

Е. А. КАМИНСКИЙ

Научный руководитель С. К. КРУТОЛЕВИЧ, канд. техн. наук, доц.

Консультант Е. Н. МЕЛЬНИКОВА

ГУ ВПО «Белорусско-Российский университет»

Nowadays, neural networks are an extremely promising and rapidly developing direction of artificial intelligence. Having taken the best features of its prototype – the brain – they have been recognized as one of the most effective methods for solving diverse problems of varying degrees of complexity in various fields. However, the possibilities for the development of neural networks have not been exhausted, and in this direction there is still a lot to be done. This paper gives a brief overview of the history of neural networks, their main components and architectures. Besides, the fields of application and some examples of applications are given.

The history of neural networks goes as far back as the 1940 s. In 1943 McCulloch and Pitts elaborated a model of human and animal neuron and explained the principles of combination of neurons, i.e. neural network. Rosenblatt's development of perceptron in 1958 contributed to further advancement in this field of science. It was aimed at recognizing alphanumeric signs. There were also attempts to use neural networks for weather forecast, identification of mathematical formulas, analysis of electrocardiogram, etc. In 1969 a monograph was published in which it was proved that one-layer perceptron-like nets have limited area of application. This fact discouraged scientists from working with perceptrons and focused their efforts on expert systems instead. In the 1980s it was proved that there are no limitations in application of multi-layer non-linear neural network, which contributed to growing interest in this field of knowledge.

Another big chapter in the history of neural networks is connected with Paul J. Werbos and his backpropagation algorithm, which effectively solved the 'exclusive or' or 'XOR' problem and accelerated the training of multi-layer networks.

The human brain, which consists of 1010 cells (neurons), is the archetype of neural networks. There are about 1015 connections (synapses) between the cells. The neuron works with the frequency from 1 to 100 Hz. Consequently, the approximated rate equals about 1018 operations per second. A neural network is a simple model of brain. It consists of great number of neurons, i. e. elements that process information.

The scheme of the neuron can be made on the basis of the biological cell. This element consists of several inputs. The input signals are multiplied by the appropriate weights and then summed. The result is recalculated by the activation function.

In accordance with this model, the formula of the activation potential  $\varphi$  is as follows

$$\varphi = \sum_{i=1}^P u_i w_i. \quad (1)$$

Signal  $\varphi$  is processed by the activation function, which can take different shapes. If the function is linear, the output signal can be described in the following way:

$$y = k\varphi. \quad (2)$$

Neural networks described by this formula are called linear neural networks. Another type of the activation function is the threshold function, where  $\varphi_h$  is a given constant threshold value

$$y = \begin{cases} 1, & \varphi > \varphi_h, \\ 0, & \varphi \leq \varphi_h. \end{cases} \quad (3)$$

The sigmoid function and the hyperbolic tangent function are the functions that more accurately describe the non-linear characteristic of the biological neuron activation function.

There are different types of neural networks that differ in their structure and direction of information flow. In general, neural networks can be divided into groups in the following way: feedforward networks (one-layer networks, multi-layer networks); recurrent networks; cellular networks.

Feedforward neural networks consist of neurons set in layers. The information flow has one direction. Each neuron in one layer has only directed connections with the neurons of the next layer (towards the output layer). Some feedforward networks permit the shortcut connections: connections that skip one or more levels. These connections may be directed only towards the output layer. Multi-layer networks usually consist of input, hidden (one or more) and output layers.

Recurrent neural networks have feedback loops (at least one); output signals of a layer are connected to its inputs. Input signals of a layer consist of input and output states (from the previous step) of the layer. There are several types of recurrences providing different effects on a network:

- direct recurrence (neurons are connected to themselves, it allows them to inhibit and therefore strengthen themselves in order to reach their activation limits);
- indirect recurrence (neurons use indirect forward connections to influence themselves, for example, by influencing the neurons of the next layer);
- lateral recurrence (connections between neurons within one layer, each neuron often inhibits the other neurons of the layer and strengthens itself and the strongest neuron becomes active).



In cellular neural networks neurons are arranged in a lattice. Connections (usually non-linear) may appear between the closest neurons. The typical example of these networks is the Kohonen Self-organising-Map.

Neural networks in medicine have almost unlimited application. The main application directions are diagnostics, prediction, prognostics and signal processing. Besides, neural networks are applied in almost all fields of medicine, like cardiology, oncology, neurology, EEG analysis, genetics and many others.

In practice, medical practitioners have to monitor more and more displays and evaluate an increasing number of signals. Neural networks, which are able to evaluate changes and interactions of physical, chemical and thermodynamical parameters, have definitely decreased the time of initiating necessary responses in case of emergency (it took only 17 seconds instead of 45 seconds necessary for medical practitioners). A backpropagation neural network was trained to recognize HVS-patterns (high voltage spike-and-wave spindle) in rats. This well-trained and optimized network can detect the presence of HVS in EEGs recorded for 12 night hours with 93–99 % sensitivity. However, falsely detected events (non-HVS, artefacts) varied over a wide range (18–40 %), but this attempt demonstrates the potential usefulness of neural networks in the recognition of EEG patterns. There are several systems available for diagnosis and selection of therapeutic strategies in breast cancer. A neural network judged the possible recurrence rate of tumors correctly in 960 of 1008 cases by using data from lymphatic node positive patients.

At present, neural networks seems to find the most interesting and the most powerful application in the field of radiology. Images contain a lot of information and they are so complicated that it is quite difficult to interpret them by using conventional rule-based systems. By selecting an appropriate training set and learning process, neural network modeling becomes suitable for noise filtering and for recognition of unusual images. For cold lesion detection and localization in SPECT (single photon emission computerized tomography) images a neural network was trained by using images with different sizes and noise levels. The network scanned the whole image and recognized alterations with high sensitivity, and with only a few false-positive errors.

So far, neural networks have not broken through many of the barriers to applied sciences. This technique has been applied only for testing mathematical models developed for solving simple problems in practice. Application of neural networks must currently be supported by conventional mathematical methods. In this way, neural networks can be more effective in pattern recognition and classification as compared to purely conventional techniques. To get a wider application, new models, which are able to solve complex real-world problems, should be developed.

