SoftwareX 26 (2024) 101696

Contents lists available at ScienceDirect

SoftwareX

journal homepage: www.elsevier.com/locate/softx

Software update

Release 2.0 — NEMSIM-RT: A real-time distributed spiking neural network simulator

Fernando M. Quintana, Juan C. de la Torre, Guillermo Barcena-Gonzalez, María P. Guerrero-Lebrero, Elisa Guerrero *

Intelligent Systems Research Group, Computer Sciences Department, University of Cadiz, Spain

ARTICLE INFO

Keywords:
Spiking neural network
Neuromorphic systems
Distributed computing
Synaptic plasticity

ABSTRACT

NESIM-RT is a specialized tool designed for simulating neuromorphic systems. In this new release we extend its capabilities to include state-of-the art models like the AdexLIF and Izhikevich, and to incorporate dynamic synaptic mechanisms such as Spike-Timing Dependent Plasticity (STDP). With these new features, researchers can now observe in real-time how different parameters influence these models and learning rules, thereby gaining deeper insights into neuronal function and network dynamics.

Code metadata

Current code version	v2.0
Permanent link to code/repository used for this code version	https://github.com/ElsevierSoftwareX/SOFTX-D-24-00143
Code Ocean compute capsule	
Legal Code License	GPL-3.0
Code versioning system used	git
Software code languages, tools, and services used	C++, Qt.
Compilation requirements, operating environments & dependencies	QtCreator, Qt5.15, Linux-based OS
If available Link to developer documentation/manual	https://github.com/ferper/nesimRT/tree/main/docs
Support email for questions	fernando.quintana@uca.es

1. Introduction

NESIM-RT [1] is characterized by its ability to implement real-time and distributed computing for neural simulations based on the Current-Based Leaky Integrate-and-Fire (CUBA-LIF) model with both excitatory and inhibitory synapses. It was conceived in a distributed way, each neuron represented as an independent node, to be executed in different computers. The communication between neurons in the network was developed through a novel implementation of the MDHCP protocol to support online changes and allow distributed simulation of the network. In this new release AdexLIF and Izhikevich neural models have been implemented. This allows to create new neuromorphic configurations, giving the possibility to create more complex networks with different behaviors. At the same time, we provide learning mechanisms through local learning rules, that consist of a Hebbian learning mechanism such as STDP, requiring only local values to the synapses to be updated.

2. Methodology

2.1. Neuron models

AdexLIF model. The variety of firing patterns that neurons could exhibit in the brain, cannot be represented using a single equation LIF neuron [3]. AdexLIF neurons consists of a coupling differential equation of the membrane potential and an adaptation current [3]. Eq. (1) represents those linear differential equations, where V represents the membrane potential and w the adaptation current that evolves with a time constant τ_w and dependant of the actual membrane value. The membrane voltage nonlinearity consists of a leaky term $-(V - V_r)$ in

DOI of original article: https://doi.org/10.1016/j.softx.2023.101349.
* Corresponding author.
E-mail address: elisa.guerrero@uca.es (Elisa Guerrero).

https://doi.org/10.1016/j.softx.2024.101696
Received 6 March 2024; Received in revised form 13 March 2024; Accepted 14 March 2024
2352-7110/© 2024 The Author(s). Published by Elsevier B.V. All rights reserved.

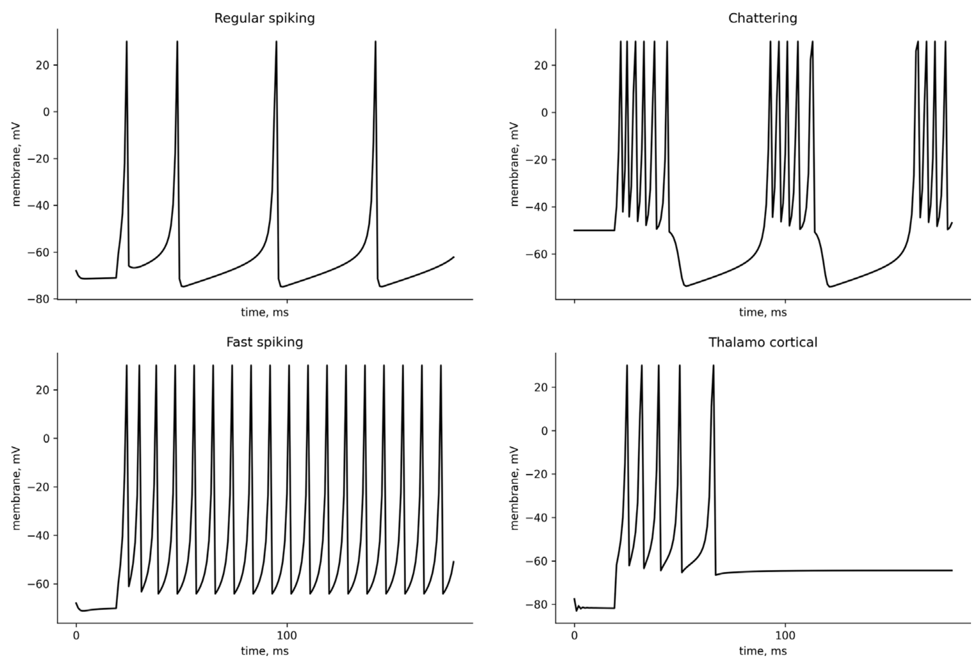

Fig. 1. Neural behavior using Izhikevich neurons with different parameter values for regular spiking, bursting, fast spiking and thalamo cortical neurons. *Source:* Adapted from [2].

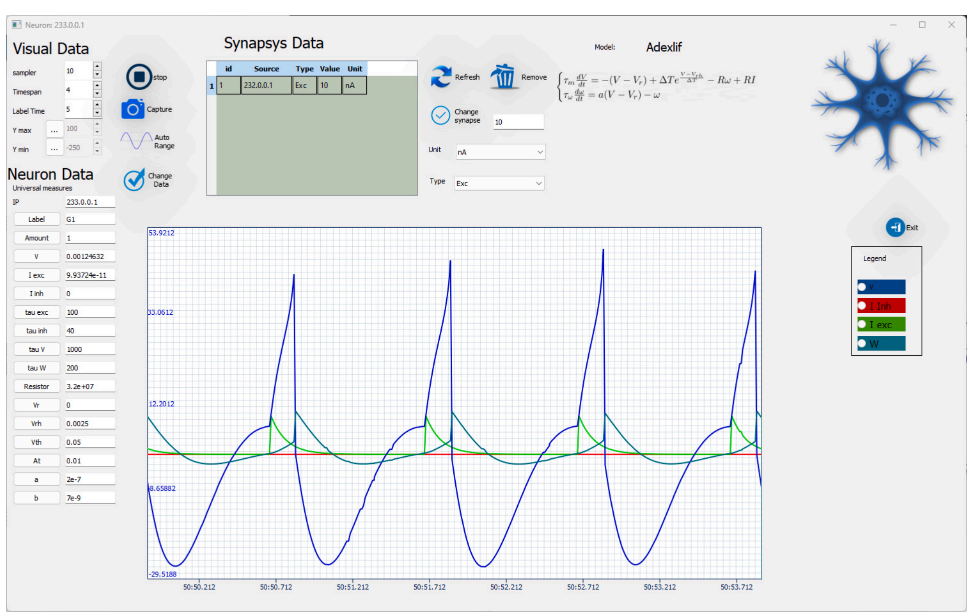

Fig. 2. AdexLIF neuron GUI. On the left we can modify all the values of the neuron. At the top we have all the synaptic connections, which we can see their current value and modify them. In the center we have a real time graph of the neuron values.

combination with an exponential term $\Delta T exp(\frac{V-V_T}{\Delta T})$

$$\tau_m \dot{V} = -(V - V_r) + \Delta T exp(\frac{V - V_T}{\Delta T}) - Rw + RI$$
$$\tau_w \dot{w} = a(V - V_r) - w \tag{1}$$

Izhikevich model. Similar to the AdexLIF, this neuron model has also an adaptation current that increases with the neuron output spike [3]. However, the membrane potential uses a quadratic function as a non linearity instead of an exponential function (Eq. (2)).

$$\dot{V} = 0.04V^2 + 5V + 140 - w + I$$
$$\dot{w} = a(bV - w) \tag{2}$$

Where V represents the membrane potential and w the recovery variable, which can be interleaved as the activation of the K+ ionic current and the inactivation of the Na+ ionic current [2]. In both models, each time the neuron emits a spike, the membrane potential is reset to a certain value and the adapting current is increased by a fixed amount b (Eq. (3)).

$$\text{if } v \geq 30 \text{ mV, then } \begin{cases} V \leftarrow V_r \\ w \leftarrow w + b \end{cases} \tag{3}$$

Both neural models could provide a wide variety of neural behavior e.g. tonic spiking, chattering or frequency adaptation (Fig. 1).

2.2. Synaptic plasticity

With neuromorphic systems and brain-inspired computing, a new computing paradigm emerges where memory and computation are co-localized [4–6], imposing local constraints when applying online and biologically plausible learning. Local learning rules for synaptic plasticity require mainly two Hebbian factors for learning: (1) a presynaptic trace, (2) a postsynaptic value. So the information needed to update the synapse values is local to the synapse at a given instant of time. Additionally it may also depend on an external factor that may be determined as a concentration of neuromodulators that affect synaptic plasticity [7]. Given the inherent nature of these learning rules, their implementation in hardware, such as that for R-STDP [8], is straightforward. This is due to their reliance on locally available synaptic information, including presynaptic and postsynaptic traces, as well as an external signal that weight modifications based on neuromodulator concentration [7].

On NESIM-RT, each synapse is represented as an independent object that receives an event asynchronously from a specific presynaptic neuron. Each time a synapse receives an input spike from the ip node (the neuron) is registered. It will increase the input current (excitatory or inhibitory) of the postsynaptic neuron by a determinate weight value. In this release, a new type of synapse has been created (see Fig. 2), that incorporates synaptic plasticity, enabling learning through local learning rules like STDP.

3. Conclusions

NESIM-RT 2.0 can be used to create different network architectures that can include different interacting neural models as well as synaptic plasticity mechanisms to apply learning to the network. The graphical interface allows to visualize in a direct way and in real time each of the values of the neurons as well as the interactions between them, helping not only to understand the functioning of the network, but also to adjust and optimize it. In addition, the network can be exported to other platforms such as neuromorphic hardware like SpiNNNaker or other simulators like Brian2.

CRediT authorship contribution statement

Fernando M. Quintana: Writing – original draft, Software, Conceptualization. **Juan C. de la Torre:** Validation, Methodology, Formal analysis, Conceptualization. **Guillermo Barcena-Gonzalez:** Methodology, Investigation, Formal analysis. **María P. Guerrero-Lebrero:** Project administration, Methodology, Investigation. **Elisa Guerrero:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

I have shared the link to the source code.

Acknowledgments

Fernando M. Quintana and Juan Carlos de la Torre are funded by the Spanish *Ministerio de Ciencia, Innovación y Universidades* under the FPU grants FPU18/04321 and FPU17/00563. This work was also supported by the project NEMOVISION from the *Ministerio de Ciencia e Innovación*, PID2019-109465RB-I00/ AEI/10.13039/501100011033 and by the Junta de Andalucía and ERDF (GENIUS – P18-2399), and ERDF (OPTIMALE – FEDER-UCA18-108393). It is also part of the project TED2021-131880B-I00, funded by MCIN/AEI/10.13039 /501100011033 and the European Union ‘‘NextGenerationEU’’/PRTR. All the authors want to thank Juan Andres Herrera Rodriguez for his support to the manuscript.

References

[1] Rosa-Gallardo D, de la Torre J, Quintana F, Dominguez-Morales J, Perez-Peña F. Nesim-RT: A real-time distributed spiking neural network simulator. SoftwareX 2023;22.
[2] Izhikevich EM. Simple model of spiking neurons. IEEE Trans Neural Netw 2003;14.
[3] Gerstner W, Kistler WM, Naud R, Paninski L. Neuronal dynamics. Cambridge University Press; 2014 [chapter 6 Adaptation and Firing Patterns].
[4] Chicca E, Stefanini F, Bartolozzi C, Indiveri G. Neuromorphic electronic circuits for building autonomous cognitive systems. Proc IEEE 2014;102:1367–88.
[5] Khacef L, Klein P, Cartiglia M, Rubino A, Indiveri G, Chicca E. Spike-based local synaptic plasticity: A survey of computational models and neuromorphic circuits. 2022.
[6] Quintana F, Perez-Peña F, Galindo P, Netfci E, Chicca E, Khacef L. Etlp: Event-based three-factor local plasticity for online learning with neuromorphic hardware. 2023.
[7] Izhikevich EM. Solving the distal reward problem through linkage of stdp and dopamine signaling. Cerebral Cortex 2007;17:2443–52, [Online]. Available: https://academic.oup.com/cercor/article/17/10/2443/314939.
[8] Quintana F, Perez-Peña F, Galindo P. Bio-plausible digital implementation of a reward modulated stdp synapse. Neural Comput Appl 2022;34.