ReSuMe learning method for spiking neural networks dedicated to neuroprostheses control

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In this paper we consider ReSuMe - a Remote Supervised Method [1] for precise learning of spatio-temporal patterns of spikes in Spiking Neural Networks (SNN) [2, 3]. The learning method is dedicated to neuroprostheses control.

Neuroprosthetic systems aim at producing functionally useful movements of the paralysed organs by stimulating muscles or nerves with the sequences of short electrical impulses [4]. Controllers of such systems are supposed to be robust and flexible. A special emphasis should be put on their good learning abilities and the adaptability to non-stationary character and nonlinearities of the human neuro-musculo-skeletal system.

Spiking Neural Networks (SNN) exhibit properties that make them particularly suitable to control neuroprostheses. SNN are not only highly adaptive and computationally very powerful. They are also particularly suitable to process information encoded in time [2]. Moreover, the representation of signals transmitted through- and produced by SNN is very similar to that required to stimulate muscles or nerves.

However, the analysis of the recent supervised learning methods for SNN [5] revealed that the existing algorithms were not sufficient for the task at hand. This led to wider exploration of other approaches, which resulted in inventing ReSuMe. ReSuMe takes advantage of the spike-based Hebbian processes [3] and integrates them with a novel concept of remote supervision introduced in [1]. In this approach the efficacy w of any synaptic connection between a presynaptic neuron n^{in} and a postsynaptic neuron n^l is modified according to the following rule:

$$\frac{\mathrm{d}}{\mathrm{d}t}w(t) = \left[S^d(t) - S^l(t)\right]\left[a + \int_0^\infty W(s)\,S^{in}(t-s)\,\mathrm{d}s\right],$$

where $S^d(t)$, $S^{in}(t)$ and $S^l(t)$ are target, pre- and postsynaptic spike trains, respectively. The spike trains are defined here by the sums of the firing times [3]. The parameter a expresses the amplitude of the non-correlation contribution to the total weight change, while the convolution function represents the Hebbian-like modifications of w. The integral kernel $W(s)$ is known as a learning window defined over a time delay s between the spikes occurring at the synaptic sites [1]. In the case of excitatory synapses the term a is positive and the learning window $W(s)$ has the shape similar as in STDP [3]. In the case of inhibitory synapses a is negative and $W(s)$ is defined similarly as for the anti-STDP rules. For the complete introduction to ReSuMe we refer to [1].

ReSuMe enables supervised learning while still inheriting interesting properties of unsupervised Hebbian approach, i.e. the locality in time and space, simplicity and the suitability for online processing. On the other hand, ReSuMe avoids drawbacks of the Hebbian- and, so called, supervised-Hebbian methods [5].

ReSuMe has been successfully applied to feedforward, recurrent and hybrid (e.g. Liquid State Machine [6]) network architectures.

The learning properties of ReSuMe have been investigated in the extensive simulation studies accompanied by the theoretical analysis. In [7] it has been demonstrated that ReSuMe can effectively learn complex temporal and spatio-temporal spike patterns with the desired accuracy and that the method enables imposing on the SNNs the desired input/output properties by learning multiple pairs of input-output patterns.

In addition, it has been shown that ReSuMe is able to successfully train the networks consisting of different models of neurons (from simple LIF, to complex biologically realistic models) [7].

In all experiments it was observed that ReSuMe learning process converged very quickly.

In [8] we demonstrated the generalization properties of the spiking neurons trained with ReSuMe. This property supports the thesis that SNN can be trained with ReSuMe to become an effective model of the reference objects, such as biological neural or neuro-muscular structures.

ReSuMe proved to be applicable not only to the modeling, but also to the control tasks. In [9] we consider an experiment in which ReSuMe was successfully applied to generate movement of the 2-DOF model of leg equipped with 4 muscles. A spiking network was trained to reconstruct the spatio-temporal patterns of impulses corresponding to the patterns of activity in the pools of motoneurons. Each pool, consisting of 40 neurons, activated the particular muscle model. The model of a limb, driven by the SNN, was able to follow the desired trajectory of movement with a high precision.

That study is recently put a step further. In a project on the adaptive Central Pattern Generators (CPG) the spiking networks are trained to produce the desired spike patterns resulting in the rhythmic movements of the limb models[1].

ReSuMe is also applied to control the limb model in a feedback-loop system. In this task the network acts not only as a pattern generator but also as a controller. The network has to correctly react to the command signals and to the possible errors between the desired and the actual plant state. The results of the closed-loop control experiment are illustrated in Fig.1. The quality of approximation of the desired trajectory is slightly worse as compared to the results obtained in the open loop case. On the other hand the closed-loop system demonstrates higher robustness to the external perturbations.

In parallel to the simulation studies, we develop the hardware system for the neuroprostheses control. So far ReSuMe method has been implemented and tested on FPGA matrices[2].

All results discussed above indicate potential suitability of the spiking networks trained with ReSuMe to control the neuroprosthetic systems. An important aspect of the future work on ReSuMe is to verify this ability in the real-world applications.

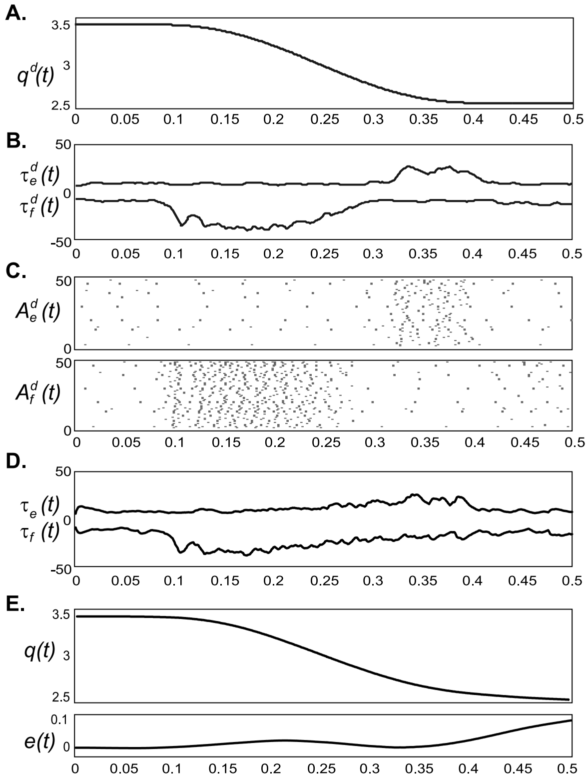

Figure 1: SNN trained to control a 1-DOF leg model in a feedback-loop. (A) Desired leg trajectory $q^d(t)$ obtained as an effect of the contractions $\tau_e^d(t)$, $\tau_f^d(t)$ at the extensor and flexor muscle models, respectively (B). (C) Required neural activity $A_e^d(t)$ and $A_f^d(t)$ for pools of extensor and flexor 'motoneurons'. $A_e^d(t)$ and $A_f^d(t)$ are the spike patterns to be learned by SNN. (D) Contraction $\tau_e(t)$, $\tau_f(t)$ of the muscle models resulting from the spike pattern $A_e(t)$ and $A_f(t)$ generated by the trained SNN. (E) Resulting movement trajectory $q(t)$ and the corresponding error: $e(t) = q^d(t) - q(t)$.

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[1] Details are given in an accompanying paper "Adaptive Central Pattern Generator based on Spiking Neural Networks"

[2] Details in an accompanying paper: "FPGA implementation of the ReSuMe learning method for SNN"