A Non-fully-Connected Spiking Neural Network with STDP for Solving a Classification Task

A. Sboev, R. Rybka, A. Serenko and D. Vlasov

Abstract This paper presents a concept of a non-fully-connected spiking network capable of solving a classification task by means of the local bio-inspired learning rule of Spike-Timing-Dependent Plasticity. The network comprises one layer of neurons, each neuron receiving a subset of the input vector components. Input vectors are encoded by mean rates of Poisson input sequences. After training several networks each on its own class, the output spiking rates contain the information on the classes, which can be extracted with a conventional learning algorithm. We demonstrate that the STDP-based classification algorithm proposed achieves competitive accuracy on both discrete-data task of handwritten digits recognition (96% $\pm$ 1%) and classification of real-valued vectors of Fisher's Iris (93% $\pm$ 3%). The attractive feature of the algorithm is the simplicity of the network structure without much loss in classification accuracy. This property gives the possibility to implement classifiers based on the proposed algorithm in robotic devices with limited resources.

Keywords Spike-timing-dependent plasticity · Synaptic plasticity · Spiking neural networks

1 Introduction

The recent time have seen an increase in interest in building locally-learnable neural network algorithms for solving classification tasks. The relevance of this topic owes to the progress in energy-efficient memristor [1] hardware implementations of neuromorphic computing devices [2, 3]. The majority of works devoted to developing spiking network topologies [3–7] consider the image recognition task, and networks are usually trained by error backpropagation [8, 9], or by various modifications of synaptic plasticity rules [4, 10], including reward-modulated STDP [5,

A. Sboev (✉) · R. Rybka · A. Serenko · D. Vlasov
National Research Centre "Kurchatov Institute", Moscow 123182, Russia
e-mail: sboev_ag@nrcki.ru

A. Sboev · D. Vlasov
National Research Nuclear University MEPhI (Moscow Engineering Physics Institute), Moscow 115409, Russia

S. Y. Misyurin et al. (eds.), *Advanced Technologies in Robotics and Intelligent Systems*, Mechanisms and Machine Science 80, https://doi.org/10.1007/978-3-030-33491-8_27

6]. For the sake of memristor implementation, local plasticity algorithms [11] seem suitable, such as the bio-inspired long-term synaptic plasticity model Spike-Timing-Dependent Plasticity (STDP) [12]. The main challenge when designing a neural network is to achieve a topology that would be both universal with regard to the type of task and at the same time uncomplicated and not prone to overfitting, within a tradeoff between the complexity of the task and the simplicity of the classifying network with its limited number of adjustable parameters (Occam's razor). This work shows that such tradeoff could be achieved by a non-fully-connected spiking network with rate encoding of input data, described in Sect. 2, which allows to achieve acceptable accuracy solving not only the image recognition task (tested on the Optdigits dataset), but also the task of classifying real-valued vectors of the Fisher's Iris dataset. The comparison of the results of this model to the ones of other models in Sect. 4 shows the former to be competitive in spite of having a fewer number of adjustable parameters.

2 Methods

2.1 Datasets

We test our model on two benchmark datasets, Fisher's Iris and Optdigits, available in the UCI repository [13]. The Iris dataset consists of 150 flowers described by four real-valued features—length and width of sepal and petal in centimeters. The flowers are divided into 3 classes, 50 in each: Iris Setosa Canadensis, Iris Virginica and Iris Versicolor.

The Optdigits dataset [14], collected in Bogazici University, Turkey, consists of 1797 8×8 images of handwritten digits 0–9 (hence the total of 10 classes), which the dataset maintainers obtained by compressing the original 32×32 images. An image is described by a 64-dimensional vector of greyscale pixel intensities, represented by integer values in the range from 0 to 16.

Before encoding any of the datasets into incoming spike sequences, it was normalized so that the Euclidian norm of each input vector equaled 1.

2.2 Neuron Model

The choice of neuron model and its parameter values, as well as the parameters of the plasticity model, are based on the preliminary study [15], where these parameters were adjusted for solving a classification task by single neurons with STDP. We use the Leaky Integrate-and-Fire neuron with the exponential form of postsynaptic current:

$$dV/dt = -(V(t) - V_{\text{rest}})/\tau_{\text{m}} + 1/C_{\text{m}} \Sigma_i \Sigma_t w_i(t_{\text{sp}})\, q_{\text{syn}}/\tau_{\text{syn}}$$
$$\exp\left(-\left(t - t_{\text{sp}}\right)/\tau_{\text{syn}}\right) \ominus \left(t - t_{\text{sp}}\right), \tag{1}$$

where V is the membrane potential, C_{m} is the membrane capacity, $\tau_{\text{m}} = 10$ ms is the membrane leakage time constant, w_i is the weight of the ith synapse, t_i are the time moments when presynaptic spikes arrive at ith synapse, and Θ is the Heaviside step function. As soon as V reaches a threshold potential $V_{\text{th}} = -54$ mV, V is instantaneously reset back to the resting potential $V_{\text{rest}} = -70$ mV, and the neuron is unable to change its potential for the refractory period $\tau_{\text{ref}} = 3$ ms. $C_{\text{m}} = 0.55$ pF for the Iris task, while for the Digits task the optimal membrane capacity was found to be $C_{\text{m}} = 2.88$ pF, probably because the neuron has to accommodate for the higher number of input synapses.

2.3 Plasticity Model

The input synapses of the network have additive Spike-Timing-Dependent Plasticity, in which a synaptic weight $0 \leq w \leq w_{\max} = 1$ changes by Δw according to the relative timing of presynaptic spikes t_{pre} and postsynaptic spikes t_{post}:

$$\Delta w = -\alpha\lambda \exp(-\left(t_{\text{pre}} - t_{\text{post}}\right)/\tau^{-}) \text{ if } t_{\text{pre}} - t_{\text{post}} < 0,$$
$$\Delta w = \lambda \exp(-\left(t_{\text{post}} - t_{\text{pre}}\right)/\tau^{-}) \text{ if } t_{\text{pre}} - t_{\text{post}} > 0. \tag{2}$$

An additional constraint is needed to prevent the weight from falling below zero or exceeding the maximum value of 1: if $\text{w} + \Delta\text{w} > \text{w}_{\max}$, then $\Delta\text{w} = \text{wmax} - \Delta\text{w}$; if $\text{w} + \Delta\text{w} < 0$, then $\Delta\text{w} = \text{w}$.

Here the learning rate λ is set as low as the computing resources permit, we set it to 10^{-3}. For the Iris task, $\alpha = 1.035$, $\tau^{-} = \tau^{+} = 20$ ms. For the Digits task, the optimal parameters adjusted are $\alpha = 1.367$, $\tau^{-} = 25$ ms, $\tau^{+} = 89$ ms. However, preliminary studies [16] showed adjusting STDP parameters to have little effect on the learning performance, thus showing the learning algorithm under consideration to be robust in a wide range of STDP parameters.

2.4 Network Configuration

The setup consists of several equivalent networks, corresponding to the number of classes in the dataset: three networks for Iris and ten networks for Digits. During training, each network receives training set samples of its corresponding class.

A network consists of one layer of LIF neurons, each of which receives its own subset of input components (see Fig. 1). For the Iris task, each neuron receives two out of four components (leading to six possible combinations). For the Digits task,

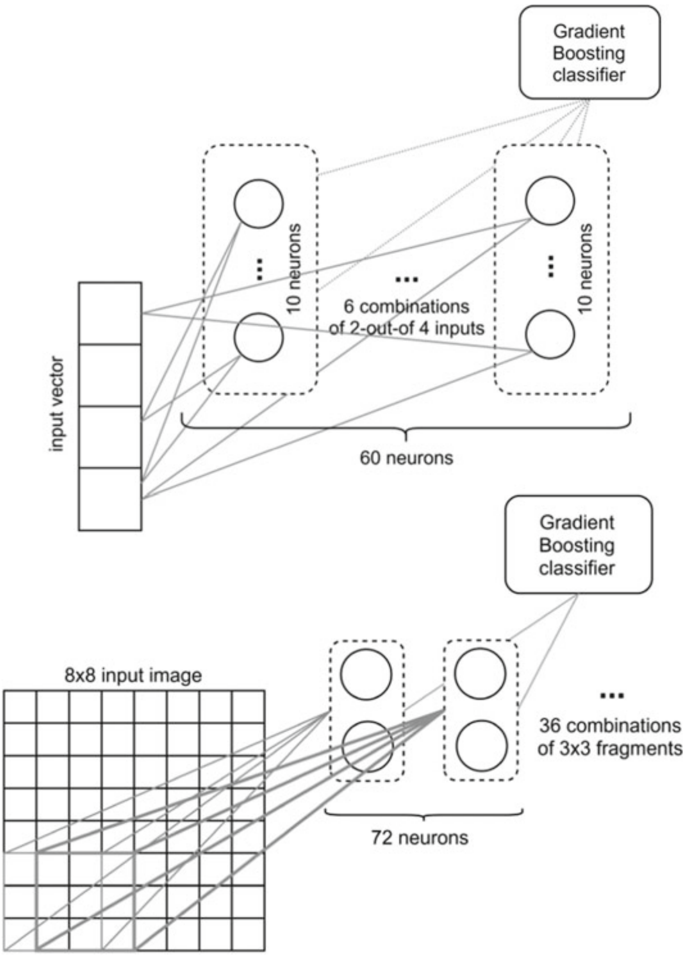

Fig. 1. The scheme of the network topology: top—for the Fisher's Iris classification task; bottom—for the handwritten digits recognition task

each neuron receives input pixels from a 3×3 square fragment. Different neurons' fragments can overlap, so the number of such fragments out of an 8×8 image is 36.

We employ redundancy in the number of neurons, letting each input combination be present in 10 neurons for the Iris task (therefore a layer has the total of 60 neurons), and in two neurons for Digits (thus the total of 72 neurons).

Input vectors are presented to the network in the form of rate encoding: a component x_i of an input vector x is encoded by a bunch of 25 (for Iris) or 7 (for Digits) independent Poisson spike sequences of the mean frequency $x \cdot 300$ Hz + 3 Hz. That way, each neuron has $25 \cdot 2 = 50$ input synapses in the Iris task, and $7 \cdot 3 \cdot 3 = 63$ input synapses in the Digits task. The duration of presenting spike sequences encoding one input vector is 2 s for Iris and 1 s for Digits (decreased in the latter case so as to speed up the simulations).

Decoding output spiking rates of the neurons into class labels is carried out with the help of the conventional Gradient Boosting classifier, with all its parameters kept at default in the scikit-learn package.

3 Experiments

Learning is performed with 5-fold cross-validation, during which 4/5 of the randomly shuffled dataset are used for training, and the remaining 1/5 for testing, after which another one fifth is selected for testing, and so on. After training each network on samples of its corresponding class, the synaptic weights are fixed, and training and testing samples of all the classes are fed to all the networks.

Decoding the output spiking rates into class labels is carried out by training the conventional Gradient Boosting classifier. The classifier is trained on the output rates of all the neurons of all the networks in response to training set samples, and then is to predict class labels of testing set samples by the neurons' spiking rates in response to them.

4 Results

The classification F1-score obtained on the Optdigits dataset is 96% ± 1%. For comparison, a one-layer formal neural network [17] gave the accuracy of 90%. An STDP spiking network of one excitatory neurons layer interconnected with inhibitory synapses achieved the accuracy of 95% on a similar MNIST handwritten digits dataset [18]. However, the accuracy on MNIST cannot be compared directly to the one obtained on Optdigits due to the higher number of samples in the former. Assessing the performance of our network on MNIST will be a goal of our future work.

The F1-score obtained on the Fisher's Iris dataset is 93% ± 3%, which is inferior to formal neural networks which achieve up to 100% [19, 20], but comparable to 96% achieved by a backpropagation-trained spiking neural network [21].

5 Conclusion

A non-fully-connected spiking network with STDP learning and rate input encoding is capable of learning not only a handwritten digits classification tasks, but also the real-valued Fisher's Iris classification task. After learning, the output spiking frequencies of the network possess the information sufficient for distinguishing the classes. Decoding the output frequencies with the help of a conventional learning algorithm shows acceptable classification accuracies of 93% ± 3% on the real-valued Fisher's iris dataset and 96% ± 1% on the Optdigits dataset. This suggests that the proposed network scheme could be used as a layer in a multilayer network, where the information inferred by the non-fully-connected layer would be extracted by the subsequent layers.

Acknowledgements The study was carried out by a Russian Science Foundation grant 17-71-20111. The work was 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/.

References

1. Saïghi, S., Mayr, C.G., Serrano-Gotarredona, T., Schmidt, H., Lecerf, G., Tomas, J., Grollier, J., Boyn, S., Vincent, A.F., Querlioz, D., La Barbera, S., Alibart, F., Vuillaume, D., Bichler, O., Gamrat, C., Linares-Barranco. B.: Plasticity in memristive devices for spiking neural networks. Front. Neurosci. **9**(MAR), 51 (32 pp.) (2015)
2. Merolla, P.A., Arthur, J.V., Alvarez-Icaza, R., Cassidy, A.S., Sawada, J., Akopyan, F., Jackson, B.L., Imam, N., Guo, C., Nakamura, Y., Brezzo, B., Vo, I., Esser, S.K., Appuswamy, R., Taba, B., Amir, A., Flickner, M.D., Risk, W.P., Manohar, R., Modha, D.S.: A million spiking-neuron integrated circuit with a scalable communication network and interface. Science **345**(6197), 668–673 (2014)
3. Esser, S.K., Merolla, P.A., Arthur, J.V., Cassidy, A.S., Appuswamy, R., Andreopoulos, A., Berg, D.J., McKinstry, J.L., Melano, T., Barch, D.R., Di Nolfo, C., Datta, P., Amir, A., Taba, B., Flickner, M.D., Modha, D.S.: Convolutional networks for fast, energy-efficient neuromorphic computing. Proc. Natl. Acad. Sci. U. S. A. **113**(41), 11441–11446 (2016)
4. Tavanaei, A., Maida, A.S.: Bio-inspired spiking convolutional neural network using layer-wise sparse coding and STDP learning. https://arxiv.org/abs/1611.03000 (2016)
5. Mozafari, M., Ganjtabesh, M., Nowzari-Dalini, A., Thorpe, S.J., Masquelier, T.: Combining STDP and reward-modulated STDP in deep convolutional spiking neural networks for digit recognition. https://www.reddit.com/r/MachineLearning/comments/8v5lrk/r_combining_stdp_and_rewardmodulated_stdp_in_deep/ (2018)
6. Mozafari, M., Ganjtabesh, M., Nowzari-Dalini, A., Thorpe, S.J., Masquelier, T.: Bio-inspired digit recognition using reward-modulated spike-timing-dependent plasticity in deep convolutional networks. Pattern Recognit. **94**, 87–95. https://arxiv.org/abs/1804.00227 (2019)
7. Kheradpisheh, S.R., Ganjtabesh, M., Thorpe, S.J., Masquelier, T.: STDP-based spiking deep convolutional neural networks for object recognition. Neural Netw. **99**, 56–67 (2018)
8. Lee, J.H., Delbruck, T., Pfeiffer, M.: Training deep spiking neural networks using backpropagation. Front. Neurosci. **10**, 508 (13 pp.) (2016)
9. O'Connor, P., Welling, M.: Deep spiking networks (16 pp.). https://arxiv.org/abs/1602.08323 (2016)
10. Beyeler, M., Dutt, N.D., Krichmar, J.L.: Categorization and decision-making in a neurobiologically plausible spiking network using a STDP-like learning rule. Neural Netw. **48**, 109–124 (2013)
11. Serrano-Gotarredona, T., Masquelier, T., Prodromakis, T., Indiveri, G., Linares-Barranco, B.: STDP and STDP variations with memristors for spiking neuromorphic learning systems. Front. Neurosci. **7**(7), 2 (15 pp.) (2013)
12. Bi, G.-Q., Poo, M.-M.: Synaptic modification by correlated activity: Hebb's postulate revisited. Annu. Rev. Neurosci. **24**, 139–166 (2001)

13. Dua, D., Graff, C.: UCI machine learning repository. http://archive.ics.uci.edu/ml, University of California, Irvine (2017)
14. Alpaydin, E., Kaynak. C.: Optical recognition of handwritten digits data set. UCI: Machine Learning Repository, vol. 64 (1995)
15. Sboev, A., Serenko, A., Rybka, R., Vlasov. D.: Influence of input encoding on solving a classification task by spiking neural network with STDP. In: International Conference of Numerical Analysis and Applied Mathematics (ICNAAM 2018). AIP Conference Proceedings, vol. 2116, p. 270007 (4 pp.) (2019)
16. Sboev, A., Serenko, A., Rybka, R., Vlasov, D., Filchenkov, A.: Estimation of the influence of spiking neural network parameters on classification accuracy using a genetic algorithm. Procedia Comput. Sci. **145**, 488–494 (2018)
17. Sotelo, D., Velásquez, D., Cobos, C., Mendoza, M., Gómez, L.: Optimization of neural network training with ELM based on the iterative hybridization of differential evolution with local search and restarts. In: Nicosia, G., Pardalos, P., Giuffrida, G., Umeton, R., Sciacca, V. (eds.) Machine Learning, Optimization, and Data Science. LOD 2018. LNCS, vol. 11331, pp. 38–50. Springer, Cham, Volterra, Italy (2018)
18. Diehl, P.U., Cook, M.: Unsupervised learning of digit recognition using spike-timing-dependent plasticity. Front. Comput. Neurosci. **9**, 99 (9 pp.) (2015)
19. Abdulkadir, R.A., Imam, K.A., Jibril, M.B.: Simulation of back propagation neural network for iris flower classification. Am. J. Eng. Res. **6**(1), 200–205 (2017)
20. Patil, P.M., Sontakke, T.R.: Rotation, scale and translation invariant handwritten Devanagari numeral character recognition using general fuzzy neural network. Pattern Recognit. **40**(7), 2110–2117 (2007)
21. Ghosh-Dastidar, S., Adeli, H.: A new supervised learning algorithm for multiple spiking neural networks with application in epilepsy and seizure detection. Neural Netw. **22**(10), 1419–1431 (2009)