Neuro-fuzzy algorithm for clustering multidimensional objects in conditions of incomplete data

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Abstract. The paper is considered development of fuzzy expert system model for identifying faults in complex systems using data mining methods based on searching for hidden patterns in databases. The use of neural network technologies makes it possible to detect nonlinear dependencies of input and output data, improve the quality of an objective assessment of the state of complex technical objects, which ultimately will reduce the number of emergency situations during operation. A method is proposed for identifying the optimal number of fuzzy clusters in the space of training examples and determining, on their basis, the parameters of the membership functions for the input variables and inference results. Considered a neuro-fuzzy algorithm for clustering multidimensional objects in conditions of incompleteness and fuzzy initial information.

1. Introduction

During the operation of complex technical objects, both during management and when searching for reasons for malfunctioning, the maintenance personnel develops solutions based on the incoming information. Due to the constant increase in the volume of controlled parameters in the course of complex automation, ensuring reliable operation, the operator is experiencing increasing difficulties in analyzing the incoming information. This is especially evident when it is necessary to make prompt decisions in emergency situations. As a result, more than 70% of emergency situations occur due to operator errors. Therefore, the development and implementation of intelligent expert systems (ES) is gaining importance and relevance, which make it possible to effectively use the monitoring results and automate the procedures for solving operational problems with the issuance of recommendations to the maintenance personnel.

As a rule, automation objects are characterized by poorly formalized dependencies of input and output data, therefore, it is not always possible to build a clear mathematical model of such objects. To solve the problem of describing the properties of a control object, it is necessary to develop intelligent models that reproduce the logic of reasoning of the decision maker (DM), the basis of which is the knowledge base (KB). The main difficulty in applying fuzzy logic in ES is the need to explicitly formulate the rules of the problem domain in the form of productions. The solution to this problem is the use of neural networks, the advantage of which is the ability to automatically transfer the knowledge of the decision
maker to the knowledge base of the ES. The disadvantage of modern monitoring systems is the inability to determine the initial stage of an object malfunction. The introduction of neural network technologies in ES when solving diagnostic problems will allow not only to compare the monitored parameters with their reference values, but also to predict the possibility of failures, both of individual elements and the object as a whole [1,2].

Hybrid technologies combine the advantages of fuzzy systems and neural networks [3]. An example of a hybrid technology is the implementation of a system of fuzzy rules based on a neural network [4,5]. Fuzzy ES use knowledge representation in the form of fuzzy products and linguistic variables [6]. The basis of a linguistic variable is a term with a membership function. The way of processing knowledge in fuzzy ES is a logical conclusion on fuzzy products. The use of a fuzzy logic apparatus in the development of Knowledge Base and ES inference mechanisms makes it possible to formalize the procedure for assessing the technical condition on the basis of fragmented, unreliable and possibly inaccurate information and reasonably make decisions on identifying faults. The Knowledge Base of a hybrid ES contains the following components: membership functions, fuzzy products, trained fuzzy neural networks, procedures for interpreting chromosomes of genetic algorithms, and optimality functions. Retrospective information stored in databases serves as the basis for forecasting using neural networks. When finding patterns that adequately reflect the dynamics of the behavior of the input parameters, there is a possibility that they can be used to successfully predict the behavior of an object.

In this work is shown, the use of fuzzy logic and neural network technologies on the example of the development of ES when solving problems of identifying complex technical objects [7,8]. In Figure 1 shows the developed architecture of the hybrid ES. At the fuzzification stage, the values of the input parameters in the form of an N-dimensional input vector $x=[x_1, x_2, \ldots, x_n]^T$ are reduced to a fuzzy set $\tilde{A}$ in accordance with their linguistic assessment and the subsequent choice of the law of variation of the membership function $\mu_{\tilde{A}}(x)$.

![Figure 1. Architecture of the Expert System](image_url)

**Fuzzification of input parameters.** The process of defining a fuzzy set based on a known value of a feature is called fuzzification or reduction to fuzziness. Fuzzification allows one to present objectively
present inaccuracy in the results of physical measurements. When developing the ES knowledge base for the main ship engine, the results of the indication were used, which were converted into three ranges of variation of the input parameter values, respectively, for three linguistic variables: low, normal and high.

**Defuzzification.** The defuzzifier transforms the fuzzy set into a fully deterministic point solution \( y \). Fuzzy set represents dependence as a function of the output variable \( y \). The result consists of the sum of fuzzy functions for the implication of all \( M \) rules that form a fuzzy inference system. The development of the structure of the neural network based on the Takagi-Sugeno-Kang (TSK) fuzzy adaptive inference system for identifying faults was carried out using ANFIS (ANFIS - Adaptive Network Based Fuzzy Inference System) of the network. The number of input and output variables is determined in the same way as when building a fuzzy inference system of the Mamdani-Zadeh type. In this system, the confinement function is defined in a fuzzy point-like manner. Due to this, a defuzzifier at the output of the system is not required, and the inference system is greatly simplified [9-11]. We represent the generalized zero-order TSK inference scheme using \( M \) rules and \( N \) variables as follows:

\[
\text{If (} X_1 \text{ this } A_1) \& (X_2 \text{ this } A_2) \& \ldots \& (X_N \text{ this } A_N) \text{ then } Y_M = K_M
\]  

(1)

where \( A_1, A_2, \ldots A_N \) – fuzzy antecedent sets; \( k \) - is a given constant.

The condition is implemented by the fuzzification function, which is represented by a generalized trapezoidal function separately for each variable. The second system is a fuzzy first order TSK inference. The fundamental difference concerns the conclusion, which is presented in the form of a form of functional dependence. The classical representation of this function, which is most often used in practice, is a first-order polynomial. The generalized inference scheme in the first-order TSK model using \( M \) rules and \( N \) variables can be represented as:

\[
\text{If (} X_1 \text{ this } A_1) \& (X_2 \text{ this } A_2) \& \ldots \& (X_N \text{ this } A_N) \text{ then } Y_M = P_{M_0} + \sum_{j=1}^{N} P_{M_j}X_j
\]  

(2)

where \( P_{MN} \) is the digital weights selected in the adaptation (learning) process. Knowledge base formalization. Basically, a knowledge base can be built using either Mamdani-Zadeh’s fuzzy inference or TSK output. The difference between the TSK knowledge base and Mamdani-Zadeh is that the conclusions of the rules are set not by fuzzy terms, but by a function of the inputs. However, the knowledge base of Mamdani-Zadeh can be built using the knowledge of the decision maker, and the knowledge base TSK is advisable to use if the operator (decision maker) does not have the necessary knowledge about the object. The construction of the TSK fuzzy system is performed in two stages. At the first stage, fuzzy rules are synthesized from experimental data using clustering. With the help of clustering, the neural network independently separates various homogeneous faults into groups (clusters) based on the similarity of features.

**Clustering.** Clustering is necessary to reduce the amount of information and the search area, which makes it possible to reduce the time for identifying a malfunction, as well as taking into account the dynamics of changes in the engine indication results over time. For the neural network was chosen, the FCM-algorithm (Fuzzy Classifier Means, Fuzzy C-Means) of fuzzy clustering. Clusters are fuzzy sets with fuzzy boundaries between them. The initial information for clustering is a matrix of parameter values obtained from the results of the main engine indication. Each row of the matrix represents the values of \( N \) diagnosed faults of one indication out of \( M \) clustering parameters. In general, the description of fuzzy clusters can be represented by the following fuzzy partition matrix:

\[
F = \{ \mu_{ij} \}_{M \times N}, \quad \text{(} i = 1, M, j = N \text{)}
\]
where \( \mu_{ij} \in [0,1] \) is the degree of belonging of the object \( X_i = (x_{i1}, x_{i2}, ..., x_{im}) \) to cluster \( C \). Matrix \( F \) must have the following properties:

1) each object must be distributed among all clusters

\[
\forall i = 1, M \left( \sum_{j=1,N} \mu_{ij} = 1 \right)
\]

2) any cluster shouldn’t be empty or contain all elements

\[
\forall j = 1, N \left( 0 < \sum_{i=1,M} \mu_{ij} < N \right)
\]

The FCM fuzzy algorithm consists in iteratively changing the matrices \( F \) and the vector of cluster centers in order to minimize the scatter criterion:

\[
\lambda = \sum_{i=1}^{C} \sum_{j=1}^{N} (\mu_{ij})^m \cdot \| v_j - x_i \|^2 \rightarrow \min
\]

where \( v_j \) - centers of fuzzy clusters; \( m \in [1, \infty] \) is an exponential weight that determines the fuzziness (blurring) of clusters. As a norm \( \| \| \) the Euclidean matrix norm is applied, \( \| v_j - x_i \|^2 \) is the Euclidean distance between the \( j \)-th center of the cluster \( v_j \) and the \( i \)-th object \( x_i \).

The main disadvantage of this clustering algorithm is the fact that all clusters have the form of a hypersphere, which may not correspond to reality and even lead to incorrect division of the initial data into clusters [12,13]. Genetic algorithms (GA) can serve as one of the methods for solving the clustering problem.

**Genetic algorithms.** The use of genetic algorithms makes it possible to take into account the peculiarities of the search space by adjusting the parameters and determine a more accurate position of the cluster centers and, therefore, improve the results of the fuzzy clustering algorithm [14]. When implementing genetic algorithms in the clustering algorithm for a given number of clusters, the \( c \) chromosome can be encoded by the coordinates of the centers of all clusters (Figure 2). When coding a chromosome by cluster centers, the chromosome length is \( c \) размах \( q \), where \( c \) is the number of clusters, \( q \) is the number of criteria: the first \( q \) coordinates correspond to the center of the first cluster, the second \( q \) coordinates correspond to the center of the second cluster, etc.

Each chromosome is assessed by a measure of its fitness function. “Fitness” for each chromosome is determined by the sum of Euclidean distances from each indexing result to the center of the corresponding cluster:

\[
f = \sum_{j=1}^{m} \sqrt{\sum_{i=1}^{c} (v_q^i - v_j)^2}
\]
where \( j \) - is the number of indexing results; \( c \) - is the number of clusters; \( v^c_q \) - is coordinate of the center of the \( c \)th cluster; \( v^j_f \) - is coordinate of the \( f \)th indexing result.

The implementation of the genetic algorithm without using the FCM algorithm turns out to be less efficient, since the clustering results will significantly depend on how well the initialization of the cluster centers is performed [15].

**Neural network.** At the second stage of building the TSK fuzzy model, the parameters of the fuzzy model are adjusted using the ANFIS-algorithm. ANFIS is a zero or first order hybrid neuro-fuzzy system of TSK fuzzy inference in the form of a five-layer feedforward neural network. ANFIS-network architecture is isomorphic to a fuzzy knowledge base and has a single output with several inputs, the terms of which are fuzzy linguistic variables [16,17]. Network entrances to a separate layer are not highlighted. In Figure 3 shows the developed neural ANFIS-network for identification of 5 states (clusters): CPG failure, cylinder overloaded, cylinder underloaded, fuel equipment failure and norm. The task of the neural network is to determine, from the input vector \( P_{mi}, P_{max}, P_{esp}, t_f, FP_{max} \), that the values belong to the cluster through the output function of the network \( y \).

The purpose of the layers is as follows:

- the 1st layer is the terms of the input variables. Each node of the 1st layer represents one term with a trapezoidal membership function. On this layer, the values of the membership functions are calculated, determining for each \( k \)th rule of inference the value of the membership coefficient in accordance with the applied fuzzification function;
- the 2nd layer is antecedents (premises) of fuzzy rules. The output of the node is the degree of rule fulfillment, which is calculated as the product of the input signals;
- the 3rd layer is the normalization of the degree of rule fulfillment;
- the 4th layer is the conclusion of the rules, forms the values of the weighted components of the output of the \( n \)th cluster \((F_n)\);
- the 5th layer is aggregation of the result obtained according to various rules. The only neuron in this layer implements the defuzzification operation.

The developed neural network makes it possible to identify faults with different degrees of membership.
Conclusion

The paper shows the implementation of a hybrid expert system for identifying faults in complex technical objects. To describe uncertainty, the apparatus of fuzzy sets was used as a combination of fuzzy logic, neural networks and genetic algorithms, which gives the expert system the following advantages: uncertainty management, learning, self-adaptation. The developed methods, models and algorithms for the expert system make it possible to ensure high validity and adequacy of decision-making in conditions of uncertainty and inaccuracy of the initial information, as well as minimize the time and financial costs associated with the need to collect accurate and complete initial data.

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