Chaotic Liquid State Machine

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ABSTRACT

The authors implement a Liquid State Machine composed from a pool of chaotic spiking neurons. Furthermore, a synaptic plasticity mechanism operates on the connection weights between the neurons inside the pool. A special feature of the system’s classification capability is that it can learn the class of a set of time varying inputs when trained from positive examples only, thus, it is a one class classifier. To demonstrate the applicability of this novel neurocomputing architecture, the authors apply it for Online Signature Verification.

Keywords: Chaos Control, Chaotic Spiking Neural Network, Chaotic Spiking Neuron, Hebbian Learning, Liquid State Machines, NDS Neuron, Nonlinear Transient Computation, One Class Classification, Online Signature Verification, Reservoir Computing, Signature Coding, STDP, Synaptic Plasticity

1. INTRODUCTION

Reservoir Computing (Maass, Natschläger & Markram, 2002; Jaeger, Maass & Principe, 2007) design methodology consists of building a neural network that is divided into three parts. The first part is an input layer. The second part is the reservoir, namely a pool, consisting of randomly and recurrently connected nodes with fixed connections’ weights. These nodes can be any type of spiking neurons. The third part is an output layer consisting of a read out mechanism that is able to read the transient activity of the pool (i.e. the activation of every node in the pool) and perform a classification task accordingly. In the context of Reservoir Computing, an input should be a time varying signal. Furthermore, the connections from the input layer to the pool, and the connections between the neurons that constitute the pool, have weights that are randomly set. All these connections maintain fixed weights during training (i.e. their weights are kept fixed and won’t undergo any changes). The connections from the pool to the output layer are also randomly set, but they have flexible weights; this means, they are the only connections of the network that undergo training (i.e. their weights are updated during training). Fundamental models of Reservoir Computing are the Liquid State Machines (LSM) (Maass, Natschläger & Markram, 2002; Maass & Markram, 2004), Echo State Networks (ESN) (Jaeger, Maass & Principe, 2007) and Nonlinear Transient Computation (NTC) (Crook, 2007). Inspired by the work of Maass and Crook, we implement the chaotic Liquid State Machine model that is presented herein. First, the

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Chaotic LSM incorporates a synaptic plasticity mechanism inside the liquid layer, which is an approach suggested by Mass et al. (2002) to enhance the ‘Separation Property’ of the machine. Second, the Chaotic LSM uses a minimal number of chaotic spiking neurons inside the liquid layer; an approach suggested by Crook (2007), which can offer a substitute to the nonlinear dynamics offered by a large number of simple Leaky Integrate and Fire (LIF) neurons that are commonly used in the traditional design of a LSM. Third, the Chaotic LSM implements the theory of Delay Feedback Control (DFC) (Pyragas, 2003); on the neurons connections, to stabilize the chaotic dynamics of the liquid when the latter is fed with external input. In such chaos control scheme, the chaotic LSM operates on the critical region between chaos and order (i.e. operates on the edge of chaos (Langton, 1990; Natschläger, Bertschinger & Legenstein, 2004)); which can contribute to its generalization capability, especially since it is combined with synaptic plasticity, synaptic scaling and the use of one class similar training inputs (Maass, Legenstein & Bertschinger, 2005; Legenstein & Maass, 2006; Legenstein & Maass, 2007).

2. LIQUID STATE MACHINES AND NONLINEAR TRANSIENT COMPUTATION

Two necessary and sufficient conditions are required for a system to perform Transient Computation on time varying signals as in Reservoir Computing and specifically Liquid State Machines (LSM) (Maass, Natschläger & Markram, 2002). The first is called SP (Separation Property) and the second is called AP (Approximation Property). SP mentions that different inputs to a pool of neurons; that constitute the Reservoir or the Liquid in LSM terms, should cause different transients in the pool, and similar inputs should cause similar transients. The AP mentions that a reliable readout mechanism should be able to learn and map these transients to specific target outputs. Both properties were confirmed in the Nonlinear Transient Computing Machine (NTCM) model (Crook, 2007). To perform transient computation on time varying signals, the NTCM uses two Nonlinear Dynamic State (NDS) (Crook, Goh & Hawarat, 2005) Neurons only; in contrast to the huge number of Leaky Integrate and Fire Neurons hypothetically required by a LSM. NDS Neurons are spiking neurons that fire chaotically (Crook, Goh & Hawarat, 2005). We recreate the NTCM model, specifically, we exploit the effect of the neural connections’ Delay Feedback Control (DFC) mechanism, by imposing a neural connections’ Synaptic Plasticity tuning strategy, inspired by the biological phenomenon of Spike Timing Dependent Plasticity. The outcome is a new version of a Reservoir Computer called Chaotic Liquid State Machine and it works as a one-class classifier. Particularly, the machine can be trained on a set of time varying inputs. Each input in the set is a sequence of time intervals that are considered as its building blocks. These building blocks constitute the elementary characteristic features of every input; their arrangement in each input, and their slight length variations in the set, characterizes a one-class object and thus identifies its unique identity. By way of an application, we choose Online Signature Verification (Jain, Griess & Connell, 2002) for two reasons: First, an online signature is a time varying input. Second, a set of instances of an online signature of a same person is in fact a repository of a set of time varying input examples that share alike kinetics. Note that the kinetics of a signature can be encoded as a sequence of timing intervals. Furthermore, the generalization of these sequences to a unique output by the means of a chaotic LSM is emphasized through the synaptic plasticity mechanism that operates on their connections weights with respect to the timing intervals and connections’ time delay. The Chaotic Liquid State Machine is illustrated in Figure 1.
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