Large enough structured neural networks are used for solving the tasks to recognize distorted images involving computer systems. One such neural network that can completely restore a distorted image is a fully connected pseudospin (dipole) neural network that possesses associative memory. When submitting some image to its input, it automatically selects and outputs the image that is closest to the input one. This image is stored in the neural network memory within the Hopfield paradigm. Within this paradigm, it is possible to memorize and reproduce arrays of information that have their own internal structure.

In order to reduce learning time, the size of the neural network is minimized by simplifying its structure based on one of the approaches: underlying the first is «regularization» while the second is based on the removal of synaptic connections from the neural network. In this work, the simplification of the structure of a fully connected dipole neural network is based on the dipole-dipole interaction between the nearest adjacent neurons of the network.

It is proposed to minimize the size of a neural network through dipole-dipole synaptic connections between the nearest neurons, which reduces the time of the computational resource in the recognition of distorted images. The ratio for weight coefficients of synaptic connections between neurons in dipole approximation has been derived. A training algorithm has been built for a dipole neural network with sparse synaptic connections, which is based on the dipole-dipole interaction between the nearest neurons. A computer experiment was conducted that showed that the neural network with sparse dipole connections recognizes distorted images 3 times faster (numbers from 0 to 9, which are shown at 25 pixels), compared to a fully connected neural network

Keywords: mathematical model, neural network, sparse dipole synaptic connections, image recognition

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BUILDING A MATHEMATICAL MODEL AND AN ALGORITHM FOR TRAINING A NEURAL NETWORK WITH SPARSE DIPOLE SYNAPTIC CONNECTIONS FOR IMAGE RECOGNITION

Vasyl Lytvyn
Corresponding author
Doctor of Technical Sciences, Professor*
E-mail: vasyl.v.lytvyn@lpnu.ua

Roman Peleshchak
Doctor of Physical and Mathematical Sciences, Professor*

Ivan Peleshchak
Postgraduate Student*

Oksana Cherniak
Postgraduate Student
Department of Mathematics
Drohobych Ivan Franko State Pedagogical University
I. Franka str., 24, Drohobych, Ukraine, 82100

Lyubomyr Demkiv
Doctor of Technical Sciences, Professor*

*Department of Information Systems and Networks
Lviv Polytechnic National University
S. Bandery str., 12, Lviv, Ukraine, 79013

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1. Introduction

Intensive research is underway on the use of neural networks to solve a wide class of problems related to intelligent data analysis (detection of non-stationary chaotic processes, clustering, intelligent control, diagnostics of biosystems, forecasting, emulation and pattern recognition). In particular, papers [1, 2] consider a technique of recognition of multispectral images with a signal amplitude commensurate to the noise level due to information resonance. The authors of [3] tackled the task of recognizing aerial photographs with a multilayer perceptron based on adaptive resonance.

Recognition of distorted images by using neural networks is a relevant issue in the field of Data Mining. In particular, study [4] analyzed the effects of white Gaussian noise, pixel maximization, and brightness minimization on image recognition quality; paper [5] examined the neural network technology of recognition of handwritten documents where the role of distorted images belongs to different styles of writing letters. In addition, it is proposed in [6, 7] to detect, and in [8, 9] to categorize, distorted images by using convolutional neural networks.

Our review of the above methods for solving the tasks of recognition of noise distorted images by neural networks reveals a number of practical issues. In particular, minimizing the size of a neural network and the architecture of synaptic connections between neurons, reducing the learning time of a neural network, and increasing its capacity, improving the degree of generalization of the functional ability of the neural network without losing its performance.

The artificial pseudospin neural network discussed in [10] is a prototype of a natural neural network consisting of dipole neurons that are structural elements of the cytoskeleton microtube [11, 12].

It is a relevant task to design the architecture of an artificial neural network with synaptic connections between the nearest dipole neurons since such a neural network could improve the efficiency of recognizing distorted images by reducing the computing resource used.

2. Literature review and problem statement

Studies [11, 12] examine the physical model of representation and recognition of images in the neuron cytoskeleton microtube. In particular, paper [11] reported a physical model of associative memory based on an unordered dipole system of the cytoskeleton microtube, which acts as a distributed structure with associative memory. It should be noted that for recording N different images-references in an unordered dipole system, it is necessary for each of these images to create their own configuration of the dipole. Different configurations of dipoles must be orthogonal. The dipole system of the cytoskeleton microtube with the relaxation law of evolution has a memory that retains some predetermined set of reference images and tries to remember one of them when it is given any of these noise-distorted images.

In [12], the microscopic physical model of representation and recognition of images in the neural dipole system of the cytoskeleton microtube was built, and the criterion for the selection of informational features of the image in the cytoskeleton microtube was formulated. It is shown that at a certain ratio of the constants of synaptic connections between the tubulin molecules, the main state of the dipole system of the microtube is dipole glass. Synaptic connections between tubulin molecules are executed in dipole approximation [12] as $\lambda_{ij} \sim 1/R_{ij}^3$ (R_{ij} is the center-to-center distance between the i-th and j-th molecules). Thus, when constructing an artificial neural network with dipole neurons, it is possible to limit the synaptic connections between the nearest neurons $\left(\lambda_{ij} \sim 1/R_{ij}^3\right)$. That would lead to a decrease in the number of synaptic connections between neurons, which could ultimately reduce the learning time of the neural network.

Papers [13, 14] report experimental data showing that in the neurons of the brain, informational protein nanopolymers – cytoskeleton microtubes – are the corresponding substrates for «quantum-statistical calculations». The basic element of the structure of the cytoskeleton is the cytoskeleton microtubes, which are hollow cylindrical tubes with an outer diameter of 25 nm and an internal diameter of about 14 nm, and a length of 1–10 μm.

In these experimental studies performed at physiological temperature, it was found that the cytoskeleton microtube consists of tubulin molecules. Each tubulin molecule has a dipole momentum of about 100 D (debay) and is a dimer consisting of α- and β-tubulins connected by a thin membrane. The tubulin dimer can exist in two different geometric configurations (conformations), that is, in two states, which, in the language of Boolean algebra, can be described by 0 and 1. Each molecule of tubulin (dimer) has a dipole moment. Dipole neurons with dipole orientation in two states +1 and 0 are the analogs of the tubulin molecule (dimer) in an artificial neural network.

In addition, papers [13, 15–17] indicate that cytoskeleton microtubes flicker optically during metabolic activity, and the resonance frequencies of tubulin molecules are approximately 10^{11}–10^{13} Hz.

With increasing requirements for efficiency in solving problems of recognition of distorted images, we propose to create a neural network with sparse dipole connections based on a prototype of the natural neural network of the cytoskeleton microtube type, which would reduce the computing resource used to recognize distorted images.

3. The aim and objectives of the study

The purpose of this work is to build a mathematical model of an artificial dipole (pseudospin) neural network with dipole synaptic connections between neurons with optimized computational resource time for the recognition of symbolic characters by this network.

To accomplish the aim, the following tasks have been set:

– to derive the ratio for the weight coefficients of synaptic connections between neurons in dipole approximation;

– to design an artificial neural network learning architecture with sparse synaptic connections and dipole neurons that have the properties of tubulin molecules in the cytoskeleton microtube;

– to build an algorithm for recognizing distorted images by an incomplete (sparse) dipole neural network.

4. The study materials and methods

Similar to the biological prototype [18, 19], paper [10] proposes the architecture of an artificial fully connected neural network consisting of neurons that are characterized by dipole momentum. It should be noted that the interaction between adjacent neurons is carried out through dipole frustrated (a large number of low-energy states (attractors)) synaptic connections. The dynamics of the dipole neuro system are set by the process of relaxation of the energy of interaction of dipoles (pseudospins). Any initial 2^N state coincides with one of these stationary states. As a result of the completion of relaxation processes in the dipole neural network, the input image is associated with one of those images that were remembered earlier. Thus, we can argue that the dipole neural network appears as a distributed structure that has an associative memory [10].

Neurons of the artificial dipole fully-connected neural network, the architecture of which is shown in Fig. 1, are located at the points of space with coordinates:

$$\overline{r_i} = m_i\overline{a}_1 + n_i\overline{a}_2 + p_i\overline{a}_3, \qquad (1)$$

$m_i, n_i, p_i \in \mathbb{Z}$; $\overline{a}_1$, $\overline{a}_2$, $\overline{a}_3$ are the basis vectors [20].

Dipole neural network is most likely for a specific implementation of a dynamic neural network. This neural network consists of N stochastic dipole neurons, which are interrelated by the synoptic connections λ_{ij} (i, j are the numbers of neurons).

The symmetrical matrix of fully related synaptic connections takes the following form [20]:

$$\hat{\lambda}^{tot} = \begin{pmatrix} 0 & \lambda_{12} & \lambda_{13} & \dots & \lambda_{1N} \\ \lambda_{21} & 0 & \lambda_{23} & \dots & \lambda_{2N} \\ \lambda_{31} & \lambda_{32} & 0 & \dots & \lambda_{3N} \\ \dots & \dots & \dots & \dots & \dots \\ \lambda_{N1} & \lambda_{N2} & \lambda_{N3} & \dots & 0 \end{pmatrix}. \qquad (2)$$

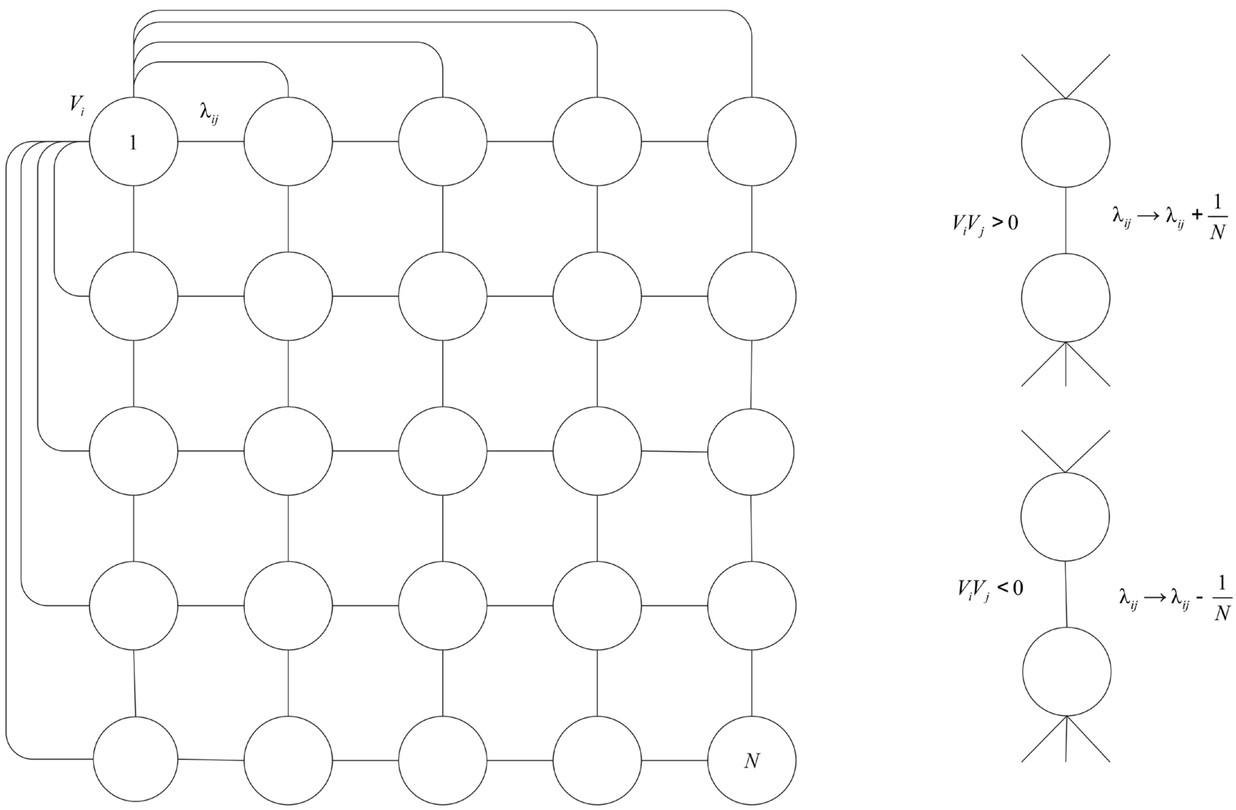

Fig. 1. Dipole neural network with fully-connected synaptic connections. The product $V_iV_j>0$ indicates the strengthening of the synaptic connection between both the i-th and j-th neuron, and $V_iV_j<0$ indicates its weakening. One neuron corresponds to each pixel

To minimize the learning time of the neural network, it is proposed to reduce the symmetrical matrix of fully-connected connections of the dipole neural network $\hat{\lambda}^{tot}$ (2) to the matrix $\hat{\lambda}$ (9) with sparse connections between the nearest adjacent neurons within the dipole-dipole interaction $\left(\lambda_{ij} = 1/R_{ij}^3\right)$.

5. Results of building the mathematical model of a dipole neural network

5. 1. Deriving the ratio for the weight coefficients of synaptic connections between neurons in dipole approximation

The energy of synaptic connections λ_{ij} between two dipole neurons in the electrostatic approximation is derived. The energy of interaction between two neurons can be considered as the potential energy of the charge system of one neuron i in the outer field, which is created by the charge system of the second neuron j:

$$\lambda_{ij} = \sum_{k=1}^{M} e_k \varphi_j(\bar{r}_k), \tag{3}$$

where $\varphi_j(\bar{r}_k)$ is the potential created by the system of charges of the j-th neuron, at the points of charge placement of the i-th neuron. If the neuron charge systems are far from each other, then the field potential $\varphi_j(\bar{r}_k)$ changes slightly in the area of space occupied by the neuron i. In this case, it is convenient to expand into a Taylor series based on the powers of $\bar{r}_k$, by selecting the location point 0 inside the charge system of the i-th neuron:

$$\varphi_j(\bar{r}_k) = \varphi_j(0) + \sum_{\beta}\left(\frac{\partial \varphi_j(\bar{r}_k)}{\partial x_{k\beta}}\right)_0 x_{k\beta} + \ldots \tag{4}$$

Upon substituting (4) in (3), we obtain:

$$\lambda_{ij} = \varphi_j(0)\sum_{k\in 0} e_k + \sum_{\beta}\left(\frac{\partial \varphi_j(\bar{r}_k)}{\partial x_{k\beta}}\right)_0 \sum_{k\in 0} e_k x_{k\beta} + \ldots =$$
$$= \varphi_j(0) q_i + \bar{d}_i \bar{\nabla} \varphi_j(0) + \ldots, \tag{5}$$

where $\bar{d}_i = e_i \bar{r}_i$ is the dipole moment of the i-th neuron. After substituting in (5), the multi-field expansion of potential $\varphi_j(0)$ (6) takes the form:

$$\varphi(\bar{R}_{ij}) = \sum_k e_k \left|\bar{R}_{ij} - \bar{r}_k\right| = \frac{q}{R_{ij}} + \frac{\bar{d}\bar{R}_{ij}}{R_{ij}^3} + \ldots, \tag{6}$$

where the first term in (5) describes the monopole-multipole interaction, and the second – dipole-multipole interaction, etc.

For electrically neutral neurons, the first term in the energy function (5) is $\bar{d}_i \bar{\nabla}\left(\left(\bar{d}_j \bar{R}_{ij}\right)/R_{ij}^3\right)$. The action of operator $\bar{\nabla}$ on the second term (5) led to the form:

$$\lambda_{ij} = \left(\frac{1}{4\pi\varepsilon\varepsilon_0 R_{ij}^3}\right)\left[d_i d_j - \frac{3\left(\bar{d}_i \bar{R}_{ij}\right)\left(\bar{d}_j \bar{R}_{ij}\right)}{R_{ij}^2}\right], \tag{7}$$

where ε is the relative dielectric permeability of the environment in which neurons are located; $\varepsilon_0 = 8.85\cdot 10^{-12}$ F/m; R_{ij} is the center-to-center distance between the i-th and j-th neurons.

It should be noted that the multipole expansion is valid over the long distances between interacting systems. A prerequisite for its fairness is the absence of overlapping charge distribution. Due to the quantum-mechanical «smearing» of charges, such an overlap is always in place but, for the case of interacting molecules of tubulin, it is very small. Since overlapping exponentially decreases in proportion to distance, the energy of electrostatic interaction in the form of a multipole series means neglect of exponentially descending terms.

After the introduction of the spherical angle $\Theta = \bar{d}_i \wedge \bar{l}$ (the angle between the directions of the dipole axis and the unity-normalized vector $\bar{l} = \bar{R}_{ij} / R_{ij}$, connecting the mass centers of the i-th and j-th neurons), the energy of the synaptic bond of two electric dipoles $\bar{d}_i$ and $\bar{d}_j$, is equal to:

$$\lambda_{ij} = \left(\frac{1}{4\pi\varepsilon\varepsilon_0 R_{ij}^3} \right) \left[\bar{d}_i \bar{d}_j - 3\left(\bar{d}_i \bar{l}\right)\left(\bar{d}_j \bar{l}\right) \right] = -\left(\frac{1}{4\pi\varepsilon\varepsilon_0 R_{ij}^3} \right) \left[3\cos^2\Theta - 1 \right] d_{ix} d_{jx}, \tag{8}$$

where d_{ix}, d_{jx} are the projections of the dipole i-th and j-th neurons onto the x axis. It follows from (8) that the resonant dipole-dipole interaction of neurons is sign-alternating. Different pairs of dipole neurons can interact with each other in both ferroelectric and antiferroelectric ways. In addition, the interaction between dipole neurons can be random in terms of signs [11, 12].

Therefore, the dipole neural network will be dipole glass in which there is a significant number of frustrations, which could lead to enormous degeneration of the ground state. Thus, within the system, there can exist a significant number of states with low energy (a large number of attractors), which is close to the energy of the ground state. The number of such states can equal $2^N = \exp(N \ln 2)$. This makes it possible to remember a large number of reference images.

Analyzing (8) has revealed that the settings of synaptic connections between neurons during neural network learning can be assigned by changing the topology of their arrangement (changing the distance R_{ij} between the i-th and j-th neurons) or by changing the angle $\Theta = \bar{d}_i \wedge \bar{l}$.

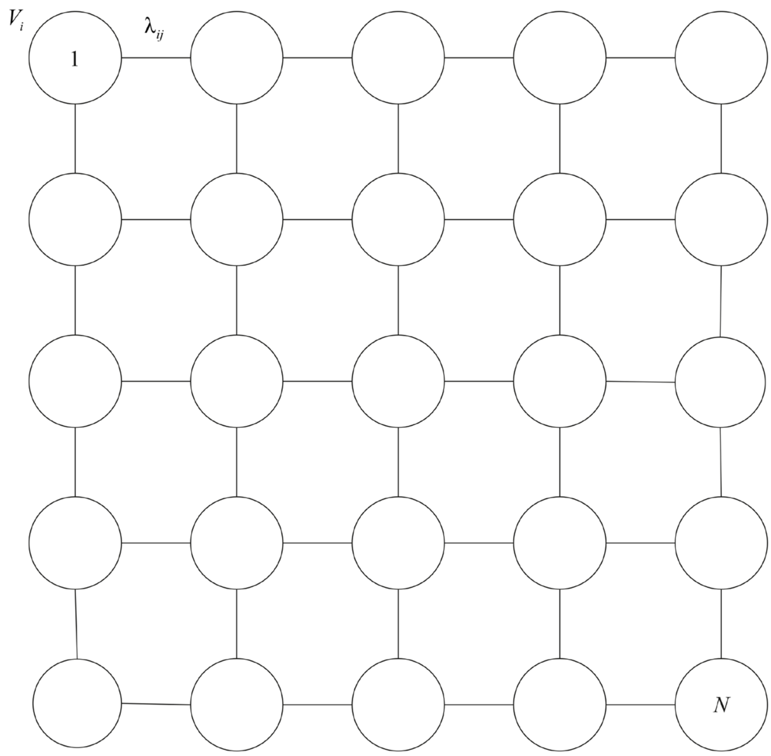

Fig. 2. Dipole neural network with sparse synaptic connections

5. 2. Building an artificial neural network architecture with dipole neurons

Within the dipole-dipole interaction between neurons, the architecture of the dipole (pseudospin) neural network with fully-connected synaptic connections (Fig. 1) takes the form shown in Fig. 2.

The synaptic connections between the dipole neural network neurons are sparse in such a way that their synaptic connections in each row and columns of the single-layer neural network exist only between the nearest adjacent dipole neurons (Fig. 2).

The incomplete sparse matrix of synaptic connections of the dipole neural network of dimensionality $n \cdot n$ (n is the number of neurons in a row or column) with the number of neurons $N = n^2$ takes the form:

$$\hat{\lambda} = \begin{pmatrix} 0 & \lambda_{12} & \dots & 0 & \dots & \lambda_{1,n+1} & \dots & 0 & \dots & 0 \\ \lambda_{21} & 0 & \lambda_{23} & 0 & \dots & 0 & \lambda_{2,n+2} & 0 & \dots & 0 \\ 0 & \lambda_{32} & 0 & \lambda_{34} & \dots & 0 & \dots & \lambda_{3,n+3} & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 0 & \dots & 0 & \dots & \lambda_{N,N-n} & \dots & 0 & \dots & \lambda_{N,N-1} & 0 \end{pmatrix}. \tag{9}$$

If $N = n^2$ is the number of neural network neurons, then the number of synaptic connections $N_{\hat{\lambda}}$ in the flat inferior neural network (9), shown in Fig. 2, is defined by:

$$N_{\hat{\lambda}} = 4n(n-1), \; n \geq 2, \tag{10}$$

where as the number of synaptic connections of the fully-connected symmetrical square matrix (2), whose main diagonal hosts zero elements $\lambda_{ii} = 0$, is determined from the following ratio [20]:

$$N_{\hat{\lambda}^{tot}} = n^2\left(n^2 - 1\right). \tag{11}$$

The number of synaptic connections in the incomplete dipole neural network relative to the fully connected one is less by a times:

$$\alpha = \frac{N_{\hat{\lambda}^{tot}}}{N_{\hat{\lambda}}} = \frac{n(n+1)}{4}. \tag{12}$$

The time for setting synaptic connections λ_{ij} (per iteration) in a fully-connected neural network is proportional to the number of synaptic connections $N_{\hat{\lambda}^{tot}}$, that is:

$$t^{tot} = k_{\hat{\lambda}^{tot}} N_{\hat{\lambda}^{tot}}, \tag{13}$$

where $k_{\hat{\lambda}^{tot}}$ is the coefficient that describes the setting time of one synaptic connection.

Similarly, the time for setting synaptic connections λ_{ij} (per iteration) in a dipole incomplete neural network is equal to:

$$t^{tot} = k_{\hat{\lambda}} N_{\hat{\lambda}}. \tag{14}$$

The coefficients $k_{\hat{\lambda}^{tot}}$ and k_{λ} depend solely on the architecture of synaptic connections in the corresponding neural networks.

Considering (10), (11), (13), (14), we obtained:

$$\frac{t^{tot}}{t} = \frac{k_{\hat{\lambda}^{tot}}}{k_{\lambda}} \alpha, \tag{15}$$

a ratio that describes how many times the time of setting up synaptic connections of an incomplete dipole neural network is less than the time of setting up synaptic connections of a fully-connected single-layer neural network.

5. 3. Designing an algorithm for recognizing distorted images by an incomplete dipole neural network

Numerical experiments were carried out using the software package «MATLAB» to recognize noised figures from 0 to 9. The figures were noised using pseudo-random evenly distributed numbers, that is, the pixel that changed in the digit image was randomly selected.

In particular, the case was considered where the dimensionality of the pixel matrix of the digital image of the input images was 5·5. Then the single-layer artificial dipole neural network would consist of 25 neurons (N=25).

The algorithm for recognizing input images is implemented using a fully connected and incomplete matrix of synaptic connections. In the case of a fully connected matrix, the number of synaptic connections is $N_{\hat{\lambda}^{tot}} = 600$, for an incomplete matrix is $N_{\hat{\lambda}} = 80$, based on formulas (11), (10), respectively.

The algorithm of training a sparse dipole neural network is depicted in the form of a flowchart (Fig. 3) and is described in writing (step by step).

The algorithm for training a sparse dipole neural network consists of the following steps:

1. Enter the input vector of the image:

$$V_i, V_j, V_i^*, V_j^*.$$

Here, V_i^*, V_j^* are the noisy signals.

2. Initialize synaptic coefficients:

$$\lambda_{ij} = \begin{cases} V_i V_j, i \neq j, \\ 0, \ , i = j. \end{cases}$$

3. At zero iteration, at the output of the j-th neuron, the value of the j-th input image is assigned:

$$Y_j(0) = V_j^*.$$

4. A new state of the j-th neurons is calculated:

$$S_j(t+1) = \sum_{i=1}^{N} \lambda_{ij} Y_i(t).$$

5. New output values are calculated:

$$Y_j(t+1) = \text{sign}\left(S_j(t+1)\right).$$

6. If $Y_j(t+1) = Y_j(t)$, then the algorithm is completed; otherwise, $Y_j(t) = Y_j(t+1)$, proceed to the execution of step 4 of this algorithm.

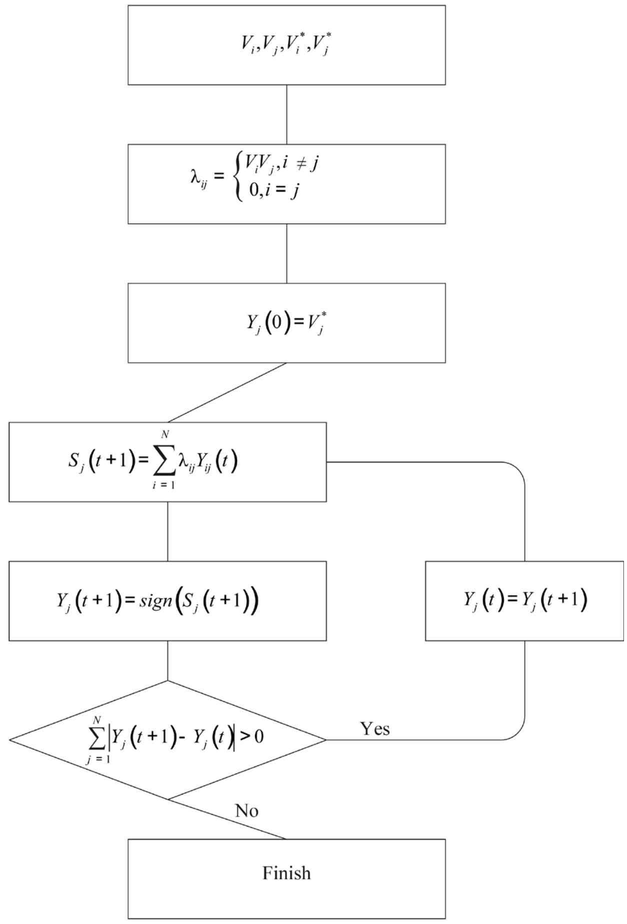

Fig. 3. Flowchart of the algorithm for training a sparse dipole neural network

Based on the given algorithm, a computer experiment was conducted, which showed that when recognizing the noisy images of digits from 0 to 9, the fully-connected dipole neural network recognized images where the maximum number of distorted pixels for each digit was 12 out of 25. For 10 distorted pixels, the number of iterations is 2. The time to recognize images by a fully-connected dipole neural network:

$$t^{tot} = 2kN_{\hat{\lambda}tot}, \tag{16}$$

where k is the coefficient that describes the time of setting one synaptic connection. When using an incomplete matrix of synaptic connections, the number of distorted pixels for each digit was 10 out of 25. At the same time, the maximum number of iterations for recognizing the input image was 5. The time for image recognition by an incomplete neural network is:

$$t = 5kN_{\hat{\lambda}}. \tag{17}$$

That is, an image of 10/25·100 %=40 % distorted pixels was recognized.

6. Discussion of results of studying the dipole neural network morphology and the time of its computational resource

According to the results (16), (17), in the case of an incomplete dipole neural network, the time t for setting synaptic connections for image recognition, which has 10 distorted pixels, is less than the time t^{tot} for image recognition by a fully-connected network by:

$$\frac{t^{tot}}{t}=\frac{2kN_{\hat{\lambda}^{tot}}}{5kN_{\hat{\lambda}}}=\frac{n(n+1)}{10}\text{ times.} \tag{18}$$

For the number of neurons $N=25$, this ratio is $t^{tot}/t=3$.

That is, the time of recognition of distorted images (10 distorted pixels out of 25) by an incomplete dipole neural network (Fig. 2) is 3 times less than that by the fully-connected one, which could improve the efficiency of solving the tasks to recognize distorted images.

The comparative analysis of the time of dipole neural network configuration with tridiagonal synaptic connections [10] with the time of setting up synaptic connections between the nearest dipole neurons (9) reveals that in the first case, the setting time is $t\sim t^{tot}/n^2$, whereas in the second – $t\sim t^{tot}/(n(n+1))$. That is, the time of setting the dipole neural network with synaptic connections between the nearest neurons (9), when compared to the tridiagonal dipole neural network [10], is less at a small number of neurons, and with an increase in the number of neurons n, the durations become almost equal.

The dipole neural network model has two main limitations:

1. The number of images that can be stored and accurately reproduced is limited.

2. The dipole neural network can be unstable if there is a mini-threshold distance between the training examples within the Euclid metrics. This issue can be resolved by the choice of orthogonal training examples.

The disadvantage of this model is that synaptic connections between neurons are described within the nearest adjacent neurons since there is a dipole-dipole interaction between neurons.

Further studies will experiment with more different images, as well as with a higher number of pixels contained in a single image.

7. Conclusions

1. The ratio for weight coefficients of synaptic connections between neurons in dipole approximation has been derived, which shows that there may be a significant number of low energy states in the system (a large number of attractors), which is close to the energy of the ground state. This could make it possible to remember a large number of reference images. The number of such states may equal $2^N=\exp(N\ln 2)$.

2. The architecture of a dipole neural network with synaptic connections between the nearest neurons has been designed, which makes it possible to reduce the used computational resource for the recognition of distorted images by 3 times relative to the fully-connected dipole neural network.

3. An algorithm of recognition of distorted images by an incomplete dipole neural network has been built; a computer experiment in the software package «MATLAB» was carried out on the basis of this algorithm, which showed that a neural network with sparse dipole connections is 3 times faster to recognize distorted images (numbers from 0 to 9, which are shown at 25 pixels) compared to the fully-connected dipole neural network.

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