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Novel Spiking Neuron-Astrocyte Networks based on Nonlinear Transistor-like Models of Tripartite Synapses

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***Abstract*— In this paper a novel and efficient computational implementation of a Spiking Neuron-Astrocyte Network (SNAN) is reported. Neurons are modeled according to the Izhikevich formulation and the neuron-astrocyte interactions are intended as tripartite synapsis and modeled with the previously proposed nonlinear transistor-like model. Concerning the learning rules, the original spike-timing dependent plasticity is used for the neural part of the SNAN whereas an ad-hoc rule is proposed for the astrocyte part. SNAN performances are compared with a standard spiking neural network (SNN) and evaluated using the polychronization concept, i.e., number of co-existing groups that spontaneously generate patterns of polychronous activity. The astrocyte-neuron ratio is the biologically inspired value of 1.5. The proposed SNAN shows higher number of polychronous groups than SNN, remarkably achieved for the whole duration of simulation (24 hours).**

I. INTRODUCTION

Human brain information processing is a complex phenomenon in which neurons and astrocyte are thought to be the mostly involved cells. In particular, considering a tripartite view of synapses, the fundamental brain activity involves two neurons (pre- and post-synaptic) whose signaling is modulated by astrocytes. The pre-synaptic neurotransmitters in the synaptic cleft, in fact, stimulate specific inositol 1,4,5-trisphosphate (IP3) production in the astrocyte leading intra- and extra cellular calcium oscillations [1], [2]. Consequently, the post-synaptic neural activity is modulated in amplitude and frequency [3]. Several biophysical models have been proposed in the literature to mathematically describe these dynamics along with others biochemical events (e.g. cascade of Glutammate, etc.) [1]–[7], especially focusing on the evoked calcium responses in astrocytes [1], [5] and its coupling with the synaptic transmission [2], [3]. The vessel contribution has been also taken into account [8]. Concerning computational models, simple minimal networks of two coupled units, a neuron and an astrocyte (the so-called dressed neuron), have been recently investigated [4], [6]. However, none of the mentioned models have been applied to implement more complex artificial spiking neuron-astrocyte network (SNAN), although the role of astrocytes has been already proven to improve the traditional neural network performances [9], [10]. Therefore, this study aims at the implementation of a novel SNAN based on the nonlinear Transistor-Like Model (TLM) of dressed neuron. This choice is justified by the fact that TLM has been proven to be computational efficient and its output is similar to the more biologically inspired Li-Rinzel model [6]. TLM assumes the dressed neuron dynamics similar to the nonlinear input-output characteristics of a bipolar junction transistor in which the pre-synaptic current and the IP3 production rate characterize the astrocyte current. The proposed SNAN considers both Regular Spiking (RS) and Fast Spiking (FS) behavior of neurons. RS and FS, in fact, are the major class of excitatory and inhibitory neurons in the neocortex, respectively. In the SNAN implementation, both neurons are mathematically described using the Izhikevich equations [11]. A pure spiking neural network (SNN) was considered as gold standard for comparison reasons. More specifically, SNN is constituted by RS and FS neurons with axonal conduction delays and spike-timing-dependent plasticity (STDP) learning rule [12]. It has been demonstrated that such a network is able to polychronize, i.e., neurons spontaneously self-organize into groups and generate patterns of stereotypical polychronous activity [12]. Accordingly, the SNAN and SNN performances were evaluated in terms of number of polychronous groups generated by the network.

Starting from the TLM vision of dressed neuron, section II reports on the implementation of the spiking neuron-astrocyte network. Experimental results are reported in section III pointing out that the inclusion of astrocyte significantly improves the network performances in terms of number of polychronous groups.

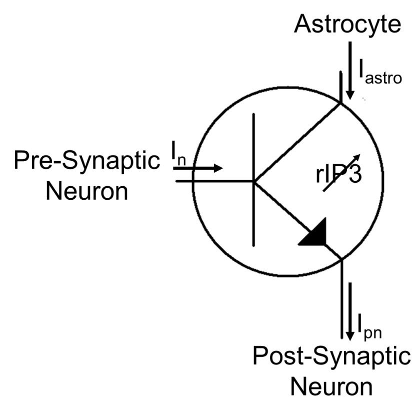

Fig. 1. Graphical representation of the dressed neuron as a nonlinear bipolar junction transistor [6]

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II. Materials and Methods

The tripartite synapse involves a pre-synaptic neuron, a post-synaptic neuron, and an astrocyte. Such a unit, called dressed neuron, is the fundamental part of the SNAN implementation and is comprised of a pre-synaptic neuron, an astrocyte, and a post-synaptic neuron whose currents are linked by the following physiologically plausible [6], [13], [14] relationship:

$$I_{pn}(t) = I_{astro}(t) + I_n(t) \tag{1}$$

where $I_{pn}(t)$ is the post-synaptic current, $I_n(t)$ is the pre-synaptic current, and $I_{astro}(t)$ is the astrocyte current.

The proposed SNAN includes the $I_{astro}(t)$ representation through the TLM and a specific learning rule for production rate of inositol 1,4,5-trisphosphate (r_{IP3}) along with axonal conduction delays and STDP learning rule of synaptic weights. Therefore, the standard SNN can be seen as an SNAN with $I_{astro}(t) = 0$, $\forall t$

A. Neuron-Astrocyte Transistor-Like Model

Since the TLM has been extensively described in [6], this paragraph reports on the basic equations useful for the SNAN implementation. The TLM concept of neuron-astrocyte interaction is shown in Fig. 1.

It has been demonstrated that $I_{astro}(t)$ can exhibit different dynamics according to a specific combination of the $I_n(t)$ and r_{IP3} [6]. Specifically, three behaviors are identified in the $I_n - r_{IP3}$ orthogonal plane defining the so-called Zone 0, Zone 1, or Zone 2. Each zone represents a specific region of the plane bounded by the following threshold curves:

$$\begin{cases} I_{th_1} = z_1 \cdot \sqrt[n_1]{r_{IP3} - p_1} \\ I_{th_2} = z_2 \cdot \sqrt[n_2]{r_{IP3} - p_2} \end{cases} \tag{2}$$

where z_i, n_i, and p_i are fitting parameters [6].

In Zone 0, the $I_{astro}(t) = 0$ since the IP3 concentration is not large enough to induce the necessary calcium oscillations. In Zone 1, the IP3 concentration induces periodic calcium oscillation such that $I_{astro}(t)$ dynamics is a positive rectified sinusoidal wave with variable delay between the start of the input current and the $I_{astro}(t)$ firing. In Zone 2, $I_{astro}(t)$ exhibits an overshoot and decaying oscillations approaching the final value, just like an underdamped second order system. Also in this case, a variable delay between the start of the input current and the $I_{astro}(t)$ firing is induced.

Mathematically, it is possible to write the nonlinear transfer function of the tripartite synapse, h_{syn}, for each zone as follows:

$$h_{syn}(t) = \begin{cases} 0 \\ if\; I_n(t) \leq I_{th_1} \\ \Theta(t - D_1) \cdot A_1 \cdot sin(H) \\ if\; I_{th_1} < I_n(t) \leq I_{th_2} \\ \Theta(t - D_2) \cdot \frac{I^*_{astro} + A_2 \cdot e^{-\frac{t}{\tau}} \cdot sin(2\pi f \cdot t)}{I_n} \\ if\; I_n(t) > I_{th_2} \end{cases} \tag{3}$$

where t is the time expressed in ms, Θ is the Heaviside function, and H is a triangular periodic waveform [6].

Then, the I_{astro} is defined as:

$$I_{astro}(t) = I_n(t) \cdot h_{syn}(t) \tag{4}$$

B. Neuron-astrocyte TLM network Implementation

The RS and FS models of neuron were used for the SNAN implementation. This choice is justified by the fact that they are the major class of excitatory and inhibitory neurons in the neocortex.

Considering the Izhikevich model of neuron [11] and eq. 1, the dynamics of a general post-synaptic neuron is as follows:

$$\begin{cases} v' = 0.04v^2 + 5v + 140 - u + I_n + I_{astro} \\ u' = a(b(v - u) \end{cases} \tag{5}$$

with the condition:

$$if\; v \geq v_{peak},\; then \begin{cases} v \leftarrow c \\ u \leftarrow u + d \end{cases} \tag{6}$$

where v represents the membrane potential, u is the recovery current, and a, b, c and d are related to the neuronal fit.

Concerning the exogenous input, a random current (random thalamic input) was considered [12]. The neural weights were updated according to the STDP rule [12], i.e., a weight is increased if the post-synaptic neuron fires after the pre-synaptic one. Such an increase is equal to $A_+ e^{-t/\tau_+}$. Otherwise, the synaptic weight is decreased of $A_- e^{-t/\tau_-}$. Concerning the r_{IP3}, the following updating rule was used:

$$r_{IP3}(t_+) = r_{IP3}(t) + 0.05(r_{IP3}(t) - r_{IP3}(t_-)) \tag{7}$$

Once the neurons and astrocytes parameters are initialized, the SNAN works with a periodic activity of one minute in which pure neural and neuron-astrocyte activity are switched each 30 s (see Fig. 2). During the first 30 s, in fact, the neural activity only is evaluated each millisecond giving an external input current I_{n_0} randomly given to each neuron. The other network parameters are updated each second according to the STDP rule. Then, during the next 30 s, the I_{astro} is also evaluated for each astrocyte according to eq. 4.

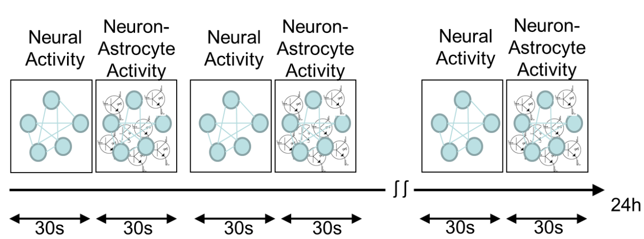

Fig. 2. Timing of the SNAN. The neural and neuron-astrocyte activities alternate each 30s.

Since a generic post-synaptic neuron has multiple pre-synaptic connections, between pure neural or tripartite synapses, each i^{th} post-synaptic current is calculated as follows:

$$I^i_{pn}(t) = \underbrace{\sum_{j=1}^{M_a} I_{n_0} I^j_{astro}(t)/I_{astro_{max}}}_{Astrocyte} + \underbrace{\sum_{j=1}^{M_n} I^j_n(t)}_{Neuron} \quad (8)$$

where M_a and M_n are the fixed numbers of astrocyte and neural connections, respectively, and $I_{astro_{max}}$ is maximum value of I_{astro} related to the Zones 1 and 2.

As performance quantifier, the number of polychronous groups generated by the SNAN was evaluated. It has been demonstrated, in fact, that spiking neural networks comprised of RS and FS neurons with axonal conduction delays and STDP updating rule are able to polychronize [12]. Therefore, for each post-synaptic, such an evaluation was performed considering the spiking activity of several combinations of its pre-synaptic neurons [12].

III. Simulation Setup and Results

We simulated a SNN of 1000 neurons having the first 800 of excitatory RS type, and the remaining 200 of inhibitory FS type. The ratio is taken according to the mammalian neocortex anatomy [12]. Each excitatory neuron is connected to $M_n = 100$ random neurons whereas each inhibitory neuron is connected to $M_n = 100$ excitatory neurons only. Inhibitory weights are not plastic, whereas excitatory weights are updated according to the STDP rule. Each synaptic connection has a fixed integer conduction delay between 1 ms and 20ms.

Then, we simulated a SNAN having 1000 neurons and 1500 associated astrocytes such that the Neuron-Astrocyte ratio is 1.5 as in the human neocortex. The SNAN architecture is similar to the SNN one with $M_a \in \{1, 2\}$ and $M_n = 100$ for each neuron. Such an M_a value ensures that at least one astrocyte is connected to each neuron, i.e., all SNAN synapses are tripartite synapsis. The $I_{astro}(t)$ was computed using the TLM with all the initial $rIP3 = 0.3$ and $I_{astro_{max}} = A_1$ when an astrocyte is in Zone 1 whereas $I_{astro_{max}} = I_{fin} + A2$ in Zone 2. The variables A_1, A_2, and I_{fin} are derived from the TLM computation [6].

Both SNAN and SNN neural parameters were initialized with values found in the literature. Specifically, the excitatory and inhibitory neural weights were set to 6 and -5, respectively [12], and updated each ms. The exogenous input current was set $I_{n_0} = 20$ pA randomly given to each neuron. The STDP parameters were $\tau_+ = \tau_- = 20ms$, $A_+ = 0.1$, and $A_+ = 0.12$ [12]. The model parameters for the RS neurons were $a = 0.02$, $b = 0.2$, $c = -65$, and $d = 8$. The FS parameters were the same for b and c but with $a = 0.1$ and $d = 2$.

The software implementing the SNN and calculus of polychronous groups was found on-line in [15]. Both SNAN and SNN were simulated for 24 hours with a time resolution of 1ms. The number of polychronous groups generated by both networks were evaluated after three, six, twelve, eighteen, and twenty-four hours. Results are shown in Fig. 3. It is straightforward to notice that the SNAN always generate higher number of polychronous groups.

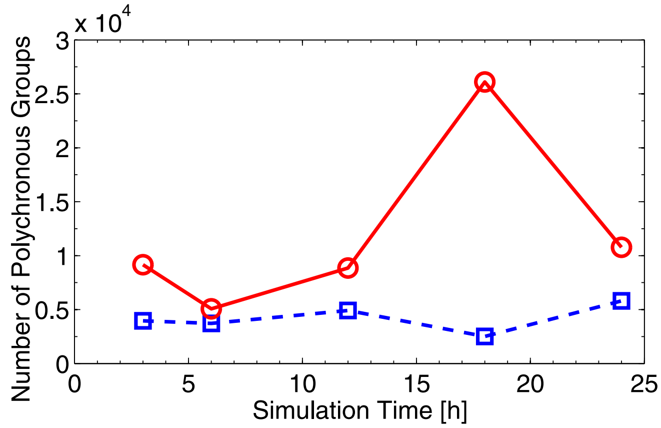

Fig. 3. Comparison, in terms of number of polychronous groups, of the network implementations. The SNAN performances are reported with the red continuous line and circles. The SNN performances are reported with the blue dashed line and squares.

Representative seconds of neural activity, independently captured after 1 hour and 4 hours of simulation, are shown in Figs. 4 and 5. We report that the theta and gamma rhythms found in the SNN during the first seconds of simulation are present also in the SNAN.

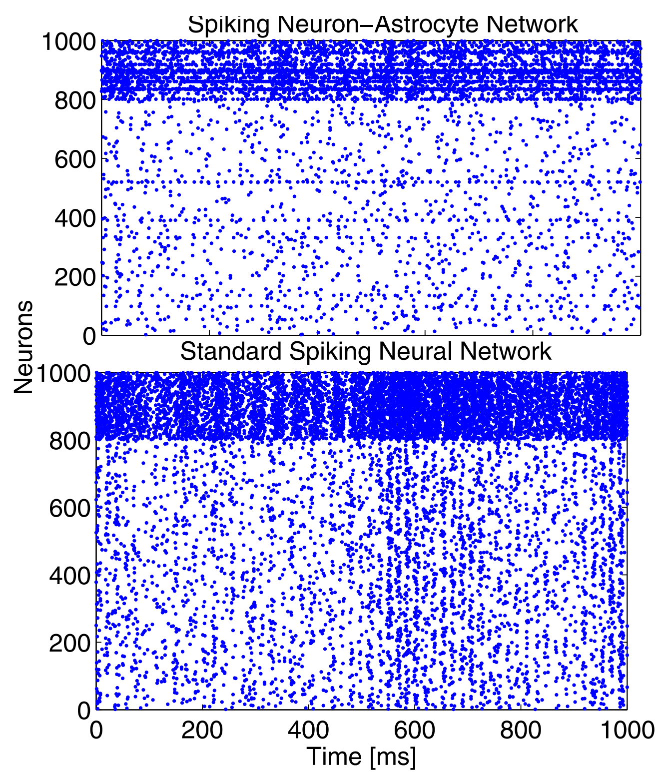

Fig. 4. Representative spiking activities within a second of a SNAN (top) and SNN (bottom) after 1hour of simulation.

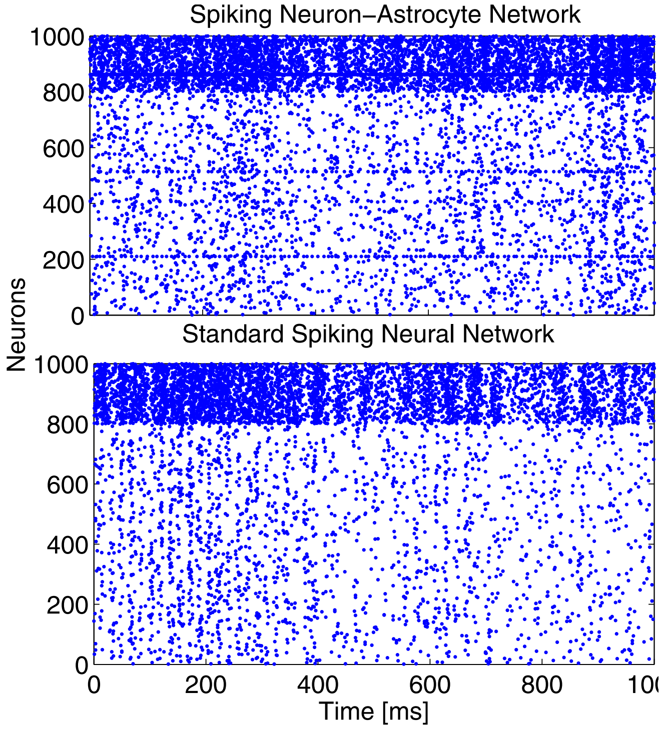

Fig. 5. Representative spiking activities within a second of a SNAN (top) and SNN (bottom) after 4 hours of simulation.

IV. CONCLUSIONS

In this pioneering work, a novel and efficient implementation of Spiking Neuron-Astrocyte Network (SNAN) was presented. It is constituted by RS and FS neurons, modeled as the Izhikevich formulation, which interact with astrocytes according to a tripartite view of synapsis. Astrocytes contribution in the network is intended as post-synaptic current whose dynamics is modeled using our previously proposed nonlinear transistor-like formulation. As the neurons and astrocytes present different time scales (neuron [ms]; astrocyte [s]), the SNAN dynamics switch between pure neural and neuron-astrocyte activity each 30s. We demonstrated that our idea of SNAN is able to generate a significant number of neural groups that spontaneously generate patterns of polychronous activity. Such performances improve the current state of the art, which is constituted by standard spiking neural network (SNN) [12].

As the polychronous neural activity has been associated to the representation of memories of the network [12], we speculate that the proposed SNAN improves such a memory representation improving the bio-inspired computer model of the human brain. Moreover, since it has been demonstrated that SNN are able to also represent coherent external stimuli (intended as deterministic input currents) as polychronized groups, the proposed SNAN could open new dramatic perspectives in other fields such as artificial intelligence for pattern recognition. Finally, the efficient computational formulation of dressed neuron as TLM allows also for an easiest hardware implementation of neuron-astrocyte networks.

Future works will progress to the comparison of SNAN and SNN implementations with different number of neurons as well as further learning rules developed ad-hoc for the continuous co-existing dynamics of neurons and astrocytes. Moreover, sensitivity analyses of important model parameters such as the fixed integral conduction delay of synaptic connection, the number of neurons and astrocytes along with their ratio will be performed.

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