Dynamic Evolving Spiking Neural Networks for On-line Spatio- and Spectro-Temporal Pattern Recognition

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Abstract

On-line learning and recognition of spatio- and spectro-temporal data (SSTD) is a very challenging task and an important one for the future development of autonomous machine learning systems with broad applications. Models based on spiking neural networks (SNN) have already proved their potential in capturing spatial and temporal data. One class of them, the evolving SNN (eSNN), uses a one-pass rank-order learning mechanism and a strategy to evolve a new spiking neuron and new connections to learn new patterns from incoming data. So far these networks have been mainly used for fast image and speech frame-based recognition. Alternative spike-time learning methods, such as Spike–Timing Dependent Plasticity (STDP) and its variant Spike Driven Synaptic Plasticity (SDSP), can also be used to learn spatio-temporal representations, but they usually require many iterations in an unsupervised or semi-supervised mode of learning. This paper introduces a new class of eSNN, dynamic eSNN, that utilise both rank-oder learning and dynamic synapses to learn SSTD in a fast, on-line mode. The paper also introduces a new model called deSNN, that utilises rank-order learning and SDSP spike-time learning in unsupervised-, supervised-, or semi-supervised modes. The SDSP learning is used to evolve *dynamically* the network changing connection weights that capture spatio-temporal spike data clusters both during training and during recall. The new deSNN model is first illustrated on simple examples and then applied on two case study applications: (1) moving object recognition using address-event representation (AER) with data collected using a silicon retina device; (2) EEG SSTD recognition for brain-computer interfaces. The deSNN models resulted in a superior performance in terms of accuracy and speed when compared with other SNN models that use either rank-order or STDP learning. The reason is that the deSNN makes use of both the information contained in the order of the first input spikes (which information is explicitly present in input data streams and would be crucial to consider in some tasks) and of the information contained in the timing of the following spikes that is learned by the dynamic synapses as a whole spatio-temporal pattern.

Keywords: Spatio-temporal pattern recognition**;** Spiking neural networks; Dynamic synapses**;** Evolving connectionist systems; Rank-order coding; Spike time based learning; Moving object recognition; EEG pattern recognition.