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EVALUATIONS OF DIAGNOSTIC EFFICIENCY OF THE STATE OF TECHNICAL SYSTEMS

Abstract: *The purpose of this paper is to study a possibility of increasing effectiveness of diagnosing the state of technical objects by constructing algorithms for processing input data and optimizing the selection of model parameters using genetic algorithms.*

Keywords: *genetic algorithm, absorbent, interface, data mining, ART-networks, neural network.*

Introduction

The process of analyzing information, namely data from a large number of sensors and devices during the diagnostics of the state of technical systems, which involves processing of a large stream of information by an engineer, is a very complicated task. Owing to the rapid development of information technologies, which enables automatic processing of information obtained from a variety of sensors, the work of the engineer becomes easier. New approaches to the automatic analysis and processing of input data for monitoring technical systems help to reduce the time of processing diagnostic information and provide decision support to the engineer carrying out the diagnosis of the technical state of the system.

Formulation of the Problem

Under the diagnostics of a technical system, we consider receiving signals from a gas sensor, on the basis of which an analysis of temporal and temperature dependencies of electrical conductivity of the absorbent in different gaseous environments and different partial pressures is carried out [1]. Sensors measuring such signals are new modern devices. As of today, automatic information processing systems for this type of sensors do not exist [2]. Therefore, there is an urgent task in developing a modern information technology for collecting, classifying, processing and analyzing data from sensors of this type. A special task of IT development lies in creation of a modern software complex, which will address the following problems: classification of input data, optimization of IT learning parameters, processing and analysis of data with the help of a genetic algorithm, convenient and intuitive interface, visualization of obtained results and convenience of settings.

Main Section

Consider the mathematical apparatus used to process data in order to implement control functions in technical monitoring systems. The main function of most information systems is recording of statistical data [3]. Large volumes of data stored in the technical monitoring databases require statistical processing. Preliminary data analysis involves assessment of the center of distribution, variance and the shape of the distribution function. The statistical methods of processing of information include such types of analysis as: variance, factor, cluster, regression and correlation analyses. Data mining [4] is used to identify hidden knowledge stored in large volumes of information. Data Mining methods include: basic iterative methods, fuzzy logic, genetic algorithms and neural networks. Thus, the mathematical apparatus of decision support systems (DSS) is represented by a sufficiently developed range of methods and approaches for collecting, processing and storing data. The hardware and software of engineering DSS are often considered separately, which does not allow one to systematically solve the tasks of technical diagnostics. This determines the direction of research on the development of an integrated system of technical monitoring, which will enable improvement of the assessment of the state of the systems.

For improvement of the diagnostic efficiency of technical systems, Adaptive Resonance Theory (ART) networks [5] have been used for processing input data. ART-networks implement a single-type clustering strategy based on self-learning, the main advantage of which is the ability to work in real time with an apriori unknown number of classes. The input data for a neural network implementing the adaptive resonance theory for the real vectors is a set L , which consists of pairs of vectors $\{x_i, y_i\}$ and has a matrix form. The peculiarity of such an approach is the arbitrary dimension of the input data, which complicates the processing of data in diagnostics in real time.

$$L = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} & y_{11} & y_{12} & \cdots & y_{1m} \\ x_{21} & x_{22} & \cdots & x_{2n} & y_{21} & y_{22} & \cdots & y_{2m} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{k1} & x_{k2} & \cdots & x_{kn} & y_{k1} & y_{k2} & \cdots & y_{km} \end{pmatrix}.$$

For data clustering it is necessary: To feed the entry of such a network with a similarity coefficient – ρ, where ($0<\rho<1$), a set of training pairs$\{X_i, Y_i\}$, an input vector of the parameters of the i-th object $X_i = \{x_{ij} | j = 1, 2, .., n\}$, a vector of belonging of the i-th object to the j-th class, n– the number of values of the object parameters (dimension of the problem) $Y_i = \{y_{ij} | j = 1, 2, .., m\}$, the number of the to-be-distinguished classesm and the number of training pairsk.

Let us form the algorithm of data processing:

1. A neural network implementingthe of adaptive resonance theory is created for vectors of real values with a similarity coefficient ρ. To the entrance of this network, a sequence of X_i is fed. In the beginning, the network contains: n neurons in the input layer andm′ neurons in the output layer ($m' = 0$). When a new vector $X_i = (x_{i1}, x_{i2} \dots, x_{in})$ is fed to the network input, the normalization is performed:

$$x_j = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}}, \qquad j = \overline{1..n}$$

after which, all the neurons of the output layer become active.

2. For all active neurons, the value of the activation function is calculated as the distance between the vector of weights and the input vector in the Euclidean metric.

$$f_j(X) = \sqrt{\sum_{i=1}^{n} \left(w_{ji} - x_i\right)^2}, i = \overline{1..m'}$$

3. Among the active neurons, the most active neuron is selected:

$$M' = \arg[\min_{j=\overline{1..m'}}\{f_j(X)\}]$$

If there are no more active neurons, then a new output neuron with the number $m' + 1$ is generated, with bonds:

$$w_{i\,m'+1} = x_i,\ C_{m'+1} = 1,\ i = \overline{1..n},$$

where C is a counter of vectors assigned to a given neuron. This step is performed until the active neuron is determined.

4. The active neuron passes the proximity check: $f_i \le (1-\rho)$. If the condition is fulfilled, then we proceed to step 5, otherwise the active neuron becomes inactive, and we jump to step 6.

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5. Correction of the connections of the winner neuron.

$$w_{ij} = w_{ij} + \frac{x_i - w_{ij}}{C_j}, \quad i = \overline{1..n}, C_j = C_j + 1,$$

where C_j is the number of vectors assigned to the j-th neuron.

6. Work with the current vector is complete.

An adaptive resonance theory network for the real vectors, to each input vector X_i, assingns a certain classC_j. After the adaptive resonance theory network for the real vectors has processed all the vectors X_i, each classC_j is converted into a vector

$$D_i = \{d_{ij} | j = \overline{1..r}\}, d_{ij} = \begin{cases} 1, & j = C_i \\ 0, \text{else} & j \neq C_i \end{cases}$$

whereris the number of classes.

The resulting clustered input vector is the initial input vector X_i with the cluster-related information added to it, which is encoded by the vector D_i. Thus, we obtain clustered vectors of the following form: $X_i^* = (x_{i,1}, x_{i,2}, \dots, x_{i,n}, d_{i,1}, d_{i,2}, \dots, d_{i,r})$.

Further on, the research data consist of a set of training pairs; each i-thtraining pair is a pair of vectors $\{x_i, y_i\}$, where $x_i = \{x_{ij} | j = 1, 2, .., n + r\}$ is the input vector; $y_i = \{y_{ij} | j = 1, 2, .., m\}$ is the expected output vector.

Letk be the number of training pairs, thenwe can denote all the input data by a matrix of the following form:

$$L^* = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1n} & d_{11} d_{12} \dots d_{1r} & y_{11} & y_{12} & \dots & y_{1m} \\ x_{21} & x_{22} & \dots & x_{2n} & d_{21} d_{22} \dots d_{2r} & y_{21} & y_{22} & \dots & y_{2m} \\ \dots & \dots & \dots & \dots & \dots & & \dots & \dots & \dots \\ x_{k1} & x_{k2} & \dots & x_{kn} & d_{k1} d_{k2} \dots d_{kr} & y_{k1} & y_{k2} & \dots & y_{km} \end{pmatrix}.$$

Training pairs are located in the rows of this matrix. In the course of repeated experiments on the learning of the neural network, the theory of adaptive resonance for the real vectors on the test samples demonstrated the correctness of the presented algorithm. The experiment also showed that this learning method has the advantages of simplicity of settings and the possibility to additionally train the adaptive resonance networks, with only one similarity parameter ρ to be chosen.

To improve the assessment of the effectiveness of diagnosing the state of technical systems, it is necessary to optimize the process of selecting a model. The process of optimizing the parameters of the algorithm can be completely automated. Optimization of the process of selection of the model is implemented with the use of the genetic algorithm [5].

On the basis of algorithms of processing of input data and optimization of the process of selection of the model, an information technology of decision support was developed.

Experimental Research

Using the information technology of decision support [7], an analysis of the of the operability of the algorithm for automated selection of input parameters and its effectiveness in general was carried out. Consider, for example, the size of the population being 40, the number of epochs – 15, the time of one epoch – 1000 and the mutation rate – 0.2. The optimal parameters obtained as the results of the work of the automated information technology have appeared to be similar to those selected by an expert in the field. An increase of the number of epochs to 200 in the experiments showed a better result than the one provided by an expert in the industry. The outcomes of the experiments showed that the information technology developed using the above algorithms works faster and provided a higher quality than the network, the parameters for which were selected manually, for example: training the system takes 17 seconds versus 30 seconds of manual selection; the error in training data was 0.62 vs. 0.77.

Conclusions

According to the results of experimental research, it is proved that the information technology developed for evaluation of the efficiency of diagnosing the state of technical systems is operational. But the developed algorithm for the classification of alcohols in the gaseous environment of sensors with the help of clustering did not provide more efficient and qualitative results, though most likely, this is a feature of diagnostics of the state of this technical system.

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