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Algorithms For The Reliability Of Information Of Non-Stationary Objects Based On Neural Networks

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Abstract – A method and algorithms for stochastic learning of a neural network based on splitting the feature space into clusters have been developed. Methods for determining whether features belong to clusters based on fuzzy terms are proposed, as well as an algorithm for synthesizing mechanisms for identifying, filtering and processing images into the structure of a neuro-fuzzy data processing network.

Keywords – Non-Stationary Object, Identification, Information Processing, Reliability, Neural Network, Neuro-Fuzzy Network.

I. Introduction

The relevance of the task. Currently, much attention is paid to research on the development of intelligent systems for processing data of non-stationary processes based on neural networks (NN) for building various practical applications, in particular systems for image visualization and micro-object recognition, technical and biomedical diagnostics, analysis and prediction of random events. In [1,2], methods for synthesizing iterative neural network learning algorithms based on gradient and multidimensional methods of nonlinear optimization were studied, and the following tasks related to the optimization of neural network learning were solved: choosing the starting point of the search, determining the nature of the local search, estimating the probability of falling into local extrema of the functional training, calculation of the derivatives of the objective function by the weights of the network, parameters of the duration and instability of the learning process [3,4].

The development of training mechanisms for neural network data processing systems in solving problems of recognition and classification of micro-objects, analysis and forecasting, taking into account the properties of the non-stationarity of the process, characterized by multidimensionality and non-linearity of object parameters, is considered a topical research topic [5].

It is required to build an object model that allows determining the calculated class number by the sample instance presented to its inputs. In addition, structures, values of model parameters, a set of features and a feature space are determined, the solution of which is given in [6,7].

II. Algorithm for the formation and division of the attribute space.

An algorithm has been developed that includes the following steps [8,9].

Step 1. Initialization. The training sample $< x, y >$ is set, where $y = 1,2,...,K$, K are the number of classes into which the images are divided.

Step 2. An initial partition of the feature space into N -dimensional rectangles is formed, for which the following methods are proposed.

Method 1. Based on the "gratings" method, the ranges of values of all features are divided into equal numbers of intervals of the same length for each feature. In this case, the boundaries of the intervals of the values of signs $\{< a_{jr}, b_{jr} >\}$ are calculated as:

$$a_{jr} = \min_{S=1,2,...,S}(x_j^S) + \frac{(r-1)}{N}\left(\max_{S=1,2,...,S}(x_j^S) - \min_{S=1,2,...,S}(x_j^S)\right);$$

$$b_{jr} = \min_{S=1,2,...,S}(x_j^S) + \frac{r}{N}\left(\max_{S=1,2,...,S}(x_j^S) - \min_{S=1,2,...,S}(x_j^S)\right), \; j = 1,2,...,N \; ; \; r = 1,2,...,N_j \, .$$

where a_{jr}, b_{jr} are, respectively, the left and right boundaries of the r th interval of values of the j th feature; N_j is the number of intervals of values for the j th feature. The value of N_j is set by the user or is selected automatically.

Rectangles are formed from these intervals, and the result of splitting the feature space will contain $Q = N_1^N$ rectangles. Note that with this method, the coordinates of the boundaries of cluster-rectangles are easily calculated. However, the partition obtained by this method roughly approximates the class boundaries and requires a preliminary specification of the number of clusters, which, as a rule, is not known in advance.

Method 2. Intervals of values $\{< a_{jr}, b_{jr} >\}$ are allocated for each j th attribute, where only instances belonging to the same class fall. Further, rectangles are formed from these intervals.

As a result, the partition of the feature space will contain $Q = \prod_{j=1}^{N} N_j$ rectangles, where N_j is the number of intervals into which the range of 1 values of the j th feature is divided. This method allows more accurate approximation of class boundaries compared to the first method, takes into account the compactness of the location of images for each attribute separately. However, this requires a large number of sorting operations to select intervals for each feature.

Method 3. The number of clusters is set equal to the number of instances of the training sample and all cluster rectangles are point, and their left and right boundaries (vertex coordinates) for each feature are set equal to the coordinates of the instance placed in the corresponding cluster: $a_j^q = x_j^q, . b_j^q = x_j^q$, $q = 1,2,...,Q$; $Q = S$. This method is simple to determine the number clusters and their boundaries.

Step 3. For each q th cluster-rectangle, the number of instances of each k th class and N_q^k that fall into it is determined. And those rectangles that contain only instances of one k th class are assigned the number of this class $K_q = k$.

Based on the instances of the corresponding cluster, the coordinates of its center of mass are determined

$$C^q = \{C_j^q\}, \; C_j^q = \frac{1}{N_q^k}\sum_{S=1}^{S}\left\{x_j^S \middle| \forall j : a_j^p \le x_j^S \le b_j^q \right|\right\}, \; j = 1,2,...,N \, ,$$

where C_j^q is the coordinate of the center of mass of the q th cluster according to the j th attribute.

Rectangles that do not include any instances are designated as empty: $K_q = 0$. Rectangles containing instances of different classes are designated as: $K_q = -1$.

Step 4. Adjacent rectangles belonging to the same class are merged. Sequentially for every two rectangles-clusters $\{< a_j^q, b_j^q >\}$ and $\{< a_j^q, b_j^q >\}$, $q \neq p$, $q = 1,2,...,Q$; $p = 1,2,...,Q$ is determined by the possibility of combining them under the following conditions:

– clusters-rectangles can be combined if they belong to the same class $(K_q = K_p)$;

– clusters-rectangles can be combined if they belong and the same class $\left(\left\{K_{(q,p)} = y^S \middle| a_j^{(q,p)} \leq x_j^S \leq b_j^{(q,p)}\right\}, \forall x^S,\ s = 1,2,...,S\right)$;

– intersection with rectangles of the same class is not prohibited;

$$\left(b_j^q < a_j^r\right) \cup \left(a_j^q > b_j^r\right) = ø,\ K_p \neq K_q,\ p \neq q;$$

– from the set of admissible pairs of rectangle-clusters of each class Ω, those two rectangles q and p are combined, which are either closest to each other according to the criterion of the greatest similarity

$$\min_{\substack{q \neq p, \\ (q,p) \in \Omega}} \left\{ \sum_{j=1}^{N} \left(C_j^q - C_j^p \right) \right\},$$

or will form the largest rectangle in terms of coverage according to the criterion of the greatest generalization:

$$\max_{\substack{q \neq p, \\ (q,p) \in \Omega}} \left\{ \prod_{j=1}^{N} \left(b_j^{(q,p)} - a_j^{(q,p)} \right) \right\};$$

– after combining a pair of rectangles, $Q = Q - 1$ is taken and the numbers of clusters are adjusted accordingly;

– all completely engulfed cluster-rectangles of the same class are determined, which must be removed from the set of clusters. In this case, Q and cluster numbers change by the corresponding values;

– rectangle q is completely absorbed by rectangle p if

$$\forall j,\ j = 1,2,...,N : a_j^p \leq a_j^q,\ b_j^p \geq b_j^q;$$

– the procedure for merging clusters ends when either the number of clusters becomes equal to the number of classes $(Q = K)$, or there are no such clusters that satisfy the merging conditions.

Step 5. In the resulting partition obtained from step 4, a rectangle of clusters Q is formed, which for each j th feature will have a left border with coordinate a_j^q and a right border with coordinate b_j^q.

Thus, as a result of the algorithm, the number of clusters is minimized and the quality of generalization of the partition properties is improved.

III. Algorithm for determining whether features belong to clusters.

When solving the problem, it is proposed to use a wide range of elementary membership functions (MF) [10,11]. The most suitable in the object of study under consideration is the trapezoidal MF, which we write more simply:

$$\mu_{jr}(x_j) = \begin{cases} 0, & x_j < a_{jr}; \\ 1, & a_{jr} \le x \le b_{jr}; \\ 0, & b_{jr} < x_j. \end{cases}$$

After the formation of fuzzy terms of features, a method is proposed for combining belonging to terms into belonging to cluster-rectangles:

$$\mu^q = \min_{j,r}\{\max(\alpha_{jr}^q, \mu_{jr})\},$$

where $\alpha_{jr}^q = 0$, if the r th interval of the j th feature is the side of the q th rectangle; $\alpha_{jr}^q = 1$, if the r th interval of the j th feature is not a side of the q th rectangle.

Next, the values of $\beta_t^q = \alpha_{jr}^q$, $q = 1,2,...,Q$; $t = \sum_{m=1}^{j-1} N_m + r$; $j = 1,2,...,N$; $r = 1,2,...,N_j$ are determined.

For the case when the feature space may contain voids that do not include a single instance of the training sample, it is advisable to set the following criterion for determining membership in clusters [12,13]:

$$\mu^q = \exp\left(-\sum_{j=1}^{N}(x_j^S - C_j^q)\right).$$

A method for synthesizing a neuro-fuzzy network (NFN) for data processing is proposed [14,15].

IV. Network functioning model

The values of features of the recognized sample are received at the network inputs [16,17].

The neurons of the first layer of the network determine whether the attribute values belong to the corresponding term-intervals of the attributes $\mu_{jr}(x_j)$. The first half of the neurons of the second layer (dashed rectangle) determines whether the instance belongs to the corresponding cluster-rectangles. The neurons of the third layer determine whether an instance belongs to classes.

The first neuron of the fourth layer combines the class membership of the instance and performs defuzzification of the result.

The second neuron of the fourth layer determines the network confidence score as a result of the $R(y)$ classification.

The discriminant functions of the network neurons will be determined by the formulas:

$$\varphi^{(\eta,i)}(w_j^{(\eta,i)}, x_i^{(\eta,i)}) = \max(w_j^{(\eta,i)}, x_j^{(\eta,i)}),\ \eta = 2,\ i = 1,2,...,Q,\ j = 1,2,...,Z,\ Z = \sum_{j=1}^{N} N_j;$$

$$\varphi^{(\eta,i)}(w_j^{(\eta,i)}, x_i^{(\eta,i)}) = \sum_{j=1}^{N}(x_j^{(\eta,i)} - w_j^{(\eta,i)})^2,\ \eta = 2,\ i = Q+1,\ Q+2,\ \dots,\ 2Q,\ j = 1,2,...,Z;$$

$$\varphi^{(\eta,i)}(x^{(\eta,i)}) = \arg\max_{j=1,2,\ldots,K}\{x_j^{(\eta,i)}\},\ \eta = 4,\ i = 1;$$

$$\varphi^{(\eta,i)}(w^{(\eta,i)}, x^{(\eta,i)}) = \sum_{j=1}^{Q} w_j^{(\eta,i)} x_j^{(\eta,i)} + w_0^{(\eta,i)},\ \eta = 4,\ i = 2.$$

The activation functions of neurons will be given as:

$$\psi^{(\eta,i)}(\varphi^{(\eta,i)}(w_j^{(\eta,i)}, x_j^{(\eta,i)})) = \min_j\{\varphi^{(\eta,i)}(w_j^{(\eta,i)}, x_j^{(\eta,i)})\},\ \eta = 2,\ i = 1,2,\ldots,Q,\ j = 1,2,\ldots,Z;$$

$$\psi^{(\eta,i)}(\varphi^{(\eta,i)}) = \exp(-\varphi^{(\eta,i)}),\ \eta = 2,\ i = Q+1,\ Q+2,\ 2Q,\ i = 1,2,\ldots,N\ \ j = 1,2,\ldots,2Q;$$

$$\psi^{(\eta,i)}(\varphi^{(\eta,i)}(w_j^{(\eta,i)}, x_j^{(\eta,i)})) = \max_j\{\varphi^{(\eta,i)}(w_j^{(\eta,i)}, x_j^{(\eta,i)})\},\ \eta = 3,\ i = 1,2,\ldots,K,\ j = 1,2,\ldots,2Q;$$

$$\psi^{(\eta,i)}(\varphi^{(\eta,i)}) = \varphi^{(\eta,i)},\ \eta = 4,\ i = 1;$$

$$\psi^{(\eta,i)}(\varphi^{(\eta,i)}) = \begin{cases} 0, & \varphi^{(\eta,i)} \le 0; \\ 1, & \varphi^{(\eta,i)} > 0; \end{cases}\ \eta = 4,\ i = 2.$$

The weight coefficients of neuro elements are calculated by the formula:

$$w_j^{(\eta,i)} = \begin{cases} \beta_j^i, \eta = 2, i = 1,2,\ldots,Q, j = 1,2,\ldots,Z; \\ C_j^i, \eta = 3, i = Q+1, Q+2,\ldots,2Q, j = 1,2,\ldots,N; \\ 0, \eta = 3, K_j \ne i, i = 1,2,\ldots,K, j = 1,2,\ldots,Q; \\ 1, \eta = 3, K_j = i, i = 1,2,\ldots,K, j = 1,2,\ldots,Q; \\ 1, \eta = 4, i = 2, j = 1,2,\ldots,Q; \\ 0, \eta = 4, i = 2, j = 0. \end{cases}$$

V. CONCLUSION

Thus, algorithms for training neural networks and inferences have been developed, which, unlike classical iterative algorithms, make it possible to train the neural network in a non-iterative mode, adapt the parameters of the components of the computational circuits of the neural network. This does not require the calculation of: derivatives of the objective function with respect to the weights of the network to select the starting point of the search in the space of weights. A scheme for the synthesis of learning algorithms for a neural network for processing data of non-stationary objects has been developed to solve the problems of recognition and classification of micro-objects, analysis and prediction of random processes.

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