Event-driven simulation of continuous-time neural networks

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INTRODUCTION

The transforming of incoming signals into action potentials by neurons is believed to be the basis for information processing in nervous systems [1,2,3]. In many cases, the accurate representation of involved timings variability is necessary for a correct computation in neural network simulations [4,5,6,7]. A lot of nervous system simulations reported in scientific literature are computed with time-step based methods. This technique is valid to describe many aspects of biological circuits, but some computational aspects (inefficiency, unreliability, etc.) have been highlighted when used in certain scenarios, especially on very large nets [8]. In this work, a very simple and effective analog spiking neural network simulator, based on LIF (Leaky Integrate and Fire) with latency neurons, is presented. It is simulated with an event-driven method, necessary to guarantee the preservation of the original process behavior. In this way, the simulation proceeds without any forcing in order to obtain a compromise between high precision and computational cost. Networks with up to 10^5 neurons for more than 10^5 spikes, can be simulated in a few minutes (using a standard PC) with a simple MATLAB tool [9]. Plasticity algorithms are also applied to develop bio-inspired applications and emulate interesting global effects as the Neuronal Group Selection [10].

NEURON MODEL, NETWORK ARCHITECTURES AND SIMULATION PROCEDURE

In this work, we have used a LIF (Leaky Integrate-and-Fire) with latency model. The following bio-inspired features are considered: subthreshold linear decay (i.e., "$-Ld\Delta t$"), spiking threshold (i.e., S_{th}), spike latency (i.e., t_f), absolute refractory period (i.e., t_{arp}), excitatory and inhibitory effects (i.e., *presynaptic inputs*, P_r), synaptic strength (i.e., *postsynaptic weights*, P_w). The latter quantity can be affected by synaptic plasticity [11]. The concepts just introduced are described by means of the following equations:

1. *Passive Mode*($S < S_{th}$): $S = S_p + P_r P_w - T_l$
2. *Active Mode* ($S \geq S_{th}$): $\begin{cases} S = S_p + P_r P_w + T_r \\ t_f = 1 / (S - 1) \end{cases}$

In which S is the Inner Neuron State (i.e., the membrane potential of the biological counterpart), whereas S_p represents the previous state. The leakage term is defined as $T_l = Ld\Delta t$, whereas the rise term $T_r = \{(S_p - 1)^2 \Delta t / [1 - (S_p - 1)\Delta t]\}$.
The neuronal behavior of this model is shown in Fig. 1.

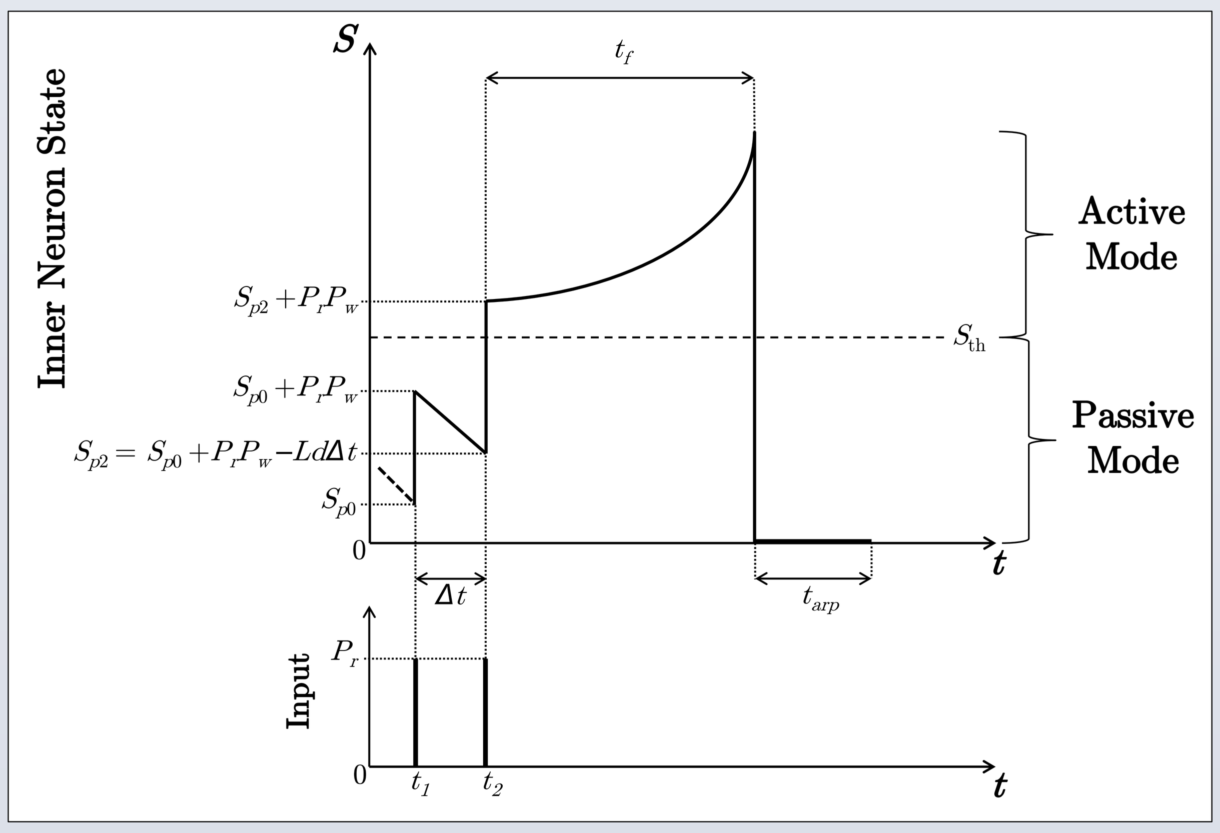

Figure 1. Example of the qualitatively inner state behavior of a neuron in *passive* and *active* modes. An incoming excitatory input at t_1 causes an instantaneous increase of the state from S_{p0} to $S_{p0} + P_r P_w$. At t_2 a second excitatory input is applied, then the state increase his value from S_{p2} to the new value $S_{p2} + P_r P_w$. Note that, $S_{p2} < (S_{p0} + P_r P_w)$, indeed, under the spiking threshold (S_{th}) the neuron is affected by a linear decay (*passive mode*). Moreover, due to the latency effect, the firing is not instantaneous but occurs after a quantity called *time-to-fire* t_f (*active mode*). Finally, after the firing, the neuron is reset to its resting potential (i.e., $S = 0$) for a time equal to t_{arp} (i.e., absolute refractory period). In the case of inhibitory inputs P_r is negative (not shown in this figure).

In Fig. 2 are reported some typical architectures that we have implemented.

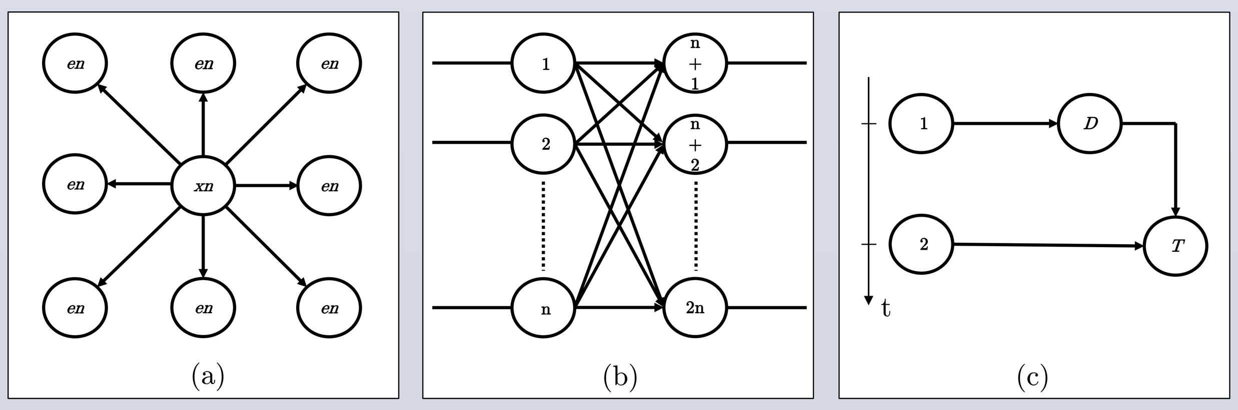

Figure 2. (a) *Cellular Neural Network-like (CNN-like) topology* [12]: each firing neuron *xn* (both excitatory and inhibitory neurons) transmits its spikes to a certain number of target neurons (i.e., its neighborhood). (b) *Feedforward Network (FFN) topology*: each neuron of a given layer can only transmit its spikes to the neurons belonging to the adjacent layer. (c) *Delayed Network topology*: simple structure in which a delayed neuron *D* is used in order to realize an effective coincidence detector.

For the purpose of emulating a *continuous-time* behavior an *event-driven* approach is required [13,14,15]. Therefore, a simple algorithm has been implemented: the simulation proceeds searching for the neuron with the minimum time-to-fire t_f, in order to determinate the next firing event to be scheduled in a spike timing array list. Then, the evaluation of firing event effects on all the directly target neurons is made.

GLOBAL EFFECTS AND APPLICATIONS

By means of the above mentioned architecture some interesting global effects can be studied, such as formation and maintaining of neuronal groups (Fig. 3) as in the Neuronal Group Selection Theory [10], or the jitter reduction [16] (Fig. 4).
Finally, it is possible to implement SNN classifiers (Fig. 5).

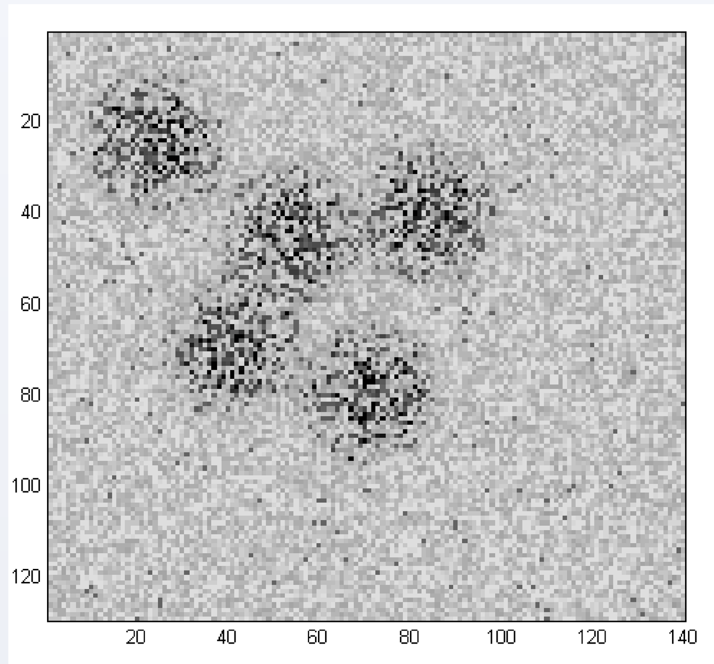

Figure 3. Spiking activity of a CNN-like network (see Fig. 2a) as a consequence of a stimulation consisting of pseudo-random spike sequences. The emerging of 5 neuronal groups can be denoted, in which the activity is higher than the rest of the network. Moreover, removing the external input these groups maintain their activity stable, preserving the shapes depicted in the figure.

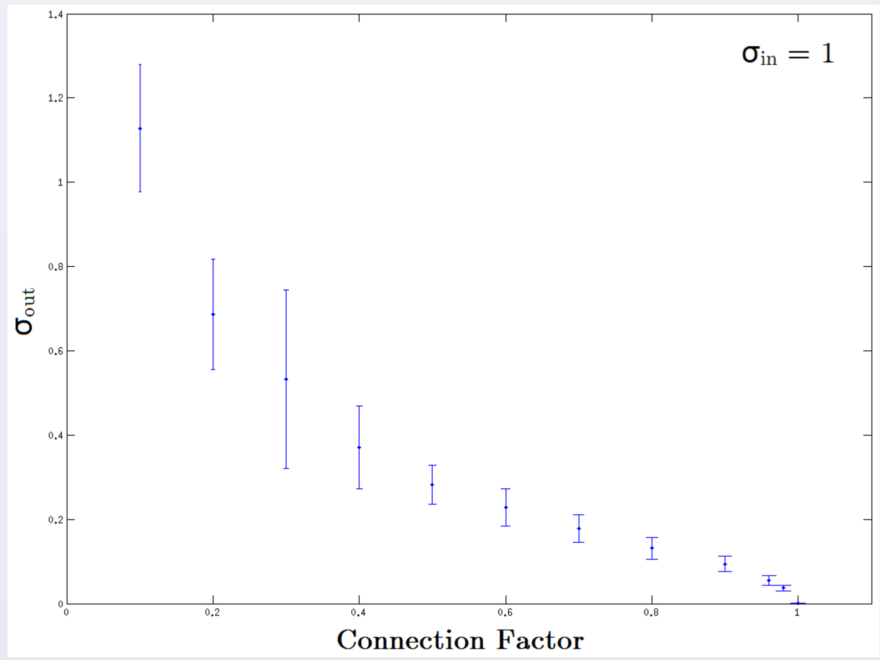

Figure 4. Considering an input consisting of a Gaussian-jittered spike sequence (in this example with a standard deviation $\sigma_{in} = 1$), it is possible to reduce the output jitter of the input spike sequence (i.e., σ_{out}), using a FFN topology (see Fig. 2b). Note that, the more the network is connected, than the connection factor approaches to 1 (i.e., fully connected network case), the more the jitter is reduced. Of course, in order to guarantee that each neuron belonging to the output layer fires, thus, the more the connections are sparse, the more P_w values have to be higher.

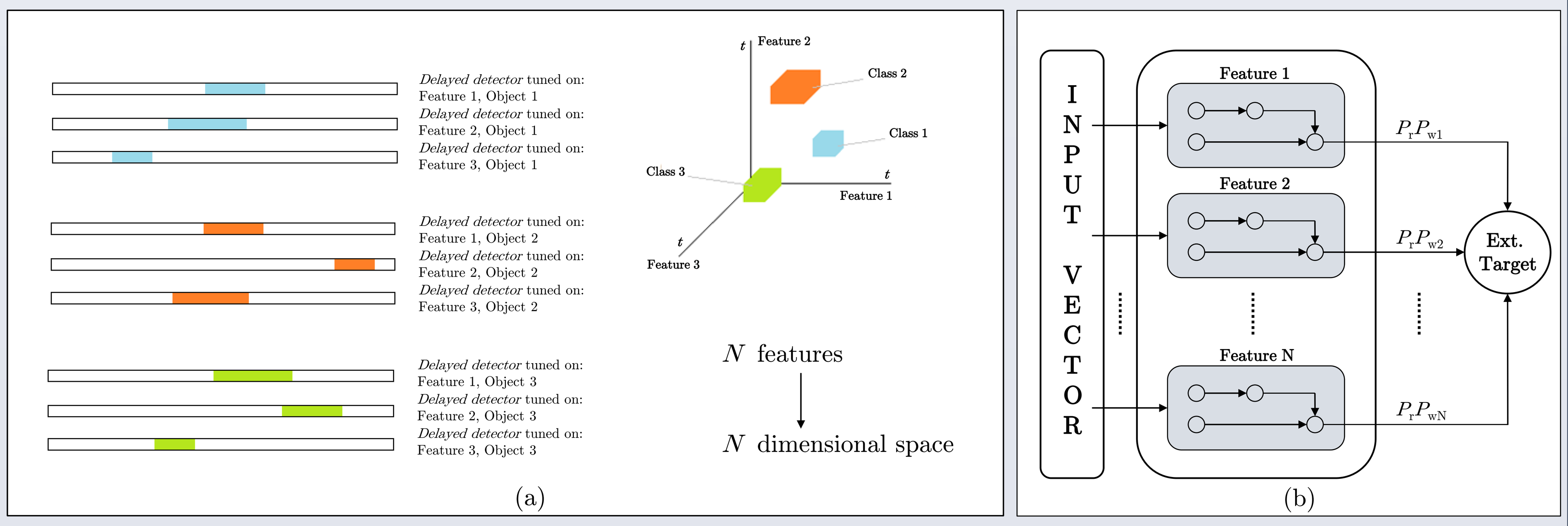

Figure 5. (a) In a three dimensional space, a single object can be represented as a set of three reference features. Each axis is referred to a time interval that permits to quantify a reference feature. For this purpose, each feature detection will be afforded by a specific sequence detector. A proper set of detectors will be necessary in order to indentify a certain class. In this example, an object is described by a set of *N*=3 features. A set of *N* sequence detectors will be necessary in this case, to identify any single class. (b) A SNN Classifier composed by: a spike timing vector that provides the input features to the *group detector*; a group detector consisting of *N spike timing sequence detectors* (see Fig. 2c); finally, an external target. The extracted features can be recognized by the related sequence detectors. The detection of the features is possible only and if only the sequence detectors are tuned to the considered "object" to be recognized. The external target fires only if at least a certain number of features are detected, then the "object" is correctly classified. Note that, the external neuron is a simple combiner with a threshold, but without subthreshold decay.

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AWARDS

Best Poster : "Continuous-time Spiking Neural Networks: general paradigm and event-driven simulation" received at 29th Annual Meeting of Circuit Theory Researchers (ET2013), Padova, June 2013.

Best Paper Category : "Spiking neural networks as analog dynamical systems: basic paradigm and simple applications" received at the International Conference *"Advances in Computer Engineering (ACE 2012)"*, Amsterdam, June 2012.