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Functional Diagnostic System for Multichannel Mine Lifting Machine Working in Factor Cluster Analysis Mode

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Abstract. The primary direction of the increase of reliability of the automated control systems of complex electromechanical machines is the application of intelligent information technologies of the analysis of diagnostic information directly in the operating mode. Therefore, the creation of the basics of information synthesis of a functional diagnosis system (FDS) based on machine learning and pattern recognition is a topical task. In this case, the synthesized FDS must be adaptive to arbitrary initial conditions of the technological process and practically invariant to the multidimensionality of the space of diagnostic features, an alphabet of recognition classes, which characterize the possible technical states of the units and devices of the machine. Besides, an essential feature of FDS is the ability to retrain by increasing the power of the alphabet recognition classes. In the article, information synthesis of FDS is performed within the framework of information-extreme intellectual data analysis technology, which is based on maximizing the information capacity of the system in the process of machine learning. The idea of factor cluster analysis was realized by forming an additional training matrix of unclassified vectors of features of a new recognition class obtained during the operation of the FDS directly in the operating mode. The proposed algorithm allows performing factor cluster analysis in the case of structured feature vectors of several recognition classes. In this case, additional training matrices of the corresponding recognition classes are formed by the agglomerative method of cluster analysis using the k-means procedure. The proposed method of factor cluster analysis is implemented on the example of information synthesis of the FDS of a multi-core mine lifting machine.

Keywords: information-extreme intelligent technology, a system of functional diagnostics, multichannel mine lifting machine, machine learning, factor cluster analysis.

1 Introduction

The use of a functional diagnostics system integrated into the automated control system of a complex electromechanical machine allows evaluating the current technical condition of the units and devices of the machine, to detect defects at an early stage and to predict their development. The reasonable forecast of the change in the technical condition of the equipment, based on which its residual life of the units is estimated, will allow to avoid the economic costs from the emergency stops and to ensure the reliable and safe operation of the control object. However, the deterrent to the widespread use of FDS is the need to overcome the stage of development of complications of a scientific and

methodological nature, due to a large amount of diagnostic information, a significant intersection in the space of diagnostic features of the recognition classes that characterize the possible technical states of the machine, and diagnostic solutions in real-time. In addition, the feature of the FDS of complex machines is the large dimensionality of the alphabet of recognition classes, which significantly complicates the adoption of highly accurate diagnostic decisions. Therefore, the use of intelligent information technologies based on machine learning and pattern recognition is the primary promising way of information synthesis of FDS with high functional efficiency.

The article deals with the problem of information synthesis of the FDS of a multichannel mine lifting

machine (MLM), which operates in the mode of factor cluster analysis, which allows retraining the system while increasing the power of the alphabet of recognition classes.

2 Literature Review

There is a wide variety of diagnostic tools for multichannel MLM nodes and devices [1–3], the main disadvantage of which is the differential approach to the technical state of the equipment. Functional diagnosis, which occurs directly during the operation of the MLM, is carried out continuous monitoring of units and devices of the machine, including the distribution of loads between the ropes. In the works [1, 4], the possibility of solving the problem of load distribution between the ropes without the use of equalization systems by establishing the tolerances of the deviations of effort in the cans and controlling their observance during the operation of the lifting unit was proved. Thus, at present, the necessary information and technical provision for the creation of FDS, capable of forming diagnostic solutions and predicting the change of the resource and the required restoration works, have been created [5, 6].

The paper [7] examines the use of an expert system with fuzzy inference logic for the construction of multi-wire FDS of an MLM is considered. But this approach is true for qualitative measurement scales of diagnostic features. In computerized FDS, diagnostic features are usually quantitative. Therefore, the use of neuron-like structures is the most common in intellectual data analysis [8–10]. However, due to the inflexibility of neural structures, there are complications associated with their retraining when expanding the dictionary of diagnostic features and the alphabet of recognition classes. As a promising direction for improving the functional efficiency of FDS is the application of ideas and methods of the so-called information-extreme intelligent technology (IEI technology) data analysis [11], which is based on maximizing the information capacity of the system in the process of its machine learning [10], where an algorithm of information-extreme machine learning of the FSD multichannel MLM based on a training matrix, formed by analysis of archival data for three functional states of the MLM electric drive, was proposed. But this work did not address the problem of retraining the FDS while increasing the power of the alphabet of recognition classes.

The purpose of this work is to provide the FDS with a multichannel MLM self-learning property by developing a method of information-extreme factor cluster analysis, which allows us to automatically retrain the system when expanding the alphabet of recognition classes.

3 Research Methodology

3.1 Formulation of the problem

The formation of alphabet class recognition classes is one of the most labor-consuming and long-lasting stages of information synthesis capable of learning FDS. The

ability to automate the formation of alphabet-recognition classes exists by implementing ideas and methods of factor cluster analysis, which allows identifying new topological patterns of data. One of the promising directions of increasing the functional efficiency of multichannel MLM is the development of a method of information-extreme machine learning integrated into the automated control system of the FDS, which operates simultaneously in the modes of cluster analysis and factor cluster analysis. In this case, the task of information-extreme cluster analysis of the input data consists of the automatic formation of the input fuzzy classified training matrix, the phasification of which is carried out in the process of information-extreme machine training. But since the power of splitting the space of recognition traits into clusters is a priori indefinable and characterized by high multidimensionality, at the present scientific and methodological level of development of the theory of cluster analysis, the solution of this problem is not available in the general case. As a way out of this situation, it is proposed to build, with the help of cluster analysis, an input fuzzy classified training matrix for the minimum ($M > 2$) alphabet of recognition classes, followed by the allocation of new classes according to the algorithm of information-extreme factor cluster analysis.

Consider the formalized formulation of the problem of information-extreme synthesis of the control system of the limb prosthesis, which operates in the mode of factor cluster analysis. Suppose, as a result of the cluster analysis of the diagnostic data obtained during the operation of the FDS, an alphabet of relatively low power

recognition classes $\{X_m^o | m = \overline{1, M}\}$ and a corresponding fuzzy classified «object-property» training matrix $\|y_{m,i}^{(j)} | i = \overline{1, N}; j = \overline{1, n}\|$, where N is the number of recognition features; n is the sample volume. In the learning matrix, the row is structured by the sequence of readings from the sensors of the information of the diagnostic signs vector-implementation of the corresponding recognition class, and the column is the training sample, which consists of random values of the corresponding diagnostic sign. According to the results of information-extreme machine learning of the FDS, decisive rules have been constructed, which allow us to recognize the technical states of nodes and devices of multichannel MLM in exam mode or directly in working mode.

It is necessary for the operation of MLM not to teach in the operating mode of the unclassified vectors-implementations of recognition classes, which the FDS is not trained to recognize, to form additional corresponding matrix matrices. In this case, an additional training matrix, upon reaching a representative volume, is added to the input training matrix, and the FDS is started for retraining. Decisive rules based on retraining should recognize the feature vectors that characterize the new recognition class.

3.2 Categorical Model

Unlike neural structures, methods of IEI technology are being developed within the functional approach to modeling the cognitive processes inherent in the human formation of conceptual images and making classification decisions. As part of this approach, it is advisable to build a categorical model of machine learning in the form of an oriented graph. The edges of such a graph are operators that reflect the sets involved in machine learning. The input mathematical description of such a category-model is represented as a structure

$$\Delta_B = \langle G, T, \Omega, Z, Y, X; f_1, f_2 \rangle$$

where G is the space of the input signals (factors); T – множина моментів часу зняття інфор multiple points of time of information withdrawal; Ω – the space of diagnostic features; Z – space of possible technical states of FDS; Y – input training matrix; X – binary working learning matrix; f_1 is the operator of forming the training matrix Y ; f_2 is the operator of forming a working matrix X . The Cartesian quadrant $G \times T \times \Omega \times Z$ forms a test universe that generates diagnostic data.

Fig. 1 shows a categorical model of information-extreme machine learning FDS in the mode of factor cluster analysis.

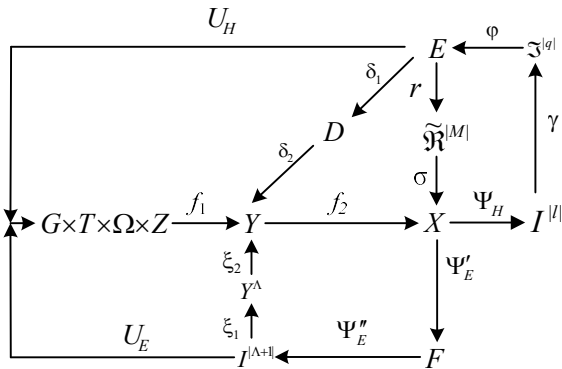


Figure 1 – Categorical model of informational-extremal factorial cluster analysis

The feature shown in Fig. 1. The model is the presence of parallel circuits of machine learning and exam. An outline consisting of a sequence of operators Ψ_H , γ , ϕ , r and σ optimizes the geometric parameters of the recognition class containers that are restored during machine learning in the radial basis of the diagnostic feature space. In this case, the classification operator tests the main statistical hypothesis of belonging to the implementation $\{x_i^{(j)} | j = \overline{1, n}, i = \overline{1, N}\}$ of class X_m^o , where $I^{|l|}$ is a set of l statistical hypotheses. Operator γ determines the set of precision characteristics of diagnostic solutions $\mathfrak{R}^{|q|}$, where $q = l^2$ is the number of precision characteristics, and operator ϕ calculates the set of values of the information criterion for optimization

of machine learning parameters E , which is functional from the precision characteristics. The operator $r: E \rightarrow \mathfrak{R}^{|M|}$ builds at each step of the learning in the general case a fuzzy division of the recognition classes $\mathfrak{R}^{|M|}$, which is obtained by the operator σ for the distribution of binary vectors of realizations of the working binary matrix X .

In the circuit that simulates the operation of the FDS in the mode of e-replacement, or directly in the operating mode, the operator of the classification of the examination vector recognition forms a composition $\Psi_E = \Psi'_E \circ \Psi''_E$, where the operator Ψ'_E calculates the membership functions and forms their term-set F , and the operator Ψ''_E calculates the decision rules. According to the results of the exam, an open set of hypotheses $I^{|M+1|}$ is formed, among which hypothesis γ_{M+1} means that the examination realization does not belong to the alphabet of the recognition classes $\{X_m^o\}$. The operator $\xi_1: I^{|M+1|} \rightarrow Y_{M+1}$ generates from the unclassified vectors an additional training matrix Y_{M+1} of the new recognition class X_{M+1}^o , which the operator $\xi_2: Y^\Lambda \rightarrow Y$ upon reaching a representative volume, adds to the input training matrix Y and starts machine retraining of the FDS. Operators $U_H: E \rightarrow G \times T \times \Omega \times Z$ and $U_E: I^{\Lambda+1} \rightarrow G \times T \times \Omega \times Z$ regulate machine learning and SFD exam, respectively.

3.3 FDS machine learning algorithm

According to the categorical model (Fig. 1), the idea of information-extremal factor cluster analysis is that a priori trained FDS recognizes a small number of recognition classes. When new functional states of nodes and devices appear during the operation of the MLM, their unclassified structured vectors of diagnostic features form additional training matrices. An additional training matrix, which reaches a representative volume, joins the input training matrix and retrains the FDS according to the information-extreme algorithm. New decisive rules are being constructed in the radial basis of containers of recognition classes obtained in the process of retraining the optimal geometric parameters of the reconnaissance class containers. Upon reaching a representative amount of an additional training matrix of another recognition class, it also joins the input training matrix, and the FDS is retrained. Since the alphabet of the classes of recognition of the technical state of a complex machine is characterized by high power, to reduce the impact of its many dimensions, machine learning FDS is carried out by the hierarchical structure of diagnostic data. The formation of additional training matrices of new recognition classes is carried out by cluster analysis of unrecognized vectors of diagnostic features according to the agglomerative algorithm. According to this algorithm, the vertex of the unclassified vector of diagnostic features is taken as the center of recognition class X_{M+1}^o , around

which the region of the corresponding radius is specified. If another unclassified vector falls into this sphere, then a new class X_{M+1}^o center is determined by the method of k -means. An unclassified vector that does not fall into the domain of class X_{M+1}^o forms the center of the class X_{M+2}^o and so on, until a representative number of unclassified vectors are accumulated. Thereafter, the radii of the taxon regions increase, and the k -means method is again implemented. If the radius of any recognition class covers the center of a neighboring class, then the "absorption" of the neighboring class takes place. The clustering process continues until an additional representative training matrix of the new recognition class is formed, which joins the input training matrix, and the FDS retraining process is started.

Consider the main stages of the implementation of the algorithm of information-extreme factor cluster analysis in the functioning of the FDS in working mode, which is similar to the exam mode. The difference between these modes is their purpose. For example, the function of the SFD in exam mode is to test the functional effectiveness of machine learning. The main task of information-extremal factor cluster analysis is the formation of an additional training matrix Y^Λ . The algorithm of forming the matrix Y^Λ is based on the method of agglomerative cluster analysis of unclassified vectors of diagnostic features- realizations of unknown recognition classes. Thus, the input data is the set of unclassified vector-realization of images, which consistently appear in the classification process; n_{\min} is the minimum number of vectors of a representative learning matrix, which is determined by the method proposed in [11, 12]; S is the number of clusters of partitioning of nonclassified vectors.

The algorithm of forming an additional training matrix Y_{M+1} has the following basic stages of implementation:

- 1) the counter of the radii of the clusters is reset $R := 0$;
- 2) $R := R + 1$;
- 3) the vertex of the first unclassified binary vector implementation of a new recognition class is taken as the geometric center of the cluster X_{M+1}^o , and a region with radius R is formed around it, and the vector refers to the class X_{M+1}^o ;
- 4) if the next unclassified vector implementation falls into the domain of cluster X_{M+1}^o , then it belongs to the training matrix of this class, and by the procedure of method k -means the average vector $x_{M+1,i}$, is calculated, the vertex of which defines the new center of the cluster, by the following rule:

$$x_{M+1,i} = \begin{cases} 1, & \text{if } \frac{1}{n_{M+1}} \sum_{j=1}^{M+1} x_{M+1,i}^{(j)} \geq \rho, \\ 0, & \text{if } \textit{else}, \end{cases}$$

where $x_{M+1,i}$ is the i -th coordinate of the class X_{M+1}^o averaged vector; n_{M+1} is the number of unclassified class X_{M+1}^o ($n_{M+1} > 2$) vectors; ρ – the quantization level of the coordinates of the averaged vector, which is 0.5 by default;

5) the number of educations of clusters is calculated, and if $s \leq S$, then the vertices of the downstream unclassified vectors that do not rely on the formed clusters are taken as centers of the new clusters, otherwise item 9 is fulfilled;

6) unclassified vectors that fall into the cluster domain are classified according to their additional training matrices;

7) determine the total number of n vectors belonging to the clusters and forming the corresponding additional matrices;

8) if $n > n_{\min}$, then item 2 is executed, otherwise – item 9;

9) if the number of vectors in any additional binary matrix reaches the value n_{\min} , then it transforms into a real matrix $\|y_{M+1,i}^{(j)}\|$, joins the input training matrix, the algorithm of information-extreme machine retraining of the system [5] is started, and the cluster X_{M+1}^o and, accordingly, its training the matrix is removed;

10) if $R < d_{\min}$, where d_{\min} is the minimum inter-center distance between the nearest adjacent clusters, then item 2 is fulfilled, otherwise the stop of the cluster radius increment counter;

11) the formation of other additional training matrices continues as new unclassified vectors appear until they reach a representative volume of the input training matrix n_{\min} .

The considered algorithm of factor cluster analysis allows to form in the general case fuzzy classified training matrices for new classes of recognition and to carry out retraining of FDS automatically. For practical reasons, this approach allows us to bypass the problem of cluster analysis of input data that has not been solved so far when expanding the alphabet of recognition classes. Increasing the power of the alphabet recognition classes should move to information-extreme machine learning according to the hierarchical data structure, which was studied in [13].

4 Results

Consider the implementation of the algorithm of information-extreme factor cluster analysis on the application of information synthesis of FDS multichannel MLM. Initially, the algorithm of informational-extreme machine learning of FDS, multichannel MLM, which functioned in the mode of cluster analysis of diagnostic features, was implemented. In our case, the cluster analysis of the input data played an auxiliary role, which consisted in the automatic formation of the input fuzzy classified training matrix for the three recognition classes:

class X_1^o , which characterized the technical state of tension of the ropes «Norm»; class X_2^o , which characterized the temperature of the windings of the drive “Norm” and X_3^o – the temperature of the windings of the drive “More norms”.

The vectors of diagnostic features that characterized the above recognition classes were selected from archival data provided by ULIS Systems, which is engaged in the modernization of the MLM management system at “DTEK Pavlogradvuhillia” (Pavlograd, Ukraine). Each structured vector consisted of 69 quantitative diagnostic features that characterized the electrical, temperature, and mechanical characteristics of the SPM units. In the initial unclassified sample set, the number of implementation vectors for each class was equal and was equal to 60. The method of cluster analysis was based on the procedure described in Section 3.3 of the k -means procedure. The formation of the input classified learning matrix was stopped when each cluster was hit with at least 40 vectors of diagnostic features. Since the procedure of k -means the vectors of realization vectors to the corresponding cluster were determined by the remote proximity criterion, then the formed input training matrix was unclear due to the intersection of recognition classes in the space of diagnostic features. Therefore, fuzzy data fuzzification was carried out in the process of information-extreme machine learning FDS with optimization of the parameter δ , which was equal to half of the symmetric field of control tolerances for diagnostic features and geometric parameters of hyperspherical containers of recognition classes, which on each machine were restored in the radial basis of the space of diagnostic features.

The algorithm of information-extreme machine learning was implemented according to the iterative procedure of finding the global maximum of the information criterion for the optimization of training parameters in the form [11]:

$$\delta^* = \arg \max_{G_\delta} \{ \max_{G_E \cap \{k\}} \bar{E}^{(k)} \}, \quad (1)$$

where $\bar{E}^{(k)}$ is the value calculated on the k -th step of machine learning alphabetically averaged classes of recognition of the information criterion of optimization of training parameters; G_δ – the range of allowable values of the parameter field of control tolerances for diagnostic features; G_E – working (valid) area for determining the optimization criterion; $\{k\}$ – many steps of machine learning.

As a criterion for optimization of machine learning parameters, a modified Kullback information measure was considered, which in the case of equally probable two-alternative a priori hypotheses has the form [6]

$$E_m = \log_2 \left(\frac{2 - (\alpha_m^{(k)}(d) + \beta_m^{(k)}(d)) + 10^{-p}}{\alpha_m^{(k)}(d) + \beta_m^{(k)}(d) + 10^{-p}} \right) * [1 - (\alpha_m^{(k)}(d) + \beta_m^{(k)}(d))], \quad (2)$$

where $\alpha_m^{(k)}(d)$ is a mistake of the first kind of decision making at the k -th step of machine learning; $\beta_m^{(k)}(d)$ – a mistake of the second kind; d – a remote measure that defines the radii of hyperspherical containers of recognition classes; 10^{-p} – a sufficiently small number that is entered to avoid division by zero.

The normalized form of criterion (2) has the form

$$E = \frac{J_m^{(k)}}{J_{MAX}}, \quad (3)$$

where J_{MAX} is the maximum value of the criterion obtained by substituting in formula (2) the zero values of errors $\alpha_m^{(k)}(d)$, and $\beta_m^{(k)}(d)$.

The machine-learning algorithm was implemented for the alphabet, which consisted of the above three recognition classes, for which an input learning matrix was formed by the cluster analysis method. The optimization of machine-to-learning parameters was carried out by a parallel procedure, which consisted of the simultaneous change of the control tolerances for diagnostic features to the same percentage value.

Fig. 2 shows a graph of the average value of information criterion (3) from parameter δ , built on the results of machine learning with parallel optimization of control tolerances for diagnostic features

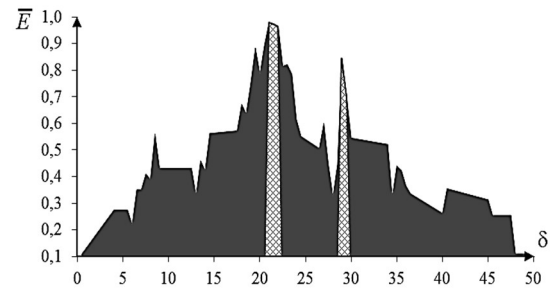


Figure 2 – Graph of information criterion dependence on the parameter of the field of tolerances

Fig. 2 shows a double hatch (a valid domain for determining the function of the information criterion (3), in which the first and second reliability of the classification decisions are exceeded by errors of the first and second kind, respectively). The optimal value of the machine learning parameter is determined by analysis of Fig. 2 shows that the optimal value of the parameter of the field of control tolerances is $\delta^* = 21$ (as a percentage of the nominal (average) value of the diagnostic criterion. st signs) when averaged normalized maximum value optimization criterion $\bar{E}^* = 1$. That is in the process

managed to build a machine learning unmistakable training matrix for decision rules as a criterion (3) takes the maximum value at zero errors of the first and second kind.

Since the decisive rules are constructed within the geometric approach, in Fig. 3 shows the graphs of the dependence of information criterion (3) on the radii of the containers of recognition classes [11] obtained in the process of machine learning at the optimal value of the parameter δ^* .

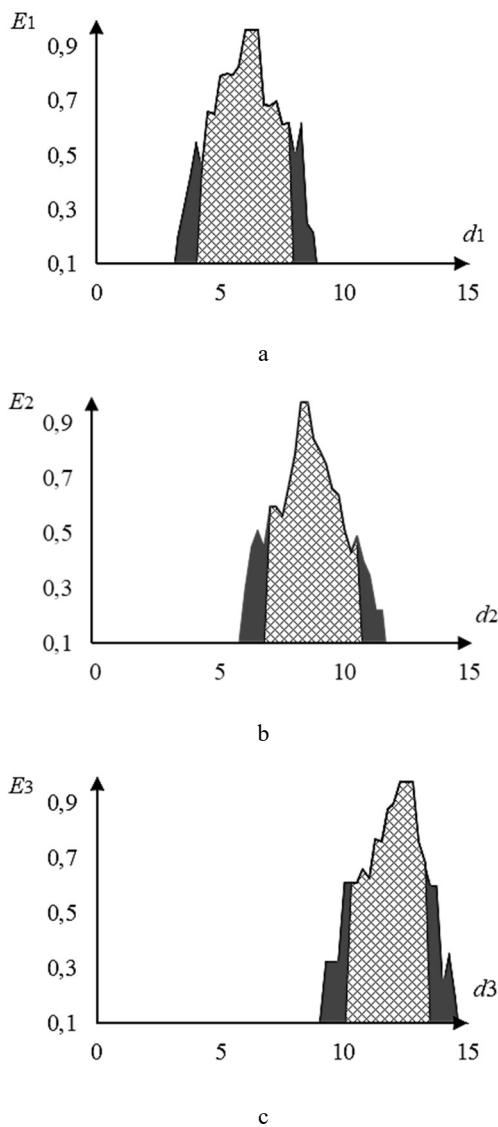


Figure 3 – Graphs of the dependence of the optimization criterion on the radii of the recognition class containers: a – class X_1^o ; b – class X_2^o ; c – class X_3^o

For testing the functional efficiency of the proposed algorithm for the input of FDS in the mode of cluster factor analysis, vectors of diagnostic features were presented, which characterized the new class of recognition X_4^o is the load balance on the ropes “More norm”. Since the FDS was not trained to recognize the

implementation vectors of the new class, an additional training matrix was formed, which consisted of 40 unclassified vectors of realization of the recognition class X_4^o . After attaching the additional matrix to the existing input training matrix, the FDS was retrained according to the same machine learning algorithm of the system for the previous three recognition classes.

Fig. 4 shows a graph of alphabetically averaged four classes of recognition of information criterion (3) from parameter δ of the field of tolerances, obtained by machine learning by the procedure (1)

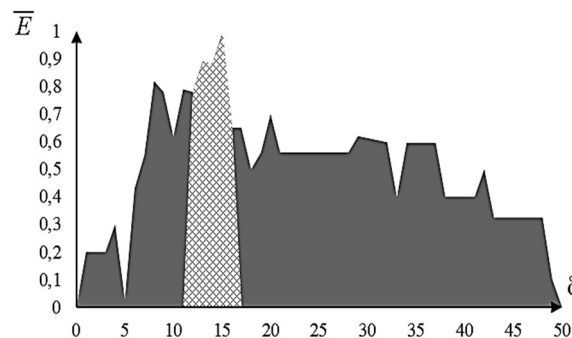


Figure 4 – Graph of the dependence of information criterion on the parameter of the field of tolerances for four classes of recognition

The analysis of Fig. 4 shows that the optimal value of the parameter δ changed and became $\delta^* = 16$ at almost the same maximum value of the average normalized optimization criterion. In this case, according to the results of comparing the graphs shown in Fig. 2 and Fig. 4, there is a tendency to decrease the optimal value of parameter δ with the increase in the power of the alphabet of recognition classes. This fact is explained by the increase in the coefficient of fuzzy compactness when expanding the alphabet of recognition classes and the constant size of the space of diagnostic features.

Fig. 6 shows the graphs of the criterion (3) on the radii of the containers of recognition classes, obtained at the optimal value of the parameter of the field of control tolerances for diagnostic features.

Analysis of Fig. 4 and Fig. 5 shows that the maximum average value of the information criterion for optimization of machine learning parameters reaches its limit value and is equal to $\bar{E}^* = 1$. In this case, the optimal radii of the corresponding containers of the recognition classes are equal in code units, respectively, $d_1^* = 6$, $d_2^* = 8$, $d_3^* = 13$, and $d_4^* = 9$.

Optimal geometric parameters of container-tails of recognition classes were obtained from the process of retraining of the FDS by decisive rules, which in the predicate form have the form

$$(\forall X_m^o \in \mathfrak{R}^{M|})(\forall x_e \in \mathfrak{R}^{M|})[if (\mu_m > 0) \& (\mu_m = \max \{\mu_m\}) \text{ then } x_e \in X_m^o \text{ else } x_e \notin X_m^o], \quad (4)$$

where x_e is a recognizable vector; μ_m is a function that determines the identity of the vector x_e of the recognition class X_m^o container.

In expression (4), the membership function for the hyperspherical container of recognition class X_m^o is determined by the following formula [11]:

$$\mu_m = 1 - \frac{d(x_m^* \oplus x_e)}{d_m^*},$$

where $d(x_m^* \oplus x_e)$ is the code distance between the optimal value of the averaged vector x_m^* diagnostic features obtained in the machine learning process and the recognizable vector x_e ; d_m^* is the optimal radius of the hyperspherical container of recognition class X_m^o .

Thus, according to the results of the physical model, the operability and reliability of the developed information and software of the FDS, which operates in the mode of information-extreme factor cluster analysis, is confirmed.

5 Conclusions

Within the framework of information-extreme intelligence-based technology of data analysis, which is based on maximizing the information capacity of the recognition system in the process of its machine learning, the method of automatic retraining of the FDS when expanding the alphabet of recognition classes is proposed. In this case, the functioning of the FDS in the mode of factor cluster analysis eliminates the main disadvantage of methods of cluster analysis of input data - a strong dependence of their functional efficiency on the power of the alphabet of recognition classes.

In addition, since the decisive rules are built in the process of information-extreme factor cluster analysis within the geometric approach, they are characterized by high efficiency of classification decisions, which allowed directly in working mode to allocate new recognition classes and carry out retraining.

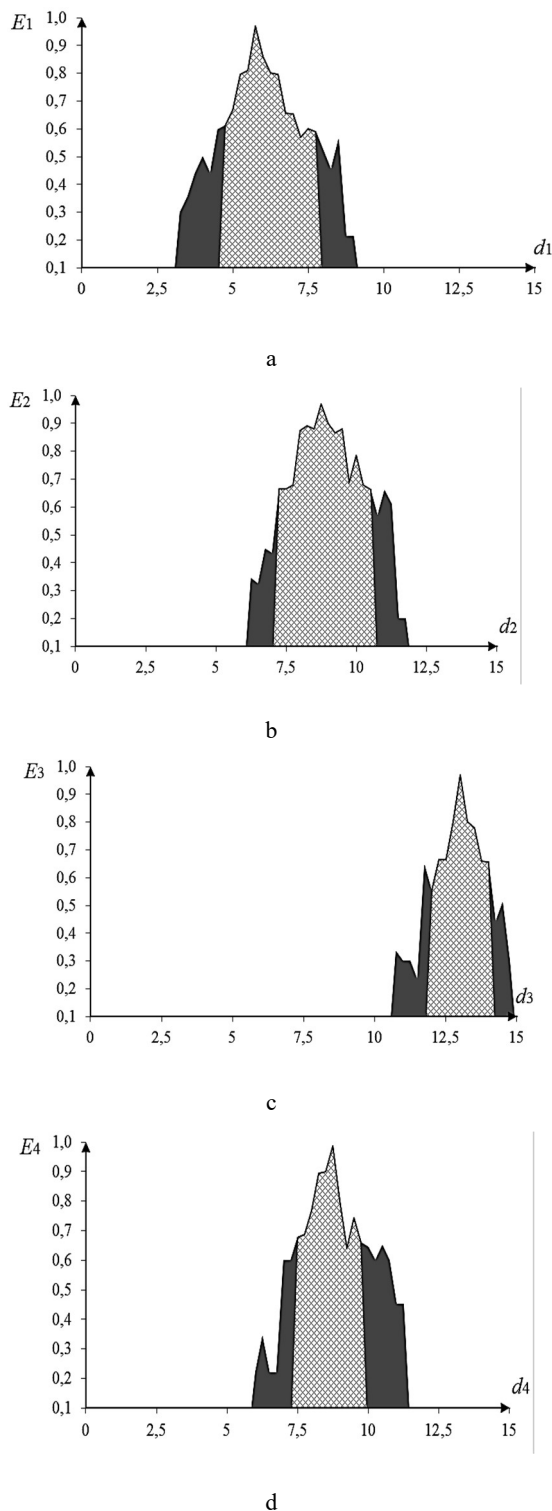


Figure 5 – Graphs of optimization criterion versus container radii of recognition classes: *a* – class X_1^o ; *b* – class X_2^o ; *c* – class X_3^o ; *d* – class X_4^o

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