Designing Simple Nonlinear Filters Using Hysteresis of Single Recurrent Neurons for Acoustic Signal Recognition in Robots

Poramate Manoonpong[1], Frank Pasemann[2], Christoph Kolodziejski[1], and Florentin Wörgötter[1]

[1]Bernstein Center for Computational Neuroscience (BCCN)
University of Göttingen, D-37077 Göttingen, Germany
{poramate,kolo,worgott}@bccn-goettingen.de
[2]Institute of Cognitive Science
University of Osnabrück, D-49069 Osnabrück, Germany
frank.pasemann@uni-osnabrueck.de

Abstract. In this article we exploit the discrete-time dynamics of a single neuron with self-connection to systematically design simple signal filters. Due to hysteresis effects and transient dynamics, this single neuron behaves as an adjustable low-pass filter for specific parameter configurations. Extending this neuro-module by two more recurrent neurons leads to versatile high- and band-pass filters. The approach presented here helps to understand how the dynamical properties of recurrent neural networks can be used for filter design. Furthermore, it gives guidance to a new way of implementing sensory preprocessing for acoustic signal recognition in autonomous robots.

Key words: Neural networks, Digital signal processing, Non-speech recognition, Autonomous robots, Walking robots

1 Introduction

To date, recurrent neural networks (RNNs) have been employed to a wide field of applications due to their excellent properties, like robustness, adaptivity, and dynamics. Examples include the use of RNNs in chaotic systems [1], [2], robot control and learning [3], trajectory generation [4], and others. Many applications require effective learning methods [5], [6] to train the networks. As a consequence, the networks, in particular for signal processing [7], [8], [9], end up with a massive connectivity or cascaded recurrent structures. The complexity of such networks requires a large memory during learning. In addition, their high dimensionality makes it difficult to analyze them and even to understand the neural dynamics in detail. However, a thorough understanding of the network dynamics is one important part to further develop and apply these networks to other applications, like robot control. This is also a basic step towards the development of complex systems [10]. As a small step forward in this direction, we want to show here how neural dynamics, e.g., hysteresis effects, can be applied to systematically design simple nonlinear low-pass, high-pass, and even band-pass filters. With one or only a few neurons such filters can be used for sensory signal processing in autonomous robots, where preprocessed signals will drive (complex) robot behavior, e.g., for (non-speech) sound recognition.

The following section shortly describes the discrete-time dynamics of a single recurrent neuron. Section 3 explains how we develop low-pass filters by utilizing hysteresis effects of the single recurrent neuron. Sections 4 and 5 show the extension of the low-pass filters to high- and band-pass ones. Section 6 presents an application of using the proposed neural filers for acoustic signal recognition in a walking robot. The last section provides summary and discussion.

2 Discrete Dynamics of a Single Recurrent Neuron

A single neuron with self-connection (see Fig. 1(a)) has several interesting (discrete) dynamical features[11]. For example, an excitatory self-connection leads to a hysteresis effect, while stable oscillation with period-2 orbit can be observed for an inhibitory self-connection. Both phenomena occur for specific parameter domains, where the input and the strength of the self-connection are considered as parameters. In this article, hysteresis effects are utilized for designing simple filters. The corresponding discrete-time dynamics is parameterized by the input I and the self-connection w_s (see Fig. 1(a)), and for a recurrent neuro-module is given by $a(t+1) = w_s f(a(t)) + \theta$ with the sigmoidal transfer function $f(a) = \tanh(a)$. The parameter θ stands for the sum of the fixed bias term b and the variable input I to the neuron. $O(t) = f(a(t))$ is the output signal. We refer the reader to [12] for the presentation of the dynamics of a neuron with excitatory self-connection in the (θ, w_s)-parameter space.

3 Low-Pass Filters

In this section we describe how simple low pass filters can be designed based on the hysteresis effect of the single recurrent neuron mentioned above. We simulate a sine wave input signal varying from 100 Hz to 1000 Hz (compare Fig. 1(b)). It is used as an input signal for the recurrent neuro-module configured as a hysteresis element L (see Fig. 1(a)). The network is constructed and analyzed using the Integrated Structure Evolution Environment (ISEE) [5] which is a software platform for developing and evolving recurrent neural networks. To observe the low-pass filter characteristics of the network, we fixed the presynaptic weight ($w_{i1} = 1.0$) from the input to the neuron and the bias term ($b_1 = -0.1$) while the self-connection w_{s1} of the output unit is varied (see Fig. 1(c)). Using this setup, the network performs as a low-pass filter at different cutoff frequencies according to the strength of w_{s1}. Figure 1(c) presents the correlation between w_{s1} and the cutoff frequency. For example, selecting $w_{s1} = 2.42$ the network suppresses signals with frequencies higher than 500 Hz. This effect together with the characteristic curve of this network is shown in Fig. 2.

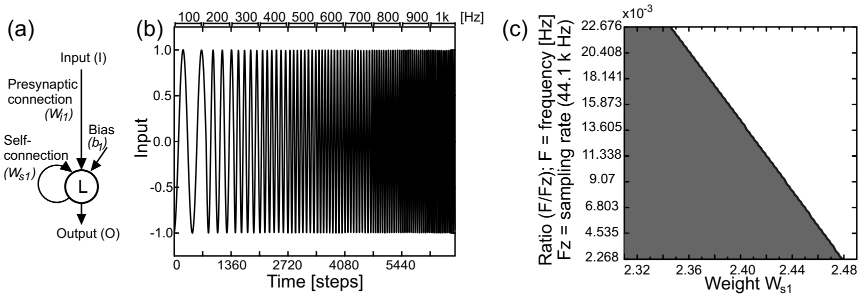

Fig. 1. Low-pass filter setup. (a) Recurrent neuro-module realizing a simple low-pass filter. Its input weight w_{i1} and bias term b_1 are fixed to 1.0 and -0.1, respectively, while the weight w_{s1} is changeable in order to obtain certain cutoff frequencies. (b) Example of the input signal at increasing frequencies (from 100 Hz to 1 kHz, 44.1 kHz sampling rate). (c) Cutoff frequency of a low-pass filter module depending on the self-connection w_{s1}. The x -axis represents the self-connection w_{s1} and the y-axis represents the ratio between frequency [Hz] and sampling rate (44.1 kHz). Note that this diagram will be used later for defining lower cutoff frequencies f_L of the band-pass filters described below.

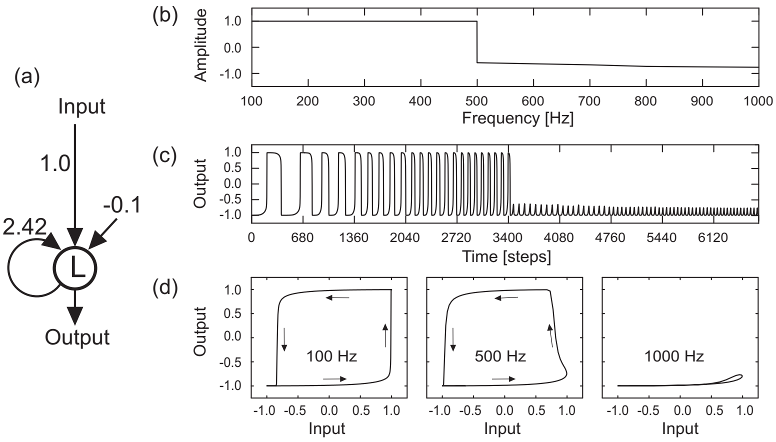

Fig. 2. Example of a low-pass filter. (a) A 500 Hz low-pass filter neuro-module. (b) Characteristic curve of the network with its cutoff frequency at 500 Hz. (c) Output signal of the network according to the given input shown in Fig. 1(b). (d) The hysteresis effect between input and output signals at certain frequencies. Due to the hysteresis effect, the shape of the output signal is distorted, e.g., 100 Hz and 500 Hz. Arrows show how the output develops according to the change of the input.

To visualize the hysteresis effect of the 500 Hz low-pass filter, output versus input signals are plotted in Fig. 2(d). This shows that the hysteresis effect disappears for the high-frequency signals (e.g., 1000 Hz), whereas for low-frequency signals (e.g., 100 Hz and 500 Hz) the hysteresis switches the amplitude between (almost) saturation values (approximately -1 and $+1$). As the bias term defines the base activity of the neuron, the amplitude of the high-frequency output oscillates with a small magnitude between around -0.6 and -0.998. Eventually it will never rise above 0.0 again. Due to the slowness of the transient dynamics and the bias term the upper saturation domain (high stable fixed points ($\approx +1$)) is never reached if high frequency signals are applied. Furthermore, because of the hysteresis effects, the low-pass filter output is slightly shifted and its shape is distorted. Therefore, the system acts as a nonlinear low-pass filter.

4 High-Pass Filters

Having established a single neuron low-pass filter, the following step is to derive networks, which behave like high-pass filters based on the presented low-pass. The simplest way to do this would be to subtract the low-pass filter output (see, e.g., Fig. 2(c)) from the input (see Fig. 1(b)). In other words, the low-pass filter neuron L (see Figs. 1(a) and 3(a)) would here act as an inhibiting neuron which inhibits transmission of all low-frequency signals of the input. However, due to the hysteresis effect, the low-pass filter output is shifted and its shape is distorted compared to the input (see Fig. 2(d)). Thus the input cannot be directly subtracted. To overcome this problem, we again utilize the hysteresis effect to shape the input to match it to the low-pass filter output. For doing this, we simply add one more hysteresis unit H (see Fig. 3(a)) receiving its input via a fixed presynaptic weight ($w_{i2} = 1.0$). Its neural parameters (self-connection w_{s2} and bias term b_2, see Fig. 3(a)) are experimentally adjusted and we set them to $w_{s2} = 2.34$ and $b_2 = -0.1$ for which a suitable hysteresis loop is achieved (see Fig. 3(b)). According to this specific weight and bias term, this hidden neuron H actually performs as a low-pass filter with a cutoff frequency of around 1000 Hz. Thus it shapes the input and allows all signals having frequencies up to around 1000 Hz to pass through. After preprocessing at H, the shaped input signal is transmitted to the output neuron O through a positive connection weight ($w_{c2} = 1.0$, see Fig. 3(a)). It is then subtracted by the low-pass filter output due to a negative connection weight ($w_{c1} = -1.0$, see Fig. 3(a)). Still the resulting signal consists of a few spikes in the low frequency components. Therefore, we add a self-connection w_{s3} together with a bias term b_3 at O to obtain an appropriate third hysteresis loop (see Fig. 3(c)) that eliminates these spikes. The neural parameters of this output unit are experimentally tuned and they are set to $w_{s3} = 2.45$ and $b_3 = -1.0$. The resulting network structure is show in Fig. 3. Using this network, we then obtain high-pass filters at certain cutoff frequencies by tuning only the weight w_{s1} shown in Fig. 1(c). For example, choosing $w_{s1} = 2.39$ the network functions as a 700 Hz high-pass filter. This high-pass effect and the characteristic curve of the network are shown in Fig. 4.

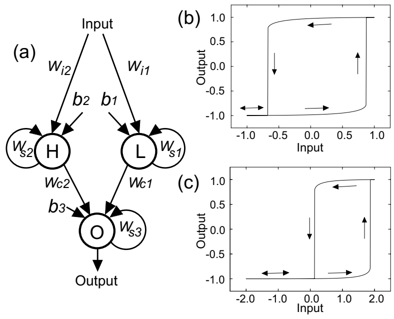

Fig. 3. High-pass filter setup. (a) Recurrent neural network realizing a simple high-pass filter. All weights and bias terms are fixed ($w_{i1,2} = 1.0$, $w_{s2} = 2.34$, $w_{s3} = 2.45$, $w_{c1} = -1.0$, $w_{c2} = 1.0$, $b_{1,2} = -0.1$, and $b_3 = -1.0$), while the weight w_{s1} is changeable according to Fig. 1(c) in order to obtain certain cutoff frequencies. (b), (c) Hysteresis effect between the input and output of the hidden neuron H and the output neuron O, respectively. The input of H varies between -1.0 and $+1.0$ while the sum of the inputs of O varies between -2.0 and $+2.0$. Due to the hysteresis effect the output of H and O has its low (≈ -1.0) and high ($\approx +1.0$) activations at different points. The output of H will show high activation when the input increases to values above 0.88. On the other hand, it will show low activation when the input decreases below -0.68. For the output of O, it will show high activation when the input increases to values above 1.86 while it will show low activation when the input decreases below 0.135. Arrows show how the output develops according to the change of the input.

5 Band-Pass Filters

In this section, we describe how band-pass filters can be achieved by simply changing the self-connections of the high-pass filter network (see Fig. 3(a)) while its structure remains unchanged. Interestingly, due to the fact that the output neuron of the network (see Fig. 3(a)) behaves as a hysteresis element, we only need to increase its self-connection w_{s3} (i.e., increasing its hysteresis size [12]) up to a certain point. As a consequence of the transient dynamics [12], the high frequency signals will then be suppressed.

To observe this phenomenon, we first let the network behave as a 100 Hz high-pass filter; i.e., it passes only signals with frequencies above 100 Hz. The neural parameters are given as follows: $w_{i1,2} = 1.0$, $w_{s1} = 2.479$, $w_{s2} = 2.34$, $w_{s3} = 2.45$, $w_{c1} = -1.0$, $w_{c2} = 1.0$, $b_{1,2} = -0.1$, and $b_3 = -1.0$. Now gradually increasing w_{s3} from approximately 2.47 to 2.57 the high frequency boundary of the network decreases. Thus, in order to design our band-pass filters, this weight will be used to set the upper cutoff frequency f_U. It defines the upper limit at which the frequencies pass through. Beyond this limit, signals will be cancelled out. The correlation between weight w_{s3} and the upper cutoff frequency f_U

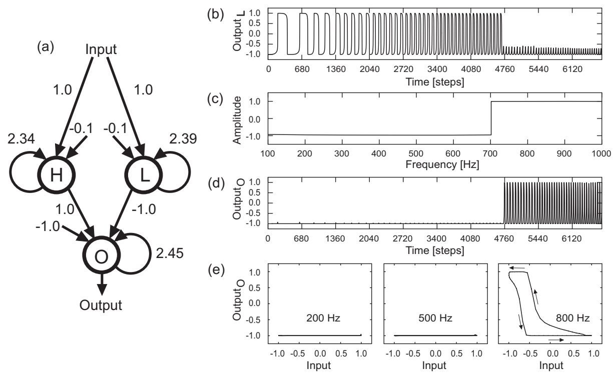

Fig. 4. Example of a high-pass filter. (a) The 700 Hz high-pass filter network. (b) Output of the low-pass filter neuron L according to the given input shown in Fig. 1(b). It suppresses the signal at frequencies above $\approx$ 700 Hz. (c) Characteristic curve of the network with its cutoff frequency at approximately 700 Hz. (d) Output signal of the network according to the given input shown in Fig. 1(b). Only the high frequency signals remain at high amplitude while the amplitude of the lower ones is reduced. (e) Relation between input and output signals at certain frequencies. Due to the hysteresis effect and the subtraction process, the shape of the output signal is distorted, e.g., 800 Hz. Arrows show how the output develops according to the change of the input.

is shown in Fig. 5(a). As shown in the previous sections, the self-connection w_{s1} is generally applied to set the frequency at which the signal will be passed (for high-pass filters) or filtered (for low-pass filters). Here we make use of this weight (w_{s1}, see Fig. 1(c)) to set the lower cutoff frequency f_L which allows only signals having frequencies *above* this point to pass. For example, selecting $w_{s1} = f_L = 2.47$ and $w_{s3} = f_U = 2.51$ from the ($w_{s1,3}$, cutoff frequencies)-spaces shown in Figs. 1(c) and 5(a), the network (see Fig. 5(b)) lets signals pass which have frequencies between 200 Hz and 850 Hz (see Fig. 5(c)). Decreasing w_{s1} to 2.455 but increasing w_{s3} to 2.532 the signal bandwidth is reduced to the range from around 300 Hz to around 600 Hz (see Fig. 5(d)). Furthermore, it is even possible set the weights to narrow the frequency range to around 500 Hz by choosing, e.g., $w_{s1} = 2.43$ and $w_{s3} = 2.542$ (see Fig. 5(e)). Thus, the network behaves as a versatile band pass filter.

6 Robot Behavior Control

To show the capability of the neural filters presented here for real world applications, we have applied, e.g., a 400 Hz low-pass filter network (see Fig. 1(a)), to generate acoustic-driven walking behavior (see Fig. 6) of our hexapod robot [2], [12]. The network receives the input–a multi frequency signal mixing be-

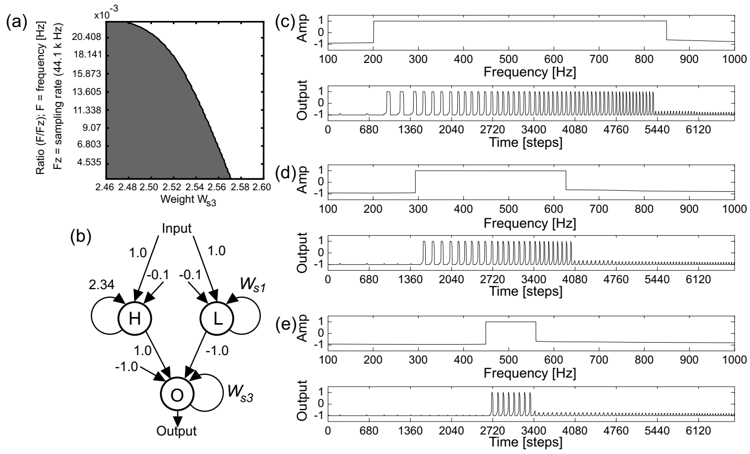

Fig. 5. Example of a band-pass filter. (a) Upper cutoff frequency f_U of a band-pass filter network depending on the weight w_{s3}. (b) The band-pass filter network. The self-connection w_{s1} of neuron L defines the lower cutoff frequencies (cf. Fig. 1(c)) while w_{s3} of the output neuron O is for controlling the upper cutoff frequencies (a). (c) Response of the network for $w_{s1} = 2.47$, $w_{s3} = 2.51$. Upper panel: Characteristic curve of the network with bandwidth from 200 Hz to 850 Hz. Lower panel: Output signal of the network according to the input given in Fig. 1(b). (d) Response of the network for $w_{s1} = 2.455$, $w_{s3} = 2.532$. Upper panel: Characteristic curve of the network with bandwidth from around 300 Hz to around 600 Hz. Lower panel: Output signal of the network using the same input as above. (e) Response of the network for $w_{s1} = 2.43$, $w_{s3} = 2.542$. Upper panel: Characteristic curve of the network with its bandpass of around 500 Hz. Lower panel: Output signal of the network. Note that Amp means the amplitude of neuron activation.

tween a target low frequency signal (e.g., 300 Hz) and unwanted noise from motors as well as locomotion (see Figs. 6(a)–(c))–from an acoustic sensor system of the robot. It suppresses the unwanted noise including acoustic signals having frequencies above 400 Hz (see Figs. 6(d) and (e)) while the low frequency signals pass through (see Fig. 6(f)). As a consequence, it enables the robot to autonomously react on a specific acoustic signal in a real environment; i.e., the robot changes its gait from a slow wave gait (default gait, see Figs 6(g) and (h)) to a fast one (acoustic-driven gait, see Fig. 6(i)) as soon as it detects the signal at the carrier frequency of 300 Hz. The video clip of the experiments can be seen at http://www.manoonpong.com/ICANN2010/AcousticDrivenBehavior.mpg. These acoustic-driven walking behavioral experiments show that the simple recurrent neural filters are appropriate for robot applications like background noise elimination, and/or non-speech sound recognition.

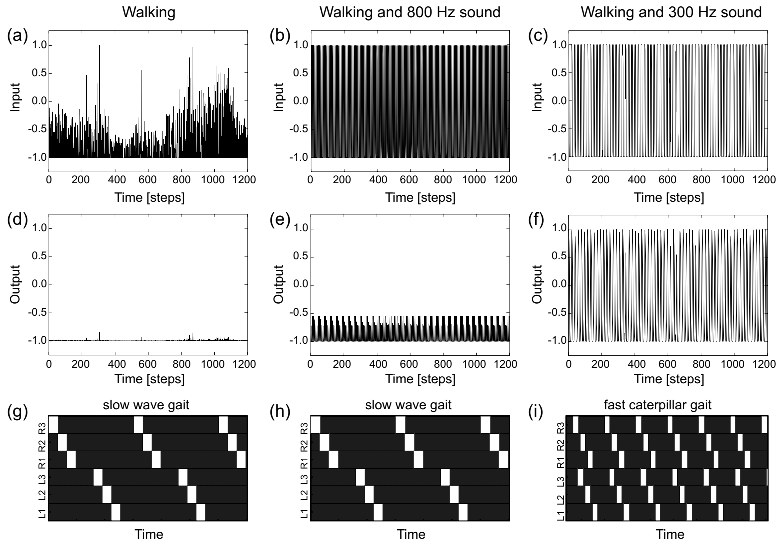

Fig. 6. Input and output signals of the 400 Hz low-pass filter network and corresponding walking patterns in three example situations (only walking (left), walking and receiving 800 Hz sound (middle), and walking and receiving 300 Hz sound (right)). (a)–(c) The input signal to the network for the different conditions. (d)–(f) The output of the network according to the given input for the different conditions. (g)–(i) Examples of the corresponding walking patterns in a certain period for the different conditions. The x -axis represents time and the y-axis represents the legs. During the swing phase (white blocks) the feet have no ground contact. During the stance phase (black blocks) the feet touch the ground. R1: Right front leg, R2: Right middle leg, R3: Right hind leg, L1: Left front leg, L2: Left middle leg, L3: Left hind leg. Note that we use an additional low-pass filter neuron to eliminate the remaining noise ((d), (e)) and smooth the desired acoustic signal (f) before activating the desired walking pattern (here, caterpillar-like gait (i) through modular neural locomotion control [2].

7 Discussion and Conclusions

In this study, we have addressed the exploitation of hysteresis effects and transient dynamics of a single neuron with an excitatory self-connection to design different filters. Starting from one single recurrent neuron, we have observed that this simple network with its specific parameters has the property of a low-pass filter. As such it has comparable properties of an infinite impulse response filter in digital filter theory (IIR filter) because its recurrent connection provides feedback to the system as the output of the IIR filter does. Based on this simple low-pass filter network, by adding two recurrent neurons we obtained high- and band-pass filters, where these neurons also act as hysteresis elements. The cutoff frequencies of the high-pass filter are controlled by only one self-connection; while the upper and lower cutoff frequencies of the band-pass filter are determined by two self-connections. An advantage of the small number and limited range of all relevant parameters ($w_{s1,3}$, see Figs. 1(c) and 5(a)) is that these parameters could be self-adjusted for obtaining a desired frequency range through a learning mechanism, like correlation based differential Hebbian learning [13], or by evolutionary algorithms [5]. Moreover, the presented filter networks can be implemented as analog filters by using Schmitt trigger circuits which also exhibit the hysteresis effect. This kind of filtering technique is different from many others [14], [15], [16], [17], [8], [7], [9] which are in use.

Several successful digital filter techniques have been developed, like Butterworth, Elliptic, Chebyshev filters, as well as by using Fourier methods [14]. In general they are based on impulse and frequency response methods. As described by [15], these classical methods, however, are founded on three basic assumptions: linearity, stationary, and second-order statistics with particular emphasis on Gaussian characteristic. Thus advanced techniques like artificial neural networks have become an alternative way for in particular nonlinear signal processing [15]. In most cases, feed-forward multi layer perceptrons (MLP) with a gradient descend based learning algorithm have been extensively used for this [16], [17]. On the other hand, the use of recurrent neural networks for digital signal processing applications is now increasing, too. For example, Hagen et al. [8] presented a multi-loop recurrent network with a cascaded structure to predict an acoustic signal. Becerikli [7] used dynamic neural networks with Levenberg-Marquardt based fast training for nonlinear filtering design. Squartini et al. [9] employed echo state networks for identification of nonlinear dynamical systems for digital audio processing. Compared to many of these approaches, we present here a minimal and analyzable filter set based on simple neural dynamics. Due to the neural dynamics, these filters provide a sharp cut-off but the shape of the output signal is distorted; i.e., the filter networks act as nonlinear filters. Thus, these networks are appropriate for applications like background noise elimination, or non-speech sound recognition as shown here. One can also combine different filter modules or modify the neural structure to achieve more complex signal preprocessing [12]. To this end, we believe that here the described technique for filter design may lead to another way of modelling sensory preprocessing for robotic systems. More demanding tasks will be a deeper investigation of the mathematical properties of these filter networks and their dynamical behavior (e.g., spectral characteristics) using the framework of a nonlinear autoregressive moving average (NARMA) model [18]. We will also intensively evaluate the capability of our networks by comparing them to conventional liner filters (i.e. IIR filters).

Acknowledgments: We thank Tomas Kulvicius for technique advises. This research was supported by the PACO-PLUS project (IST-FP6-IP-027657) as well as by BMBF (Federal Ministry of Education and Research), BCCN (Bernstein Center for Computational Neuroscience)–Göttingen W3.

References

1. Dayhoff, J. E., Palmadesso, P. J., Richards, F.: Oscillation Responses in a Chaotic Recurrent Network. In: Recurrent Neural Networks: Design and Applications, CRC Press, pp. 153–177 (1999)
2. Steingrube, S., Timme, M., Wörgötter, F., Manoonpong, P.: Self-Organized Adaptation of a Simple Neural Circuit Enables Complex Robot Behaviour. Nature Physics 6, 224–230 (2010)
3. Ziemke, T.: On Parts and Wholes of Adaptive Behavior: Functional Modularity and Dichronic Structure in Recurrent Neural Robot Controllers. In: 6th International Conference on Simulation of Adaptive Behavior, pp. 115–124 (2000)
4. Zegers, P., Sundareshan, M. K.: Trajectory Generation and Modulation using Dynamic Neural Networks. IEEE T. Neural Networ. 14 (3), 520–533 (2003)
5. Hülse, M., Wischmann, S., Pasemann, F.: Structure and Function of Evolved Neuro-Controllers for Autonomous Robots. Connect. Sci. 16 (4), 249–266 (2004)
6. Williams, R. J., Peng, J.: An Efficient Gradient–Based Algorithm for On–Line Training of Recurrent Network Trajectories. Neural Comput. 2 (4), 490–501 (1990)
7. Becerikli, Y.: Nonlinear Filtering Design using Dynamic Neural Networks with Fast Training. In: Computer and Information Sciences - ISCIS 2003, vol. 2869, pp. 601–610 (2003)
8. Hagen, M. T., De Jesus, O., Schultz, R.: Training Recurrent Networks for Filtering and Control. In: Recurrent Neural Networks: Design and Applications, CRC Press, pp. 325–354 (1999)
9. Squartini, S., Cecchi, S., Rossini, M., Piazza, F.: Echo State Networks for Real-Time Audio Applications. In: Advances in Neural Networks ISNN 2007, vol. 4493, pp. 731–740 (2007)
10. Beer, R. D.: The Dynamics of Active Categorical Perception in an Evolved Model Agent. Adapt. Behav. 11 (4), 209–243 (2003)
11. Pasemann, F.: Dynamics of a Single Model Neuron. Int. J. Bifurcat. Chaos 3 (2), 271–278 (1993)
12. Manoonpong, P.: Neural Preprocessing and Control of Reactive Walking Machines: Towards Versatile Artificial Perception-Action Systems. In: Cognitive Technologies, Springer (2007)
13. Kolodziejski, C., Porr, B., Wörgötter, F.: Mathematical Properties of Neuronal TD-Rules and Differential Hebbian Learning: A Comparison. Biol. Cybern. 98 (3), 259–272 (2008)
14. Oppenheim, A. V., Schafer, R. W., Buck, J. R.: Discrete-time Signal Processing. Prentice Hall (1999)
15. Haykin, S.: Neural Networks Expand SP's Horizons. IEEE Signal Processing Magazine, 24–49 (1996)
16. Hanna, A. I., Mandic, D. P., Razaz, M.: A Normalised Backpropagation Learning Algorithm for Multilayer Feed-Forward Neural Adaptive Filters. In: the 2001 IEEE Workshop on Neural Networks for Signal Processing, pp. 63–72 (2001)
17. Uncini, A.: Audio Signal Processing by Neural Networks. Neurocomputing 55 (3–4), 593–625 (2003)
18. Mandic, D., Chambers, J.: Recurrent Neural Networks for Prediction: Learning Algorithms, Architectures and Stability, Wiley (2001)