Neuromorphic Computing Based on Physical Systems with Biologically Inspired Learning Rules

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Abstract. This work considers an application in neuromorphic computing, whereby physical components are employed to undertake computing applications, inspired by the human brain and nervous system. The present system is based on a coupled network of FitzHugh-Nagumo oscillators, with each oscillator characterized by a temporal spiking response based on the inputs from those oscillators to which it is coupled. With a biologically inspired learning rule, the coupling between oscillators is modified so that the output oscillators fire a specified times. This work explores the application of different forms of coupling as well as different learning rules based in part on spike timing dependent plasticity, the mechanisms believed to underlie how the human brain learns.

Introduction

A system of N FitzHugh-Nagumo oscillators is described by the equations of motion

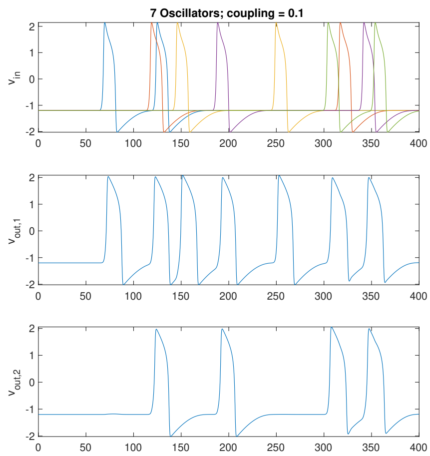
$$\dot{v}_i = v_i - \frac{v_i^3}{3} - w_i + \sum_{j=1}^{N} f_{ij}, \quad \tau\,\dot{w}_i = v_i + a - b\,w_i, \qquad i = 1, \ldots, N, \tag{1}$$

where f_{ij} represents a coupling between oscillator i and oscillator j. Note that this is a simplified version of the Hodgkin-Huxley model of a spiking neuron and also is a generalization of a van der Pol circuit. In this neuromorphic computing application the network is trained so that individual output oscillators fire at specific predetermined times [1]. For example, in a motor control application such firing could relate to the timing of different actuators acting in a large-scale system. The coupling between oscillators is assumed to accumulate voltage, so that an oscillator i fires only when the input voltage, represented by $\sum_j f_{ij}$ reaches a sufficient voltage level.

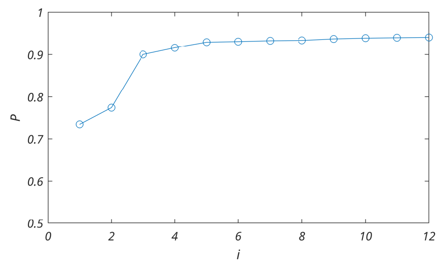
Results and Discussion

The performance goal is based on a specified output spike timing, while learning is implemented based on spike timing dependent plasticity [2], commonly described as "neurons that fire together wire together" and assumed to underlying changes in the architecture of the human brain.

In Figure 1a, an example response of a network with $N = 7$ oscillators is shown. In this system, 5 oscillators are excited and serve as inputs, so that each oscillator fires twice during the time interval shown. Each input oscillator is then coupled to each of the 2 output oscillators. Note that the firing of these output oscillators is determined by the response of the input layer. Based on a biologically inspired learning rule, the network coupling is altered dependent on the overall performance of the system, so that as the system learns the actual timing of the output neurons approaches the target values, as illustrated in Figure 1b.



(a) Output spike train



(b) Timing performance

Figure 1: Network of FitzHugh-Nagumo oscillators; 5 input oscillators, 2 output oscillators

References

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[2] Frémaux N., Sprekeler H., Gerstner W. (2010) Development/plasticity/repair functional requirements for reward-modulated spike-timing-dependent plasticity. *The Journal of Neuroscience* **30**(40:13326–13337.

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