TIME-VARYING SIGNALS CLASSIFICATION USING A LIQUID STATE MACHINE

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Abstract The liquid state machine is a novel computation paradigm based on the transient dynamics of recurrent neural circuitry. In this paper it is shown that this systems can be used to recognize complex stimuli composed by non-periodic signals and to classify them in a very short time. Even if the network is trained over a segment of the signal the classification task is completed in a time interval significantly shorter than the time-window used for the training. Stimuli composed by many complex signals are recognized and classified even if some signals are absent.

Keywords: Liquid State Machine, classification, Spiking Neurons

1. Introduction

Reaction times of biological systems are usually very short, so short that there is not time to integrating or averaging over a long–time window; a stream of input signals is usually processed in few *m secs*, a time interval that allows to generate a small number of neural spikes. Neural microcircuits, small networks of spiking neurons, are usually identified as the new generation of neural networks; the dynamic of this systems is complex and difficult to constrain and manipulate so that one of the approach is to take a weighted sum of the activity of the neurons using a suitable read-out circuit. In [Joshi and Maass., 2004] this activity is defined as *liquid state* $x(t)$ and models the impact that a neuron of the circuit may have on the membrane potential of a generic read-out neuron.

In [Maass and Natschlager, 2002] a new computational model, called the Liquid State Machine (LSM), that exploits the liquid state as a resource for a real time computing system was presented. The LSM is constituted by two separated subsystems: the liquid, that is used to obtain a very complex time-varying vector state, and the readout function: a memoryless subsystem

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(usually a simple perceptron or a set of neurons without connection loops) that is used to extract information from the liquid. The LSM is capable to process time-varying inputs without stable states, but using the perturbed state of the liquid that, at any moment, is the result of the present and past inputs.

The plasticity of the microcircuits is not exploited in LSM, as said in [Joshi and Maass., 2004], all the plasticity and adaptation is implemented in read-out circuits trained to produce the desired output.

2. The Neuron Model

The liquid dynamics is an important issue or the implementation of the LSM: the liquid should have two very important features:

1 a complex but not chaotic dynamics because virtually it should contain the transition functions of many finite state machines;

2 the separation property that allows to separate the states due to two different input signals.

Both properties were introduced in [Maass and Natschlager, 2002]: while the second one is clearly stated and defined, the first one is introduced when the liquid fading memory and the need of dynamic synapses is discussed. The dynamic of the liquid is also in relationship with the length of the neural connections. To obtain this equilibrium between a complex dynamics and a not chaotic response it is necessary to pay a special attention to the neuron model: a rich model is needed to obtain a complex dynamics but a low computational complexity is necessary for an efficient simulation.

On the two opposite sides are the simple Integrate & Fire model (I&F model) and the Hodgkin-Huxley model: both of them used in LSM simulations [Maass and Natschlager, 2002], [Kaminski and Wojcik, 2004]. The Hodgkin-Huxley model is a complex model constituted by 4 differential equations and tens of biophysically meaningful parameters, it is complete but very expensive to simulate and it is not a suitable choice especially if it is necessary to simulate a large array of neurons as in a LSM.

In [Izhikevich, 2004] some of the models of spiking neurons are compared in order to evaluate their applicability to a large-scale simulation. A simple model capable to exhibit a very complex behavior is presented in [Izhikevich, 2003]. This model is simple to implement and, using only 4 parameters, is capable to reproduce many firing patterns, as the bursting, continuous spiking with frequency adaptation, and chattering. This model was used in our simulation.

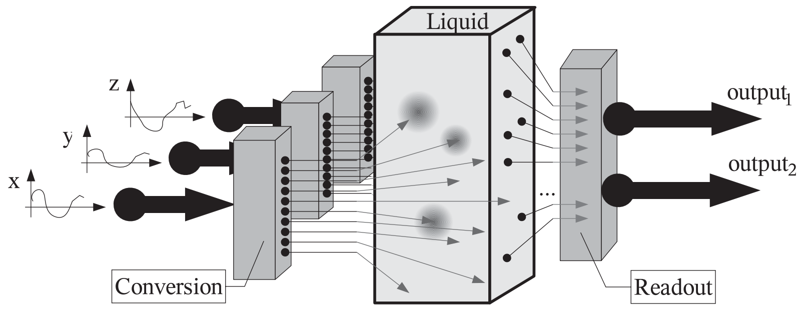

Figure 1. A representation of the Liquid State Machine: on the left side the conversion subsystem, one for each input signal connected to the liquid using 10 lines; on the right the readout subsystem and the output lines.

3. The System Implementation

The liquid is a set of neurons organized in a three-dimensional structure, in our implementation the liquid is made by a set of $25 \times 10 \times 4$ neurons connected using the same random pattern explained in [Maass and Natschlager, 2002]. The probability of a sinaptic connection from neuron *a* to neuron *b* is defined by a Gaussian probability distribution with an average value of 4 (the smaller dimension of the structure of the liquid) and variance $\lambda = 8$ that controls the average distance between neurons synaptically connected. The weight of connections are randomly chosen with a mean value of $w_e = 1$ if the connection is excitatory and $w_i = -2$ if the connection is inhibitory and in a way that 80% of the connections are excitatory and 20% inibitory, according to [Izhikevich, 2003]. The four parameters of the neural model are randomly varied in order to obtain different spiking patterns.

In our system a converter was added in order to bring a time function in input to the liquid (see fig. 1). The time-varying inputs signals are converted in impulse trains using the mechanism described in [Bothe et al., 2002] and a set of ten Class 1 excitable neurons: values of the input waves are converted in a set of 10 impulse trains that are applied to the liquid. Each converter uses 5 impulses to transform a single value of the input signal.

Each impulse train is connected to the liquid using the same connection schema used to build the connections among the neurons in order to obtain an activation area when an input impulse is present. This situation is represented on the left of fig. 1 by the blurred circle areas on the surface of the liquid.

The output is constituted by the liquid state: the set of all membrane potentials. The readout neurons are modeled as a set of perceptrons that take the contributions of all the liquid neurons filtered with a membrane time constant of 20 msec, the filter output is weighted and applied to a threshold to obtain a boolean response. Instead of this boolean output we will refer to the weighted sum of membrane potentials.

4. The experimental setup

In this preliminary work we chose to focus on the recognition and classification of input stimuli that approximate real-world signals. The classification task is accomplished just after the stimulus is presented, not after the end of a fixed time window or pre–defined number of samples. Moreover the system is capable to recognize a stimulus composed by many signals even if just few of them are presented. All the stimuli taken into account are constituted by two or three time-varying signals that are non periodic, generated convolving a Gaussian kernel with a set of random impulses. The first experiment is focused to the recognition speed of stimuli composed by two signals and to highlight that the status of the liquid can be maintained even if just a part of the stimulus is presented. The second experiment is aimed to verify that the liquid is capable to recognize a complex stimulus from a part of it and to evaluate the output to ambiguous stimulus.

First Experiment

The first task to accomplish is to recognize the two couples of input waves (two stimuli), when presented to the liquid inputs. Two output perceptrons are trained to recognize the input stimuli: the first perceptron is trained to recognize the input stimulus $x_1 - y_1$, the second perceptron is trained to recognize the input stimulus $x_2 - y_2$. After a successfully training of the output perceptron the liquid is capable to recognize the signal from just a part of them. To do that the input is constituted by the couple $x_1 - y_1$ during the first half of the time interval (125 msec), and then switched to $x_2 - y_2$ during the second part of the time interval. An example of the response of the liquid is plotted in fig. 2, the values plotted are the weighted sum of the states of the liquid using the set of weights of the first perceptron. The average time needed to recognize the signal is about 7 *msec* so that there is not time to complete the signal. The efficacy of the classification task measured as the sum of the square classification error is not a function of the distance of the two stimuli (measured, as defined in [Maass and Natschlager, 2002], as the L^2 norm of the difference of the two couple of signals), results not shown here.

The next task is aimed to understand if the response of the liquid can be maintained even if the input of the liquid is not complete. This is obtained submitting to the liquid the couple $x_1 - y_1$ during the first half of the time interval and $x_1 - 0$ during the second interval. Fig. 3 shows that the input in the second half of the time interval is difficult to recognize and the output is oscillatory. The output of the system is above the threshold for some time

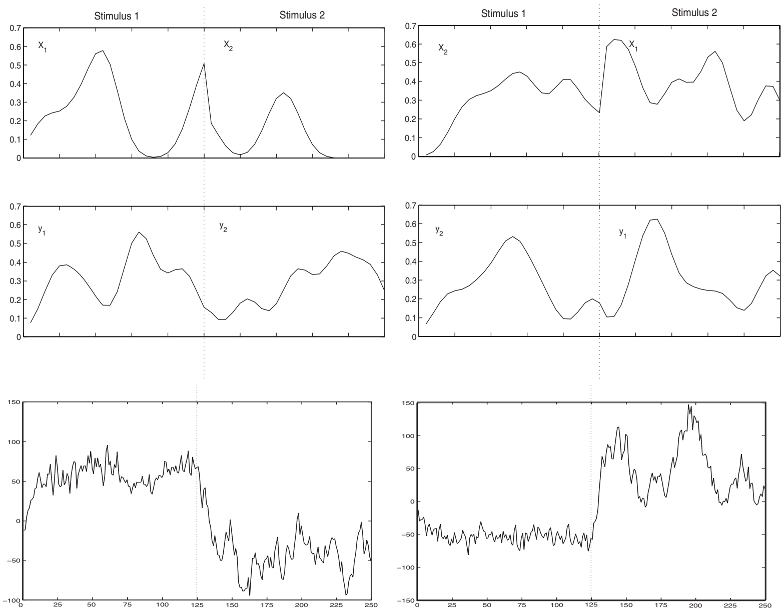

Figure 2. (Upper left) the input sequence $x_1 - y_1, x_2 - y_2$; (lower left) output of the system (weighted sum of the membrane potential of all neurons); (upper right) the input sequence $x_2 - y_2, x_1 - y_1$; (lower right) the output signal

and then goes below the threshold after some oscillations. This is due to the memory of the liquid that maintains for some time the effect of the last input.

The last task is constituted by the signal $x_2 - 0$ for the first half of the time window and $x_1 - y_1$ for the second half of the time window. In the first part of the input the liquid maintains a response below the threshold, but the output goes above the threshold when the next stimulus is recognized. The precedent state of the liquid allow to obtain a response just above the recognition threshold.

Second Experiment

In the second experiment the goal is to understand if the system is capable to classify a stimulus if only a part of it is available or if two stimuli are very similar.

The two stimuli are built using the five signals and labeled x_1, y_1, z_1, x_2, z_2; the two stimuli are constituted by the signal combinations $x_1 - y_1 - z_1$, and $x_2 - y_1 - z_2$, where y_1 is the common part. The output perceptron can be successfully trained and the system correctly classify the two stimuli (results not shown). Left side of fig. 4 shows what happens if the stimuli $x_1 - y_1 - 0$

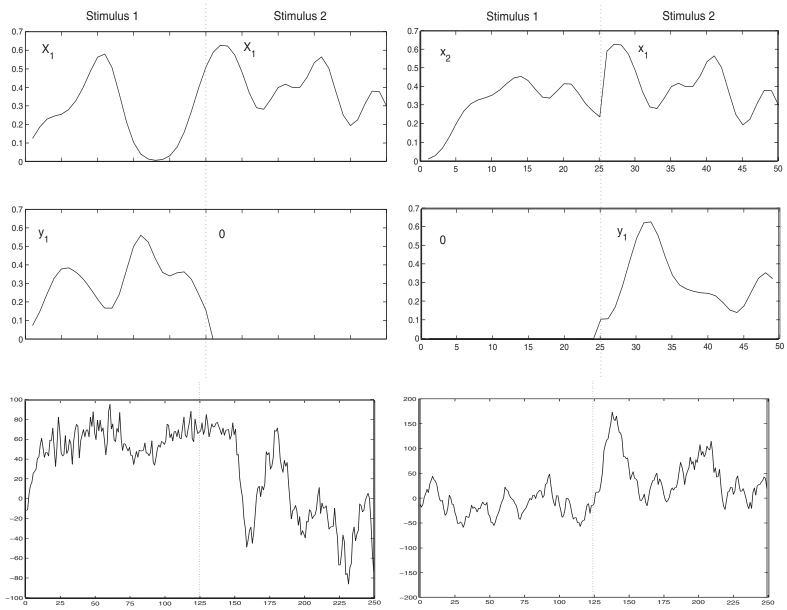

Figure 3. (Upper left) the input sequence $x_1 - y_1, x_1 - 0$; (lower left)output of the system (weighted sum of the membrane potential of all neurons); (upper right) the input sequence $x_2 - 0, x_1 - y_1$ (lower right) the output signal.

is presented to the system. The liquid maintains an output over the recognition threshold even is the stimulus is not complete.

The right side of figure 4 shows what happens if the input is just the common part of the input stimuli (the signal y_1), the liquid state is oscillating between two states corresponding to the two different input stimuli.

5. Conclusions and Future Works

Liquid State Machines are an interesting paradigm suitable or computing in real time systems, and in this work it was demonstrated that LSM can be used to classify time varying-signal. Although the tasks proposed are similar to a real world situation were input signals are not periodic and need to be quickly recognized even if not completed, it it necessary to understand what kind of limitations the liquid has. Another problem is related to the readout system, because many of the performances of the system depends on it.

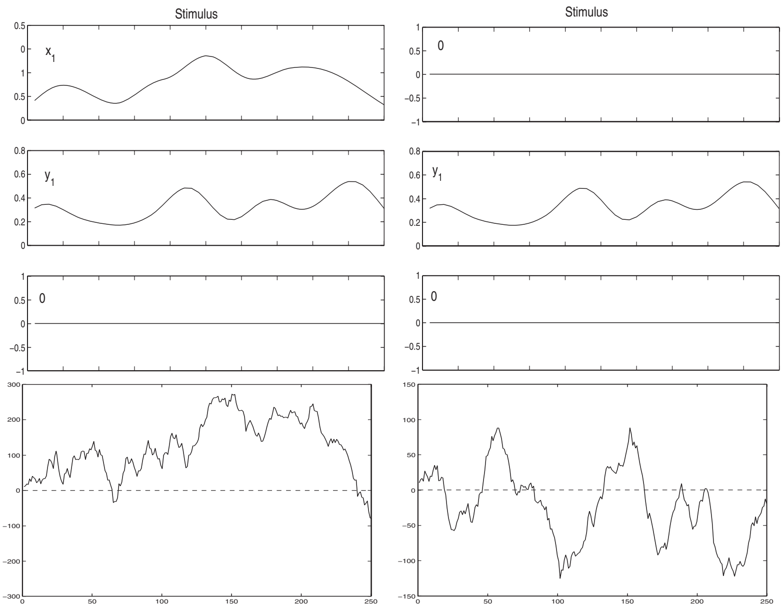

Figure 4. (Upper left) the composition of signals $x_1 - y_1 - 0$; (lower left) the output of the liquid; (upper right) the input stimuli compose by $0 - y_1 - 0$;(lower right) the system output.

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