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Recognition of Images of Micro-Objects Based On a Neural Network of a Transparent Structure

Djumanov Olimjon Israilovich

Candidate of Technical Sciences, Associate Professor, Department of Information Technologies, Samarkand State University, Samarkand, Uzbekistan

Nazarov Bahrom Mustafaevich

Graduate student, Department of Information Technologies, Samarkand State University, Samarkand, Uzbekistan

Abstract: Scientific and methodological foundations, models and mechanisms for training neural networks of a transparent structure have been developed to solve the problems of recognition and classification of micro-objects with a minimum size of the training subset. A software package has been created using the example of pollen grain image recognition.

Keywords: micro-object, recognition, classification, neural network, algorithm, identification, modification, learning.

Relevance of the topic. The use of intelligent systems based on neural networks (NN) is associated with the solution of a wide spectrum of complex scientific and technical problems of recognition, display and prediction, approximation, adaptive control, etc. As one of the little-studied research topics in this direction, one can single out image visualization, recognition, classification and systematization of micro-objects based on the use of the NN mathematical apparatus. The relevance of solving these problems lies in the fact that micro-objects differ from each other in their external structure, and in developments related to the processing of images of micro-objects, it is required to quickly and accurately determine the types of objects, belonging to any class based on their geometric shapes, signs characteristics and other specific characteristics [1].

In the present study, the theoretical results were obtained for a loosely coupled neural network (NN), which is able to most transparently reflect the connections between neurons in the main and intermediate layers [2].

The mechanism of formation of the training subset of the NN. There are many options for constructing the structure of the NN and the art of skillful use of the NN lies in the development of optimal methods and algorithms for organizing the work of its main components [3, 4].

It has been determined that the smaller the number of layers and neurons in these layers, the more transparent the network becomes, and in many practical cases, despite its simplicity, a three-layer forward NN, when learning with a teacher, can more effectively solve problems compared to multilayer NNs with back propagation of errors [5,6].

Let's consider the variant of NN training with a teacher. To do this, we represent the training sample as a set of $E_0 = \{S_1,...,S_m\}$ objects described in a table using n quantitative features.

The set of objects E_0 includes representatives of non-overlapping subsets (classes) $K_1,...,K_l$.

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If we assume that from E_0 it is possible to single out the $\mu(l \le \mu \le m)$ of objects that can be used as standards for recognition by the minimum distance, then it is possible to determine the number of standards required for division into classes with a minimum error.

Let us introduce the Euclidean metric $p(x, y)$ on the set of admissible R^n objects. Then each $S_i \in E_0 \cap K_j$, $i = \overline{1, m}$, $j = \overline{1, l}$ forms a sequence $S_{i_0}, S_{i_1}, ..., S_{i_{m-1}}$, where $S_i = S_{i_0}$.

It is required to allocate $S_{i_p} \in K_r$, $r \ne j$, $p \in \{1, ..., m-1\}$ as the closest object to the S_i that is not included in the K_j class.

Denote by $R(S_i)$ the area of a circle area radius $\rho(S_i, S_{i_p})$ and center S_i, which includes objects that satisfy the condition $\rho(S_i, S_{i_t}) < \rho(S_i, S_{i_p})$, $t = \overline{1, p-1}$.

Proceeding from this, in $R(S_i)$ we introduce the criterion for selecting an object S_{i_r}, $r \in \{0, ..., p-1\}$, as

$$\rho(S_{i_p}, S_{i_r}) = \min_{S_{i_r} \in R(S_i)} \rho(S_{i_r}, S_{i_p}). \quad (1)$$

Based on (1), we create a set $L(E_0) = \{S_{i_r}\}$, which is used as an initial approximation for the formation of a training sample for a finitely descending learning algorithm for loosely coupled neural networks.

Mechanisms of NN learning. To achieve the goal of the work, it is of interest to construct an effective learning rule for solving problems of recognition and classification of micro-objects. In this regard, we write down the well-known Hebb learning rule

$$dw_{ij}(k) = \lfloor r \cdot x_j(k) \cdot y_i(k) \rfloor,$$

Where r is the learning rate coefficient of the set of discrete samples of the (x_i, y_i). Here, when two neurons with (x_i, y_i) outputs are simultaneously excited at the t -th learning step, the weight of the synaptic connection between them increases, otherwise it decreases.

When constructing a learning algorithm for one intermediate layer of a supervised neural network, the calculation of a continuous output signal of a neuron is carried out as [7]:

$$y(t) = f(\sum_{i=1}^{N} w_i(t) \cdot x_i(t) - b)$$

Where $w_i(t)$ is the weight of the connection from the *i*-th element of the input signal to the continuous neuron at time *t*, *b* is the phase shift of the activation function.

The modification of the weight values according to the Hopfield rule, which modifies the Hebb rule, has the form:

$$w_i(t+1) = w_i(t) + r[d(t) - y(t)] \cdot x_i(t),\ i = 1, ..., N,$$

Where *r* is the learning rate (less than 1); $d(t)$ is the desired output signal.

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However, the heuristic nature of learning and building algorithms based on the above models does not allow sufficient use of mathematical formalism in solving problems [8,9].

In this regard, a learning mechanism for a loosely coupled NN is proposed, which provides transparency and more acceptable convergence compared to self-organizing NNs with an insufficient volume of the training sample, which is typical for the representation of information of a continuous nature, in particular, in problems of recognition and classification of micro-objects [10,11].

Modified NN learning mechanisms. Usually, the work of any NN with a teacher is reduced to the classification (generalization) of input signals belonging to the n-dimensional hyperspace, according to a certain number of classes. From a mathematical point of view, this happens by partitioning the hyper-space with hyper-planes (recording for the case of a single-layer perceptron)

$$\sum_{i=1}^{n} x_i \cdot w_{ik} = T_k \ , \ k = 1...m$$

Each resulting scope is the scope of a separate class. The number of such classes is less than or equal to 2^m, where *m* is the number of network outputs.

However, for example, a single-layer perceptron, consisting of one neuron with two inputs, is not able to divide the plane (two-dimensional hyperspace) into two half-planes in such a way as to classify input signals even into two classes [12,13].

In this regard, each learning objects from $E_0 = \{S_1,...,S_m\}$, can be represented as a description with the help of n features, *r* of which are quantitative $(0 \le r \le n)$, $(n-r)$ and qualitative ones.

Denote by *I* and *J*, respectively, the set of numbers of quantitative and qualitative features.

Let $S^j \in E_0(S^j = (x_{j1},...,x_{jn}))$ denote the sampling standard. Then, to calculate the weight of a quantitative feature of a continuous neuron, we introduce the expressions

$$w_{j0} = -\frac{1}{2}\sum_{t\in I} w_{jt}^2. \text{ и } w_{jt} = x_{jt} \forall \ \ t \in I \ .$$

Moreover, the limiting values of the weights are common for all features, including qualitative ones, and are calculated as:

$$w_{\max} = \max_{S_j \in E_0}(-2w_{j0}/r), \ \ \lambda_{\max} = \sum_{t=1}^{l} |K_t|(|K_t|-1), \ \ \beta_{\max} = \sum_{t=1}^{l} |K_t|(m-|K_t|),$$

Where $w_{\max}$ is the estimate of the difference in the values of quantitative characteristics, $\lambda_{\max}$ is the estimate of infraclass correlation, and $\beta_{\max}$ is the estimate of interclass correlation.

Note that when data that is continuous in nature, for example, information about micro-objects, are considered as objects, then both quantitative and qualitative features are characterized by a wide range of values, i.e. in frequent cases, their behavior is non-stationary [14].

Therefore, the introduction of procedures for grading the process depending on its nature is required. To do this, we denote by the *p*-number of gradations of the attribute $c \in J$, g_{dc}^t -the number of values of the *t*-th $(1 \le t \le p)$ gradation of the attribute in the description of objects of class K_d. Then

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$$\lambda_c = \sum_{i=1}^{l}\sum_{t=1}^{p} g_{ic}^t (g_{ic}^t - 1), \quad \beta_c = \sum_{i=1}^{l}\sum_{t=1}^{p} \begin{cases} g_{ic}^t(|CK_i| - b_{ic}^t), & g_{ic}^t \neq 0, \\ b_{ic}^t |K_i|, & g_{ic}^t = 0. \end{cases}$$

Where b_{ic}^t is the number of values of the *t*-th gradation of the *c*-th feature in the CK_i complement of the K_i class?

With this in mind, we write the formula for determining the weight of each quality feature of $c \in J$

$$w_{jc} = (\frac{\lambda_c}{\lambda_{\max}})(\frac{\beta_c}{\beta_{\max}}) w_{\max}.$$

Hence, after some mathematical transformations and substitutions, we can write an expression for calculating the value of the weighted sum for the reference object $S^j \in E_0$ for an arbitrary admissible object $S = (a_1, ..., a_n)$:

$$\varphi(S, S^j) = \sum_{i \in I} w_{ji} a_i + \sum_{i \in J,\ x_{ji} = a_i} w_{ji} + w_{j0}. \quad (2)$$

According to the supervised learning paradigm of the NN, the object *S* belongs to the class, the value of the weighted sum (2) for the reference object from which is maximum.

Mechanisms for recognition of images of micro-objects. Let us denote the minimum training sample with reference objects from E_0 through the set $\Pi_j = \{S_1, ..., S_a\},\ \alpha \le m,\ \Pi_j \in E_0,\ j = 1, 2, ...$.

A function is introduced that produces three values:

$$f(r, a, b) = \begin{cases} \xi, & a \in S^r \ \text{или} \ b \in S^r \\ 0, & a \neq b, \\ 1, & a = b, \end{cases}$$

where ξ is the degree of belonging of a qualitative feature to the class K_d and $S^r \in (K_d \cap \Pi_j)$, depending on the accepted gradation; *a*, *b* are objects from the set of Π_j.

To recognize the belonging of an arbitrary admissible object $S = (b_1, ..., b_n)$ to the $K_1, ..., K_i$ classes according to Π_j, the display of $(b_1, ..., b_n) \to (y_1, ..., y_\delta)$ and the calculation

$$\varphi(S, S^r) = \sum_{i \in I^*} w_{ri} y_i + \sum_{i \in J^*} f(r, x_{ri}, y_i) w_{ri} + w_{r0}, \quad (3)$$

where $\{w_{r0}, w_{r1}, ..., w_{r\delta}\}$ are the weights of the network neurons, determined by the reference object of the $S^r = (x_{r1}, ..., x_{r\delta})$.

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The measure of interclass difference according to the *c*-th attributes of classes K_d and S^r is defined as

$$\lambda_{dc} = 1 - \frac{\sum_{t=1}^{p} g_{dc}^{t} \overline{g_{dc}^{t}}}{\theta_{dc} \overline{\theta_{dc}}} \quad (4)$$

where *p* is the number of gradations of the attribute $c \in J^*$; $g_{dc}^t, \overline{g_{dc}^t}$ -number of values of the *t*-th $(1 \leq t \leq p)$ gradation of the *c*-th feature in the description of objects; $\theta_{dc}, \overline{\theta_{dc}}$ is the number of values of the *c*-th feature in the S^r class.

Now let's define a measure of intraclass similarity:

$$\beta_{dc} = \frac{\sum_{t=1}^{l_{dc}} g_{dc}^{t}(g_{dc}^{t} - 1)}{D_c},$$

$$D_c = \begin{cases} (\theta_{dc} - l_{dc} + 1)(\theta_{dc} - l_{dc}), \ p > l, \\ \theta_{dc}(\theta_{dc} - 1), \ p \leq 1; \end{cases} \quad (5)$$

where $l_{dc}, \overline{l_{dc}}$ is the number of gradations of the *c*-th feature in the S^r class. Evidence of the fulfillment of the condition $\theta_{ic} > l_{ic}, \ \forall i \in \{1,\ldots,l\}$ can be traced in the formula (4).

It should be noted that measures of interclass and intraclass similarity are used as the ξ value of the $f(r,a,b)$ function.

Thus, a simplified formula is obtained

$$w_{rc} = \lambda_c \beta_{dc}$$

according to the results (4), (5). The results of the study are used to calculate the weight coefficient of the recognizable c-th feature of the $S^r \in (\Pi_j \cap K_d)$ object.

Conclusion. Thus, the developed scientific and methodological foundations for processing information of non-stationary objects is of great interest in the synthesis of NS with a minimum structure and the solution of a wide range of problems of recognition and classification of objects of various nature, in particular, text elements, codograms of bench test schedules, technological parameters of production, etc.

References

1. Галушкин, А. И., & Цыпкин, Я. З. (2015). Нейронные сети: история развития теории: Учебное пособие для вузов. *М.: Альянс*, *840*.

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2. Widrow, B., & Lehr, M. A. (30). Years of Adaptive Neural Networks: Perceptron, Madaline, and BP. *Proc. IEEE*, 1550-1560.

3. Aruchamy, V., Ramasamy, V., & Venkatraman, S. (2021). A novel strength behavior prediction model of self-compacting concrete with foundry sand and hybrid fibers. *Structural Concrete*.

4. Zhu, G., Porikli, F., & Li, H. (2016). Robust visual tracking with deep convolutional neural network based object proposals on pets. In *Proceedings of the IEEE conference on computer vision and pattern recognition workshops* (pp. 26-33).

5. Viola, P., & Jones, M. J. (2004). Robust real-time face detection. *International journal of computer vision*, *57*(2), 137-154.

6. Ciregan, D., Meier, U., & Schmidhuber, J. (2012, June). Multi-column deep neural networks for image classification. In *2012 IEEE conference on computer vision and pattern recognition* (pp. 3642-3649). IEEE.

7. Jumanov, I. I., Safarov, R. A., & Xurramov, L. Y. (2021, November). Optimization of micro-object identification based on detection and correction of distorted image points. In *AIP Conference Proceedings* (Vol. 2402, No. 1, p. 070041). AIP Publishing LLC.

8. Jumanov, I. I., Djumanov, O. I., & Safarov, R. A. (2021, September). Methodology of Optimization of Identification of the Contour and Brightness-Color Picture of Images of Micro-Objects. In *2021 International Russian Automation Conference (RusAutoCon)* (pp. 190-195). IEEE.

9. Ibragimovich, J. I., Isroilovich, D. O., & Abdullayevich, S. R. (2020, October). Recognition and Classification of Pollen Grains Based on the Use of Statistical, Dynamic Image Characteristics, and Unique Properties of Neural Networks. In *World Conference Intelligent System for Industrial Automation* (pp. 170-179). Springer, Cham.

10. Israilovich, D. O., Makhmudovich, K. S., & Uktomovich, Y. F. (2021). Increasing The Credibility Of Forecasting Random Time Series Based On Fuzzy Inference Algorithms. *International Journal of Progressive Sciences and Technologies*, *26*(1), 12-15.

11. Холмонов, С. М., & Тоштемиров, З. (2018). Оптимизация сглаживания изображений микрообъектов сплайн-функциями на основе отбора информативных элементов. *Наука, техника и образование*, (3 (44)), 39-43.

12. Жуманов, И. И., Холмонов, С. М., & Каюмова, Н. (2018). Повышение достоверности обработки данных нестационарных объектов на основе применения мультиконтекстных рекуррентных нейронных сетей. *Наука и мир*, *1*(3), 52-54.

13. Холмонов, С. М., & Облакулов, С. М. (2019). Программный комплекс идентификации временных рядов для прогнозирования нестационарных объектов. *Наука и мир*, *2*(5), 72-74.

14. Ibrahimovic, Z. I., Mahmudovich, H. S., & Maratovna, T. B. (2017). Methods of increase in accuracy of the data based on indistinct conclusions in system of monitoring of production and technological indicators. *Современные материалы, техника и технологии*, (1 (9)), 6-15.

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