CONTROL PROCESSES

The peculiarities of modern military conflicts significantly increase the requirements for the efficiency of object state assessment. Therefore, it is necessary to develop algorithms (methods and techniques) that can assess the state of the monitoring object from different sources of intelligence for a limited time and with a high degree of reliability. Accurate and objective object analysis requires multi-parameter estimation with significant computational costs. That is why the following tasks were solved in the study: the formalization of the assessment of monitoring objects was carried out, a method of increasing the efficiency of assessing the condition of monitoring objects was developed and an efficiency assessment was carried out. The essence of the proposed method is the hierarchical hybridization of binary classifiers and their subsequent training.

The method has the following sequence of actions: determining the degree of uncertainty, constructing a classifier tree, determining belonging to a particular class, determining object parameters, pre-processing data about the object of analysis and hierarchical traversal of the tree.

The novelty of the method lies in taking into account the type of uncertainty and noise of the data and taking into account the available computing resources of the object state analysis system. The novelty of the method also lies in the use of combined training procedures (lazy training and training procedure for evolving neural networks) and selective use of system resources by connecting only the necessary types of detectors.

The method allows you to build a top-level classifier using various low-level schemes for combining them and aggregating compositions. The method increases the efficiency of data processing by 12–20 % using additional advanced procedures

Keywords: special-purpose information systems, efficiency of information processing, computing power

DEVELOPMENT OF A METHOD TO IMPROVE THE RELIABILITY OF ASSESSING THE CONDITION OF THE MONITORING OBJECT IN SPECIAL-PURPOSE INFORMATION SYSTEMS

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1. Introduction

The growing volume of information circulating in various systems of collection, processing and transmission of information leads to significant use of computing resources of hardware. The armed forces of technically developed countries have integrated decision-making architectures based on:

− artificial intelligence and nanotechnology;
− efficient processing of large amounts of information;

– multifunctional processors with real-time decision-making support;

– data compression technologies to increase their processing speed.

At the same time, the use of information systems with elements of artificial intelligence increases the effectiveness of operations (military operations), affects the doctrine, organization and application of groups of troops (forces).

However, increasing the dynamics of operations, increasing the number of different sensors and the need to integrate them into a single information space create a number of problems [1–8]:

– implemented algorithms for determining correlations among events do not fully take into account the reliability of intelligence sources and the reliability of information in the dynamics of hostilities;

– forms of information presentation complicate its transmission through communication channels;

– limited computing power of hardware;

– limited capacity of data transmission channels;

– electronic suppression of shortwave and ultrashort-wave radio channels and cybernetic impact on information systems;

– increase in the number of indicators by which the condition of monitoring objects is assessed;

– variety of indicators by which the condition of monitoring objects is assessed;

– the need to process a large amount of input data by which the condition of monitoring objects is assessed;

– variety of intelligence sources;

– transition to the principle of monitoring object assessment «everything affects everything at once», covering the total network and computing resources of all types of armed forces.

Therefore, it is necessary to develop algorithms (methods and techniques) that can assess the state of the monitoring object from different sources of intelligence for a limited time and with a high degree of reliability.

Given the above, the urgent scientific task is to develop a method for assessing the state of the monitoring object in special-purpose information systems.

2. Literature review and problem statement

The work [9] presents a cognitive modeling algorithm. The main advantages of cognitive tools are determined. The disadvantages of this approach include the lack of consideration of the type of uncertainty about the analysis object state.

The work [10] reveals the essence of cognitive modeling and scenario planning. A system of complementary principles of construction and implementation of scenarios is proposed, different approaches to the construction of scenarios are allocated, a procedure of scenario modeling based on fuzzy cognitive maps is described. The approach proposed by the authors does not take into account the type of uncertainty about the analysis object state and the noise of the initial data.

The work [11] carried out an analysis of the main approaches to cognitive modeling. Cognitive analysis allows you to: investigate problems with fuzzy factors and relationships; take into account changes in the external environment and take advantage of objectively formed trends in

the situation. However, the question of describing complex and dynamic processes remains unexplored in this paper.

The work [12] presents a method for analyzing large amounts of data. This method is focused on finding hidden information in large data sets. The method involves the operations of generating analytical baselines, reducing variables, detecting sparse features and specifying rules. The disadvantages of this method include the inability to take into account different strategies for evaluating decisions, the lack of consideration of the type of uncertainty of the input data.

The work [13] shows the mechanism of transformation of information models of construction objects to their equivalent structural models. This mechanism is designed to automate the necessary operations of transformation, modification and addition during such an exchange of information. The disadvantages of this approach include the inability to assess the adequacy and reliability of the information transformation process and make appropriate adjustments to the resulting models.

The work [14] carried out the development of an analytical web platform to study the geographical and temporal distribution of incidents. The web platform contains several information panels with statistically significant results by territory. The disadvantages of the analytical platform include the inability to assess the adequacy and reliability of the information transformation process, as well as high computational complexity. Also, the disadvantages of the research include the ambiguity of solution search.

The work [15] developed a method of fuzzy hierarchical assessment of the quality of library services. This method allows you to evaluate the quality of libraries by a variety of input parameters. The disadvantages of this method include the inability to assess the adequacy and reliability of the assessment and, accordingly, determine the assessment error.

The work [16] carried out an analysis of 30 algorithms for processing large amounts of data. Their advantages and disadvantages are shown. It is found that the analysis of large amounts of data should be carried out in layers, in real time and have the ability to self-study. The disadvantages of these methods include high computational complexity and the inability to verify the adequacy of the estimates.

The work [17] presents an approach to evaluating input data for decision support systems. The essence of the proposed approach is to cluster the basic set of input data, analyze them, and then train the system based on the analysis. The disadvantages of this approach are the gradual accumulation of evaluation and learning errors due to the inability to assess the adequacy of decisions.

The work [18] presents an approach to processing data from different sources of information. This approach allows processing data from various sources. The disadvantages of this approach include the low accuracy of the estimate and the inability to verify the reliability of the estimate.

The work [19] carried out a comparative analysis of existing decision support technologies, namely: analytic hierarchy process, neural networks, fuzzy set theory, genetic algorithms and neuro-fuzzy modeling. The advantages and disadvantages of these approaches are indicated. The scope of their application is determined. It is shown that the analytic hierarchy process works well with complete initial information, but it has a high share of subjectivity due to the need for experts to compare alternatives and choose evaluation criteria. The use of fuzzy set theory and neural networks

is justified for forecasting problems in conditions of risk and uncertainty.

The work [20] developed a method of structural-target analysis of the development of poorly structured systems. An approach to the study of conflict situations caused by contradictions in the interests of the subjects affecting the development of the studied system and methods for solving poorly structured problems based on the formation of scenarios. The problem is defined as a mismatch of the existing state of the system to the required one, specified by the subject of management. However, the disadvantages of the proposed method include the problem of local optimum and the inability to conduct a parallel search.

The work [21, 22] presents a cognitive approach to the simulation of complex systems. The advantages of this approach, describing the hierarchical composition of the system, are shown. The disadvantages of the proposed approach include the lack of consideration of the computing resources of the system.

An analysis of the works [9–21] showed that common shortcomings of the above studies are:

– not taking into account the impact of destabilizing factors affecting the efficiency of special-purpose information systems;

– the existing methods of assessing the condition of the monitoring object are intended for general-purpose information systems, which does not allow using them for special-purpose systems;

– variety of information sources;

– lack of the possibility to form a hierarchical system of indicators;

– lack of consideration of computing resources of the system;

– lack of mechanisms for adjusting the system of indicators during the evaluation;

– lack of mechanisms for deep learning of knowledge bases;

– lack of accounting for computing resources available in the system.

To this end, it is proposed to develop a method of increasing the efficiency of assessment in special-purpose information systems.

3. The aim and objectives of the study

The aim of the study is to increase the efficiency of data processing in special-purpose information systems with a given reliability.

To achieve the aim, the following objectives were set:

– to set a task of assessing the monitoring object state in special-purpose information systems;

– to develop a method of increasing the efficiency of assessing the monitoring object state in special-purpose information systems;

– to give an example of using the proposed method in the analysis of the operational situation of a group of troops (forces).

4. Materials and methods of the study

The study used the general provisions of the theory of artificial intelligence to solve the problem of object state analysis in intelligent decision support systems. Thus, the theory of artificial intelligence is the basis of this study. The study used fuzzy cognitive models, an improved genetic algorithm, and evolving artificial neural networks. The simulation was performed using MathCad 2014 software (USA) and Intel Core i3 PC (USA).

5. Results of the study on the development of a method for assessing the monitoring object state in special-purpose information systems

5. 1. Setting the task of assessing the monitoring object state in special-purpose information systems

Let the control system of the object state analysis process be represented by a sign-oriented graph. In general, the task of determining the state of the monitoring object is reduced to calculations by the formula:

$$A_i(k+1) = f\left(\left(A_i(k) + \sum_{j \neq i, j=1}^{N} A_j(k)W_{ij}\right) \times \iota_{ij}\right) \times \zeta_{ij}, \qquad (1)$$

where $A_i(k+1)$ is the new state of the graph vertex; $A_i(k)$ is the previous state of the graph; W_{ij} is the weight matrix; f is the threshold function of the graph; ι_{ij} is the operator taking into account the degree of awareness of the object state; ζ_{ij} is the operator taking into account the degree of noise of the object state data. The calculation process is iterative – after setting the initial states of the vertices, the values of the states are recalculated until the difference between the current and previous states is less than a given value.

Expression (1) allows you to form a description of the state of the monitoring object by presenting it in the form of a graph. The graph is built for each individual object. This description is universal and allows you to describe the object of analysis, taking into account the hierarchy and individual specifics of each monitoring object. While writing expression (1) as a multidimensional time series, the description process can be given for a dynamic system. Expression (1) while constructing a mathematical description of the monitoring object state takes into account the degree of awareness about the object state and data noise.

5. 2. Development of a method to increase the efficiency of evaluation in intelligent decision support systems

The evaluation method in intelligent decision support systems consists of the following sequence of actions (Fig. 1).

The algorithm for implementing the proposed method consists of the following sequence of actions:

1. Entering initial data. At this stage, the initial data on the state of the monitored object is entered. The number of sources of monitoring devices, type of initial data and their volume are determined.

2. Determining the degree of uncertainty of the initial data. At this stage, the degree of uncertainty of the initial data is determined based on the authors' previous studies. The degree of uncertainty of the initial data is as follows: complete uncertainty; partial uncertainty and full awareness [2, 23].

3. Construction of a classifier tree.

This stage of the method can be described as preparatory, including the choice of:

– the structure of individual binary classifiers (detectors);

– dimensions and number of layers;

– training parameters and algorithms;

– types of activation, membership and nuclear functions [24–28].

A set of training rules is developed for each detector. Defining different sets of such rules, you can form a group of detectors, each of which is built on the basis of an evolving artificial neural network. Detectors within each group are combined into a classifier based on one-vs-all, one-vs-one approaches, or their various derivative variations [28–35].

In the first approach, each detector

$$F_{jk}^{(k)} : \mathbb{R} \rightarrow \{0,1\}\,(k=1,...,m)$$

is trained from data $\{x_l, [c_l = k]\}_{l=1}^{M}$ and the operation of the group of detectors $F_{jk}^{(k)}$ is described by the principle excluding:

$$F_j^{(i)}(z) = \begin{cases} \{0\}, \text{if } \forall k \in \{1,...,m\}\, F_{jk}^{(i)}(z) = 0, \\ \left\{k \left| F_{jk}^{(i)}(z) = 1\right.\right\}_{k=1}^{m}, \text{other way.} \end{cases} \quad (2)$$

In the second approach, each of the $C_{m+1}^2 = \dfrac{(m+1)\cdot m}{2}$ detectors $F_{jk_0 k_1}^{(k)}$ is trained from a set of objects belonging to only two classes with labels $k_0, k_1, -\left\{(x_l, 0 | \overline{c}_l = k_0)\right\}_{l=1}^{M} \bigcup \left\{(x_l, 1 | \overline{c}_l = k_1)\right\}_{l=1}^{M}$, $0 \le k_0 < k_1 \le m$ and the operation of the group of detectors $F_j^{(i)}$ is determined by max-wins voting:

$$F_j^{(i)} = \left\{\arg \max_{\overline{c} \in \{0,...,m\}} \sum_{k=\overline{c}+1}^{m} \left[F_{j\overline{c}k}^{(i)}(z) = 0\right] + \sum_{k=0}^{\overline{c}-1} \left[F_{j\overline{c}k}^{(i)}(z) = 1\right]\right\}. \quad (3)$$

4. Identifying available hardware computing resources.

At this stage, the available hardware computing resources of the network are determined. Based on this, possible classification options are determined: binary classification tree, genetic algorithm, fuzzy cognitive models and acyclic graph.

Table 1 shows the characteristics of the considered schemes of combining detectors into a multi-class model, designed to correlate the input object of one or more of the $(m+1)$ class labels.

Table 1

Characteristics of detector combining schemes

Combining scheme	Number of detectors to be trained	Minimum number of detectors involved in object classification	Maximum number of detectors involved in object classification
one-vs-all	m	m	m
one-vs-one	$\dfrac{(m+1)\cdot m}{2}$	$\dfrac{(m+1)\cdot m}{2}$	$\dfrac{(m+1)\cdot m}{2}$
Classification binary tree	m	1	m
Directed acyclic graph	$\dfrac{(m+1)\cdot m}{2}$	m	m
Fuzzy cognitive model	$(m^*x)^*m$	(m^*x)	$(m^*x)^*m$
Genetic algorithm	(m^*x)	m	(m^*x)

5. Determining the membership of the monitoring object to a certain class.

The classification binary tree can be mentioned as one of the derivative variations of the previous approaches for combining detectors [25]. Formally, this structure is given recursively as follows:

$$CBT_\mu = \begin{cases} \left\langle F_{jL_\mu R_\mu}^{(i)}, CBT_{L_\mu}, CBT_{R_\mu}\right\rangle, \text{if } \#\mu \ge 2, \\ \mu, \qquad\qquad\qquad\qquad \text{if } \#\mu = 1, \end{cases} \quad (4)$$

where $\mu = \{0,...,m\}$ is the original set of class labels; $L_\mu \subsetneq \mu$ is the arbitrarily generated or defined subset; $\mu(\#L_\mu < \#\mu)$, $R_\mu = \mu \setminus L_\mu$ is the left classification subtree; CBT_{R_μ} is the right classification subtree; $F_{jL_\mu R_\mu}^{(i)}$ is the nodal detector trained on the elements of the set:

$$\left\{(x_l, 0) | \overline{c}_l \in L_\mu\right\}_{l=1}^{M} \bigcup \left\{x_l, 1 | \overline{c}_l \in R_\mu\right\}_{l=1}^{M}.$$

The output of the detector is set to 0 if the input object x_l belongs to a class with a label $\overline{c}_l \in L_\mu$, and 1 if the object x_l belongs to a class with a label $\overline{c}_l \in L_\mu$.

Therefore, the operation of the group of detectors $F_j^{(i)}$ represented as nodes of such a tree is described by the recursive function $\varphi_j^{(i)}$ that specifies the sequential dichotomy of the set μ:

$$F_j^{(i)} = \phi_j^{(i)}(\mu, z),$$

$$\phi_j^{(i)}(\mu, z) = \begin{cases} \mu, \qquad\qquad \text{if } \#\mu = 1, \\ \phi_j^{(i)}(L_\mu, z) \text{ if } \#\mu \ge 2 \wedge F_{jL_\mu R_\mu}^{(i)}(z) = 0, \\ \phi_j^{(i)}(R_\mu, z) \text{ if } \#\mu \ge 2 \wedge F_{jL_\mu R_\mu}^{(i)}(z) = 1. \end{cases} \quad (5)$$

Applying the function $\phi_j^{(i)}$ to the original set of class labels and the monitoring object allows you to unambiguously search for the class label of this object. This is because as you go down the classification tree, a disjunctive division of the set of class labels occurs. Once the terminal detector is reached and triggered, there is only one possible label left to classify the input object z as the output $F_j^{(i)}$. Therefore, conflicts are not possible for the classification tree when classifying objects that may occur for the other two combining approaches.

Another approach is a directed acyclic graph, which organizes $C_{m+1}^2 = \dfrac{(m+1)\cdot m}{2}$ detectors into a coherent dynamic structure, which can be given by the following formula:

$$DAG_\mu = \begin{cases} \left\langle F_{j\mu k_0 k_1}^{(i)}, DAG_{\mu \setminus \{k_0\}}, DAG_{\mu \setminus \{k_1\}}\right\rangle, \\ \text{if } \#\mu \ge 2, \text{ where } k_0 \in \mu, k_1 \in \mu, \\ \mu, \text{if } \#\mu = 1. \end{cases} \quad (6)$$

Here, as in the one-vs-one approach, each node detector $F_{j\mu k_0 k_1}^{(i)}$ is trained from the elements

$$\left\{(x_l, 0 | \overline{c}_l = k_0)\right\}_{l=1}^{M} \bigcup \left\{(x_l, 1 | \overline{c}_l = k_1)\right\}_{l=1}^{M} (k_0 < k_1).$$

Traversal of the considered graph is performed using the recursive function $\xi_j^{(i)}$ that specifies the elemental «splitting» from the set μ:

$$F_j^{(i)} = \xi_j^{(i)}(\mu, z),$$

$$\xi_j^{(i)}(\mu, z) = \begin{cases} \mu, \text{ if } \#\mu = 1, \\ \xi_j^{(i)}(\mu \setminus \{k_1\}, z), \text{if } \#\mu \ge 2 \wedge F_{j\mu k_0 k_1}^{(i)}(z) = 0, \\ \xi_j^{(i)}(\mu \setminus \{k_0\}, z), \text{if } \#\mu \ge 2 \wedge F_{j\mu k_0 k_1}^{(i)}(z) = 1. \end{cases} \quad (7)$$
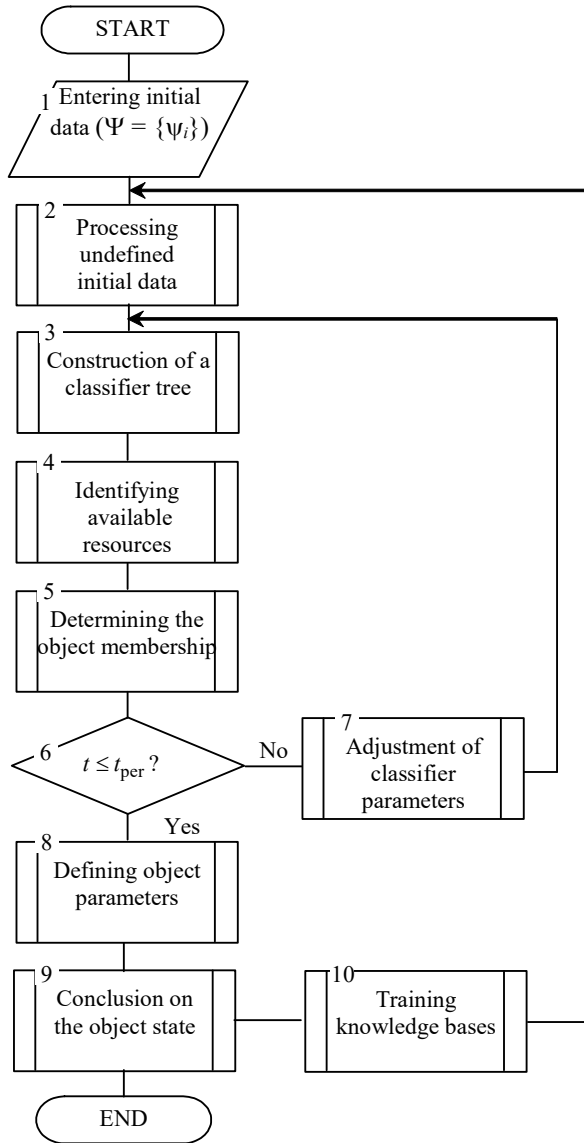
Fig. 1. Algorithm for implementing the method of object state analysis

If the detector $F^{(i)}_{juk_0k_1}$ votes for the k_0-th class for the object z, i.e. $F^{(i)}_{juk_0k_1}(z)=0$, the label k_1 is removed from the set μ as obviously incorrect, and if not, the label k_0 is excluded. The process is repeated until the set μ degenerates into a single element.

Of the six schemes considered, only the classification binary tree has a variable number of detectors that can be used in the object classification process.

The minimum value is reached when the detector $F^{(i)}_{jL_\mu R_\mu}$ located at the root of the tree is activated and trained to recognize only one class of objects among all the others, and $F^{(i)}_{jL_\mu R_\mu}(z)=0\left(F^{(i)}_{jL_\mu R_\mu}(z)=1\right)$, i. e. when $\#L_\mu=1(\#R=1)$. The maximum value is reached when the tree is represented by a sequential list and the most remote detector is activated.

In the case of a balanced tree, this indicator can be $\lfloor\log_2(m+1)\rfloor$ or $\lceil\log_2(m+1)\rceil$. Each classifier $F^{(i)}(i=1,...,P)$ contains q_i groups $F^{(i)}_j(j=1,...,q_i)$, each of which combines m detectors $F^{(i)}_{jk}(k=1,...,m)$ using the one-vs-all approach. Each of the groups $F^{(i)}_j$ of detectors is trained from different random samples, which may include repeated and rear-

ranged elements from the original training set $\Upsilon_{\chi^{(LS)}_c}$. The groups $F^{(i)}_j$ are combined into the classifier $F^{(i)}$ based on a hybrid rule, which is a mixture of majority voting and max-wins voting:

$$F^{(i)}(z)=\left\{\overline{c}\,\Big|\underbrace{\sum_{j=1}^{q_i}\Big[\overline{c}\in F^{(i)}_j(z)\Big]}_{\Xi_i(\overline{c})}>\frac{1}{2}\cdot q_i \wedge \atop \wedge\Xi_i(\overline{c})=\max_{\overline{c}'\in\{0,...,m\}}\Xi_i(\overline{c}')\right\}^m_{\overline{c}'=0}. \qquad (8)$$

In this formula, due to the requirement $\Xi_i(\overline{c})>\frac{1}{2}\cdot q_i$, the classifier $F^{(i)}$ becomes unable to resolve conflicts that arise under the condition

$$\#\left\{\overline{c}\,\Big|\Xi_i(\overline{c})=\frac{1}{2}\cdot q_i\wedge\Xi_i(\overline{c})=\max_{\overline{c}'\in\{0,...,m\}}\Xi_i(\overline{c}')\right\}^m_{\overline{c}'=0}=2$$

(in this case, the output of the classifier is an empty set $\varnothing$).

During the operation of the interpreter, the correctness of the processed data is checked and the fields of the objects inside the classifier tree are initialized. By using such a structure within the proposed method, it becomes possible to build multi-level schemes.

This method has a distributed architecture, in which data are collected by secondary sensor nodes (intelligence devices) and all processing of aggregate data streams is performed on a centralized server.

6. Defining the parameters of the object of the corresponding class.

This stage of the method performed on the side of sensors (intelligence devices) consists in compiling raw intelligence into classification blocks, selecting their parameters and performing analysis using several parallel template search algorithms.

The essence of the procedure is to break down a given time interval $\Delta^{(L)}_0=[0,L]$ of length L, during which a number of parameters are continuously monitored, into slightly smaller intervals $\Delta^{(L')}_0,\Delta^{(L')}_\delta,...,\Delta^{(L')}_{\delta(k-1)}$ of equal length $0<L'\le L$, the beginning of each of which is offset $0<\delta\le L'$ from the beginning of the previous interval. $\bigcup_{i=0}^{k-1}\Delta^{L'}_{\delta i}\subseteq\Delta^{(L)}_0$ and $\bigcup_{i=0}^{k}\Delta^{L'}_{\delta i}\not\subseteq\Delta^{(L)}_0$, so $k=1+\left\lfloor\frac{L-L'}{\delta}\right\rfloor$. During the time intervals $\Delta^{(L')}_0,...,\Delta^{(L')}_{\delta(k-1)}$, the values of $\omega_0,...,\omega_{k-1}$ parameters are recorded, and their average value (intensity) and within the time window of length L' is calculated by the formula $\overline{\omega}=\frac{1}{k}\cdot\sum_{i=0}^{k-1}\omega_i$.

The study used an interval with the value of the parameter L equal to five seconds. The length of the smoothing interval L' was chosen as one second. The offset δ was specified as half a second. This approach eliminates rare and random network bursts and thus reduces the number of malfunctions.

7. Pre-processing of analysis object data.

Before the detectors are trained, the data of the parameters are pre-processed to reduce the effect of their strong variability.

Many methods, including neural networks and the principal component method, are sensitive to such fluctuations and require that all features of the processed vectors have the same scale.

7. 1. Normalization of vector components.

The first step of pre-processing each component x_{ij} of the vector $x_i\in\{x_k\}^M_{k=1}$ involves normalizing it with the function

$f\left(x_{il}\right)=\dfrac{x_{ij}-x_j^{(\min)}}{x_j^{(\max)}-x_j^{(\min)}}$ (in the case of $x_j^{(\max)}=x_j^{(\min)}$, we can consider $f\left(x_{ij}\right)=0$), where $x_j^{(\min)}=\min\limits_{1\le i\le M}x_{ij}$ and $x_j^{(\max)}=\max\limits_{1\le i\le M}x_{ij}$.

7.2. Minimizing the feature space.

Reducing the number of significant features using the principal component method [26–30], described as a sequence of the following steps.

7.2.1. Calculation of the mathematical expectation of a random vector, presented in this case as elements of the training data set:

$$\left\{x_i=\left\{x_{ij}\right\}_{j=1}^{n}\right\}_{i=1}^{M}:$$
$$\overline{x}=\left(\frac{1}{M}\cdot\sum_{i=1}^{M}x_{i1},...,\frac{1}{M}\cdot\sum_{i=1}^{M}x_{in}\right)^{T}.\qquad(9)$$

7.2.2. Formation of elements of unbiased theoretical covariance matrix:

$$\sum=\left(\sigma_{ij}\right)_{\substack{i=1,...,n\\j=1,...,n}}:$$
$$\sigma_{ij}=\frac{1}{M-1}\cdot\sum_{k=1}^{M}\left(x_{ki}-\overline{x}_i\right)\cdot\left(x_{kj}-\overline{x}_j\right).\qquad(10)$$

7.2.3. Finding the eigenvalues $\left\{\lambda_i\right\}_{i=1}^{n}$ and eigenvectors $\left\{v_i\right\}_{i=1}^{n}$ of the matrix $\sum$ as the root of the equations (Jacobi's rotation method was used for this purpose):

$$\begin{cases}\det\left(\sum-\lambda\cdot\mathbf{I}\right)=0,\\\left(\sum-\lambda\cdot\mathbf{I}\right)\cdot v=0,\end{cases}\qquad(11)$$

where $\mathbf{I}$ is the identity matrix of size $n\times n$.

7.2.4. Ranking the eigenvalues $\left\{\lambda_i\right\}_{i=1}^{n}$ in descending order and their corresponding eigenvectors $\left\{v_i\right\}_{i=1}^{n}$:

$$\lambda_1\ge\lambda_2\ge...\lambda_n\ge0.\qquad(12)$$

7.2.5. Selection of the required number $\hat{n}\le n$ of main components:

$$\hat{n}=\min\left\{j\middle|\varsigma(j)\ge\varepsilon\right\}_{j=1}^{n},\qquad(13)$$

where $\varsigma(j)=\dfrac{\sum_{i=1}^{j}\lambda_i}{\sum_{i=1}^{n}\lambda_i}$ is the measure of informativity [1], $0\le\varepsilon\le1$ is the expert selected value.

7.2.6. Centering of the feature vector $z:z_c=z-\overline{x}$.

7.2.7. Designing the feature vector z_c into a new coordinate system defined by orthonormal vectors $\{v_i\}_{i=1}^{\hat{n}}$:

$$y=\left(y_1,...,y_{\hat{n}}\right)^{T}=\left(v_1,...,v_{\hat{n}}\right)^{T}\cdot z_c,$$

$y_i=v_i^{T}\cdot z_c$ is called the i-th principal component of the vector z.

8. Hierarchical traversal of the classifier tree by width.

This stage of the method is the most time-consuming in terms of computing resources and consists of the following recursively repetitive sequences of actions: calculating the dependencies of the current classifier, generating input signals for the current classifier and training the current classifier.

Training of each classifier generates a request to train the lower-level classifiers specified in the list of its dependencies and generate their output data to form the input data of the top-level classifier.

The consequence of cascade training is the «lazy» loading of classifiers: the training (recognition) involves those classifiers that are found in the list of dependencies of the classifier responsible for forming a general solution in the set of classification rules.

This property is especially useful while analyzing the dynamic rules of training classifiers, i.e. the rules, the successful or unsuccessful operation of which affects the initialization of another rule. In particular, this is typical for a classification tree, where the rules are nested.

The method makes it possible to build multilevel schemes with arbitrary nesting of classifiers and their «lazy» connection during the analysis of the input vector.

5.3. An example of applying the proposed method in the analysis of the operational situation of a group of troops (forces)

Simulation of the solution search method was carried out according to the algorithm in Fig. 2 and expressions (1)–(13). Simulation of the proposed evaluation method was performed in the MathCad 14 software environment (USA). The task to be solved during the simulation was to assess the elements of the operational situation of the group of troops (forces).

Initial data for assessing the operational situation using the proposed method:

– the number of sources of information on the condition of the monitoring object – 3 (radio monitoring devices, earth remote sensing devices and unmanned aerial vehicles). «Kolchuga-M» radio reconnaissance equipment (Ukraine), images from the «Sich-1M» satellite (Ukraine) and intelligence from «Leleka» unmanned aerial vehicles (Ukraine) were used as sources of intelligence. The simulation was carried out as part of monitoring the group of Russian armed forces on the border with Ukraine. To simplify the simulation, the same number of each tool was taken – 4 tools;

– the number of information features to determine the monitoring object state – 12. These parameters include: affiliation, type of organizational and staff structure, priority, minimum width on the front, maximum width on the front. The number of personnel, the minimum depth on the flank, the maximum depth on the flank, the total number of personnel, the number of samples of weapons and military equipment (weapons), the number of types of weapons and the number of communication devices are also taken into account;

– options of organizational and staff structures – company, battalion, brigade.

We indicate the parameters considered for each type of operator. The method was tested with proportional selection (volume 18 %); recombination: average. To determine the most effective combination of settings for each individual scheme considered, all other search parameters must be left the same. The population size was chosen as 50, the number of populations – 50. These data are taken in accordance with the estimated number of command posts of the operational and tactical grouping of troops (forces). Comparison of the algorithms is based on the criterion of suitability of the obtained solutions. The number of

independent runs in the experiments – 100. The speed was estimated as the average generation where the algorithm finds the global optimum.

Several different optimization algorithms for solving the extreme problem were compared (15). Among them: classical binary genetic algorithm; valid genetic algorithm; proposed method and genetic algorithm with Population-Level Dynamic Probabilities (PDP) tuning algorithm. The number of calculations of the objective function for the operation of genetic algorithms was chosen equal to the number of measurements of the objective function, in the cycles of which local improvement was used [24].

Table 2 shows the results of the comparison of the proposed method and known ones in the unidirectional, bidirectional and tridirectional search.

The analysis of the data given in Table 2 shows that the proposed method has an acceptable computational complexity. The proposed method gives adequate solutions with a complex hierarchical structure of the monitoring object. The efficiency of the proposed method averages from 12 to 20 % for different combination schemes.

6. Discussion of the results of developing an evaluation method

The developed formalized approach allows evaluating highly dynamic, complex and hierarchical objects. This creates a versatile approach and allows you to evaluate different types of objects that have different origins and membership to the management.

A method for assessing the condition of the monitoring object in special-purpose information systems has been developed.

The main advantages of the proposed evaluation method are:

– a flexible hierarchical structure of indicators, which allows reducing the task of multi-criterion evaluation of alternatives to one criterion or using a vector of indicators for selection (expression (1));

– unambiguity of the obtained assessment of the object state (expressions (1)–(13), Table 1;

– versatility of application due to adaptation of the system of indicators in the course of work (expressions (1), (4));

– does not accumulate learning errors through the use of training procedures;

– takes into account the type of uncertainty and noise of the original data (expression (1));

– high reliability of the obtained solutions in multi-directional solution search (expressions (1)–(13));

– the possibility of combining heterogeneous solvers without strict binding to the composition that aggregates their outputs (expressions (1)–(13));

– the ability to choose the best scheme for combining solvers (expressions (1)–(13)).

The disadvantages of the proposed method include:

– the loss of informativeness in assessing the condition of the monitoring object by building a membership function;

– lower accuracy of estimation for a single estimation parameter of the object condition;

– loss of reliability of the obtained solutions in simultaneous multi-directional solution search;

– lower accuracy of estimation compared to other estimation methods.

This method allows you:

– to assess the object condition;

– to identify effective measures for improving management efficiency;

Table 2

Time and system costs of training and testing

Indicators			Combination schemes			
			one-vs-all	one-vs-one	CBT	DAG
Training: number of training samples – 8,000						
Single-stream mode	Time (sec.)	min	11,235.000	4,569.000	4,679.000	4,660.000
		max	12,228.000	5,218.000	5,092.000	6,148.000
		avg	11,822.000	4,967.333	4,880.000	5,217.333
	CPU utilization (%)	min	92.700	92.700	92.700	92.700
		max	100.000	100.000	100.000	100.000
		avg	99.215	99.194	99.219	99.220
	RAM utilization (%)	min	62.496	64.309	62.492	64.324
		max	92.352	98.996	94.219	99.563
		avg	95.487	97.688	99.067	97.435
multidirectional mode	Time (sec.)	min	1782.000	754.000	900.000	743.000
		max	6,996.000	875.000	1,228.000	880.000
		avg	2,767.429	823.429	1,059.143	831.571
	CPU utilization (%)	min	92.700	92.700	92.700	92.800
		max	800.000	800.000	800.000	800.000
		avg	455.184	579.644	445.293	610.500
	RAM utilization (%)	min	62.496	64.305	62.504	64.324
		max	83.867	66.070	68.820	66.090
		avg	263.452	480.843	248.808	480.758
Training: number of training samples –16,000						
Single-stream mode	Time (sec.)	min	383.000	985.000	176.000	296.000
		max	387.000	1,019.000	182.000	301.000
		avg	384.667	996.667	179.000	298.000
	CPU utilization (%)	min	92.800	92.800	92.700	92.800
		max	100.000	100.000	100.000	100.000
		avg	99.197	99.177	99.123	99.212
	RAM utilization (%)	min	63.656	65.289	63.395	65.348
		max	88.957	90.816	88.125	90.500
		avg	82.348	84.368	79.987	83.629
multidirectional mode	Time (sec.)	min	644.000	1,764.000	288.000	563.000
		max	701.000	1,789.000	324.000	576.000
		avg	660.857	1,776.857	308.286	569.429
	CPU utilization (%)	min	86.400	86.300	59.800	59.700
		max	93.000	96.100	93.000	72.800
		avg	113.028	119,584	99.806	100.081
	RAM utilization (%)	min	64.477	66.301	63.934	67.000
		max	91.031	92.215	88.473	91.250
		avg	82.987	84.877	80.397	84.525

– to increase the speed of object condition assessment;

– to reduce the use of computing resources of decision support systems.

The proposed approach should be used to solve problems of evaluating complex and dynamic processes characterized by a high degree of complexity.

This study is a further development of research aimed at developing methodological principles for improving the efficiency of information and analytical support published earlier [2, 4–6, 23]. Further research should be aimed at reducing computational costs when processing various types of data in special-purpose systems.

– accurate training of detectors by combining training procedures (lazy training and training procedure developed in [2]);

– selective use of system resources by connecting only the necessary types of detectors;

– building a top-level classifier using various low-level schemes for combining them and aggregating compositions.

3. An example of using the proposed method in assessing the operational situation of the group of troops (forces) is given. This example showed an increase in the efficiency of data processing by 12–20 % using additional advanced procedures.

7. Conclusions

1. The description of the problem of analyzing the object state in special-purpose information systems, which is flexible and universal, is formalized. A criterion for the effectiveness of this method was the efficiency of the process of object state analysis with a given reliability of the obtained estimate. In the course of the research, the concept of the evaluation method in special-purpose information systems is formulated. In this concept, the analysis process is presented as a hierarchical graph. This allows you to create a hierarchical description of a complex process by levels of generalization and conduct an appropriate analysis of its state.

2. We defined the algorithm for implementing the method, which allows:

– taking into account the type of uncertainty and noise of data;

– taking into account the available computing resources of the object state analysis system;

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