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Initial Experiments Evolving Spiking Neural Networks with Supervised Learning Capability

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Abstract

There is currently much research activity aimed at synaptic plasticity methods for spiking neural networks. While many methods have been proposed, there are few that provide for supervised learning. A fundamental premise of the work reported here is that the network topology is key to defining the network's capabilities: the topology IS the algorithm. Hence, learning at the level of the whole network is an emergent phenomenon of the learning mechanism operating on individual synapses and the topology. Therefore, the topology and the learning mechanism(s) must be designed together, and evolutionary computation (EC) is a suitable technology for this.

We report on initial experiments on a relatively simple test problem, the tonic burster, using several types of learning including supervised. We see that EC can locate seemingly good solutions that actually do not solve the desired task; they "cheat" by simply exploiting the supervisory signals. A simple modification of the train-test protocol can solve this. We introduce an approach we call "artificial neurology" for systematically examining the behaviour of a SNN in order to understand how it achieves its performance. Experiments indicate that a combination of Hebbian and supervised learning works best for this task.

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Keywords: Spiking neural networks; evolutionary computation; supervised learning; ReSuMe; Hebbian learning; spike time dependent plasticity; tonic burster

1. Introduction

There is currently much research activity in the domain of neuromorphic computing. Building machines that may

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exhibit some of the cognitive abilities of human brains has been a long-standing dream, and borrowing ideas from neurobiology has been an important element in this pursuit. One such critical ability is learning. The field of spiking neural networks (SNNs) has included several forms of learning since its emergence about 17 years ago. Two particularly prominent learning models are Hebbian[2] long-term plasticity and a transient (short-term), frequency-dependent plasticity proposed by Markram et al. in the late 1990s. While supervised learning models have been vigorously developed in machine learning in general, relatively few supervised learning models have been studied for SNNs. The complexity of recurrent SNN dynamics clearly presents a challenge for learning.

A fundamental premise of the work reported here is that with neural networks, the network topology is key to defining the network's capabilities: the topology IS the algorithm. Hence, learning at the level of the whole network is an emergent phenomenon of the learning mechanism operating on individual synapses and the topology. Therefore, in order to enable task-learning at the level of the whole network, the topology and the learning mechanism(s) must be designed together, and evolutionary computation (EC) is a suitable technology to accomplish this.

We have previously described a SNN growth algorithm that is driven by genes provided by a genetic algorithm (GA) [8] whose chromosome length grows only O(n) where n is the number of neurons. The number of neurons is one of the genes, and other genes provide all the network's initial parameter values. This approach was capable of evolving small network topologies for two toy tasks, and it was seen that the activation of Hebbian synaptic plasticity enabled swifter evolution of networks with performance superior to that of networks with static synapses. Hebbian learning is unsupervised and long-lasting. In this paper, we extend this approach by adding two new forms of learning, an unsupervised and transient scheme proposed by Markram et al. [5] and a supervised and long-lasting scheme proposed by Ponulak [6]. All these methods come under the label spike time dependent plasticity (STDP).

Nomenclature

CAS	Complex adaptive systems
EC	Evolutionary Computation
GA	Genetic algorithm
HUX	half uniform crossover
MP	membrane potential of a neuron
MPC	the MP components (the PSPs that sum to yields the MP)
PSP	Post synaptic Potential (the voltage wave produced at a synapse when a spike arrives)
ReSuMe	Remote Supervised Method (a supervised learning approach by Ponulak)
SNN	Spiking neural network
STDP	Spike time dependent plasticity
TB	tonic burster, the experimental task

2. Methods

The experiments reported here involve a combination of a genetic algorithm (GA) [1] and a spiking neural network simulator (SSNNS [10]). The task to be accomplished is defined by a set of input spikes and the corresponding target output spike pattern. The fitness of any evolved SNN is a computation of the error between the produced and expected spike patterns [9]. SSNNS currently has three STDP methods: the soft-bound Hebbian plasticity of van Rossum et al. [11], the transient plasticity of Markram et al. [5], and two variants of supervised plasticity, the original ReSuMe method of Ponulak [6] and a simplified variant of it. Since the supervised learning behaviors are the main focus of this paper, these methods will be described in a bit of detail.