Simple Recurrent Neural Filters for Non-Speech Sound Recognition of Reactive Walking Machines

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Abstract:

Biological neural networks in particular in brains consist of extensive recurrent structures implying the existence of neural dynamics, like chaotic [1], oscillatory [2], and hysteresis behavior [3]. This suggests that complex dynamics plays an important role for different brain functions, e.g., for processing sensory signals and for controlling actuators [4]. From this point of view, in this article, we exploit hysteresis effects of a single recurrent neuron [5] in order to systematically design minimal and analyzable filters. Due to hysteresis effects and transient dynamics of the neuron, at specific parameter configurations, the single recurrent neuron can behave as many adjustable low-pass filters (see Supplementary Fig. 1). Extending the neural module by two recurrent neurons we even obtain high- and band-pass filters (see Supplementary Fig. 1). The networks presented here are hardware oriented, so we have successfully implemented, e.g., a low-pass filter network, on a mobile processor of our hexapod robot. As a consequence, it filters motor noise and enables the robot to autonomously react on a specific auditory signal in a real environment. Such that the robot changes its gait from slow to fast one as soon as it detects the auditory signal at a carrier frequency of 400 Hz (see Supplementary video at http://www.nld.ds.mpg.de/~poramate/BCCN2009/AuditoryDrivenWalkingBehavior.mpg). This auditory-driven walking behavioral experiment shows that the simple recurrent neural filters are appropriate for applications like background noise elimination, or non-speech sound recognition in robots. To a certain extent the approach pursued here sharpens the understanding of how the dynamical properties of a recurrent neural network can benefit for filter design and may guide to a new way of modeling sensory preprocessing for robot communication as well as robot behavior control.

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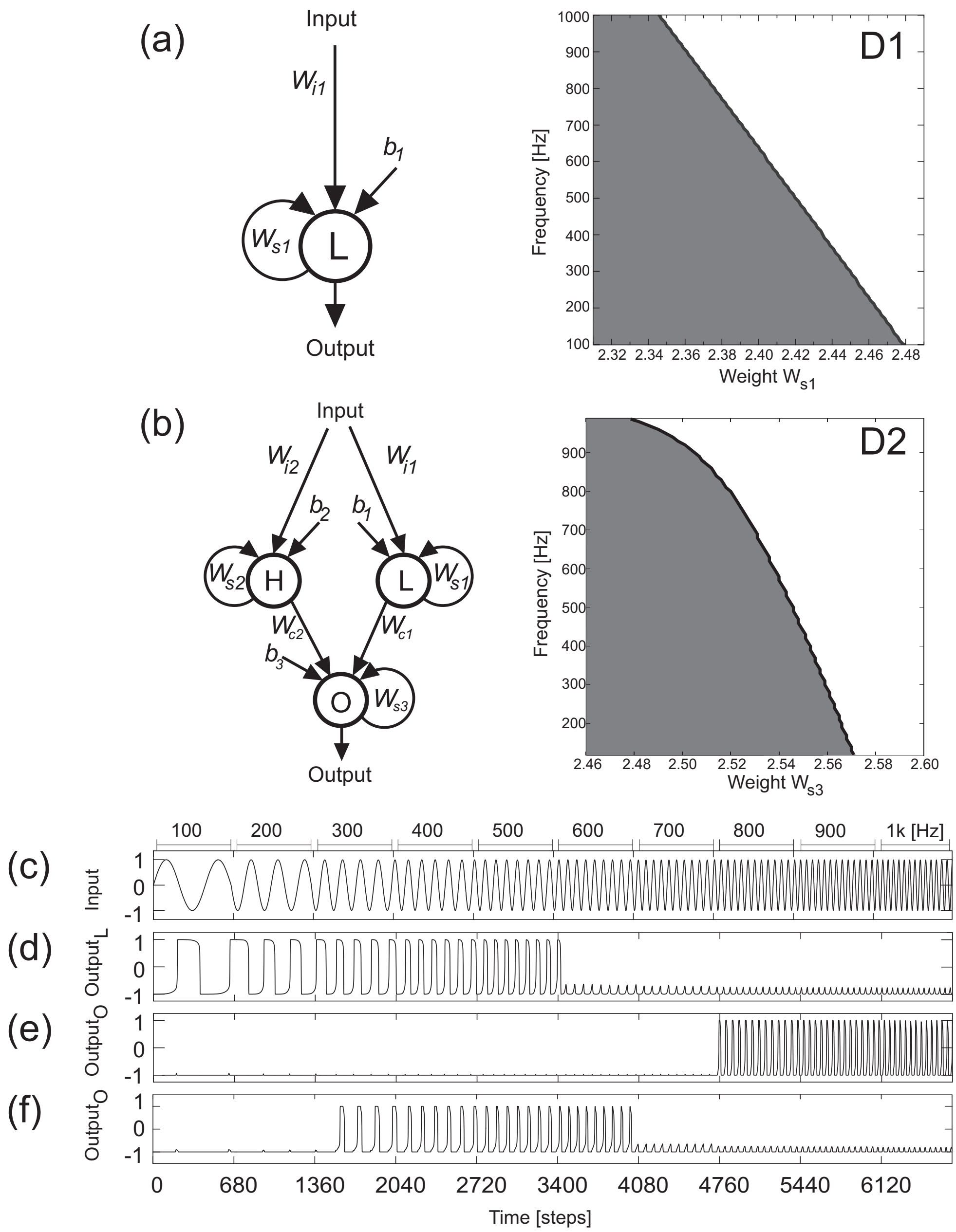

Supplementary Figure 1: (a) Recurrent neuro-module realizing a simple low-pass filter. Its input weight w_{i1} and bias term b_1 are fixed to 1.0 and -0.1, respectively, while the weight w_{s1} is changeable according to the diagram **D1** in order to obtain certain cutoff frequencies. For example, selecting w_{s1} = 2.42 the network suppresses signals with frequencies higher than 500 Hz (d). (b) Recurrent neural network realizing simple high- and band-pass filters. For the 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 the diagram **D1** in order to obtain certain cutoff frequencies. For example, choosing w_{s1} = 2.39 the network functions as a 700 Hz high-pass filter (e). To achieve the band-pass filter, all parameters are set as the high-pass filter while w_{s1} and w_{s3} are adjustable to define a lower cutoff frequency f_L and an upper cutoff frequency f_U, respectively. For example, choosing $w_{s1} = f_L = 2.455$ and $w_{s3} = f_U = 2.535$ from the ($w_{s1,3}$, cutoff frequencies)-spaces (shown in the diagrams **D1**, **D2**) the network lets signals pass which have frequencies between around 300 Hz and 600 Hz (f). (c) Simulated sine wave input signal with an update frequency of 44.1 kHz on a 1-GHz personal computer (PC). It varies from 100 Hz to 1000 Hz and is used as an input signal for testing the recurrent neural filter networks ((a), (b)). (d)$-$(f) Output signal of the low-, high-, and band-pass filter networks, respectively. Note that the diagram **D1** presents the correlation between w_{s1} and the cutoff frequency of the low- and high-pass filter networks. It also serves to control the lower cutoff frequency f_L of the band-pass filter network. The diagram **D2** shows the correlation between weight w_{s3} and the upper cutoff frequency f_U of the band-pass filter network. All neurons are modelled as discrete-time non-spiking neurons with the hyperbolic tangent transfer function.