DEVELOPMENT AND SIMULATION OF SPIKE NEURAL NETWORK ARCHITECTURE

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A review of different models of spike neural networks has been conducted. A spike type neural network is developed in the article. The mathematical model of exchange of neurotransmitters between neurons is proposed. An algorithm for network operation and neuron interaction is proposed, as well as an approach to training the network based on the formation of new connections from dendrites and increasing the signal transmission coefficient. The model of neural network was created in Python using the developed algorithm and mathematical model. To speed up the calculations, they were paralleled using the Numba library. The library Matplotlib was used for visual modelling and plotting the number of neurotransmitters on neurons. Experimental studies of the developed model of biological type network were carried out. It was shown that the developed network after training responds faster to the signals that were applied to it in the process of training.

KEYWORDS

spiking neural network, simulation, neuron, axon, dendrite, neurotransmitters

1 INTRODUCTION

Understanding biological neural networks has opened horizons for the development of artificial neural network systems, which are used for various applications today [Abiodun 2019, Bohusik 2023, Pavlenko 2019, Saga 2020, Yamazaki 2022]. By developing artificial neural network models more neurobiologically realistic, we can increase their biological validity and make them better tools for understanding complex brain functions. Biological neural networks can run asynchronously in parallel, have a neural network model structure with a small fraction of strongly connected neurons and a large number of less connected ones, while the layers of artificial neurons are usually fully connected [Pulvermuller 2021]. Thus, the development of a biological type neural network model is relevant for understanding the nervous system, developing artificial neural networks, improving artificial neural network models, studying the differences between artificial and biological neural networks, and solving cognitive problems [Powell 2022].

The most promising direction is the development of spike neural networks (SNN), because they are the closest to the biological analogue [Gerstner 2002]. A number of works [Savikhin 2011, Andreeva 2001, Krishnan 2019, Nandakumar 2020, Ponulak 2011] are devoted to the development of new SNN. In [Savikhin 2011], several models of neural networks for the implementation on computer are proposed, taking into account different biological properties of cells and neurons. The authors in [Andreeva 2001] consider the problem of modeling and training of SNN, pay special attention to the synaptic delay between the arrival of an impulse to a neuron and the appearance of a signal on its output. The effectiveness of the developed model is confirmed through computer simulation. The article [Krishnan 2019] proposes the combined use of frequency and spike neural networks. After the initial phase of learning, the authors convert the frequency and simulate the autonomous phase of sleep, then convert the SNN into artificial neural network again and evaluate the quality of the updated network. The study showed the effectiveness of this approach [Hu 2022]. Research in [Nandakumar 2020] evaluates the feasibility of implementing high-throughput event-driven learning systems using nanoscale and stochastic analog memory synapses. For the first time, the ability of analog memory synapses to generate precisely synchronized bursts in the SNN is experimentally demonstrated. In [Ponulak 2011] the possibilities of real practical application of SNN are investigated.

The purpose of this work is to develop a model of a spike neural network architecture, study its reorganization processes as a result of signals of different nature passing through it, and study the main concepts of its functioning. The work is based on machine modeling of the formation of neural connections for a system of randomly spaced neurons. The main structural elements of the network are neurons, axons and dendrites, and the main unit of data exchange are neurotransmitters. Multipolar neuron, i.e., the neuron itself and its offshoots: axon and several dendrites [Molnar 2015, Stepanov 2014] are chosen as the basis for this network. Axons in the model are responsible for transmission of neurotransmitters, and dendrites for reception [Kuric 2021]. Neurons in the system have three states: resting state - neuron receives neurotransmitters, but does not distribute them; active state - neuron releases neurotransmitters, but does not receive them; state of absolute refractory [Molnar 2015] – neuron neither distributes nor receives neurotransmitters for some period of time t_{refr}. The time t_{refr} period corresponds to the refractory period in a biological neuron, during which the tissue on the soma surface restores its ability to form a pulse and does not respond to the potential change at that location [Molnar 2015]. The model also implements dendrite extinction in case it does not receive a signal for a certain period of timecomplex.

2 MATHEMATICAL MODEL AND ALGORITHM

When developing a model of a spike neural network, mathematical models of interaction between neurons were determined through the exchange of neurotransmitters.

1. An exponential function is chosen as an activation function in this model. The number of neurotransmitters transmitted by the *j*-th neuron at each step:

$$N_j(t_i) = N_{max} \cdot e^{-\alpha t_a}, \quad (1)$$

where N_{max} is the maximum number of neurotransmitters per neuron, $\propto$ is the coefficient of the rate of propagation of neurotransmitters in the system, t_i is the number of the time step, t_a is the number of the step after neuron activation. You can select another function as the activation function in the system.

2. a) The number of neurotransmitters $P_j(t_i)$, which transmits the *j*-th axon to the *k*-th dendrite, depending on the distance of its location $r_{i,k}$:

$$P_{j,k}(t_i) = A_j(t_i) \cdot \frac{e^{-\beta r_{j,k}}}{\sum_{m=1}^{N_D} e^{-\beta r_{j,m}}}, \quad (2)$$

where β is the coefficient of intensity of neurotransmitter uptake by dendrites in the system, N_D is the number of dendrites in the region.

2. b) Number of neurotransmitters absorbed by the k-th dendrite at each step:

$$D_k(t_i) = \begin{cases} D_{max}, & npu \sum_{j=1}^{N_A} P_{j,k}(t_i) \geq D_{max}; \\ \sum_{j=1}^{N_A} P_{j,k}(t_i), & npu \ \ 0 < \sum_{j=1}^{N_A} P_{j,k}(t_i) < D_{max}, \end{cases} \quad (3)$$

where N_A is number of axons in the area where the dendrite is located, D_{max} is maximum number of neurotransmitters a dendrite can take in one step. Since dendrites have a limit on the number of neurotransmitters they can accept (which agrees with the biological analogue) some part of neurotransmitters from the axon is lost (due to this, the system has signal attenuation, it does not become closed, when neurons are located close to each other).

3. The growth of dendrites occurs after an impulse has come to them for several consecutive steps with the number of arrived neurotransmitters being maximal $(D_k(t_i) = D_{max})$. The equilibrium of forces acting on the dendrite from all axons in the region is described by the formula:

$$\bar{F} = \sum_{j=1}^{N_A} (\bar{v}_{j,k} \cdot P_{j,k}(t_i)), \quad (4)$$

where $\bar{v}_{j,k}$ is the vector from the *j*-th axon to the *k*-th dendrite. Thus, the vector of dendrite growth at step t_i is equal:

$$\bar{V}_{D_k(t_i)} = \begin{cases} \frac{\bar{F}}{|\bar{F}|} \cdot L_{D_{max}}, & if \ |\bar{F}| \geq L_{D_{max}}; \\ \bar{F}, & if \ |\bar{F}| < L_{D_{max}}, \end{cases} \quad (5)$$

where $L_{D_{max}}$ is the maximum amount of dendrite growth in one step.

Tab. 1 shows a general learning algorithm of SNN operation, taking into account the created mathematical models. At the first stage, after creating the general structure of the network, signals are generated on several neurons. The number of neurotransmitters in them is set equal, and their state becomes active.

Table 1. Proposed algorithm for developed model of spike neural network

1. Initialization of the network structure: the number of sensory areas and, the number of areas and linking axons between areas. Creation of an array of neurons $N[i]$, their axons A$[i]$ and dendrites $D_{i1} \ldots D_{ik}$. Generation of input signals S_i on neurons in sensory areas.
2. Repeat for each t= $0, \ldots T$:
2.1. Repeat for each neuron in the network $i = 0, \ldots M$:
2.1.1. Is neuron $N[i]$ active? then
2.1.1.1. Computation of released neurotransmitters $A[i][t]$ by formula (1).
2.1.1.2. Computation of absorbed neurotransmitters for neighboring dendrites D$[i \ldots k][t]$ by formula (2) otherwise go to step 2.1.
2.2. Repeat for each neuron in the network $i = 0, \ldots M$:
2.2.1. Computation of absorbed neurotransmitters for dendrites $D[i \ldots k][t]$ by formula (3).
3. Saving the state of the trained network to a file.

At the second stage, axons start transmitting neurotransmitters to neighboring dendrites, and the calculation of neurotransmitters released by axons into the system is performed. Then neurotransmitters absorbed by dendrites are calculated.

3 RESULTS AND DISCUSSION

Based on the described models, a software application SNN was developed. To study the resulting neural network, we selected 2 sensory areas and one output area, which receives neurotransmitters through 10 % of efferent neurons from the sensory areas. In Fig. 1 neurons a, b are marked in dark blue, dendrites - in light blue, and axon - in red.

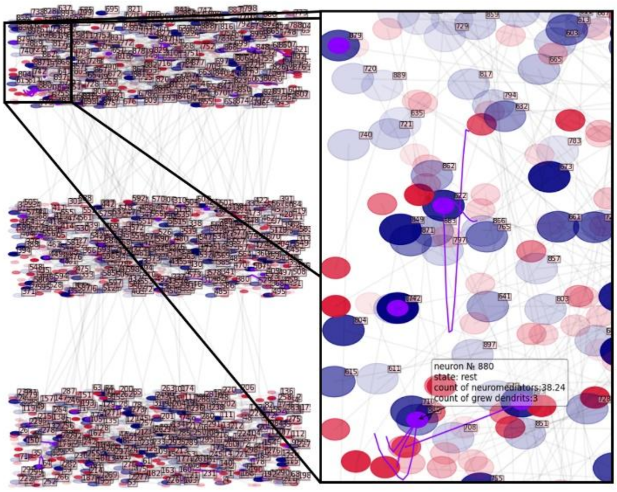

Figure 1. SNN on 3 areas consisting of 900 neurons, the figure on the left shows a general view of the network, on the right shows a close-up view and information about the neuron

In the process of learning, the dendrites start "growing" in the direction of the axon, from which the greatest impulse spreads, and, if the dendrites are not affected for several steps, the dendrite dies off. In each of the sensory areas, input neurons are randomly selected, to which a set of signals is fed as a binary set. The system was tested on a set of 10 different signals (Tab. 2).

Table 2. Test of the trained network model on 10 different input signals

№	Input signal	Output neurons that were activated
1	0,0,0,0,0,1,1,1,1,1,1,1,1,1,1,0,0,0,0,0	419, 449, 473, 475, 535, 560, 582
2	1,0,1,0,1,0,1,0,1,0,1,0,1,0,1,0,1,0,1,0	419, 449, 473, 475, 535, 560, 582
3	0,1,0,1,0,1,0,1,0,1,0,1,0,1,0,1,0,1,0,1	419, 449, 473, 475, 535, 560, 582, 589
4	1,1,0,0,1,1,0,0,1,1,0,0,1,1,0,0,1,1,0,0	419, 432, 449, 473, 475, 535, 537, 544, 560, 582
5	0,0,1,1,0,0,1,1,0,0,1,1,0,0,1,1,0,0,1,1	432, 449, 473, 475, 535, 537, 544, 582
6	1,1,1,1,1,0,0,0,0,0,0,0,0,0,0,1,1,1,1,1	411, 420, 432, 449, 473, 475, 535, 537, 538, 544, 582
7	1,0,0,0,1,0,0,0,1,0,0,0,1,0,0,0,1,0,0,0	411, 420, 432, 449, 473, 475, 535, 537, 538, 544, 582
8	0,1,1,1,0,1,1,1,0,1,1,1,0,1,1,1,0,1,1,1	411, 420, 432, 449, 473, 475, 535, 537, 538, 544, 582
9	0,0,0,1,0,0,0,1,0,0,0,1,0,0,0,1,0,0,0,1	411, 420, 432, 449, 473, 475, 535, 537, 538, 544, 582
10	1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,0,0,0,0,0	411, 420, 432, 449, 473, 475, 535

When testing the model's ability to learn, 20 input neurons were selected to which an impulse was applied (1 – impulse is applied, this is equivalent to 100 neurotransmitters; 0 – no impulse is applied, this is equivalent to 0 neurotransmitters). During training, this set of signals arrives randomly in cycles, on the order of several thousand steps, promoting the growth of dendrites in the output region and increasing the speed of the system's response to the input signal by reducing the distance between dendrites and axons. In addition, when the dendrite and axon get as close as possible, the β coefficient for a given dendrite increases. Analysis of Tab. 1 shows that after training the developed model from 10 signals only signals 3, 4, 5, 10 are unambiguously decoded. Signals 1-2, 6-9 for the trained model are not distinguishable. These results prove that the developed model is trained. However, due to the fact that the input set of neurons does not change, it propagates neurotransmitters to a certain set of surrounding neurons (449, 473, 475, 535), the correction of this deficiency is possible if the coordinates of neurons in the system are changed in time. Further development and investigation of this problem will be the subject of future research. Fig. 2 shows plots of pulse traversal in neurons, for different coefficients α and β, where the *X*-axis shows the steps in the system and the *Y*-axis shows the number of neurotransmitters in the neuron. From the analysis of sources [Yamazaki 2022, Abiodun 2019, Pulvermuller 2021] it follows that the SNN is closest to the biological analogue when the coefficients in the system are equal to $\alpha = 0.5$ and $\beta = 1.5$.

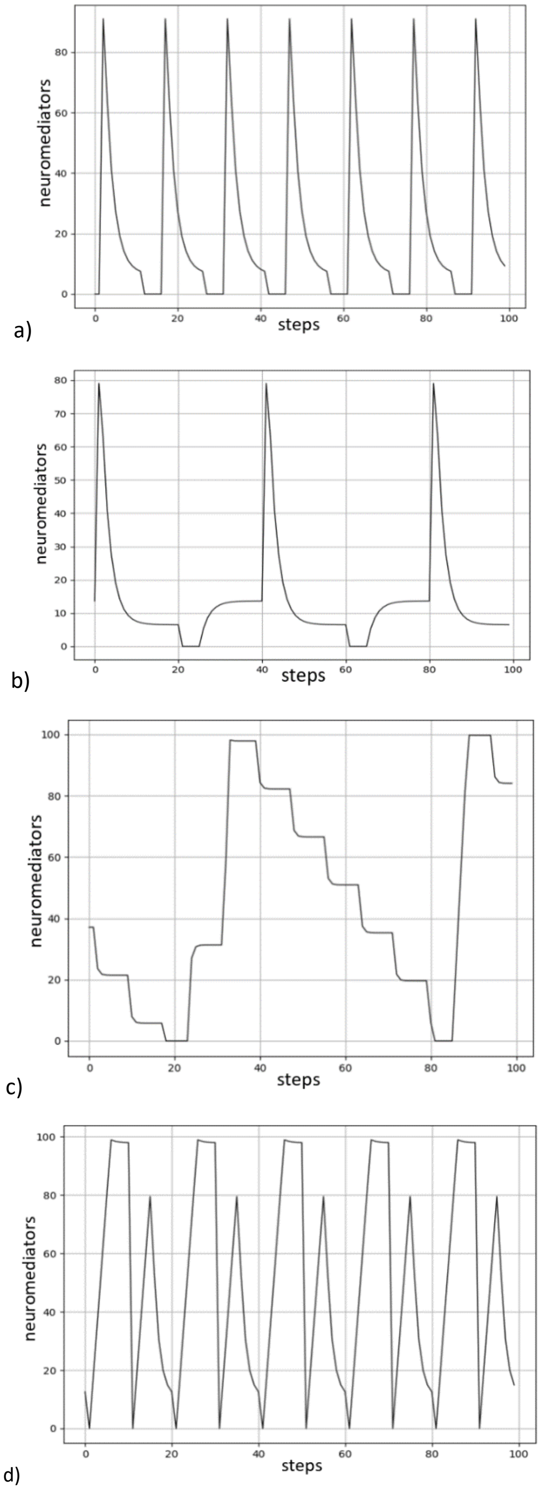

Figure 2. Graphs of the pulse generated on the neurons in the output region with different parameters α and β: a) $\alpha = 0.5$ and $\beta = 1.5$; b) $\alpha = 0.5$ and $\beta = 2$; c) $\alpha = 1.5$ and $\beta = 1$; d) $\alpha = 2$ and $\beta = 2$

4 CONCLUSION

In this paper, a theoretical model of the spiking neural network was created, the basic principles of its training were shown, and the results of the first training of the network were shown. Based on the described models, a software application was developed in Python using the developed algorithm and mathematical model. To speed up the calculations, they were paralleled using the Numba library. Further research concerns the study of the dynamics of neural network growth with its topological properties. The described model did not take into account the possibility of moving the neuron itself. With the change of physical parameters of neurons, the whole structure of the network can change significantly. Of theoretical interest is also the study of the influence of the ratio of length and number of axons and dendrites on the perception and formation of neural network clusters responding to individual signals.

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