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RESEARCH ARTICLE | SEPTEMBER 01 2023

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AIP Conf. Proc. 2849, 400009 (2023)
https://doi.org/10.1063/5.0162397

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Solving a Classification Task With Temporal Input Encoding by a Spiking Neural Network With Memristor-Type Plasticity in the Form of Hyperbolic Tangent

Alexander Sboev[1,2,a)], Roman Rybka[1,b)], Danila Vlasov[1,c)] and Alexey Serenko[1,d)]

[1]*National Research Centre "Kurchatov Institute", Moscow, Russia*
[2]*National Research Nuclear University MEPhI, Moscow, Russia*

[a)]Corresponding author: Sboev_AG@nrcki.ru
[b)]rybkarb@gmail.com
[c)]vfked0d@gmail.com
[d)]serenko@phystech.edu

Abstract. The article shows that classification problems can be solved using a single-layer spike neural network with time coding and synapses with memristive plasticity in the form of a hyperbolic tangent. It has been shown that memrisitive plasticity can exhibit the effect of remembering a repetitive spike pattern. The model was tested on the Fisher and Wisconsin breast cancer datasets. The obtained accuracy is comparable with the canonical models of plasticity.

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INTRODUCTION

The problem of training spiking neural networks based on local synaptic plasticity mechanisms, in which the conductance change of a synapse is determined solely by its current conductance and the spiking activities of its presynaptic and posysynaptic neurons, is increasingly relevant thanks to the development of memristors that could serve as a potential component basis for synaptic connections in the hardware implementations of neural networks [1, 2].

In particular, nanocomposite memristors $(CoFeB)_x(LiNbO_3)_{1-x}$ have been recently [3] shown to exhibit the following hyperbolic-tangent dependence of the change ΔG in the synapse conductivity G on the time difference Δt between a presynaptic spike and a postsynaptic spike:

$$\Delta W(\Delta t) = \{ A_+ \frac{1 + \tanh(-)(\Delta t - \mu_+)}{\tau_+}) \quad \text{if} \Delta t > 0, A_- \frac{1 - \tanh(\Delta t - \mu_-)}{\tau_-}) \quad \text{if} \Delta t < 0. \tag{1}$$

A numerical model of a network with input synapses modeling such memristors has been shown to learn to classify the MNIST handwritten digits encoded by mean input spike rates.

This work considers another approach for encoding input data into input spike sequences presented to the network: temporal encoding, in which an input vector is transformed into relative timing of individual input spikes. Since temporal encoding uses fewer input spikes, the processing of each input vector by the network may consume less time and energy. In the literature, the possibility of learning to solve classification tasks with temporal encoding has been shown for the Spike-Timing-Dependent Plasticity (STDP) model [4, 5]. The aim of the current work is to show the possibility of solving classification tasks using synaptic plasticity of the form of the hyperbolic tangent (which models the changes in memristor conductivity) with temporal encoding of input data. With this purpose, we show that a neuron presented with a repeating input spike pattern learns to be specifically sensitive to that pattern, emitting early output spikes in response to it. Then, we demonstrate the possibility of utilizing such effect for solving the benchmark classification tasks of Fisher's Iris and Wisconsin breast cancer.

International Conference of Numerical Analysis and Applied Mathematics ICNAAM 2021
AIP Conf. Proc. 2849, 400009-1–400009-4; https://doi.org/10.1063/5.0162397
Published by AIP Publishing. 978-0-7354-4589-5/$30.00

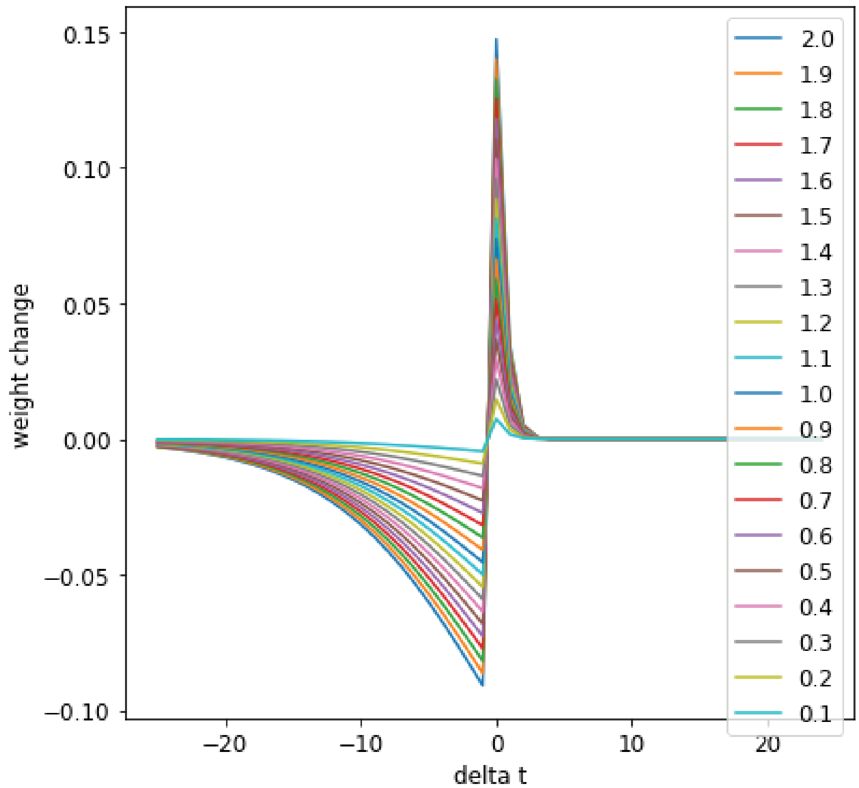

FIGURE 1. The curve of spike timing dependence for the memristive plasticity used: the dependence of the change in synaptic conductance on the interval Δt between a presynaptic spike and postsynaptic spike. Different curves correspond to different initial values of synaptic conductance.

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NEURON AND SYNAPSE MODELS

Leaky Integrate-and-Fire neuron with an exponential form of postsynaptic current was chosen as a neuron model:

$$\frac{dV}{dt} = -\frac{V(t) - V_{\mathrm{rest}}}{\tau_{\mathrm{m}}} + \frac{1}{C_{\mathrm{m}}} \sum_i \sum_{t^i_{\mathrm{sp}}} w_i \left(t^i_{\mathrm{sp}}\right) \frac{q_{\mathrm{syn}}}{\tau_{\mathrm{syn}}} e^{-\frac{t - t^i_{\mathrm{sp}}}{\tau_{\mathrm{syn}}}} \Theta\left(t - t^i_{\mathrm{sp}}\right) + I_{\mathrm{ext}}.$$

When the membrane potential $V(t)$ exceeds the threshold V_{th}, the neuron is considered to fire an output spike, after which $V(t)$ is reset to 0. The neuron gets insensitive to input spikes during the refractory period t_{ref}. Here $q_{\mathrm{syn}} = 5$ fC, $\tau_{\mathrm{syn}} = 5$ ms. The constants V_{th}, τ_{m}, and t_{ref} are adjusted for the optimal classification performance and presented in Table 1. I_{ext} is the external stimulation current applied during training, which will be described further. t^i_{sp} are the times if input spikes arriving at i-th input. w_i is the dimensionless weight of i-th input synapse, which models the conductivity of a memristor and changes after each presynaptic and postsynaptic spike in accordance with Eq. 1 (see Fig. 1). The parameters of the plasticity model are taken from the literature [3], except τ^+ and τ^-, which are adjusted for each classification task.

DATASETS

Two benchmark classification tasks are considered: Fisher's Iris and Wisconsin breast cancer. The Fisher's Iris dataset consists of 150 4-dimensional vectors belonging to three classes, 50 vectors in each. The Wisconsin breast cancer dataset contains 569 30-dimensional vectors, 357 of which belong to the class "benign" and 212 belong to the class "malignant".

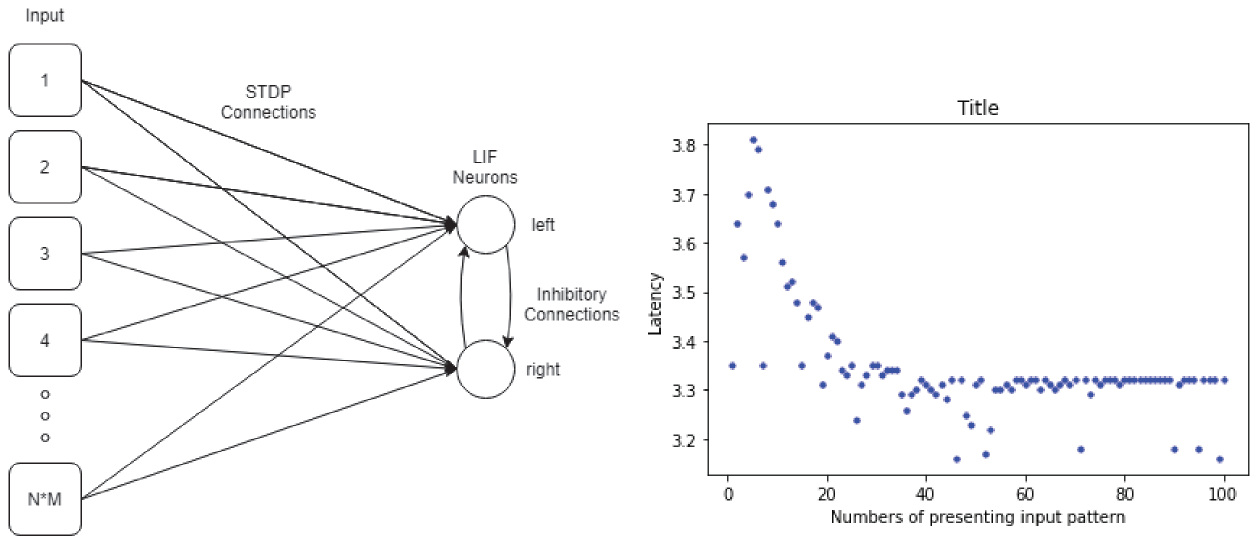

FIGURE 2. At the left: the neural network topology. At the right: the latency between an output spike and the beginning of presenting the input pattern, depending on how many times the input pattern has been presented.

Before being inputted to the spiking network, the input vectors are normalized so that each component are in the range of 0 to 1, and then are processed with Gaussian receptive fields [6, 7, 8]. The latter transform an N-dimensional vector $\vec{x}$ into an $N \cdot M$-dimensional vector, where M is the number of receptive fields. Each vector component x^i is converted into M components $g(x^i, \mu_0), \ldots, g(x^i, \mu_M)$, where $g(x^i, \mu_j) = \exp\left(\frac{(x^i - \mu_j)^2}{\sigma^2}\right)$. Here $\mu_j = X^i_{\text{min}} + (X^i_{\text{max}} - X^i_{\text{min}}) \cdot \frac{j}{M-1}$ is the center of the j-th receptive fields, and X^i_{max} and X^i_{min} are the maximum and the minimum of the i-th vector component over all vectors of the training set.

After processing with receptive fields, the vector $\vec{x}$ is presented to the input of spiking neurons, encoded by spike times: i-th input synapse of a neuron receives an input spike at time $T \cdot (1 - x_i)$, where $T = 25$ ms is the duration of presenting one input vector.

EXPERIMENTS

We begin by checking that the memristive plasticity exhibits the repeating spike pattern memorizing effect shown previously [9, 10] for Spike-Timing-Dependent Plasticity. We simulate a single neuron receiving one vector from the Fisher's Iris dataset, alternated with random Poisson input spike sequences.

Then, we evaluate the performance of solving the classification tasks of Fisher's Iris and Wisconsin breast cancer. For this, a learning algorithm is employed in which the neurons' memorizing their own classes is induced by a reinforcement stimulation. The network consists of as many neuron as many classes are there in the classification task, and each neuron is assigned its class beforehand. The neurons have input synapses with memristive plasticity and are also connected to each other via non-plastic inhibitory synapses (see Fig. 2, at the left). During training, the neurons receive input spike patterns that encode the training set vectors, and the neuron that corresponds to the class of a vector being inputted is stimulated by a brief impulse of external current at the beginning of presenting the input pattern, so that to make that neuron fire a spike. The output spike thus induced causes the synaptic plasticity to facilitate the inputs that receive input spikes early at the beginning of the input patterns. At the same time, thanks to the inhibitory inter-neuronal connections, the induced spike of a neuron corresponding to the current class decreases the probability of spikes of other neurons, thus preventing the facilitation of their weights during the presentation of classes the neurons are not assigned to.

Learning is performed using 5-fold cross-validation. The classification performance is assessed by the F1-macro score.

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RESULTS

Presenting a repeating spike pattern to a neuron causes the plasticity to establish such synaptic weights that the neuron spikes earlier and earlier, close to the beginning of presenting the input pattern (see Fig. 2, at the right), and at the same time gradually ceases to fire spikes in response to Poisson noise.

The accuracies of solving the Fisher's Iris and Wisconsin breast cancer classification tasks, along with the neuron and synapse model parameters for each of these tasks, are presented in Table 1.

TABLE 1. The neuron and synapse model parameters of a spiking neural network based on memristive plasticity and temporal encoding, and the accuracy (by the F1-score metric) of solving the Fisher's Iris and Wisconsin breast cancer (WBC) classification tasks with this network

Classification task	V_{th}, mV	τ_m, ms	t_{ref}, ms	τ^+, ms	τ^-, ms	μ^+, ms	μ^-, ms	F1-score, %
Iris	8	13	10	1	12	0	0	97
WBC	8	13	10	1	12	0	0	91

CONCLUSION

The results obtained prove the possibility of solving classification tasks based on synaptic plasticity of the form of hyperbolic tangent, which models the plasticity of memristors, using temporal encoding of input data. The accuracies obtained, though inferior to those of formal neural networks, are comparable to results achieved by spiking networks with other synaptic plasticity models [11].

This result is a step towards a systematic study of learning methods for spiking neural networks with various memristive plasticity forms for solving practical tasks.

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ACKNOWLEDGMENTS

This work has been supported by the Russian Science Foundation grant No.21-11-00328 and carried out using computing resources of the federal collective usage center Complex for Simulation and Data Processing for Mega-science Facilities at NRC "Kurchatov Institute", http://ckp.nrcki.ru/.

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