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Optimization of data processing of non-stationary objects with neural network learning regulators

Djumanov Olimjon Israilovich, Kholmonov Sunatillo Makhmudovich, Ganiev Jasur Muhammad o‘g‘li

Candidate of Technical Sciences, Associate Professor, Department of Information Technologies, Samarkand State University, Samarkand, Uzbekistan
PhD in Technical Sciences, Department of Information Technologies, SamarkandStateUniversity, Samarkand, Uzbekistan
Graduate student, Department of Information Technologies, SamarkandStateUniversity, Samarkand, Uzbekistan

ABSTRACT: The problem is formulated and the methodological foundations for the design of methods for optimizing the training of a neural network (NN) in data analysis systems of non-stationary objects are developed. Mechanisms have been developed to optimize NN learning based on a simplified search, determination and adjustment of neuron weights, coefficients of synaptic connections, activation functions, the number of neurons in NN layers. The effectiveness mechanisms of optimization for learning neural networks is shown using the example of numerical results.

KEYWORDS: non-stationary object, data processing, neural network, variable controller, database, knowledge base

I. INTRODUCTION

The application of training methods for neural networks (NN) with forward and backward propagation of errors traditional gradient methods, least-squares methods, and their modifications is associated with solving large dimension problems that require significant computational costs [1].

This work is devoted to the development of new and improvement of existing methods of teaching neural networks, which are aimed at using mechanisms that can substantially improve the accuracy of data analysis and processing, the sustainability of algorithms with the lowest time costs [2].

Methods and algorithms for optimizing the training of neural networks based on simplified search procedures and mechanisms for setting parameters using GA are proposed [3].

II. CONSTRUCTIVE APPROACHES, PRINCIPLES, MECHANISMS FOR OPTIMIZING THE TRAINING OF NEURAL NETWORKS

The principles of designing methods for searching and adjusting the parameters of structural components of a multilayer neural network for training optimization involve the development of methods for the synthesis of a genetic algorithm (GA) with algorithms for stochastic modeling, search with annealing, prohibitions, as well as self-organizing learning [4].

Methods for the synthesis of NN and GA acquire such dignity as the possibility of a simplified description of the search multitudes and making a variety of decisions; a significant effect is achieved in determining local and global minima; the system becomes insensitive to the growth in the dimension of the tasks [5].

The improvement and development of methods for optimizing the training of neural networks is carried out through the execution of genetic operators to generate a bank of individuals, which serve as additional information support when determining and adjusting the parameters of synaptic connections, neuron weights, activation functions [6].

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To determine the suboptimal set of parameters of the NN components and reduce the search time, the tasks of storing the necessary data on previous searches (successful and unsuccessful), setting up heuristic algorithms for each new iteration of training, forming knowledge bases (KB), logging all launches that represent the results of the analysis, are solved. extraction of statistical parameters, dynamic characteristics, useful properties, and patterns of data [7].

The algorithms include synthesis mechanisms for random search with annealing and with stochastic modeling, which are used to select informative parameters about successful previous searches [8].

Other key tasks of optimizing the training of neural networks based on the hybrid model are the formation of knowledge bases, block creation of a generation unit, and getting new individuals [9].

The main chromosome consists of the following genes

K_{inp} - the number of inputs of the NS;
K_{Out} – the number of NS outputs;
Layers - the number of layers of the neural network;
T/S – activation function types;
Alpha – activation function coefficient;
LR – learning rate mode;
TL – the threshold level of neurons;
PO – types of procedures of methods of optimization of training NN.

To genes K_{inp}, K_{Out}, and Layers daughter chromosomes are attached, which respectively determine the immediate inputs, outputs, and the number of neurons in the layers [10].

The integrated operator at each iteration work of the GA operation with a modified chromosome is represented in the form:

$$\{mutation_{OX}(\gamma_1);\ mutation_{X3}(\gamma_2);\ crossover_{OX}(\gamma_{31});\ inversion_{OX}(\gamma_4);\ inversion_{X1}(\gamma_5);\ inversion_{X2}(\gamma_6)\},$$

where γ_i – probability of executing a certain operator.

III. FUZZY LOGIC ALGORITHMS IMPLEMENTATION PRINCIPLES

Implemented multilayer neural network with backpropagation algorithm. The proposed network synthesizes the zero-order Sugeno fuzzy inference model, has two input variables EZ and EF, and the network output is determined by the VK linguistic variable [11].

For the linguistic assessment of the input variable EZ, seven terms are used, for variable EF, one term with direct and inverse output, which are used when reducing the number of terms.

The considered algorithm of fuzzy logical inference of the network contains 8 fuzzy rules. The dimension of the term set of the output variable T_{VK} is equal to the number of rules. The coinciding values of the terms correspond to the condition $v_{k7} = v_{k8} = 0$. In the implemented five-layer neural network, the layers have the following purpose.

Layer 1. Defines fuzzy terms of input parameters. The outputs of the nodes of this layer are represented meanings of the membership functions (MF) at specific values of the inputs.

Each node of the layer is adaptive with MF $\mu_{A_i}(x)$, where x is the input of the i-th node, TT, $i = 1,...,n$;

A_i – linguistic fuzzy variable associated with a given node.

For the terms of the input variables, triangular, trapezoidal, S-shaped, and Z-shaped MFs are selected.

Layer 2. This layer is an non-adaptive and forms the premises of fuzzy rules [12]. Each node is connected to those nodes of the first layer that form the prerequisites of the corresponding rule. In the layer, a fuzzy logical "AND" operation is performed on the parameters of the rule parcels. The outputs of the neurons of this layer are the degrees of truth (weight) of the parcels of each j-th fuzzy rule, calculated by the condition

$$w_j = \min\lfloor \mu_{EZj}(EZ), \mu_{EFj}(EF) \rfloor,\ j = 1,...,7.$$

The weight of eight fuzzy rules is determined by the formula

$$w_8 = 1 - \mu_{EF8}(EF).$$

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Layer 3. Normalizes rule fulfillment degrees rule fulfillment rates. Non-adaptive nodes of this layer count on the relative degree (weight) of the fuzzy rule fulfillment

$$\overline{w_j} = w_j \sum_{j=1}^{8} w_j .$$

Layer 4. A crisp number v_{kj} specifying the leading conclusion of each j-th rule is considered as a fuzzy set with a singleton MF. The adaptive nodes of this layer count on the contribution of each fuzzy rule to the network output

$$y_j = \overline{w_j v_{kj}} , \; j = 1,...,8 .$$

Layer 5. The non-adaptive node of this layer sums up the contributions of all rules:

$$y = \sum_{j=1}^{8} y_j .$$

The discrepancy error between the experimentally measured v_L parameter and the calculated output of the VK network is determined by the condition

$$\delta = \sqrt{\frac{1}{N} \sum_{t=1}^{N} [v_L(t) - VK(t)]^2} \to \min ,$$

where N –number of measurements in the v_L training data sample.

The hybrid learning algorithm is a combination of least squares and backpropagation of the error. Modeling of control processes was performed in the MATLAB environment with the Fuzzy Logic Toolbox extension package.

The training sample contains observation $N = 947$. The initial value of the 10^{-4} step in the direction of the δ criterion is specified when changing the parameters of the FP. Allowable change in step magnitudes per iteration - 20%. Before training the network, the value of the learning criterion $\delta = 0{,}0972$, and after 200 iterations of the $\delta = 0{,}0859$. A decrease in the δ parameter is achieved due to the synthesis mechanisms of heuristic search algorithms with annealing and stochastic modeling based on the Markov chain.

IV. CONCLUSION

An analysis of the research results of the considered example of identifying a conditional technological parameter shows that the combination of NN with GA and NFN with GA makes it possible to attain a decrease in the variation of the statistical parameters of the initial non-stationary process at the output of the data mining system, while the relative sample variance of the calculated data does not exceed 5%, which confirms achieving the required accuracy of analysis and data processing with significantly lower computational costs.

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