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THE PROCEDURE FOR THE DETERMINATION OF STRUCTURAL PARAMETERS OF A CONVOLUTIONAL NEURAL NETWORK TO FINGERPRINT RECOGNITION

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ABSTRACT

The article is devoted to improve the efficiency of the system of biometric authentication on the basis of neural network fingerprint recognition. Analysis of modern neural network biometric authentication tools shows that it is possible to increase efficiency by adapting the structural parameters of the convolutional neural network to the peculiarities of the fingerprint recognition problem. The specified parameters include the size of the input field, the number of input and output neurons, number of neurons in fully connected layer, the number of convolutional layers, the number of feature maps in each convolutional layer and others. It is also shown that the main features of the recognition problem are the number of prints to be recognized, the size and quality of scanned images of prints, as well as the number and parameters of minutiae taken into account. A number of principles of adaptation of structural parameters was formed by analogy with the known solutions in the field of neural network recognition of biometric parameters. Based on the proposed principles and the identified features of the fingerprint recognition problem, a corresponding procedure for determining the structural parameters of the convolutional neural network is developed. The efficiency of the developed procedure is proved by numerical experiments, which confirmed the sufficient accuracy of recognition. It is determined that the prospects for further research are to develop a mechanism for optimizing the mathematical apparatus of the convolutional neural network with respect to the conditions of the problem of fingerprint recognition in the biometric authentication system.

Keywords: *Fingerprint Recognition, Biometric Authentication, Minutiae; Convolution Layer, Neural Network*

1. INTRODUCTION

Currently, one of the fastest growing areas in the field of information security is the development of neural network means of biometric authentication of users. This is due to the increase in the flow of confidential information, the expansion of the class of information systems in which it is required to provide a service for the distribution of user access rights, proven fundamental shortcomings of classical user authentication systems, as well as objective requirements to ensure the secrecy and remoteness of access control systems in different areas of its use [1-5].

The results of the analysis of modern neural network systems of biometric authentication allow us to assert that the most widespread are systems that authenticate the user based on the analysis of the geometry of the handshape, ear shape, face, blood vessels on the hands or the surface of the fundus, as well as the skin of the user's fingers (fingerprints). The advantages of the latter include ease of use, high

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classification accuracy, good approbation and low cost of reading devices. Such systems are based on the uniqueness and constancy (in an adult) of the pattern of papillary lines of fingers. It is believed that the probability that two people will have the same fingerprints is $2*10^{-12}$ [6,7].

The prospects of biometric user authentication systems based on the analysis of fingerprint geometry is confirmed both by the wide application of appropriate technologies (for example, in biometric passports) and by a large number of relevant theoretical and practical studies [8-11]. At the same time, practical experience, as well as the results of a number of works [3, 6, 12] indicate the need for significant modernization of modern biometric neural network user authentication systems based on the analysis of fingerprint geometry in the direction of reducing resource consumption, increasing recognition accuracy, reducing the development time and increasing adaptation to many features of modern information systems, which determines the relevance of research in this direction.

2. ANALYSIS OF NEURAL NETWORK SOLUTIONS FOR BIOMETRIC FINGERPRINT AUTHENTICATION

The paper [8] deals with the problem of biometric fingerprint authentication of users. Proposed neural network model for authentication based on the two-layer perceptron whose number of input neurons 90, the number of hidden neurons is 10 and the number of output neurons 4. It is noted that the specified parameters of the network architecture were calculated experimentally. The geometric characteristics of local features are used as input parameters: coordinate (X), coordinate (Y), direction vector (Q). It is common to use 30 local features. It is shown experimentally that the neural network classifier of selection deviation has the error level of the first kind of 5.2 %, and the error level of the second kind — 0 %. Based on this, it is argued that the constructed neural network model is effective in relation to other biometric authentication technologies. Similar results are presented in [6] which further describes the mathematical apparatus on which the functioning of a two-layer perceptron is based.

Article [9] is devoted to the use of neural networks in the fingerprint identification system. It is indicated that identification difficulties are caused by the fact that during the fingerprint scanning process, the image generated by the scanner may differ slightly during each scan. To level these difficulties, it is proposed to use a neural network model based on a multilayer perceptron with one hidden layer. The choice of neural network architecture is explained by its simplicity and approbation. The source of input information for the neural network model is a scanned fingerprint image of 188x240 pixels. 12 geometric moments are calculated, each of which corresponds to one of the input neurons. The number of output neurons taken equal to six. The number of hidden neurons is 25, determined on the basis of Kolmogorov's theorem. Sigmoid is used as activation function. The network was trained using the classical error back propagation algorithm. The training sample consisted of 100 fingerprints. The number of training epochs is 1000. The claimed accuracy of recognition of training examples was 100%, which, according to the authors, indicates the prospects of neural network fingerprint recognition systems.

In [7] it is noted that fingerprints of different people may have the same global characteristics, but it is impossible to have the same local characteristics (minutiae). Therefore, the identification process usually consists of two stages. The first step is to classify fingerprints by global criteria, using databases to divide them into classes. The second step is to recognize the fingerprint based on a comparison of the structure and the coefficient of coincidence of the minutiae points. The proposed algorithms for the classification of fingerprint images according to the types of papillary patterns on the basis of application of the Gabor filter, wavelet transform Haar, Daubechies and multilayer neural network. Numerical experiments are carried out and the results of the proposed algorithms are presented. It is shown that the algorithm based on the joint application of the Gabor filter, five-level wavelet transform Daubechies and multilayer neural network-type double-layer positron, makes it possible to achieve the accuracy of classification of about 75%.

In [10] a study of recognition methods of the fingerprint image based on neural networks such as a two-layer perceptron architecture 81-27-3. The module and the argument of the vector field of the gradient of dactyloscopic images are used as input parameters of the neural network. The conclusion about the need to increase the power of the input vector of the neural network to 400 is formulated.

Work [11] is devoted to the analysis of characteristics of fingerprints used in biometric neural network systems of identification of the person. It is noted that on the image of the finger surface it is possible to determine a sufficiently large number of small details (minutiae), which are the basis for the classification. Minutiae are characterized by type, coordinates, and direction.

The article [12] describes in detail the local and global characteristics of the fingerprint used in biometric authentication systems. It is shown that the possibility of distinguishing characteristic features that can be used in the future for identification largely depends on the quality of the fingerprint image. It is also indicated that common fingerprint scanners provide a resolution of 500 dpi, the image is characterized by 256 levels of brightness, and the maximum angle of rotation of the print from the vertical is not more than 15 degrees. At the same time, as characteristic features, it is proposed to use the end points in which the papillary lines end "distinctly", as well as the points of branching in which the papillary lines are bifurcated. It is noted that in the images of the finger surface with a resolution of about 1000 dpi, it is possible to detect details of the internal structure of the papillary lines themselves (pores of the sweat glands) and use their location in order to significantly improve the accuracy of identification. However, the current level of technical support of common biometric authentication systems does not provide the possibility of obtaining images of such quality.

In work [13] the technology of designing and operation of neural network system of two-level fingerprint recognition is considered. At the first level, the allocation of characteristic features is implemented, and at the second level, the analysis of the selected features is implemented, the result of which is the identification of the user. It is shown that the performance of the recognition system is affected by the accuracy of the selection of informative features of fingerprints, which, in turn, largely depends on the quality of the recognized image. This explains the presence of a module in the system to improve the quality of the original (obtained from the scanner) image. The peculiarity of the operation of this module is that the improvement of the quality of the fingerprint structure should not damage the minutiae. To do this, it is proposed to use Gabor filters and the so-called skeletonizing, which converts a gray-scale fingerprint into a black and white image, where the ridges are only 1 pixel wide. In the proposed system, neural networks are used at both levels of recognition. In both cases, we are talking about a two-layer perceptron, the hidden layer of which contains 200 neurons, with a symmetrical sigmoid as a transfer function. The number of output neurons for the two-layer perceptron used at the first recognition level is 5, and for the same perceptron used at the second recognition level is 2. The empirical character of the determination of these parameters is noted. The presented results of numerical experiments show the recognition accuracy of 92%. It is declared that the prospects for further research are associated with the use of deep neural networks and parallelization of computational processes associated with learning and recognition.

The article [14] is devoted to the comparison of fingerprint classifier efficiency on the basis of modern neural networks with respect to the probability fuzzy classifier. It is noted that the main prerequisite for the study is the declared prospects for the use of deep neural networks in the analysis of graphic images. A multilayer perceptron with three hidden layers of neurons was used as a basic model. Pre-training perceptron implemented on the basis of sparse autoencoder. The results show that the change in the number of hidden neurons in the range from 200 to 1250 does not affect the accuracy of recognition, which is about 93%. At the same time, the classification carried out with the help of a fuzzy classifier showed higher results, about 97%. This allowed the authors to formulate a conclusion about the lack of efficiency of neural network methods of fingerprint recognition. At the same time, the article does not substantiate the plan of experiments aimed at studying the impact on the accuracy of recognition of the structural parameters of the neural network model. In addition, it raises the question of the appropriateness of the pre-training process, which is critically needed only in the case of insufficiency of labeled training examples and the use of the logistic activation function.

Articles [15, 16] are devoted to the issues of fingerprint recognition using convolutional neural networks. At the same time, the work [15] is mainly focused on proving the feasibility of using a convolutional neural network. It is shown that the convolutional neural network can significantly reduce the computational resource of the recognition process. The reduction is due to the possibility of abandoning pre-processing of fingerprint images. At the same time, with the help of numerical experiments proved the possibility of achieving an acceptable accuracy of recognition of one fingerprint at about 95%. The experiments involved convolutional neural networks, the input of which was supplied with a fingerprint of the middle finger size of 224×224 pixels. The network structure provided for 19 layers, of which 5 layers were convolutional. In hidden layers, a rectified linear unit (ReLU) is used. Softmax activation function was used in the output layer, which allowed to obtain the output signal in the probabilistic form. The training was based on the NIST SD4 database. In [16] it is proved that the use of convolutional neural networks increases the accuracy and speed of recognition with respect to traditional methods of analysis. In addition, convolutional neural networks are better suited for recognition of low-quality fingerprints. In the described experiments, several structural solutions of convolutional neural networks were used, the input of which was fingerprinted with the size of 227×227 pixels. Types of activation functions are the same as in [15]. Note that in all analyzed convolutional neural networks the convolution kernel size was 3×3. All other parameters were chosen empirically.

Thus, as a result of the analysis of modern neural network solutions in the field of biometric fingerprint authentication, it can be argued that an important direction to improve their efficiency is to adapt the structure of the neural network model to the conditions of use. Since the source of information is a two-dimensional fingerprint image, a convolutional neural network should be used for recognition. After all, for the analysis of two-dimensional graphical information, convolutional neural networks are reasonably considered to be the most suitable neural network architecture. At the same time, there is no description in the available literature of the mechanism of adaptation of structural parameters of convolutional neural network to the problem of biometric fingerprint authentication of users [8-21]. This negatively affects the accuracy of fingerprint recognition, which in turn can lead to unauthorized access to the information of the protected system and/or blocking information for legitimate users.

3. METHODOLOGICAL BASIS FOR ADAPTATION OF STRUCTURAL PARAMETERS OF CONVOLUTIONAL NEURAL NETWORK

Development of a procedure for determining the structural parameters of the convolutional neural network used for biometric fingerprint authentication of users. To achieve the goal of the publication, the following tasks should be solved: to determine the methodological basis for the adaptation of the structural parameters of the convolutional neural network; to determine the features of the fingerprint recognition problem that require the adaptation of the structural parameters of the neural network model; to detail the components of the procedure; to conduct experimental studies aimed at the verification of the proposed solutions.

Convolutional neural network is a further development of multilayer perceptron adapted to the problem of image classification. The typical structure of a convolutional neural network is shown in Fig. 2 [16].

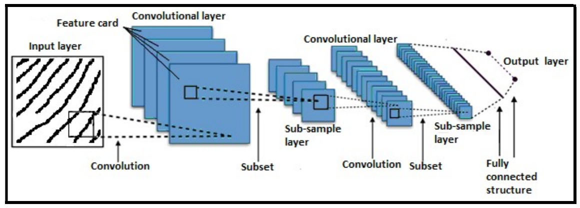

Figure 1: typical structure of convolutional neural network

Typically, the input parameters of a convolutional neural network correspond to individual pixels. Therefore, the number of input parameters is equal to the size of the image. The number of output neurons is equal to the number of recognized images. The structure of hidden neural layers is chosen empirically.

The total input signal of a neuron convolutional layer is calculated as follows:

$$x_k^{(i,j)} = f\left(x_{0,k} + \sum_{s=1}^{K}\sum_{t=1}^{K} w_{k,s,t}\, x^{((i-1)+s,(j+t))} \right), \quad (1)$$

where $x_k^{(i,j)}$ - input signal *(i,j)*-th neuron of the *k-th* feature map, $x_{0,k}$ is the offset of the neurons of *k-th* feature map, K - the size of the receptive field of the neuron (the size of the convolution kernel), $w_{k,s,t}$ - weighting factor *(s,t)* synaptic connections of the *k-th* feature map neuron, x - output of the neuron of the previous layer.

The output signal of the feature maps neuron is calculated by substituting the input signal into the activation function:

$$y = f(x) \quad (2)$$

In modern versions of convolutional networks, the ReLU function is used as an activation function of hidden neurons. In this case, expression (2) changes as follows:

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$$y = \max(0, x), \quad (3)$$

where a , d – specified coefficients.

In the neurons of the output layer, the activation function of the Softmax type is usually used:

$$y_i = \frac{\exp(q_i)}{\sum_{k=1}^{L_{out}} \exp(q_k)}, \quad (4)$$

where y_i -output of the i neuron of the output layer, - q_k -the total input signal for the *k-th* neuron of the output layer, L_{out} - number of output neurons.

On the basis of theoretical works devoted to convolutional neural networks [16-18] it can be argued that their main structural parameters are:

- The size of the input field - a_0.

- Number of input neurons - L_{in}.

- Number of output neurons - L_{out}.

- Number of neurons in a fully connected layer - L_f.

- Number of convolutional layers - K_{ls}.

- Number of feature maps in each convolutional layer - $L_{h,k}, k \in [1, K_{ls}]$.

- The number of layers of sub-sampling - K_{ld}.

- The scale factor for each layer a subsample - $m_l, l \in [1, K_{ld}]$. The size of the lst layer of the subsample is calculated as follows:

$$c_l = a_k / m_l, \quad (5)$$

where a_k - the size of the convolutional layer, which precedes the lst layer of sub-sampling.

- The size of the convolution kernel for each k convolutional layer $(b \times b)_k, k \in [1, K_{ls}]$.

- Displacement of the receptive field during each *k-th* convolution procedure $d_k, k \in [1, K_{ls}]$.

- Feature map size for each *k-th* convolutional layer- $(a \times a)_k, k \in [1, K_{ls}]$. Herewith:

$$a_k = (a_{k-1} - b_k + 2r_k)/d_k + 1 \quad (6)$$

where r_k - the number of complementary zeros for the *k*-th convolutional layer.

- The structure of relations between adjacent layers of the convolution/subsampling. This structure can be represented as a matrix:

$$Q_{i,i+1} = \begin{Vmatrix} q_{(i,1),(i+1,1)} & \cdots & q_{(i,1),(i+1,j)} \\ \cdots & \cdots & \cdots \\ q_{(i,G),(i+1,1)} & \cdots & q_{(i,G),(i+1,J)} \end{Vmatrix}, \quad (7)$$

where G - number of maps in the *i-th* layer, J – number of maps in (i+1)-th layer. $Q_{i,i+1}$ - a matrix whose components determine the existence of links between the i and (i+1) hidden layers, $q_{(i,g),(i+1,j)}$ - component indicating the presence/absence of connection between the g map of the i layer and the j map (i+1) layer, $q_{(i,g),(i+1,j)} = 1$, if there is a connection between the g map of the i layer and the j map (i+1) layer,

$q_{(i,g),(i+1,j)} = 0$, if there is no connection between the g map of the i layer and the j map (i+1) layer.

It is obvious that these parameters can be adapted to the conditions of application of convolutional neural network.

Taking into account the need to minimize recognition errors, the model of optimization of structural parameters of convolutional neural network can be written using the expression

$$\begin{cases} \Delta\left(L_{in}, L_{ls}, L_{out}, K_{h,k}, b_k, K_{ls}, \left|Q_{i,i+1}\right|_{K_{ls}}\right) \to \min \\ R \le R_{\max} \end{cases}, \quad (8)$$

where Δ- recognition error, $\left|Q_{i,i+1}\right|_{K_{ls}}$ - a vector consisting of matrices that define connections between adjacent hidden layers of neurons, R - the carrying capacity network, $R_{\max}$ - the maximum carrying capacity of the network.

It is proposed to adapt the structural parameters of the convolutional neural network based on the fact that in biometric authentication systems the process of recognition of the convolutional neural network of fingerprints should be as close as possible to its biological prototype. The biological prototype refers to the process of recognition of geometric parameters of fingerprints

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by an expert. Integration of the proposed approach with the concept of functioning of convolutional neural network allowed to formulate the following group of principles of adaptation:

Principle 1. The number of convolutional layers should correspond to the number of levels of fingerprint recognition by the expert.

Principle 2. The number of feature maps in the *n* convolutional layer must be equal to the number of features at the *n* recognition level.

Principle 3. The feature map of the *n* layer corresponding to the *j* recognition feature is associated only with those feature maps of the previous layer that are used to build the specified shape.

Principle 4. The size of the convolution kernel for the *n* convolution layer must be equal to the size of the recognized features at the *n* hierarchical level.

Principle 5. The use of convolutional layers should not distort the geometric parameters of the features used for fingerprint recognition.

4. SPECIAL FEATURES OF FINGERPRINT RECOGNITION PROBLEM

The human skin consists of two layers, the lower layer forms a set of projections - papillary, at the top of which there are holes in the output ducts of the sweat glands. On the main part of the skin, the sweat glands are located chaotically and are difficult to observe. In some areas of the skin of the limbs papillaries strictly ordered in line (crests), forming a unique papillary patterns.

There are three types of papillary patterns (arc, curls, circular) and two macro types. The features of the papillary pattern corresponding to the global characteristics of fingerprints are illustrated in Fig. 2 [12]. However, for biometric authentication is mainly used by local characteristics (minutiae) fingerprints. The main types of minutiae are shown in Fig. 3.

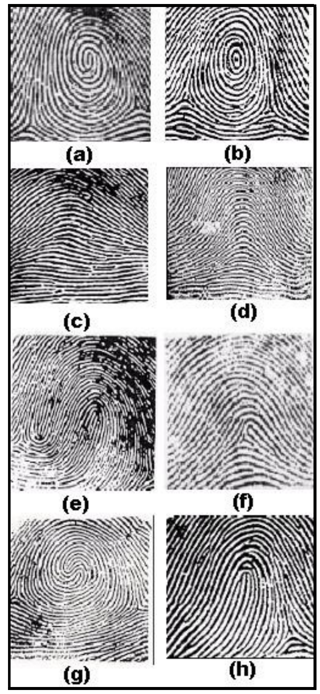

Figure 2: The global characteristics of a fingerprint: (a) – curl (spiral); (b) – curl (concentric circles); (c) – simple arc; (d) – narrow arc; (e) – double loop; (f) – delta; (g) – mixed sign; (h) – normal loop

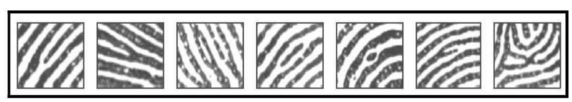

Figure 3: Local characteristics of the fingerprint

The recognition system removes the papillary pattern from one of the fingers of the applicant's access rights and compare it with the reference pattern. Fingerprints are considered to belong to one person if they match at least 65%. To remove the papillary pattern, various types of sensors are used, the cost of which is quickly reduced.

Manufacturers of biometric authentication systems based on fingerprint analysis in advertising their products estimate errors of the first kind at the level of 2%, and errors of the second kind at the level of 0,000000001%. At the same time, according to the results of independent testing, errors of the first kind for systems of this class range from 10% to 20%. It is indicated that sufficiently large values of the error of the first kind are obtained by taking into account unfavorable cases of dry skin, as well as by including persons with poorly expressed papillary patterns in the test

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group. As a rule, these are women and persons of Asian origin.

According to the regulatory requirements in the field of information security [19], the maximum size of fingerprints to be stored in the biometric databases of users is 40.6×38.1 mm (1.6×1.5 inches). Each pixel of the print is characterized by grayscale from 0 to 256. At the recommended resolution of 500 dpi, the specified print size is characterized by 800×750 pixels. The minimum brightness level of the point corresponding to the black color must be zero. The maximum brightness level of the point corresponds to the white color. However, in a publicly accessible database stores the fingerprints of size 512×512, 300×300, 256×364, 448×478, 240×320 pixels, each of which also describes the gradations of gray from 0 to 256 [20]. Note that common fingerprint scanners allow you to reconstruct the image of the print with a size of approximately 25×14 mm, which corresponds to 500×280 points. Regardless of the sensors used for biometric authentication in the papillary picture (Fig. 4) usually only two types of local features (minutes) representing the beginning (end) of papillary lines or their merging (branching) are analyzed [12]. Each print can contain from 30 to 70 minutiae or more.

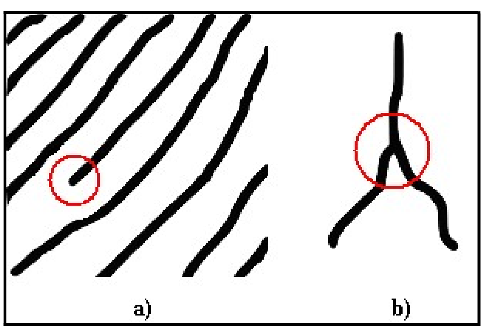

Figure 4: local fingerprint features: a-ending; b-branching

The generally accepted technology of minutiae selection is implemented by local processing of the entire image of the print using a mask of small size, usually 9×9 pixels. The processing counts the number of pixels that are around the center of the mask and have nonzero values. The Central pixel is taken as a minutiae if it has a single value and the number of neighbors is 1 (the end of the line) or 2 (the split line).

Also, the analysis of scanning technology indicates that the allowable angle of rotation of the print is within $\pm 15^{\circ}$ and its size varies within $\pm 10\%$. This can significantly reduce the requirements for convolutional neural network in terms of recognition of affine fingerprint transformations.

Thus, as a result of the study of the problem of fingerprint recognition, it is determined that in General, the convolutional neural network should be adapted to the number of recognized fingerprints (the number of recognized users), the size and quality of the scanned fingerprint image, as well as to the number and parameters of minutes taken into account.

5. THE PROCEDURE FOR DETERMINING THE CNN STRUCTURAL PARAMETERS

Based on the methodology of constructing neural network recognition systems [1-5], it is determined that the starting point for the development of convolutional neural network is to determine the number of input and output neurons. It is assumed that the number of output neurons of the network should be equal to the number of recognized users, and the number of input neurons – equal to the number of pixels in the fingerprint. When used as a data source for modern commercial scanners $L_{in} = 500 \times 280 = 140000$, and if we proceed from the regulatory requirements, $L_{in} = 800 \times 750 = 600000$. In the future, the procedure for determining the network parameters was based on the formulated principles of adaptation. So by expert evaluation it is determined that the minimum number of levels of fingerprint recognition can be taken as 3. On the first level there are recognized signs of minutiae, the second separate minutiae and on the third level by filing fully connected layers of the selected minutiae is implemented classification of the total mark. Thus, the minimum number of convolution layers $K_{ls,\min} = 2$. Also by the analysis shown in Fig. 3 and Fig. 4, the images of the different types of minutiae is determined that enough of them 4 different ways oriented segment length of 5 pixels. The size of the segments is chosen based on the fact that the segment should correspond to half of the minimum minutiae size, which according to [11] is 9 pixels. As shown in Fig. 5 orientation of segments-horizontal, at an angle $\pm 45^{\circ}$, vertical. Accordingly, each of the segments can be inscribed in a square of 5×5 pixels. Another sign necessary to highlight the end of the minutiae is an empty square

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of the same size.

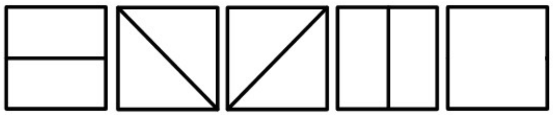

Figure 5: recognized signs of minutes

Hence the size of the convolution kernel $(b \times b)_1 = (5 \times 5)$, and the number of feature maps in the first convolutional layer $L_{h,1} = 5$.

Also, based on the data [2, 17, 18] and taking into account the need to minimize the computational resources of the network, it is determined that the displacement of the receptive field should be:

$$d_k = Round(b_k / 2), \qquad (9)$$

So $d_1 = 3$. Substituting the results into expressions (6), it is determined that the size of the feature map of the first convolutional layer is equal to

$$a_1 = (a_0 - 5 + 2r_1)/3 + 1, \qquad (10)$$

where a_0 - the size of the fingerprint.

Adopted background about the map matching the characteristics of the second convolutional layer with the basic types of minutiae, differently oriented in space. Due to the fact that the implementation of the convolution procedure may adversely affect the determination of the angle of inclination of the minutiae, it is customary to abandon the subsampling layer located between the first and second convolution layers. Based on the generally accepted statement about the admissibility of the fingerprint rotation by an angle $\pm 15^\circ$,, the value of the pitch of the angle of inclination 15° of the minutes is accepted. Therefore $L_{h,2} = 360/15 \times 2 = 48$. By analogy with the first convolutional layer, it is determined that $(b \times b)_2 = (5 \times 5)$, $d_2 = 3$, and the size of the feature map of the second convolutional layer is calculated using the expression (6).

Based on the analysis of Fig. 3-5 and using the third principle of adaptation, the necessity of a fully connected structure of links between adjacent layers of convolution/subsampling is determined.

Note that in accordance with the fifth principle, the final calculation of the number and scale coefficients of the subsample layers should take into account the need for convolution of the two-dimensional input dataset to the feature vector.

The calculation of the minimum number of neurons of a fully connected layer can be made on the basis of the positions of the minimum sufficiency by a certain Hecht-Nielsen theorem:

$$L_{f,\min} = 2(L_{h,K} + 1) \qquad (11)$$

where $L_{h,K}$ - number of feature maps in the last convolutional layer.

Given [3, 4] the maximum number of neurons in the fully connected layer is:

$$L_{f,\max} = 20 L_{f,\min} \qquad (12)$$

Finally, the number of neurons in the fully connected layer should be determined by numerical experiments.

Отметим, что научная новизна предложенной процедуры заключается в применении аналогии между конфигурацией сверточной нейронной сети и процессом распознавания отпечатков пальцев человеком-экспертом. При этом научно-практическая ценность процедуры заключается в том, что при определении структурных параметров сети использование численных экспериментов предусмотрено только для расчета оптимального количества нейронов полносвязного слоя. Все остальные параметры определяются путем экспертной оценки.

Note that the scientific novelty of the proposed procedure is to apply an analogy between the configuration of a convolutional neural network and the process of fingerprint recognition by a human expert. At the same time, the scientific and practical value of the procedure lies in the fact that in determining the structural parameters of the network, the use of numerical experiments is provided only for calculating the optimal number of fully connected layer's neurons. All other parameters are determined by expert evaluation.

6. EXPERIMENTAL RESEARCH

To verify the developed procedure for determining the structural parameters of the convolutional neural network, experiments were carried out to recognize the fingerprints of the index finger of 10 users presented in the database FVC2000. The size of the analyzed fingerprints was 300×300 pixels. Therefore,

$a_0 \times a_0 = 300 \times 300$, $L_{in} = 89401$, $L_{out} = 10$. Using the developed procedure, by trivial substitutions in expressions (6, 9), the following parameters of convolutional neural network are calculated: $a_1 = 98$, $a_2 = 30$. The calculation takes into account that the developed procedure has already defined the following parameters: $(b \times b)_1 = (b \times b)_2 = (5 \times 5)$, $d_1 = d_2 = 3$, $K_{ls,\min} = 2$, $L_{h,1} = 5$, $L_{h,2} = 48$, $r_1 = 1$, $r_2 = 0$. The calculation of the parameters r_1 and r_2 was based on the fact that the number of feature maps in the convolutional layer determined by the expression (6) should be an integer. The subsequent construction of a convolutional neural network is realized based on the need to reduce the two-dimensional map of size features $a_2 \times a_2$ to the feature vector. An analogy with the classical convolutional neural network is used [17, 18]. As a result, the network was supplemented with two verification layers and two subsampling layers. Selected layer options: $(b \times b)_3 = (5 \times 5)$, $(b \times b)_4 = (4 \times 4)$, $d_3 = d_4 = 1$, $r_3 = r_4 = 0$, $m_1 = m_2 = 2$, $L_{h,3} = 48$, $L_{h,4} = 32$. In accordance with the expression (6): $a_3 = 26$, $c_1 = 13$, $a_4 = 10$, $c_2 = 5$. Note that the imposition of the fifth convolution kernel of the size $(b \times b)_5 = (5 \times 5)$ on the maps of the fourth layer of the subsample allows the final convolution of the input field to the feature vector. By using the expression (11, 12) it was received $L_{f,\min} = 66$, $L_{f,\max} = 1280$. Finally, the number of neurons in the fully connected layer $L_{f,\max} = 512$ is chosen by analogy with [21] based on the balance of the required computing resources and network memory. Structural parameters of the constructed convolutional neural network are presented in the table. 1

Table 1. Structural parameters of convolutional neural network adapted to fingerprint recognition

Параметр	Значение параметра
The size of the input field	$(a_0 \times a_0) = (300 \times 300)$
Number of input neurons	$L_{in} = 89401$
Number of output neurons	$L_{out} = 10$
Number of neurons in a fully connected layer	$L_f = 512$
Number of convolutional layers	$K_{ls} = 4$
Number of feature maps in the first, second, third, and fourth convolutional layers	$L_{h,1} = 5$; $L_{h,2} = 48$; $L_{h,3} = 48$; $L_{h,4} = 32$
The number of layers of sub-sampling	$K_{ld} = 2$
The size of the first, second, third, fourth, and fifth convolution kernels	$(b \times b)_1 = (b \times b)_2 = (b \times b)_3 = (b \times b)_5 = (5 \times 5)$
The size of the fourth convolution kernel	$(b \times b)_4 = (4 \times 4)$
The offset of the receptive field when performing 1-St and 2-nd convolution procedures	$d_1 = d_2 = 3$
The offset of the receptive field when performing the 3-th and 4-th convolution procedures	$d_3 = d_4 = 1$
Feature map size for the first, second, third, and fourth convolutional layer	$(a_1 \times a_1) = (98 \times 98)$; $(a_2 \times a_2) = (30 \times 30)$; $(a_3 \times a_3) = (26 \times 26)$; $(a_4 \times a_4) = (10 \times 10)$
Number of complementary zeros for the first, second, third, and fourth convolutional layer	$r_1 = 1$; $r_2 = r_3 = r_4 = 0$
The scale factor for the first and second layer of subsample	$m_1 = m_2 = 2$
Map size for the first and second layer of the subsample	$c_1 = 13$; $c_2 = 5$

The constructed convolutional neural network became the basis for the development of the software (Fingerprint Recognition) designed for fingerprint recognition. The program is written in Python programming language using TensorFlow library. The recognition system was trained and tested on a sample from the database FVC2000 DB1. In the experiments, the accuracy of recognition of test examples was calculated for different numbers of training epochs (t_e) and the number of feature maps in 1, 2, 3 and 4 convolutional layers ($L_{h,1}, L_{h,2}, L_{h,3}, L_{h,4}$). The investigated range of changes of the specified parameters $L_{h,1} \in [4,5,6]$, $L_{h,2} \in [38,48,58]$, $L_{h,3} \in [38,48,58]$, $L_{h,4} \in [22,32,42]$ $t_e \in [10,30,50,70,100]$. For experiments, a computer with an Intel Core i7-7700 processor (3.6 - 4.2 GHz) and 16 GB of RAM, which operated under the Windows 10 operating system, was used. The results of the experiments are partially shown in Fig. 6, 7.

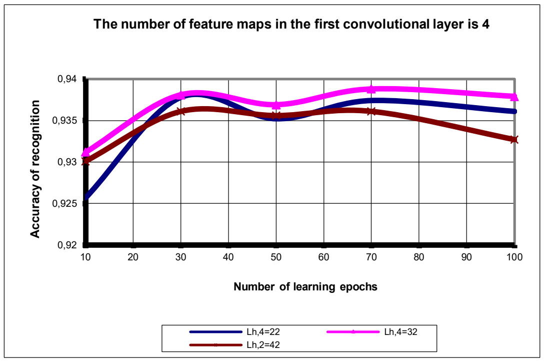

Figure 6: Dependence of recognition accuracy on the number of learning epoch with $L_{h,1} = 4$, $L_{h,2} = 38$, $L_{h,3} = 38$ *and different values of* $L_{h,4}$

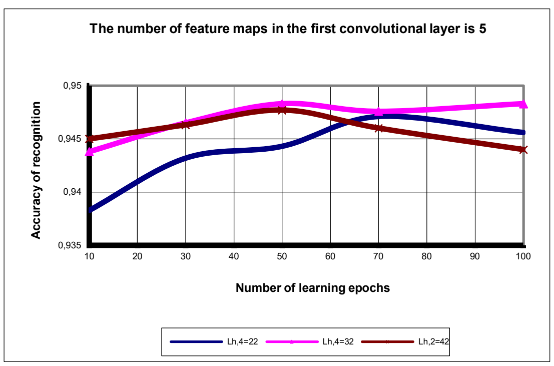

Figure 7: Dependence of recognition accuracy on the number of learning epoch with $L_{h,1} = 5$, $L_{h,2} = 48$, $L_{h,3} = 48$ *and different values of* $L_{h,4}$

The maximum recognition accuracy of about 0.95 is achieved in the table 1 configuration parameters of convolutional neural network. The results obtained generally correspond to the best indicators of such systems [8-16] and indicate the prospects for further research in this direction.

Also, the results of the studies confirm the possibility of determining the optimal values of the structural parameters of a convolutional neural network without implementing long-term numerical experiments, which confirms the scientific and practical value of the proposed procedure.

7. FUTURE RESEARCH

In accordance with the methodology developed in [1-5] for the application of neural networks in the field of information security, the main directions of further research are related to the development of a method for optimizing the parameters of convolutional neural networks used for biometric authentication based on user fingerprint recognition. To date, this method does not exist. It is generally accepted that such a method should include the following procedures: building a neural network model architecture, determining the nomenclature of informative input and output parameters, forming a training sample, preprocessing the parameters of training examples, interpreting the output parameters.

The need for the formation of these procedures and determines the ways of further research. At the same time, the proposed principles and procedure for determining the structural parameters are most fully correlated with the issues of building the architecture of the neural network model, the solution of which is also associated with the adaptation of the mathematical support of the convolutional neural network to the problem of fingerprint recognition. Therefore, it is advisable to correlate the next step of research with the formation of the principles of adaptation of the main components of mathematical support to the features of fingerprint recognition of users in a biometric authentication system.

8. SUMMARY

As a result of the research, the methodological base of adaptation of structural parameters of convolutional neural network designed for fingerprint recognition in the biometric authentication system is developed. In contrast to the known solutions, the development provides for the use of the proposed principles of adaptation:

- The number of convolutional layers should correspond to the number of levels of fingerprint recognition by the expert.
- The number of feature maps in the n-th convolutional layer should be equal to the number of features at the n-th recognition level.
- Feature map of the n-th layer corresponding to the j-th recognition feature is associated only with those feature maps of the previous layer that are used to build the specified shape.
- The size of the convolution kernel for the n-th convolution layer should be equal to the size of the recognized features at the n-th hierarchical level.
- The use of convolutional layers should not distort the geometric parameters of the features used for fingerprint recognition.

It is determined that the main features of the problem of fingerprint recognition, requiring the

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adaptation of the neural network model, are the number of recognized fingerprints, the size and quality of scanned images of fingerprints, as well as the number and parameters of minutiae taken into account.

Based on the proposed principles and the identified features of the fingerprint recognition problem, a corresponding procedure for determining the structural parameters of the convolutional neural network intended for fingerprints in the biometric authentication system is developed. Computer experiments have shown satisfactory recognition accuracy, which confirms the prospects of the proposed solutions.

It is shown that it is expedient to correlate the next step of research with the formation of the principles of adaptation of the main components of mathematical support to the features of fingerprint recognition of users in the conditions of biometric authentication system.

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