Compartmental spiking neuron model for pattern classification

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Abstract. One of the directions of development within the framework of the neuromorphic approach is the development of anatomically similar models of brain networks, taking into account the structurally complex structure of neurons and the adaptation of connections between them, as well as the development of learning algorithms for such models. In this work, we use the previously presented compartmental spike model of a neuron, which describes the structure (dendritic tree, soma, synapses) and behaviour (temporal and spatial signal summation, generation of action potential, stimulation and suppression of electrical activity) of a biological neuron. An algorithm for the structural organization of neuron models into a spike neural network is proposed for recognizing an arbitrary impulse pattern by introducing inhibitory synapses between trained neuron models. The dynamically adapting neuron models used are trained according to a previously proposed algorithm that automatically selects parameters such as soma size, dendrite length, and the number of synapses on each of the dendrites in order to induce a temporal response at the output depending on the input pattern encoded using a time window and temporal delays in the vector of single spikes arriving at a separate dendrite of a neuron. The developed algorithms are evaluated on the Iris dataset classification problem with four training examples from each class. As a result of the classification, separate disjoint clusters are formed, which demonstrates the applicability of the proposed spike neural network with a dynamically changing structure of elements in the problem of pattern recognition and classification.

1. Introduction

Modelling neuromorphic architectures is stimulated by the desire to understand and technically implement such key features of the neural structures of the brain as low energy consumption, high speed, high performance, scalability, the ability to deal with a parallel and distributed way of processing information, as well as adaptability to a changing environment and learning. These advantages are extremely promising for the creation of management systems based on behavioural models.

As is well known, biological neural networks have the property of plasticity and the ability to continuously learn, supplement and correct existing knowledge, based on new information received.
The problem of plasticity to significant changes in the functioning environment in the nervous system is solved by flexibility, first of all, within the framework of the possibilities for structural adaptation of both the topology of neural structures and the dendritic trees of individual neurons. Neurogenesis, as one of the mechanisms of brain plasticity, consisting in the appearance of new neurons, structural restructuring of connections between them, the formation of new synapses and changes in synaptic transmission, is important for learning and memory processes.

Most of the architectures of artificial neural networks do not consider the issue of plasticity of the network topology and restructuring. Moreover, the network topology is fixed within the framework of a specific architecture, and artificial formal neurons do not take into account the structurally complex structure of neurons and the peculiarities of the mechanisms of neural interaction.

Within the framework of a highly effective neuromorphic approach, spike (impulse) neural networks (SNN) have received the greatest development. They belong to the third generation of neural networks, in which, in contrast to common artificial neural networks on formal neurons, information is encoded by discrete impulses (spikes) [1]. When training spike neural networks, the non-differentiable threshold activation function does not allow the use of standard methods of training artificial neural networks. Therefore, research in this area is aimed at adapting the methods of artificial neural networks (ANN) to the SNN, namely, at solving the problem of non-differentiability, as well as at developing biologically similar algorithms based on plasticity depending on the spike time [2-5].

The existing simplest models of a spike neuron [6 - 8] implement basic neural operations, but, like formal neurons, do not take into account the structural features of a biological neuron (dendritic tree, soma, synapses). Therefore, to increase the biological likelihood of the network, the so-called compartmental models of neurons are used [9, 10]. And also, the architectures of neural networks are being developed, allowing to carry out learning in dynamics (online). The biological principles of the brain have inspired researchers to create spike, dynamically developing neural networks that can work in real time. For the majority of spike neural networks, a traditional development strategy has been created, which does not fix the structure, but regulates the number of neurons in the learning process, and also dynamically adapts the weights of neurons [11–15].

In this work, to solve the classification problem, not parametric, but structural adaptation of the network is used at the level of complication of the model of each node by switching to compartmental models of neurons. In the following sections, the used neuron model and the principles of its training are briefly described, the organization of a group of neurons data for solving the problem of classifying the Iris dataset is shown, and experimental results are presented, as well as comparison with existing solutions.

2. Used neuron model
This work is based on a compartmental spike model of a neuron with the possibility of structural adaptation, previously proposed by the authors [15]. In this model, it is assumed that spike streams arrive at the inputs of a neuron, which are converted at synapses into analogue values describing the processes of release and decay of a transmitter in the synaptic cleft. The input and output signals of the neuron are equal to zero in the absence of an spike, and constant for the duration of the spike.

The features of the proposed neuron model that play an essential role in solving the problem of developing algorithms for structural learning of a neuron model are:

- the ability to create an arbitrary number of segments of the neuron body. From the point of view of the problem solved in this work, this means the ability to change the dimension of the input spike pattern;
- the ability to independently increase the length of the dendrites. Since the dendrites carry out spatial and temporal summation of signals at significant time intervals, an increase in the length of the dendrite leads to a time delay in the signal and a decrease in its amplitude;
- the possibility of adding an arbitrary number of synapses on an arbitrary part of the membrane (body, dendrite). The addition of a synapse leads to an increase in the signal amplitude;
• the possibility of arbitrary organization of connections (both excitatory and inhibitory) between individual elements.

All of the above allows, through structural reconfiguration (adaptation) of the neuron model, to synchronize (by changing the time of arrival of a single spike from each of the dendrites to the soma of the neuron) and normalize the signal (by changing its amplitude). The output signal is generated in the low-threshold zone of the neuron (action potential generator) and is a single spike, or a series of single-amplitude spikes generated when the potential value exceeds the threshold. The very value of the potential inside the low-threshold zone is nonlinearly related to the sum of signals that arrived at the input of the neuron, therefore, in order to overcome the threshold and generate the action potential, we need to maximize the sum of contributions to the potential inside the low-threshold zone from all dendrites, which is achieved by synchronizing the actions of the input signals of the neuron and compensating the loss of the amplitude of the potential by an individual dendrite when increasing its length.

Thus, dynamically adapting neuron models are able to train by automatically selecting parameters of the neuron model, such as soma size, dendrite length, and the number of synapses on each dendrite in order to induce a temporal response at the output depending on the input pattern encoded using a time window and time delays in the vector of single spikes arriving at a separate dendrite of the neuron. The developed algorithm for the structural organization of neuron models into a spike neural network makes it possible to recognize arbitrary patterns of spikes by introducing inhibitory synapses between trained neuron models.

3. Experimental studies and results

For modelling, the software platform previously proposed by the authors [16] was used.

The developed pattern recognition algorithm was evaluated on the classification problem of the Iris dataset [17] with four training examples from each class.

Before feeding the input data to the network, it is necessary to encode the numeric signs into the values of time delays. Let the input dataset 

\[ X = \{(x_1^1; x_2^1; \ldots; x_N^1; y_1^1), (x_1^2; x_2^2; \ldots; x_N^2; y_2^2), \ldots, (x_1^M; x_2^M; \ldots; x_N^M; y_M^M)\}, \]

where \( M \) is the total amount of input data, \( N \) is the dimension of the feature space. According to [18], the delay of the \( n \)-th feature of the \( m \)-th example of input data \( X \) can be calculated as

\[ d_{nm}^m = \frac{x_{mn}^m - x_{mn}^n}{x_{mn}^n - x_{mn}^0} \cdot T, \]

where \( x_{mn}^0 \) and \( x_{mn}^n \) respectively, the minimum and maximum value of the \( n \)-th feature over the entire dataset, \( T \) is the width of the time window.

Obviously, in the process of recognizing a pattern of spikes, only the relative displacements of individual spikes in the pattern are significant, the displacement of the entire pattern in time scale does not affect the recognition result in any way. Since in the problem under consideration, in addition to the relative values, the absolute values of the spike times are also significant, it is necessary to bind the impulse pattern to some absolute value. To solve this problem, an additional - calibration - dendrite is introduced into the model. This dendrite becomes basic, and the value of the time delay on it always takes the maximum value, i.e., equal to the width of the time window. Thus, when adding a calibration dendrite to the input vector, the dimension of the feature space becomes equal to \( N+1 \).

The dataset contains examples belonging to \( K \) (\( K = 3 \)) classes. \( P \) (\( P = 4 \)) examples were selected from each class. To classify Iris data into four training examples from each class, the previously described input spike neurons NeuronTrainer \((k, p)\) corresponding to class \( k = 1..K \) and training example \( p = 1..P \) were organized according to the diagram presented in figure 1. Generation of input spikes is carried out by generators Source \((n)\), where \( n = 1..N + 1 \). OrNeuron \((k)\) neurons, corresponding to the \( k \)-th class,
receive all signals of NeuronTrainer (k, p) neurons as input, performing a logical "OR" operation, i.e. generating an output signal when at least one NeuronTrainer (k, p) of the k-th class arrives at the input. The introduction of inhibitory connections between OrNeuron (k) neurons leads to the response of the neuron whose output pulse was generated faster, or, as mentioned above, whose input pattern turned out to be the closest to the training example. Spike generation at the output of the low-threshold zone of OrNeuron neurons (k) is the result of classification.

It is worth noting the possibility of spike generation by several OrNeuron (k) neurons, if signals arrived at their inputs within the same time interval. We will call such a case "uncertain recognition".

Figure 1. Organization diagram of compartmental models of neurons for solving the problem of classification of the Iris dataset.

The diagram presented in figure 2 shows the distribution of correctly classified examples (confident recognition), errors, unclassified examples (lack of recognition). It can be seen that the confidently classified examples formed separate clusters around the training examples, linearly separable from each other. Uncertain and incorrect recognition can be seen in the class intersection area, since the examples in this area are similar. Some examples, from which the geometric distance to any of the training examples is large enough, were not recognized by any neuron. This is explained by the ability of the proposed neuron model to respond to spike patterns only to a certain extent different than the spike pattern that this neuron model was trained for.
Figure 2. Results of classification of the entire Iris dataset.

A quantitative assessment of the classification accuracy of the Iris dataset by an organized group of spike segment neurons is presented in table 1.

Table 1. Classification accuracy of the Iris dataset.

| Class | Certain recognition | Invalid recognition | Uncertain recognition | Lack of recognition |
|-------|---------------------|---------------------|-----------------------|--------------------|
|       | Quantity | %      | Quantity | %      | Quantity | %      | Quantity | %      |
| 1     | 50       | 100.0  | 0        | 0.0    | 0        | 0.0    | 0        | 0.0    |
| 2     | 46       | 92.0   | 1        | 2.0    | 3        | 6.0    | 0        | 0.0    |
| 3     | 29       | 58.0   | 4        | 8.0    | 15       | 30.0   | 2        | 4.0    |
| Outcome | 125     | 83.3   | 5        | 2.0    | 18       | 12.0   | 2        | 1.3    |

Comparison of the developed spike neural network with existing solutions is presented in table 2.

Table 2. Comparative table of existing algorithms on the Iris dataset.

| Method | Accuracy, % |
|--------|-------------|
| Machine learning and the multilayer perceptron | MLP (50-10-3) 95.7 |
|        | kNN 92.0    |
|        | SVM 96.0    |
|        | DBSCAN [19] 80.7 |
|        | ReSuMe [3] 88.0 |
|        | Tempotron [4] 86.6 |
| Spike neural networks | SpikeProp (50-10-3) [2] 96.1 |
|        | SWAT (16-208-3) [5] 95.3 |
|        | Belatreche 2012[14] 90.3 |
| Dynamically developing spike neural networks | SRESN [11] 97.0 |
|        | Wang 2014 [13] 86.1 |
|        | SpikeCD [18] 98.0 |
| SNN with compartment neurons | Proposed network 83.3 |

4. Conclusions
Using the developed algorithm for SNN on segment models of a neuron, the data were divided into separate disjoint clusters. Considering the fact that in the experiment in this work only four examples
from each class were used for training, we can talk about promising prospects for using the SNN on compartmental models of a neuron in classification problems.

The disadvantage of this approach is that the result of the calculations depends on the specific examples selected for training. In addition, the great computational complexity of the proposed network is due to the high computational complexity of the spike neuron model.

The advantage of the proposed approach lies in the use of a compartmental model of a neuron as an alternative strategy for constructing a spike neural network, taking into account the structural features of a biological neuron (dendritic tree, soma, synapses). The proposed model does not require adjustment of internal parameters during operation; all changes in functionality are determined by a modification of the structural organization. In further studies, it is planned to train on a large sample, implement incremental training with dynamically adding neurons to the network and changing the network topology. Also, a promising direction for the development of work on this topic is the study of deep spike neural networks and various teaching methods, including the biologically similar rule of unsupervised learning STDP (Spike-Timing-Dependent Plasticity) and, in the future, implementation on neuromorphic equipment.

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