Nonlinear Dynamics and Neuroscience

Izvestiya Vysshikh Uchebnykh Zavedeniy. Applied Nonlinear Dynamics. 2024;32(2)

Article DOI: 10.18500/0869-6632-003092

Study of the influence of synaptic plasticity on the formation of a feature space by a spiking neural network[1]

A. A. Lebedev[1], *V. B. Kazantsev*[1,2], *S. V. Stasenko*[1,2]✉

[1]National Research Lobachevsky State University of Nizhny Novgorod, Russia
[2]Moscow Institute of Physics and Technology, Russia
E-mail: lebedev_rf_unn@mail.ru, kazantsev@neuro.nnov.ru, ✉stasenko@neuro.nnov.ru
Received 5.10.2023, accepted 18.11.2023, available online 19.02.2024, published 29.03.2024

Abstract. The *purpose* of this study is to study the influence of synaptic plasticity on excitatory and inhibitory synapses on the formation of the feature space of the input image on the excitatory and inhibitory layers of neurons in a spiking neural network. *Methods.* To simulate the dynamics of the neuron, the computationally efficient model "Leaky integrate-and-fire" was used. The conductance-based synapse model was used as a synaptic contact model. Synaptic plasticity in excitatory and inhibitory synapses was modeled by the classical model of time dependent synaptic plasticity. A neural network composed of them generates a feature space, which is divided into classes by a machine learning algorithm. *Results.* A model of a spiking neural network was built with excitatory and inhibitory layers of neurons with adaptation of synaptic contacts due to synaptic plasticity. Various configurations of the model with synaptic plasticity were considered for the problem of forming the feature space of the input image on the excitatory and inhibitory layers of neurons, and their comparison was also carried out. *Conclusion.* It has been shown that synaptic plasticity in inhibitory synapses impairs the formation of an image feature space for a classification task. The model constraints are also obtained and the best model configuration is selected.

Keywords: spiking neural network, synaptic plasticity, machine learning, image classification.

Acknowledgements. In terms of studying model configurations when generating an indicative description from an excitatory population of neurons the work was supported by grant from the Government of the Nizhny Novgorod Region for young scientists (agreement No. 316-06-16-111a/23 from 4 july 2023), in terms of studying model configurations when generating an indicative description from an inhibitory population of neurons the work was supported by grant from the Russian Science Foundation (project No. 23-11-00134).

For citation: Lebedev AA, Kazantsev VB, Stasenko SV. Study of the influence of synaptic plasticity on the formation of a feature space by a spiking neural network. Izvestiya VUZ. Applied Nonlinear Dynamics. 2024;32(2): 253–267. DOI: 10.18500/0869-6632-003092

[1]The paper presents materials of a talk given at the conference "Neuroinformatics — 2023".

Introduction

Encoding information in spiking neural networks is an active research topic in neuroscience and machine learning. This approach to information processing has its unique advantages, such as low power consumption, high computational efficiency and the ability to process signals in real time. In the article, by information encoding we will understand the mapping of input data vectors into input spike trains, and the transformation of input spike trains into output ones, which is performed by a spiking neural network, will be called the selection of significant features. Currently, various encoding methods have been proposed.

One common encoding method is the spacing between spikes. For example, in rate coding, information is represented by the number of spikes in a specific time window. The more spikes a neuron generates over a certain period of time, the higher the value of the transmitted information. This encoding method has been widely studied in both biological systems and spiking neural networks. For example, Song et al [1] showed that spiking neural networks can achieve robust frequency encoding by adjusting synaptic weights between neurons. Another method is time coding. Here, information is encoded by the time interval between successive spikes. The relative time between pulses can carry specific information about the stimulus. For example, a shorter interval may mean the transmission of a unit of information, and a longer one may mean a zero. Thorpe et al [2] proposed the concept of "temporal coupling" and showed that spiking neural networks can use precise firing timing to efficiently encode and process information. There are also other encoding methods such as rank-order coding [3] and phase coding [4]. Burst coding relies on the collective activity of a group of neurons to represent information. The pattern of activity in a population carries encoded information. A study by Bohte et al [5] showed that spiking neural networks can learn to encode input signals using distributed burst dynamics. The choice of a specific coding method depends on the task and characteristics of a particular spiking neural network. In addition, decoding of spike information plays an important role in the analysis and interpretation of these data.

The involvement of spike-timing-dependent synaptic plasticity (STDP) in information encoding is one of the important topics in the study of spiking neural networks. STDP is a form of synaptic plasticity that is based on the timing of spikes in presynaptic and postsynaptic neurons. STDP weakens or strengthens connections between neurons based on the time intervals between spikes. If a presynaptic neuron spikes before a postsynaptic neuron, the synapse is strengthened, causing the connection to increase in weight. If a presynaptic neuron spikes after a postsynaptic neuron, the synapse weakens, resulting in a decrease in connection weight. Such feedback, along with other mechanisms, allows the neural network to learn and adapt to the presented stimuli and images [6–9]. The STDP rule can be used to encode and store information in the [10] network. Neurons that fire frequently at the same time can form stronger connections among themselves, while neurons that fire weakly can have weaker connections. The work of Masquelier et al [11] showed that STDP can enable a spiking neural network to extract features from natural images. STDP is also actively researched and applied in the field of machine learning and intelligent systems. The application of STDP to the problem of information processing based on spiking networks opens up new opportunities for creating efficient and energy-efficient learning and recognition algorithms.

Extracting new features from images using spiking neural networks is an active area of research that has the potential to develop efficient methods for image processing and analysis [12]. Spiking neural networks are a powerful tool for image analysis and classification because they can take into account the timing of signals and provide low processing latency.

In this paper, we propose a model for extracting significant image features using a spiking neural network with synaptic plasticity for the recognition task. The number of spikes on each neuron in the inhibitory and excitatory layers is used as a new feature space. Based on the proposed model, we study the influence of synaptic plasticity at excitatory and inhibitory synapses on the formation of a new feature space of the input image on the excitatory and inhibitory layers of neurons of the spiking neural network.

1. Methodology

1.1. Mathematical model of a neuron. The neuron dynamics in our model were described using the Leaky-Integrate-and-Fire (LIF) neuron model [13]. The system of equations describing the dynamics of the membrane potential of a LIF neuron can be written as follows:

$$\begin{cases} \tau_V \dot{V}_i = (V_{\text{rest}} - V_i) + g_i^E (V_{\text{syn}}^E - V_i) + g_i^I (V_{\text{syn}}^I - V_i), \\ \dot{g}_i^E = -\dfrac{g_i^E}{\tau_{g_i^E}} + \sum\limits_i w^E \cdot \delta\,(t - t_{\text{spike},i}), \\ \dot{g}_i^I = -\dfrac{g_i^I}{\tau_{g_i^I}} + \sum\limits_i w^I \cdot \delta\,(t - t_{\text{spike},i}). \end{cases} \tag{1}$$

Here V_i is the membrane potential; V_{rest} is reverse potential; $V_{\text{syn}}^{E,I}$ is reversible potential for excitatory and inhibitory synapses; $g_i^{E,I}$ is synaptic conductance; τ_v is time constant of membrane potential relaxation; $\tau_{g_i^{E,I}}$ is time constant of relaxation of synaptic conductance; $t_{\text{spike},i}$ are time points of successive presynaptic spikes. When the membrane potential reaches the threshold value V_{thr}, a spike is generated and the membrane potential value returns to V_{reset}. The refractoriness for excitatory neurons was 5 ms, for inhibitory neurons it was 2 ms. The membrane potential equation for an inhibitory neuron included only the synaptic conductance of excitatory synapses.

A spiking neural network consists of many such neurons, each of which integrates input signals and generates spikes depending on its state. The spikes generated by one neuron can be coupled to the input currents of other neurons in the network, allowing information to be transferred and processed within the neural network.

In our work, we propose to use two populations of neurons interacting with each other: excitatory and inhibitory.

For the model of excitatory neurons, the following parameters were used: $V_{\text{rest}}^E = -60$ mV, $V_{\text{reset}}^E = -65$ mV, $V_{\text{thr}}^E = -52$ mV, $V_{\text{syn}}^E = 0$ mV, $V_{\text{syn}}^I = -100$ mV, $\tau_V^E = 100$ ms, $\tau_{g_i^E} = 5$ ms and $\tau_{g_i^I} = 10$ ms.

For the model of inhibitory neurons, the following parameters were used: $V_{\text{rest}}^I = -60$ mV, $V_{\text{reset}}^I = -45$ mV, $V_{\text{thr}}^I = -40$ mV, $\tau_{g_i^E} = 5$ ms.

For connections “excitatory neuron – inhibitory neuron” the value of synaptic weight was taken equal to 3, for connections of the type “inhibitory neuron – excitatory neuron” the value of synaptic weight was taken equal to 0.3.

1.2. Synaptic plasticity. STDP synaptic plasticity is responsible for regulating the strength of connections between neurons in the brain. It allows neurons to change the strength of their connections based on the time difference between the signals they transmit to each other. A study by Guo-qiang Bi and Mu-ming [14] identified changes in synaptic connections as a function of the relative timing of pre- and postsynaptic spikes. The results of their experiment are shown in Fig. 1 with black dots. As a result of approximating the obtained data with exponential

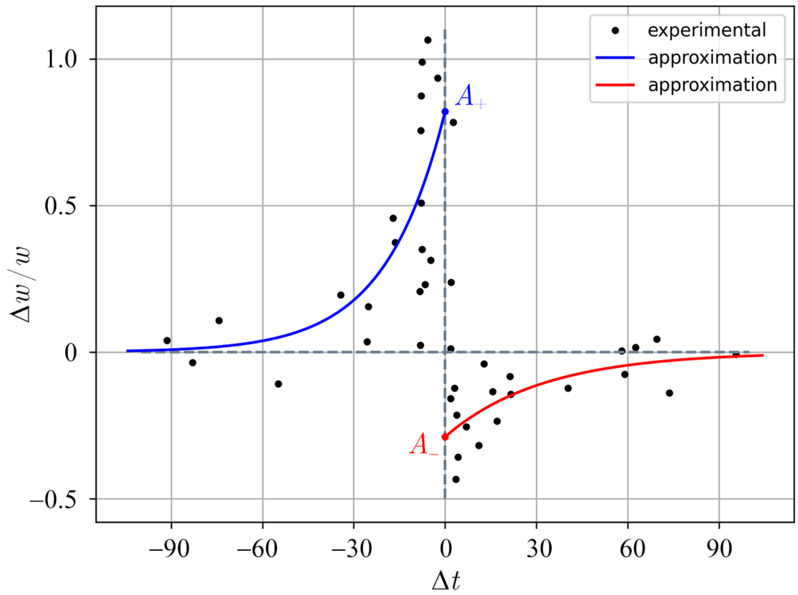


Fig 1. Experimental dependence of the change in synaptic weight on the difference in the times of occurrence of spikes, obtained in the work [14]. Black dots indicate experimental data. The red and blue curves are an approximation of the exponential dependence of the experimental data (color online)

dependences, it is possible to write a system of equations

$$\Delta w = \begin{cases} A_+ \cdot \exp(\Delta t/\tau_-), & \Delta t < 0, \\ A_- \cdot \exp(-\Delta t/\tau_+), & \Delta t > 0. \end{cases} \tag{2}$$

Here $\Delta t = t_{\text{pre}} - t_{\text{post}}$ is the time difference between the pre- (t_{pre}) and postsynaptic spike (t_{post}); τ_- and τ_+ are conductivity relaxation times. The constants A_+ and A_- were obtained by approximating experimental data.

The STDP model parameters were assumed to be as follows: $\tau_- = 20$ ms, $\tau_+ = 20$ ms, $A_+ = 0.01$ and $A_- = 0.01$.

Thus, synaptic weights, in accordance with the stated plasticity rule, depending on each pair of pre- and postsynaptic spikes, will change as follows:

$$w \leftarrow w + \Delta w. \tag{3}$$

In this case, a change in synaptic conductance will occur when a spike occurs on the presynaptic neuron for an excitatory synapse as $g_i^E \leftarrow g_i^E + w^E$ and for an inhibitory synapse as $g_i^I \leftarrow g_i^I + w^I$.

1.3. Data. The classical task of image classification requires a significant amount of labeled data of the same type, which can be easily processed and analyzed. To explore the issue of feature space extraction using spiking neural network, we chose the MNIST database (http://yann.lecun.com/exdb/mnist) [15]. Each image in the dataset is a single-channel square matrix consisting of 784 pixels, each encoded by one byte.

In general terms, the classification problem can be described as follows.

1. Allocation of feature space based on data features.
2. Identification of significant features.
3. Divides the selected space into classes according to the selected metric.
4. Estimate results based on statistics obtained from an “unknown” sample.

In this work, special attention is paid to the feature space of neuronal responses to an input stimulus and the quality of its choice, which is influenced by synaptic plasticity in the spiking neural network model.

1.4. Formation of the input signal. The input image is converted into a sequence of input spikes distributed according to a Poisson process [16] with a frequency equal to the pixel intensity value. This transformation forms the zero layer (input layer), where an event in the spike train determines the timing of the presynaptic spike. The algorithm for generating a sequence of spikes is shown schematically in Alg. 1. The frequency is determined proportionally to the pixel intensity with a proportionality factor of 0.5.

Algorithm 1. Generating an input stimulus from a single-channel MNIST image

```
forall pixels ∈ image do
    Set the average intensity of the Poisson process according to the pixel intensity
      → λ
    Set the duration of the time interval on which the process → T will be generated
    Calculate the average time between events (intensity inversion) → t_inv
    Initialize an empty array to store event timestamps
    while current timestamp will not exceed the duration of the time interval (T) do
        Generate a random number from a uniform distribution on the interval
          [0, 1] → n
        Calculate the value: t_inv · ln(n) → τ
        Increment current timestamp by τ
        Add timestamp to events array
    end
    Generate spikes from timestamps
    Use the received signal as input for each neuron of the corresponding layer
end
```

1.5. Description of the network. In our work, we propose the application of image recognition and classification processes using spiking neural network coding. For this purpose, a two-layer model of a spiking neural network was built, shown in Fig. 2. To ensure homogeneity, the generated signal was synchronously applied to all neurons of the excitatory layer of the model. In Fig. 2 the layer of excitatory neurons is indicated in red, and the layer of inhibitory neurons is indicated in blue. Each layer consists of 100 neurons. The layer of excitatory neurons is connected to the layer of inhibitory neurons by the "one to one" rule, where each neuron from one layer influences the corresponding neuron of the opposite layer. In contrast, feedback from the layer of inhibitory neurons is determined by the rule "one to all but one" where the inhibitory neuron influences all excitatory neurons except one. This type of connection implements the Winner Take All mechanism, which includes lateral inhibition.

To train and test the network, a stimulus presentation procedure was developed, schematically presented in Fig. 3 and consisting of the following main steps:

1) sending a useful signal for 350 milliseconds;
2) period of silence for 150 milliseconds.

1.6. Classification. As a result of stimulation of the network with signals encoding the pixels of the MNIST dataset images as a spike trains, spikes will appear on the neurons. The number of spikes received on each of the excitatory or inhibitory layer neurons in response to an

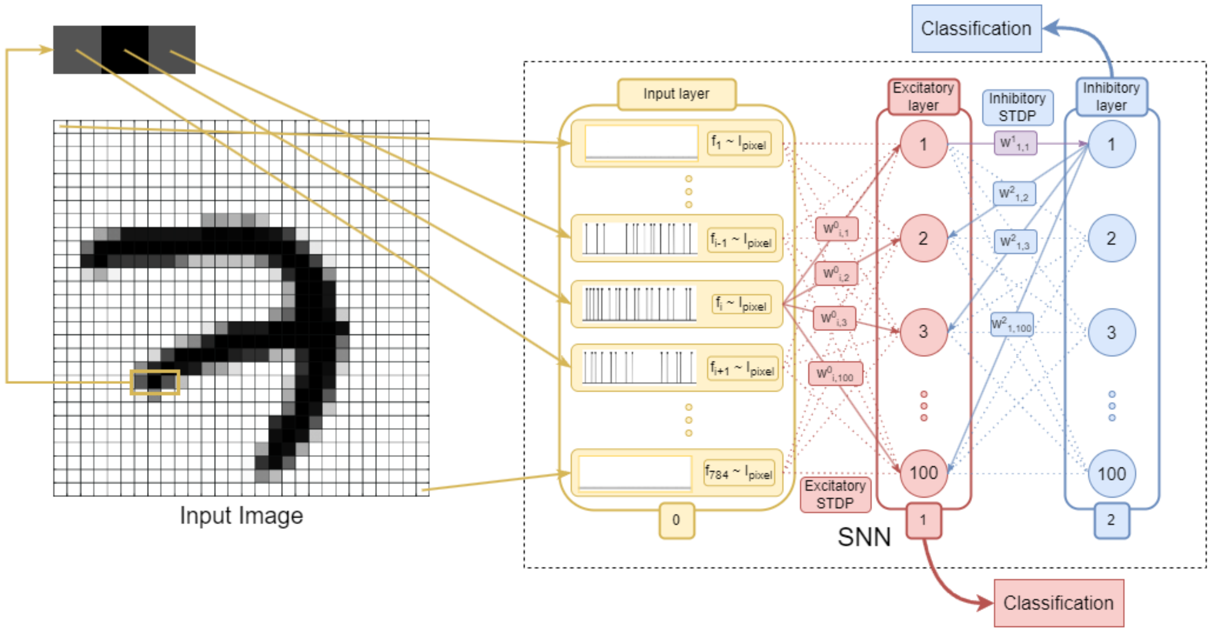


Fig 2. Scheme for creating a new feature description of an image with a detailed diagram of a spiking neural network with synaptic plasticity. The input layer (zero layer) is highlighted in yellow, representing a set of spike sequences distributed according to a Poisson process with a frequency (f_i) equal to the intensity of individual pixels in the image (I_{pixel}). The number of spike sequences is equal to the number of pixels in the encoded image. The excitatory population of neurons (first layer) is denoted in red, and the inhibitory population of neurons (second layer) is shown in blue. Red arrows on the diagram represent excitatory synapses, characterized by a set of excitatory synaptic weight coefficients $w^0_{i,j}$, where $i = \overline{1,784}, j = \overline{1,100}$, evolving according to the synaptic plasticity rule. Blue arrows represent inhibitory synapses, characterized by a set of inhibitory synaptic weight coefficients $w^2_{i,j}$, where $i = \overline{1,100}, j = \overline{1,100}, i \neq j$. Purple synaptic weights do not evolve, and their weight coefficients are constant and equal to 0.03. Initial values of excitatory and inhibitory synaptic weights were randomly chosen according to a uniform distribution in the range from 0 to 1. Classifiers are also provided. The classifier denoted in blue takes data from the inhibitory layer as input, and the classifier denoted in red takes data from the excitatory layer (color online)

input stimulus has been proposed as two different features. The process of encoding an image into a new feature space is schematically presented in Fig. 3. To classify the obtained data, a random forest algorithm was used with a maximum tree depth of 4.

2. Results

2.1. Evolution of synaptic weights. To study the dynamics of synaptic weights, an experiment was conducted in which a sample of 100 random images from the MNIST dataset was compiled and fed to the network input using the previously described method. Next, we examined the evolution of synaptic weights in the presence of synaptic plasticity in the layers of excitatory and inhibitory neurons. Let us consider the evolution of synaptic weights between a layer of excitatory neurons and an input signal. A raster diagram illustrating the normalized synaptic weights between the input signal and the layer of excitatory neurons of the model is shown in Fig. 4. Over time, as a stimulus is presented, synaptic weights adapt due to synaptic plasticity, as shown in a graph of changes in synaptic weights over time for several neurons, as well as in the corresponding distributions of synaptic weights (Fig. 4).

Synaptic weights between inhibitory and excitatory neuron layers in the presence of

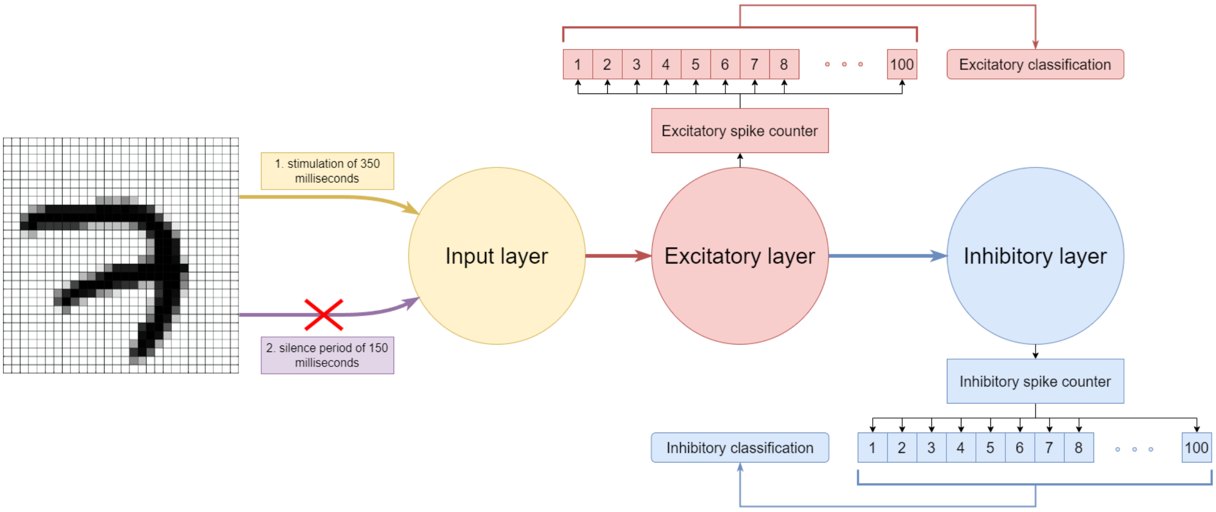


Fig 3. A scheme for forming a new feature space of an image using a spiking neural network with a stimulus presentation procedure. In the study, the network's response to the input image is represented by the number of spikes of each neuron in the examined layer (color online)

synaptic plasticity were also analyzed. The results are shown in Fig. 5. It should be noted that there is a significant difference from the first case both in the distribution of synaptic weights and in their adjustment.

2.2. Feature space. To analyze the feature space, the dimension of which corresponds to the number of neurons in the population, the total value of spikes for the entire layer was chosen as a metric for assessing the quality of clustering. It was assumed that the distribution of spikes among the neurons of the group is uniform, given that each neuron in the excitatory layer of the model is connected to all pixels of the input image. On average, all neurons in each population receive the same signal, allowing the sum of spikes to be used as a metric for the feature space. To analyze and calculate the metric, it was proposed to use data obtained from the excitatory and inhibitory layers of neurons. To do this, the constructed model for both cases was trained on 100 random images of the MNIST database.

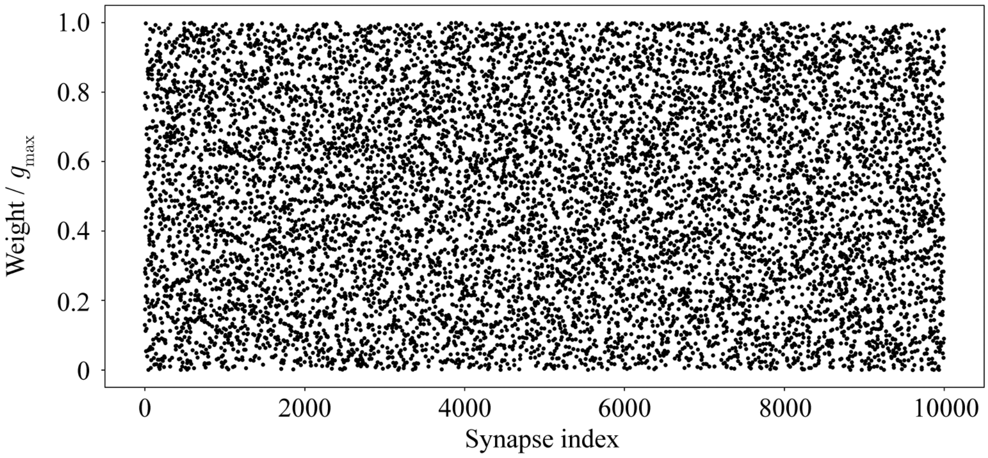
Table 1. Feature comparison table for samples of 100 images of each class

	Excitatory		Inhibitory	
Class	$\overline{x}$	σ	$\overline{x}$	σ
"0"	517	131	1817	396
"1"	146	93	534	290
"2"	432	146	1551	496
"3"	413	127	1311	534
"4"	305	117	1013	449
"5"	330	137	753	313
"6"	380	133	1183	372
"7"	287	106	869	338
"8"	397	133	1351	183
"9"	303	105	882	235

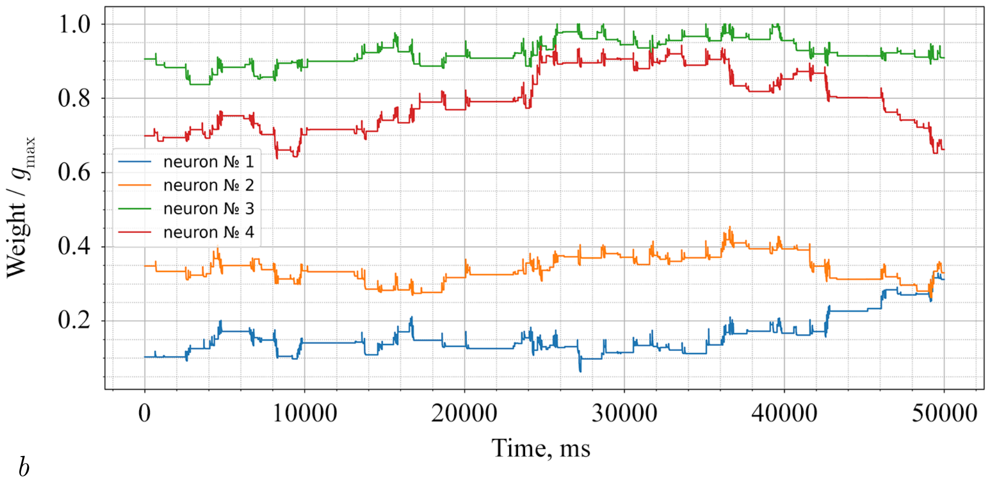
Here $\overline{x}$ is the average number of spikes in the neural network layer; σ is standard deviation

Based on the analysis, a comparative table was compiled (Table 1), demonstrating the selected metric for a sample of 100 images of each class.

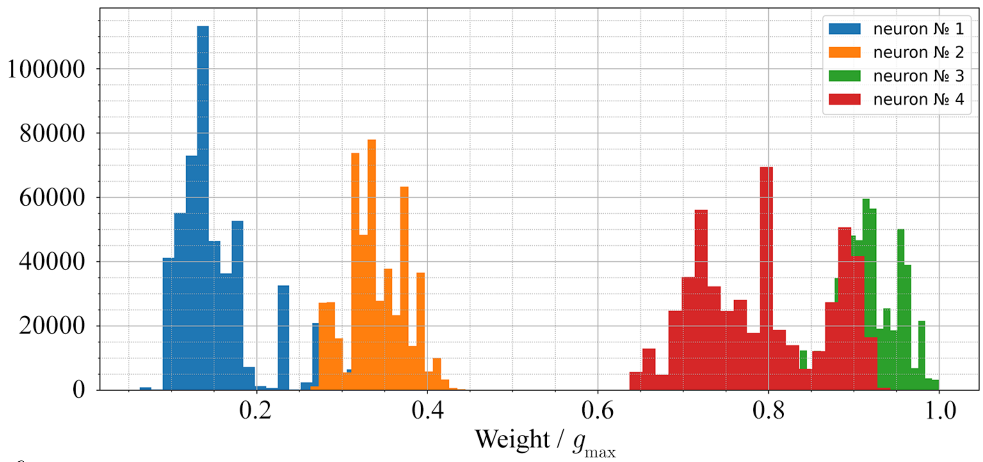
As a result of the analysis, it was discovered that the selected feature leads to the intersection of image classes, which prompted us to exclude some of them from further analysis. The classes selected for the experiment are highlighted in color in the table. In addition, dependences were constructed showing the distribution of the total number of spikes in the



a



b



c

Fig 4. Analysis of the evolution of the synaptic weights of the excitatory layer of neurons: *a* — raster diagram of the distribution of the normalized value of the synaptic weight for each synapse; *b* — changing synaptic weights over time; *c* — histogram of distribution of synaptic weights for neurons fig. 4, *b* (color online)

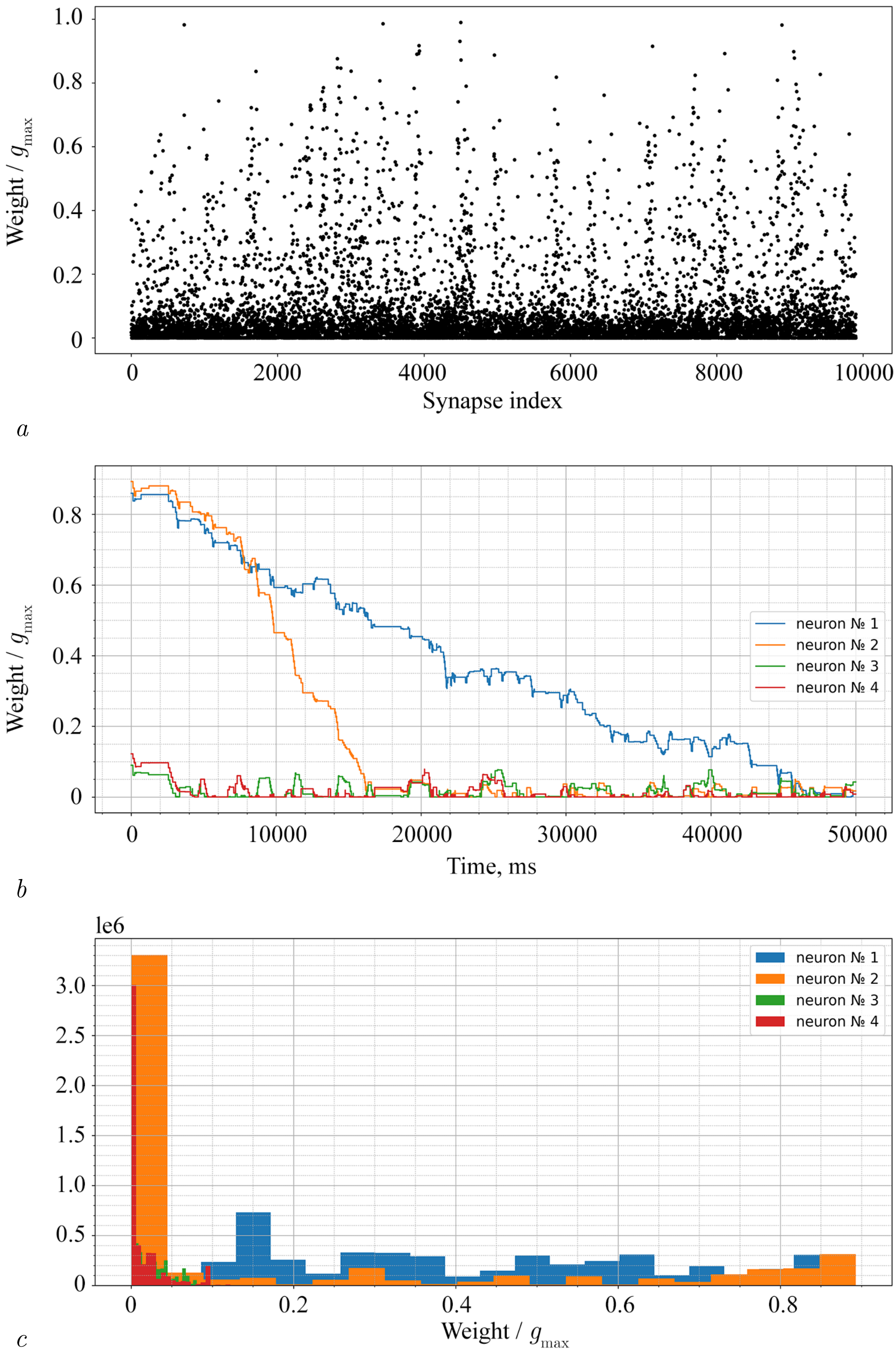


Fig 5. Analysis of the evolution of the synaptic weights of the inhibitory layer of neurons: *a* — raster diagram of the distribution of the normalized value of the synaptic weight for each synapse; *b* — changing synaptic weights over time; *c* — histogram of distribution of synaptic weights for neurons fig. 5, *b* (color online)

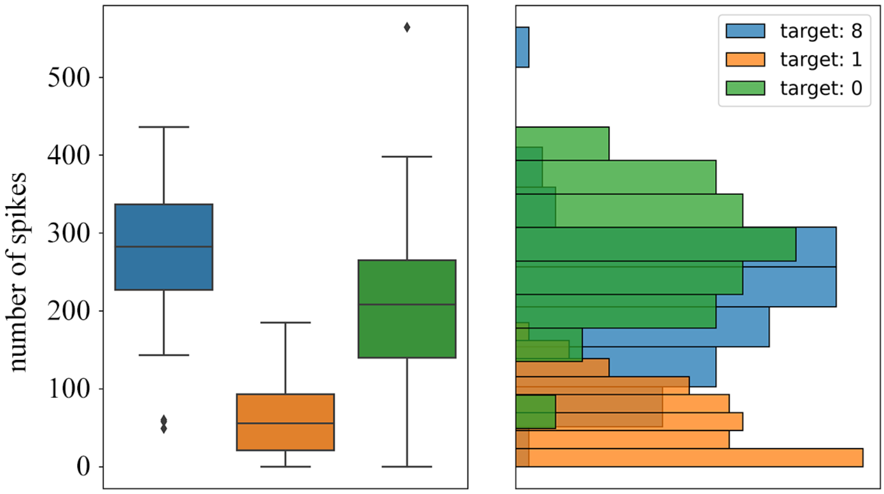


Fig 6. The dependence of the sum of spikes of the excitation layer during the response of the network to images from different classes. Blue color indicates data collected from images belonging to class “0” — target 0; orange color indicates data collected from images belonging to the class “1” — target 1; green color indicates data collected from images belonging to the class “8” — target 8

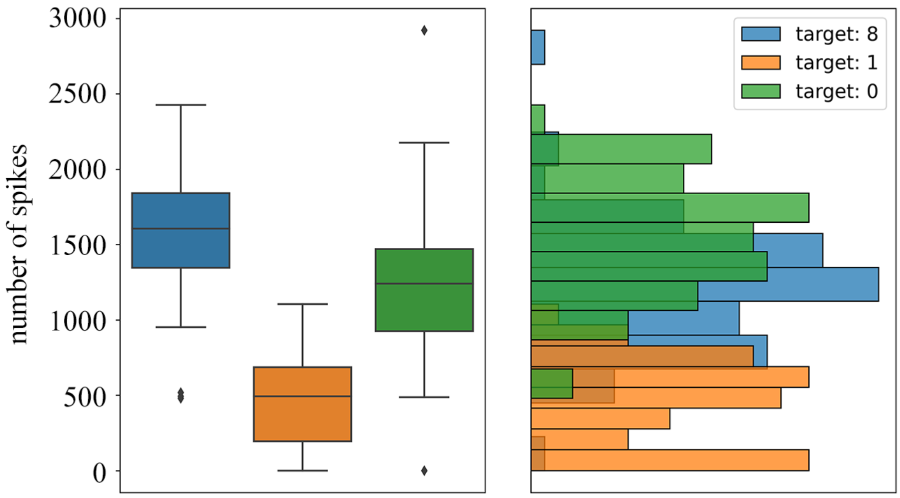


Fig 7. The dependence of the sum of inhibitory layer spikes in the response of the network to images from different classes. Blue color indicates data collected from images belonging to class “0” — target 0; orange color indicates data collected from images belonging to the class “1” — target 1; green color indicates data collected from images belonging to the class “8” — target 8 (color online)

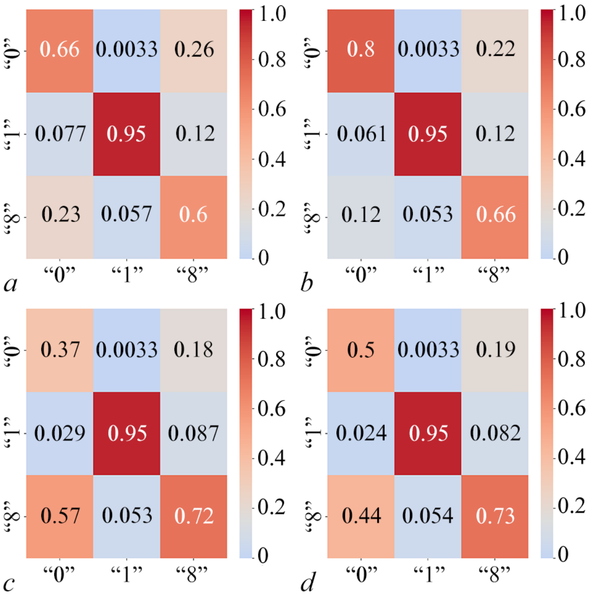


Fig 8. Confusion matrices for classifying data from the excitatory population: *a* — confusion matrix for the model with excitatory and inhibitory plasticity; *b* — confusion matrix for the model with excitatory plasticity; *c* — confusion matrix for the model with inhibitory plasticity; *d* — confusion matrix for a model without plasticity (color online)

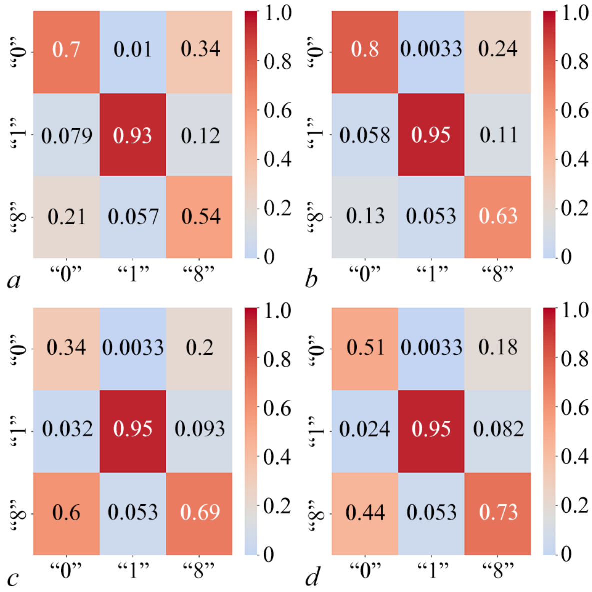


Fig 9. Confusion matrices for classifying data from the inhibitory population: *a* — confusion matrix for the model with excitatory and inhibitory plasticity; *b* — confusion matrix for the model with excitatory plasticity; *c* — confusion matrix for the model with inhibitory plasticity; *d* — confusion matrix for a model without plasticity (color online)

excitatory and inhibitory layers, shown in Fig. 6 and 7.

2.3. Study of the influence of synaptic plasticity. In order to study the influence of synaptic plasticity on the quality of feature space formation, eight model configurations were considered, reflecting the participation of synaptic plasticity in different connections of neuron populations, as well as obtaining a feature space only from the excitatory population of neurons or only from the inhibitory population of neurons. To train and test the models, a data sample of 6000 random images was formed, of which 5000 images were used to form the feature space, and 1000 images were used for testing. As a result, error matrices were constructed to evaluate the performance of the models (see Fig. 8 and Fig. 9).

The classification accuracies of each model configuration were also listed in separate tables: from the exciting population — Table 2, braking — Table 3.

As can be seen from the presented tables, the highest classification accuracy is achieved in the configuration of only excitatory synaptic plasticity for both of the considered cases.

Table 2. Accuracy comparison table for 4 model configurations

	eSTDP ON	**eSTDP OFF**
iSTDP ON	0.736	0.683
iSTDP OFF	0.803	0.745

Table 3. Accuracy comparison table for 4 model configurations

	eSTDP ON	**eSTDP OFF**
iSTDP ON	0.742	0.700
iSTDP OFF	0.813	0.745

eSTDP is synaptic plasticity between input stimuli and the excitatory layer of neurons; iSTDP is synaptic plasticity between inhibitory and excitatory layers. The model configuration that produces the best results is highlighted in color.

In contrast, the lowest accuracy is achieved when using only synaptic plasticity between the inhibitory and excitatory layers. If we independently compare the classification configurations from the excitatory and inhibitory populations, the case with the classification of images from the excitatory group with active synaptic plasticity between the input stimuli and the excitatory layer of neurons performed best.

Conclusion

A model was proposed for image encoding using spiking neural network to solve the recognition problem. The number of spikes of each neuron in the excitatory and inhibitory layers was used as new features representing the response of the neural network to a sensory stimulus. The model demonstrated the most efficient feature separation for digit images from the MNIST database when spike-timing-dependent plasticity (STDP) was used at excitatory synapses. The model also showed the worst feature separation in the presence of STDP for inhibitory synapses.

It should be noted that to improve the separation of image classes based on the new feature space, additional improvements can be made to the resulting feature space, the model configuration, or the method of delivering the input stimulus. These areas can be considered as potential avenues for future research and experimentation.

References

1. Song S, Miller KD, Abbott LF. Competitive Hebbian learning through spike-timing-dependent synaptic plasticity. Nature Neuroscience. 2000;3(9):919–926. DOI: 10.1038/78829.
2. Thorpe S, Delorme A, Van Rullen R. Spike-based strategies for rapid processing. Neural Networks. 2001;14(6–7):715–725. DOI: 10.1016/S0893-6080(01)00083-1.
3. Loiselle S, Rouat J, Pressnitzer D, Thorpe S. Exploration of rank order coding with spiking neural networks for speech recognition. In: Proceedings. 2005 IEEE International Joint Conference on Neural Networks, 2005. 31 July 2005 - 04 August 2005, Montreal, QC, Canada. New York: IEEE; 2005. P. 2076–2080. DOI: 10.1109/IJCNN.2005.1556220.
4. Yamazaki K, Vo-Ho V-K, Bulsara D, Le N. Spiking neural networks and their applications: A review. Brain Sciences. 2022;12(7):863. DOI: 10.3390/brainsci12070863.
5. Bohte SM, Kok JN, La Poutré H. Error-backpropagation in temporally encoded networks of spiking neurons. Neurocomputing. 2002;48(1–4):17–37. DOI: 10.1016/S0925-2312(01)00658-0.
6. Markram H, Gerstner W, Sjöström PJ. Spike-timing-dependent plasticity: a comprehensive overview. Frontiers in Synaptic Neuroscience. 2012;4:2. DOI: 10.3389/fnsyn.2012.00002.
7. Stasenko SV, Kazantsev VB. Dynamic image representation in a spiking neural network supplied by astrocytes. Mathematics. 2023;11(3):561. DOI: 10.3390/math11030561.
8. Stasenko SV, Kazantsev VB. Information encoding in bursting spiking neural network modulated by astrocytes. Entropy. 2023;25(5):745. DOI: 10.3390/e25050745.
9. Stasenko SV, Mikhaylov AN, Kazantsev VB. Model of neuromorphic odorant-recognition network. Biomimetics. 2023;8(3):277. DOI: 10.3390/biomimetics8030277.
10. Gordleeva SY, Tsybina YA, Krivonosov MI, Ivanchenko MV, Zaikin AA, Kazantsev VB, Gorban AN. Modeling working memory in a spiking neuron network accompanied by astrocytes. Frontiers in Cellular Neuroscience. 2021;15:631485. DOI: 10.3389/fncel.2021.631485.
11. Masquelier T, Guyonneau R, Thorpe S. Spike timing dependent plasticity finds the start of repeating patterns in continuous spike trains. PLoS ONE. 2008;3(1):e1377. DOI: 10.1371/journal.pone.0001377.

12. Guo W, Fouda ME, Eltawil AM, Salama KN. Neural coding in spiking neural networks: A comparative study for robust neuromorphic systems. Frontiers in Neuroscience. 2021;15: 638474. DOI: 10.3389/fnins.2021.638474.
13. Börgers C. Linear integrate-and-fire (LIF) neurons. In: An Introduction to Modeling Neuronal Dynamics. Vol. 66 of Texts in Applied Mathematics. Cham: Springer; 2017. P. 45–50. DOI: 10.1007/978-3-319-51171-9_7.
14. Bi G-Q, Poo M-M. Synaptic modifications in cultured hippocampal neurons: Dependence on spike timing, synaptic strength, and postsynaptic cell type. J. Neurosci. 1998;18(24): 10464–10472. DOI: 10.1523/JNEUROSCI.18-24-10464.1998.
15. Deng L. The MNIST database of handwritten digit images for machine learning research [best of the web]. IEEE Signal Processing Magazine. 2012;29(6):141–142. DOI: 10.1109/MSP.2012.2211477.
16. Sterratt D, Graham B, Gillies A, Willshaw D. Principles of Computational Modelling in Neuroscience. Cambridge: Cambridge University Press; 2011. 390 p. DOI: 10.1017/CBO9780511975899.
17. Chen Y. Mechanisms of winner-take-all and group selection in neuronal spiking networks. Frontiers in Computational Neuroscience. 2017;11:20. DOI: 10.3389/fncom.2017.00020.