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STRUCTURAL PECULARITIES OF NEUROLIKE OBJECT CLASSIFIER

Classification of the objects of various designation is the most involved procedure in the sphere of image recognition. Classification procedure is especially efficient in medical diagnostics where input features are biomedical symptoms and the output data is the disease diagnosis. In case, when the statistical methods of objects description are used, discriminant analysis has performed well, in particular, on the base of discriminant functions. On the other hand, methods of classification, applying neural technologies are of great interest.

The given study contains the analysis of structural peculiarities of neurolike object classifier, used in the process of discriminant functions classification. Kohonen map SOFM was taken as a basic model, it has 2D organization and determines metric and topologic dependences of the input signals. The study also considers the alternative approach to the quantitative measure of proximity as classification criterion. The approach is used where the formation of linear discriminant functions and their pairwise comparison is not performed, this enables «not to grow» linear discriminant functions but process on the level of their addends with gradual resetting to the moment, when one non-zero linear discriminant function is left. In this case there exists the possibility to form object occurrence ranks to the determined classes.

Two dimensional structure of neurolike classifier is suggested, basic unit of which is matrix calculator (maximizer). It is realized in the form of two maps – 2D computational map and 1D map of features. Neurosimilarity of the structure of the suggested classifier is stipulated by the fact that for the formation of the computation map three basic self-organization processes are used, namely, competition, cooperation and synaptic adaptation. The given paper contains the table with the comparative characteristic of Kohonen map and the suggested matrix calculator as a part of neurolike classifier.

Key words: *objects classifier, discriminant function, matrix, neural network, self organization map.*

Introduction

Classification procedure of objects of various nature is basic in the context of wider notion of objects recognition, which also includes clusterization, forecasting, identification, approximation, image compression, etc. [1 – 3]. This is also connected with wide involvement of the classifiers in modern intelligent systems [2 – 5].

Relevance of the subject matter

In recent years for the construction both of software and hardware tools for image recognition and, in particular, objects classification aspects of neural technologies of various designations are used [6 – 11]. Medical diagnostics [12], handwritten symbols recognition [13], problems of biometric identification and authentication of people [14] can be set as an example. Such approach to the realization of objects classification procedure enables to increase sufficiently the level of its intellectualization and enhance functional possibilities of the classifier, for instance, due to the ranking of the obtained results [11].

Besides, among widely known methods of objects classification method of classification, based on discriminant analysis is the most promising [1, 4, 15 – 17]. This approach uses such known matching criterion as maximum of one of the determined discriminant functions (“1 from N”) and provides sufficient level of classification accuracy, using statistical methods of the classified objects description [1, 4, 15].

Objective

Objective of the study is analysis of the structural peculiarities of neurolike object classifier, using the discriminant functions in the process of classification.

Problem setting

Among neural networks, realizing objects classification it is worth mentioning single layer perceptron, Hamming network, Gaussian classifier, Boltzmann machine and Kohonen map [6, 7]. Kohonen map SOFM (Self-Organizing Feature Map) is of special interest due to its 2D organization unlike widely known single-layer and multi-layer networks with 1D by the structure layers.

Besides, SOFM is a model of features reflection or the map of self-organization where the transformation of the input vectors of random dimensionality into 1D or 2D discrete map is performed [6]. This transformation is of adaptive character and has topographically arranged form. Thus, Kohonen model belongs to the class of algorithms of vector coding due to topological reflection, that enables to compress data (decrease dimensionality of the input signal) [6]. Hence, usage of 2D neural network SOFM, which determines matrix and topological dependences of the input signals enables to realize complex intelligent tasks and is a promising architectural solution.

Meanwhile, it is known, that for all the types of the recognition facilities the determination of classification criterion (proximity measure) of the input objects is important. In the Kohonen map as proximity measure of two objects x_1 and x_2 $_{OF\ n}$ dimensionality the Euclidian distance of the form [4, 18] is realized:

$$d_e(\boldsymbol{x}_1, \boldsymbol{x}_2) = \|\boldsymbol{x}_1 - \boldsymbol{x}_2\| = \sqrt{\sum_{i=1}^{n}\left(x_{1_i} - x_{2_i}\right)^2}. \tag{1}$$

In this case, besides of the Euclidian distance as the similarity (proximity) measure other metrices are used in the process of object recognition, namely, Hamming distance, Minkowski metric, Tanimoto similarity measure, variational methods, correlation functions, Levenshtein distance, etc. [18]. Thus it is expedient to consider the possibilities of using other quantitative similarity measures, regarding the problem of objects classification.

Structural models of the classifier on the base of the discriminant analysis

Usage of the linear discriminant functions (LDF) in the process of objects qualification requires the realization of the basic operation of the form [4]:

$$LDF_i = w_{i1} \cdot x_1 + \ldots + w_{ij} \cdot x_j + \ldots + w_{in} \cdot x_n , i = \overline{1,m} \tag{2}$$

where x_j is the j^{th} element of the input n-dimension vector X; w_{ij} – is the coefficient (weight) of the j^{th} element x_j in the weight matric W; m – is number of classes (groups).

In this case LDFi (2) is considered without taking into account the thresholds of processing (free elements). Decisiveruleofclassification in this case has the form:

$$y_k = \{1 | \max LDF_k, k = \overline{1,m}\} \Rightarrow X \in c_k \tag{3}$$

where $\mathrm{Y} = \left(\mathrm{y}_{1,} \ldots, \mathrm{y}_\mathrm{m}\right)$ – is output vector of classification, $\mathrm{C} = \left\{\mathrm{c}_{1,} \ldots, \mathrm{c}_\mathrm{m}\right\}$ – is the set of classes.

For the realization of the basic operation (2) and decisive rule (3), which provide classification by LDF the known scheme of neuro-networking classification can be applied [19]. It contains besides the input and output layers two additional components as the hidden layers [10]: single layer perceptron and competitive layer, which in this case is considered as a maximize “ 1 from N” (Fig. 1).

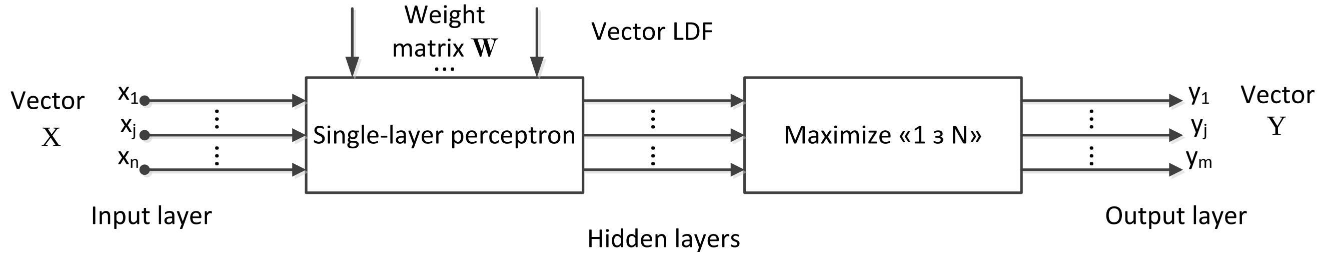

Fig. 1. Neural-networking organization of the classifier

In this case single-layer perceptron performs vector-matrix multiplication W·X with the formation of vector with the elements LDF_1, …, LDF_m. Characteristic feature of this scheme is that input, output and intermediate data are vectors and weight matrix W is formed before the start of the neural network operation [10].

There exists an alternative approach to the processing of the elements LDF_1, …, LDF_m, revealing among them maximum by value, for which the structural organization of the digital filter as the basic node of neural-like classifier is developed [5]. In general form such model of classifier (Fig. 2) has its peculiarities unlike neural-networking classifier (Fig. 1).

First, instead of vector-matrix multiplication W·X, performed by a single-layer perceptron (Fig. 1), matrix multiplier (Fig. 2) performs the multiplication of elements of the i^{th} row of the weight matrix W by the elements x_1, …, x_n of the input X element- wise without formation of their sums. As a result at the output of the multiplier matrix of m x n dimensionality is formed:

$$\boldsymbol{A}^0 = \begin{bmatrix} a_{11}^0 & \dots & a_{1j}^0 & \dots & a_{1n}^0 \\ & & \dots & & \\ a_{i1}^0 & & a_{ij}^0 & & a_{in}^0 \\ & & \dots & & \\ a_{m1}^0 & & a_{mj}^0 & & a_{mn}^0 \end{bmatrix}, \tag{4}$$

elements a_{ij}^0 of which are addends of i^{th} LDFi (2), namely:

$$a_{ij}^0 = w_{ij} \cdot x_j. \tag{7}$$

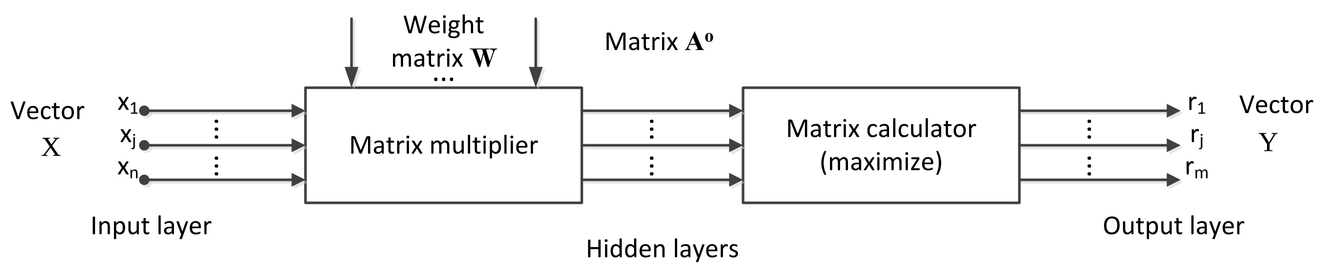

Fig. 2. Structure of neurolike classifier

Second, neurolike classifier realizes in matrix calculator (Fig. 2) processing of the elements m LDF_1, …, LDF_m by the method of retail sections (RS) [5, 17]. In this case processing by RS enables to combine execution by the expressions (2) and (3). As a result operation of the decrement (decrease) of the corresponding eponymous elements in all the columns of the current matrix $\mathbf{A}^t$ is performed , starting from the initial matrix $\mathbf{A}^0$ in the first processing cycle, simultaneously by the value of similarity q^{t-1}_j, i. e., by minimal non-zero element a^{t-1}_{ij} in j^{th} column, $t = \overline{1, N}$, where N – is the number of processing cycles.

Such actions, aimed at elimination of the smallest LDF_i are repeated till the moment when the last LDF_k is left, at least with one non-zero element. It is maximum LDF_k among all the initial, i. e., the condition of the relation (3) is fulfilled.

Thirdly, parallel processing on all the columns of the initial matrix $\mathbf{A}^0$ and current matrices $\mathbf{A}^t$ provides the formation in the first $(t-1)^{th}$ cycle vector-raw of the minelements of the form [5]::

$$\boldsymbol{q}^{t-1} = (q_1^{t-1}, \ldots, q_n^{t-1}), t = \overline{1, N}. \quad (6)$$

Fourth, maximizer in the form of matrix calculator (Fig. 2) instead of maximizer "1" "N" (Fig. 1) determines the location of the maximal sum of the elements of the specific row of the matrix $\mathbf{A}^0$, i. e., transforms the input matrix $\mathbf{A}^0$ into the output vector Y, as a result of the formation of zeroing features of the corresponding LDF_i, $i = \overline{1, m}$.

Thus, in the process of execution of the classical classification method on the base of LDF, first it is necessary to calculate the total value of each of LDF_1, …, LDF_m by the expression (2), and then determine among them maximum by the value in the process of pairwise comparison and form the feature of this result, namely, single value of the corresponding element y_k of the output vector Y [6, 19].

In the suggested model of classification simultaneous processing by P3 is performed in all the columns of matrices $\mathbf{A}^t$, starting from the matrix $\mathbf{A}^0$ (4) [5]. As a result, such approach enables not to "grow" m sums of the form LDF_1, …, LDF_m, but start their comparison in the process of processing of corresponding elements by columns [20].

Besides, in the course of processing elements of matrices $\mathbf{A}^0$ and $\mathbf{A}^t$, where $t = \overline{1, N}$, not only the output vector Y can be formed by the decisive rule (3), the ranks R vector can be formed [5]. This possibility proves the functional power of P3 method regarding the processing of LDF elements. This, in its turn, requires the complication of the structural organization of the output layer of neuro-like classifier (Fig. 2) as the node of features analysis.

2D structure of neuro-like classifier

Taking into account the possibility of formation at the output of neuro-like classifier (Fig. 2) of not only vector Y, belonging of the input vector X to certain class c_k, but also vector of R ranks [5], it is expedient to determine the output layer of the classifier as the node of features analysis.

One more feature of the classification process in the suggested neural-like classifier is specific similarity measure of the form $\mathbf{q}^{t-1}$ (6). On the one hand, this measure of similarity can be considered as the linear matrix by the analogy with the orthogonal matrix – Manhattan distance, which has the form of the coordinate- wise displacement and is partial case ($\lambda = 1$) of Minkowskyi matrix form [18]:

$$d_m(\mathbf{x}_1, \mathbf{x}_2) = \left(\sum_{i=1}^{n} (x_{1i} - x_{2i})^{\lambda}\right)^{\frac{1}{\lambda}}. \quad (7)$$

On the other hand, in the process of classification on the base of P3 vector linear proximity matrix (6) is used unlike the scalar, for instance, linear matrix – Manhattan distance. Hence, vector similarity matrix (6) proves, in its turn, 2D (space-distributed) character of P3 processing on all $\mathbf{A}^t$ matrices of elements LDF_1, …, LDF_m in the process of objects classification [20]

Thus, matrix calculator (Fig. 2) can be considered as computational map, supplemented with classification features map. Computational map has the form of 2D grate ПЕ (matrix block), and features map – 1D grate PE (analysis node) (Fig. 3).

Structure of the computational map, presented in Fig. 3, can be called artificial topographic map as it is a model of features representation and has the following properties (along with the map of features):

- spatial location of the outputs corresponds to specific area of data features, located in the input space;
- topology of reflection contains transformation of 2D input space into 1D space of features;
- transformation is of adaptive character;

- criterion of maximum of discriminant functions is used as compliance criterion;
- vector of minelements as component elements of vector arrays is used as similarity measure;
- map of features has the topology of 1D grate, set by the output space.

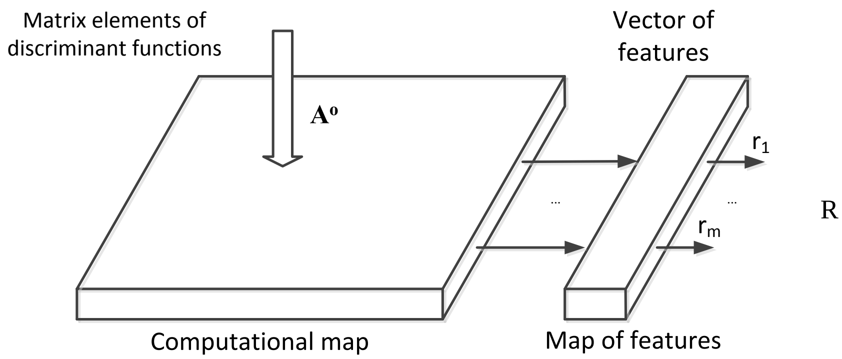

Fig. 3. Structure of matrix calculator

Results of the research

Computational map can be determined as the map with self organization, if the map of features in it (Fig. 3) is considered as the layer of neurons, output of which is R ranks vector, which is the weights vector of the corresponding LDF_i, making part of matrix $\mathbf{A}^0$ in the form of vector arrays (rows) A_i^0.

Table 1 shows the comparative characteristics of the Kohonen map [6, 7] and the suggested matrix calculator.

Table 1

Comparative characteristic of Kohonen map (SOFM) and matrix calculator map

Characteristics of the map	Kohonen map	Matrix calculator
Topology of the map	Grate	Grate
Dimensionality	2D	2D
Number of map layers	One	Two
Topology of elements	Connection with nonboring neurons	Connection by columns and by rows in computational map
Ratio between map dimensionality and processing result	Number of neurons in the layer is determined by the number of clusters to be recognized	Number of rows in computational map determines the number of classes, number of columns determines the dimensionality of the input vector
Type of the input space	Continuous	Discrete
Type of the output space	Discrete	Discrete
Type of the features map	2D grate	1D grate
Weights adjustment	Competitive study (without teacher)	Calculation of ranks as the weights of the corresponding rows of the matrix of the weighted input signals
Metrix	Euclidean distance	Vector of minelements
Maximum credibility (compliance criterion)	Criterion of minimal Euclidean distance	Criterion of maximum discriminant functions
Functional possibilities	Division of vector input signals into groups (clusters). Synaptic weights of the network determine clusters after study.	1. Determination of the array with maximum sum of its elements. 2. Determination of ranks (ranking of arrays according to the sum of its elements). 3. Sorting by the ranks of the arrays.
Spheres of application	Image recognition, clustering, image compression.	Classification, data compression.

Thus, the initial value of elements of R ranks vector can be considered as the initialization of the synaptic weights of the neuro-like structure. In this case, three basic processes of self organization are used for the formation of the computation map [6, 19]:

1. Competition, which takes place at the determination of maximum LDF_i.

2.Cooperation, as the process of sorting of the obtained ranks not only corresponding class for the input array of signals by maximum rank can be determined but the closest to it class, as the possible variant in the process of clusterization .

3. Synaptic adaptation, as the ranks of the corresponding LDF_i increase with each elimination of the smallest of them by the sum of its elements to the moment, when at least one LDF_k is left in the form of non-zero array.

Conclusions

Organization of topographic map which differs from the known self-organization Kohonen map of features by the compliance criterion and metrics as quantitative measure of similarity and by the functional principle is possible. But the same objective is obtained, namely, realization of procedure of objects classification and obtaining the results of structural (topological) presentation of the input data in the form of feature vectors.

The presented neuro-like object classifier can be realized in such systems of artificial intelligence where the principle of self organization of neuro-like systems is applied, when spatial location of the output neurons in the topologic map corresponds to the specific area of data features, allocated from the input space.

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Editorial office received the paper 23.11.2023.
The paper was reviewed 28.12.2023.

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