Networks 21, 642–653 (2008)
4. Manoonpong, P., Pasemann, F., Wörgötter, F.: Sensor-driven neural control for omnidirectional locomotion and versatile reactive behaviors of walking machines. Robotics and Autonomous Systems 56, 265–288 (2008)
5. Marder, E., Bucher, D.: Central pattern generators and the control of rhythmic movements. Current Biology 11, R986–R996 (2001)
6. Matsuoka, K.: Sustained oscillations generated by mutually inhibiting neurons with adaptation. Biological Cybernetics 52, 367–376 (1985)
7. Nadim, F., Manor, Y.: The role of short-term synaptic dynamics in motor control. Current Opinion in Neurobiology 10, 683–690 (2000)
8. Ochs, K.: A comprehensive analytical solution of the nonlinear pendulum. European Journal of Physics 32, 479–490 (2011)
9. Ozturk, M., Dongming, X., Príncipe, J.: Analysis and Design of Echo State Networks. Neural Computation 19, 111–138 (2007)
10. Pasemann, F., Hild, M., Zahedi, K.: SO(2)-Networks as Neural Oscillators. In: Mira, J., Álvarez, J.R. (eds.) IWANN 2003. LNCS, vol. 2686, pp. 1042–1042. Springer, Heidelberg (2003)
11. Righetti, L., Buchli, J., Ijspeert, A.: Dynamic Hebbian learning in adaptive frequency oscillators. Physica D 216, 269–281 (2006)
12. Ronsse, R., Kieboom, J., Ijspeert, A.: Automatic Resonance Tuning and Feedforward Learning of Biped Walking Using Adaptive Oscillators. In: Proceeding of the Conference in Multibody Dynamics, ECCOMAS Thematic Conference (2011)
13. Tao, Z.: Neural oscillations and information flow associated with synaptic plasticity. Sheng Li Xue Bao Acta Physiologica Sinica 63, 412–422 (2011)
14. Zucker, R., Regehr, W.: Short-Term Synaptic Plasticity. Annual Review of Physiology 64, 355–405 (2002)