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HOMOGENEOUS MULTILAYERED NEURAL NETWORK OF DIRECT DISTRIBUTION WITH LOCAL CONNECTIONS WITH LERANING CONDITIONED-REFLEX MECHANISM ON THE BASIS OF TWO-THRESHOLD EQUILIBRIUM NEURON-LIKE ELEMENTS

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The classical model of artificial neuron has been examined. Two-threshold equilibrium neuron is suggested to use in multilayered neural network of direct distribution. Conditioned-reflex learning mechanism is described.

Introduction

In the course of development and research of various intellectual devices and systems, the attention is not enough paid to mechanisms of management and learning in wildlife, major elements of which are reflexes. As nervous systems of the overwhelming majority of live organisms represent difficultly organized neural networks, the modeling and research of the conditioned-reflex learning mechanism on the basis of neural networks is rather relevant. Great importance is given here to principles of construction not only of the model of neural network, but also the model of neurons, forming a neural network.

1. Neuron model

It is known that artificial neuron simulates properties of biological neurons [1, 2], which serve as building elements of a brain. The majority of construction concepts of artificial neural networks existing today use the model of artificial neuron [3] learning of which is based on change in weight coefficients w_i [4, 5].

Let us modify the classical neuron model as follows. Let us assume that all connections have individual weights, and total input excitation is defined as the algebraic sum of values of corresponding input signals. Let us also enter the neuron inhibition threshold P_t. The linear activizational function for neuron equilibrium two-threshold model is represented in fig. 1.

Values of excitation thresholds P_v and inhibition P_t will define a range of values of the algebraic sum of input signals – a range of activization at which on neuron output the level of excitation, which is distinct from zero, is formed.

Use of individual connections, and also excitation thresholds P_v and inhibition P_t as the parameters corrected during the learning process of multilayered neural network of direct distribution (MNNDD), allows us to escape from necessity of adjustment of each weight coefficient separately, to simplify training algorithm.

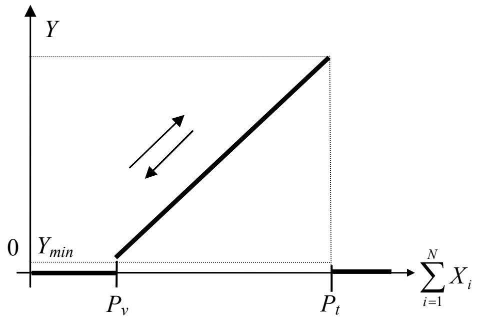

Fig. 1. *The linear activizational function for neuron equilibrium two-threshold model; P_v – neuron excitation threshold, P_t – neuron inhibition threshold, Y_{min} – minimal output excitation Y*

The modified neuron model is described by expression:

$$Y = \begin{cases} k_n\left(\sum_{i=1}^{N} X_i - P_v\right) + Y_{\min} & \text{at} \quad \sum_{i=1}^{N} X_i \in [P_v; P_t); \\ 0 & \text{at} \quad \sum_{i=1}^{N} X_i \notin [P_v; P_t). \end{cases} \quad (1)$$

2. Neural network model

The important problem, solved at construction of MNNDD, where neurons of each layer are not connected among themselves, is the formation of neuron connections structure between the adjoining layers. The output signal from each neuron of the previous layer acts, as a rule, on inputs of all neurons of the following layer. Feedback between neural layers is absent [6, 7].

Let us examine MNNDD where neurons of the previous layer are not connected with all neurons of the following layer, but only with those that are located within the limits of excitation radius of corresponding neuron. Let us consider as excitation radius R of the given neuron the quantity of lateral connections located to the left or to the right of the central connection, and connections itself are local. Letus explain previously said by means of fig. 2.

Generally, regardless of excitation radius, the quantity of lateral connections N_b can be less than R, and the central connection – be absent. As in the considered neural network the excitation extends on neuron layers from previous to the subsequent layer, the transfer of excitation between the adjoining layers can be described by expression (2), following from (1).

$$Y_{i+1,j}=\begin{cases} k_n\left(\sum\limits_{s=j-R}^{s=j+R} X_{i,s}-P_{v\,i+1,j}\right)+Y_{\min} \\ \quad \text{at} \sum\limits_{s=j-R}^{s=j+R} X_{i,s}\in[P_{v\,i+1,j};P_{t\,i+1,j}); \\ 0 \\ \quad \text{at} \sum\limits_{s=j-R}^{s=j+R} X_{i,s}\notin[P_{v\,i+1,j};P_{t\,i+1,j}). \end{cases} \qquad (2)$$

where i is the number of a neural layer, j is the neuron number in a layer, s is the neuron number in the previous layer i, connected with j neuron of the subsequent i+1-st layer, $Y_{i+1,j}$ is the neuron excitation of the subsequent layer i+1, $Y_{i,s}$ is the neuron excitation of the previous layer i, connected with j neuron of the subsequent i+1-st layer.

In fig. 3. examples of fragments of pictures of MNNDD excitation are shown, calculated according to (2) for variants of the structure assignment of local connections. Excited neurons are lighter, not excited are darker.

3. The conditioned-reflex mechanism of neural network training

Let us examine the conditioned-reflex mechanism of network learning [8], where the neuron two-threshold equilibrium model is used. Let us assume, that in our case the activizational function and quantity of communications N are identical to all neurons, therefore letus consider MNNDD as **homogeneous.**

Realization of the conditioned-reflex mechanism of MNNDD learning is possible with use of the variant, assuming division of this network on functional blocks (fig. 4).

Let us call the limited area of the neural network as **the functional block,** described by certain scenario of corresponding neurons learning, and also the certain initial values of excitation thresholds P_v and inhibition P_t. In such a way, in the elementary case, considered MNNDD should be divided into three blocks, carrying out certain functions.

The elemental variant of conditioned-reflex learning is possible to realize with use of two learning signals (conditional *F1* and unconditional *F3*), submitted on different sections of the upper layer of MNNDD.

Block 1 is intended for distribution of conditional signal F1. Block 2 (intermediate or protective) is used as an area of space-time interaction of excitations from conditional F1 and unconditional F3 signals. In this block the formation of conditioned-reflex «nerve way» from Block 1 into Block 3 (output) during training is happening. Formation of this «nerve» way is the main criterion of the neural network **t**raining. The excitation,

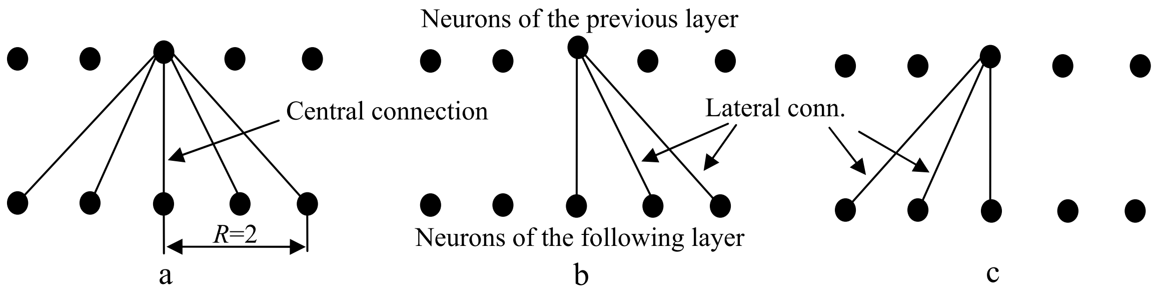

Fig. 2. *The structure of local MNNDD connections: a) symmetric connections, b) left asymmetry, c) right asymmetry*

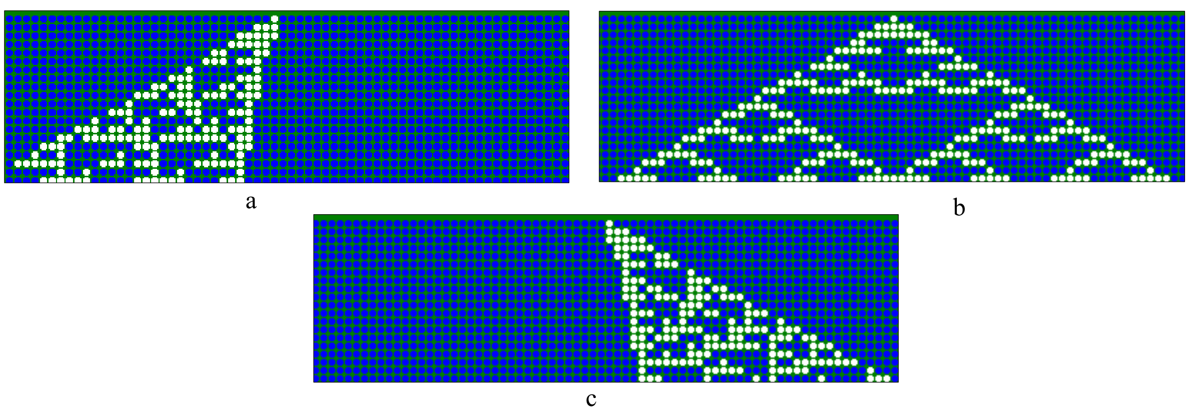

Fig. 3. *Fragments of pictures of MNNDD excitation for variants of local connections assignment: a) right asymmetry, b) symmetrical connections, c) left asymmetry*

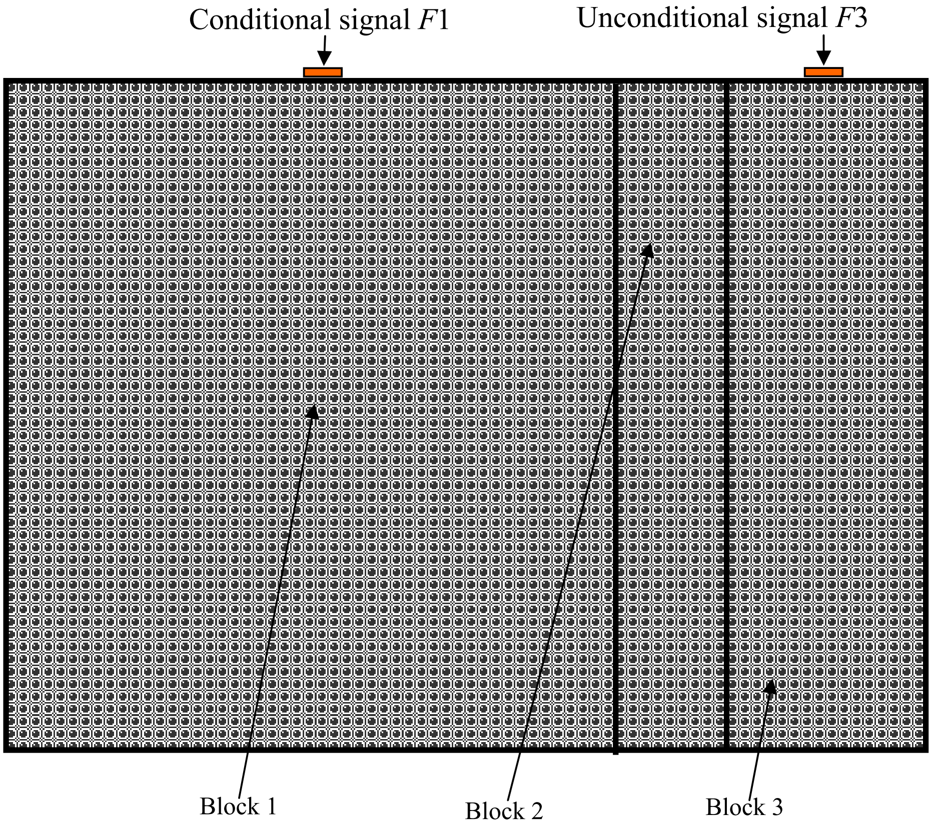

Fig. 4. *Functional division of a neural network*

extending in Block 3, is the analogue of «nerve current», starting any unconditional-reflex reaction.

Let us assume that for distribution of conditional excitation from signal *F1* all available space MNNDD is potentially opened. While unconditional excitation *F3* does not influence parameters of Block 1 neurons. It only «paves the way» for overcoming of initially higher thresholds of Block 2 neurons by conditional excitation.

Let us define as **an individual discrete time interval (step-rate)** *t* – time of excitation passing through all layers of MNNDD from input layer to output. Let us set the signal *F3* stronger than *F1* and let us submit it on *n* step-rates later than *F1,* since the best conditions in formation of conditioned reflex is precedence of weaker conditional signal *F1* than stronger unconditional *F3* [8]. Time diagrams of abidance of learning signals *F1* and *F3* are shown in fig. 5.

Let us call **a full cycle of learning** of MNNDD an interval of time containing *n* step-rates of learning, including training combination of signals *F1* and *F3*, and also pause T_{pc} up to a following learning combination.

Formation of the conditioned reflex we shall fix on some step-rate of MNNDD learning, when after a numerous time combination of conditional *F1* and unconditional *F3* signals, the excitation from prearranged signal from Block 1 through Block 2 passes into Block 3, causing neurons excitation of the output layer of Block 3 (corresponding «nerve way» is formed). Achievement of this result will depend on selection of initial values of parameters of MNNDD.

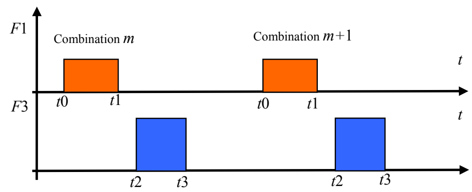

Fig. 5. *Time diagrams of abidance of learning signals; duration of signals and pauses between them:* T_{F1} *– conditional signal [t0; t1],* T_{F3} *– unconditional signal [t2; t3],* T_p *– pause between conditional and unconditional signal (t1; t2),* T_{pc} *– pause between combinations of conditional and unconditional signals (t3; t0)*

It is difficult to define precisely ranges of values of neurons thresholds of functional blocks, at which formation of the conditioned reflex is possible. Schematically one of possible approximate correlations of their values is shown in fig. 6.

Let us define values of thresholds of Block 3 neurons by fixed, and Block 1 and Block 2 – varied, i.e. changing during learning.

Let us establish the following **criterion of neuron thresholds change** of Block 1 and Block 2. On each discrete step-rate during neural network learning the excitation thresholds P_v and inhibition P_t should be changed in the event that corresponding neurons were in the excited condition ($Y_{i,j}$>0). The size of values transformation of neuron excitation and inhibition thresholds on each step-rate let us call the **step** *h* of their changes.

In considered MNNDD the function of short-term memory is realized. For this purpose the counter of going successively neuron unexcited conditions $P_{m\,i,j}$ is entered.

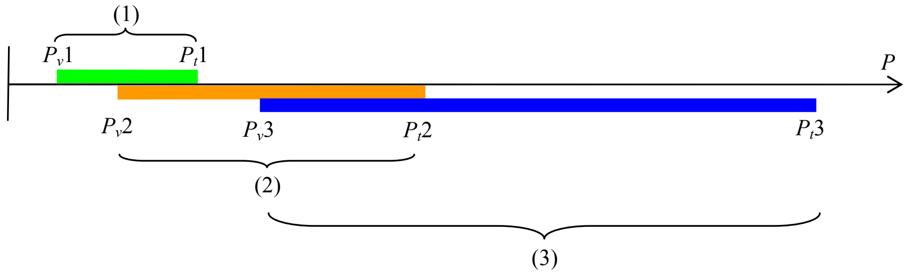

Fig. 6. *Approximate correlations of thresholds values of excitation P_{v0} and inhibition P_{t0} of Block 1 neurons (1), Block 2 (2) and Block 3 (3); values of thresholds are given in relative units*

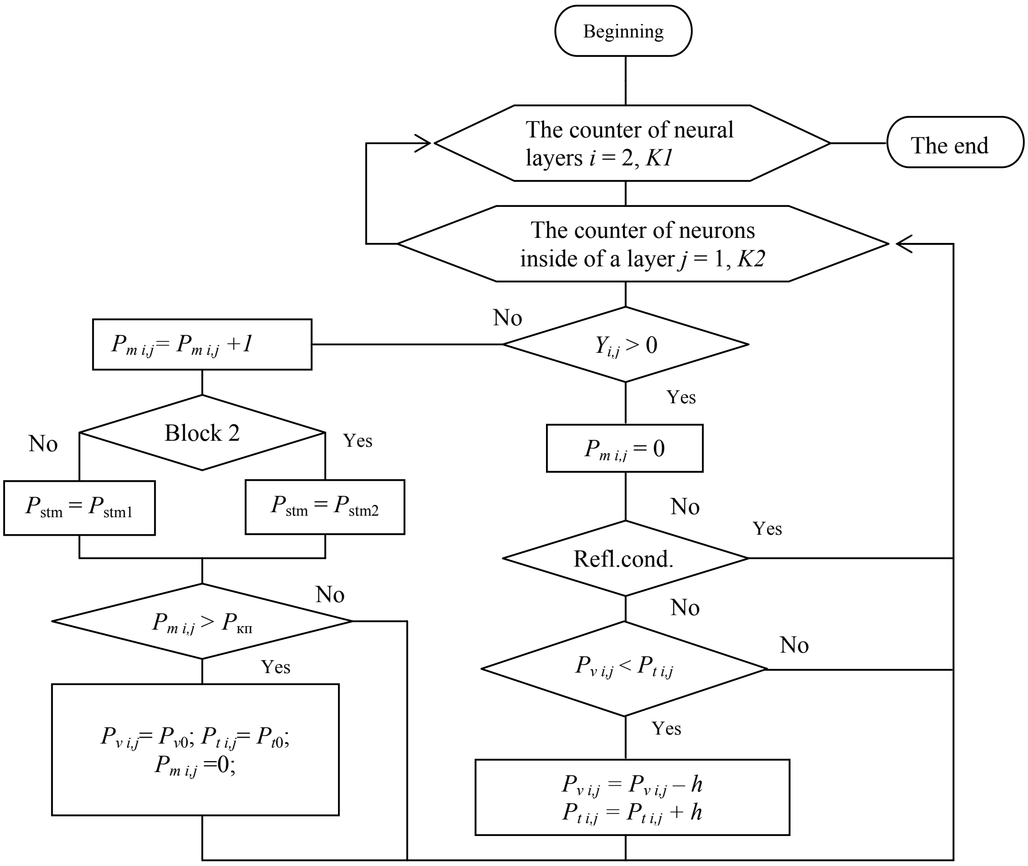

Fig. 7. *The block diagram of MNNDD learning algorithm*

Let us suppose that during a certain number of going successively step-rates of neural network learning some neurons were in unexcited condition. At the same time, change of corresponding neuron thresholds, happened at learning, are forgotten, i. e. thresholds possess initial values. The condition of forgetting by neurons of their thresholds changes, which have been saved up during learning, will look like this:

$$P_{mi,j} > P_{stm},$$

where P_{stm} is the **threshold of short-term memory.**

The block diagram of one step-rate learning algorithm of MNNDD is shown in fig. 7.

At learning, the time associative communication is formed between conditional *F1* and unconditional *F3* signals (conditioned-reflex «channel» from Block 1 into Block 3) as a result of ranges crossing of functional blocks' corresponding neurons activation. The learned neural network will react to signal *F1* by excitation of Block 3 neurons. Values of signals *F1* and *F3* are defined as constants of the whole type on outputs of the final number of neurons of the first layer.

The given algorithm of learning can be applied to recognition of the repeating symbolical combination set as conditional signal *F1*, connected in time with the main (unconditional) signal *F3*. Various symbolical combinations can be set on various sections of the first layer of a neural network. Thus, during neural network learning the quantity of combinations *F1* and *F3*, demanded for recognition of association *F1* and *F3*, is defined. Necessary quantity of combinations is possible to obtain by search of initial values of varied parameters – Block 2 neuron thresholds in some chosen range.

The considered algorithm of learning can be classified as algorithm of self-learning without a teacher, not demanding greater computing expenses. The desirable output is formed under rigidly certain scenario of neuron thresholds change, depending on a parity of their initial values in various functional blocks of the neural network, short-term memory threshold and time parities of learning combinations *F1* and *F3*.

4. Experimental research of training algorithm

Modeling and experimental research of the conditioned-reflex learning of MNNDD, using neuron two-threshold equilibrium model, in Delphi programming environment has shown that the best scenario of neuron thresholds change is increase in the range of their activation at reduction of excitation thresholds P_v and increase in inhibition thresholds P_t.

Let us consider an example of recognition of some symbolical combination *F1*, associated in time with signal *F3*. Varied parameters at learning are excitation P_v (decrease) and inhibition P_t (increase) thresholds of Block 1 and block 2 neurons. Constant parameters of the neural network (including the parameters of distinguished combination *F1* and signal *F3*) are shown in table 1.

In the given example nine learning series, independent from each other, have been done, for various initial values of Block 2 neuron inhibition thresholds. As a result of learning, corresponding values of a number of combinations *F1* and *F3*, required for recognition of the given association, have been received. Results of learning are shown in table 2.

The resulted example is one of the possible applications of conditioned-reflex learning. Besides, during research of the presented algorithm, consideration of learning series for various values of short-term memory threshold – P_{stm} is possible, and other parameters shown in table 1 are also possible.

Table 1. *Constant parameters of the neural network*

Parameter	Value
Quantity:	
•neural layers	220
•neurons in a layer	245
•neurons in each layer of Block 2	35
Neurons' excitation thresholds:	
•Block 1 (initial values)	4
•Block 2 (initial values)	20
•Block 3	20
Neurons' inhibition thresholds:	
•Block 1 (initial values)	15
•Block 2 (initial values)	80
•Block 3	200
Number of connections:	
•lateral (left asymmetry) for Block 1 neurons	2
•straight (symmetry) for Block 2 and Block 3 neurons	5
Number of excited neurons of the first layer (symbolical combination *F1*)	7
Number of the first excited neuron in combination *F1*	88
Number of the last excited neuron in combination F1	94
Neurons' excitation of the first layer (symbolical combination F1)	5
Number of excited neurons of the first layer (signal *F3*)	6
Number of the first excited neuron from signal *F3*	228
Number of the last excited neuron from signal *F3*	234
Neurons' excitation of the first layer (signal *F3*)	25
Step of excitation and inhibition thresholds' change	1
Short-term memory threshold (quantity of step-rates)	12
Duration:	
•influences of combination *F1* (quantity of step-rates)	4
•influences of signal *F3* (quantity of step-rates)	7
•pauses between signals *F1* and *F3* (quantity of step-rates)	1
•pauses of combinations *F1* and *F3* (quantity of step-rates)	5
•one training cycle (quantity of step-rates)	17

Table 2. *Results of the natural network learning*

Number of combinations	3	5	6	8	9	14	26	47	75
P_{t02}	80	75	70	65	60	55	50	45	40

Conclusions

1. Neuron two-threshold equilibrium model for use in a homogeneous multilayered neural network of direct distribution with local connections has been developed.
2. Division of the network into functional blocks has allowed realizing in it the conditioned-reflex mechanism of learning.
3. As a result of modeling and the experimental research of conditioned-reflex learning of multilayered neural network of direct distribution, the best scenario of neuron excitation and inhibition thresholds has been determined.
4. Modeling and the experimental research of conditioned-reflex learning of the neural network can be useful at construction of various technical devices and systems, in particular for solution of problems of repeating symbolical combinations recognition, associated in time with the main signal.

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