Building a model of recognizing operators based on the definition of basic reference objects

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Abstract. The paper considers issues related to the construction of a model of recognizing operators, focused on the classification of objects in conditions of high dimensionality of a feature space. A new approach to constructing a model of recognition operators based on the construction of multi-level proximity functions is proposed. In this case, the construction of the model was carried out within the framework of recognition algorithms based on the calculation of estimates.
The goal of this work is develop a model is to form independent subsets of interrelated objects, highlighting a set of representative pairs of features. A distinctive feature of the proposed operator model is the definition of a suitable set of threshold functions when constructing an extremal recognition operator.
The purpose of this article is to develop a model of recognizing operators based on the calculation of estimates using two-dimensional threshold rules. Scientifically, the results of this work in aggregate represent a new solution of a scientific problem related to the issues of increasing the reliability of recognizing operators based on the evaluation of estimates. The practical significance of the results lies in the fact that the developed operators and programs can be applied in medical and technical diagnostics, geological forecasting, biometric identification and other areas where it is possible to solve the problem of classifying objects defined in a space of large dimensionality.

1. Introduction

At present, an ever wider circle of specialists is paying attention to the problem of pattern recognition, and the number of scientific publications on this subject is constantly growing. This is due to the fact that in recent years, pattern recognition has become increasingly used in science, technology, manufacturing and everyday life [1, 2]. One of the rapidly developing branches of modern science is the study of complex objects that are characterized by multidimensionality of parameters. To determine the state of such objects, a large number of parameters (features) are used. It is known that with an increase in the number of signs describing the object of study, the probability that interconnectivity appears among them increases. The analysis of literary sources for recognition, as well as the experience of solving a number of model problems, shows that in the context of the interrelatedness of features, many well-known recognition algorithms do not work correctly. In this regard, the task of improving existing and developing new algorithms for the recognition of objects defined in the space of interrelated signs are relevant.

The goal of this paper is to develop a model of multilevel recognition operators based on the definition of basic reference objects. As an initial model, recognition algorithms based on the calculation of estimates are considered. A distinctive feature of the proposed model is the construction of recognition operators based on multi-level separating functions, within the framework of the model for calculating estimates. It should be noted that this work is a logical continuation of the research of the scientific school of Academician of RAS Yu.I. Zhuravleva.

2. Basic concepts and notation

In order to formulate a range of questions related to these studies, we introduce the necessary concepts and notation borrowed from [1-4]. The object of recognition is understood as a multidimensional vector, the components of which are specific values of n features. In this case, it is required that the specific values of these signs should be determined within the framework of a given alphabet. An object is said to be admissible if all signs accept values from a given alphabet. For example, an arbitrary object S is given. It is assumed that for this object in the feature space $X = \; x_1, \dots, x_i, \dots, x_n)$ it is possible to match the description vector $\mathcal{I}(S) = (a_1, .., a_u, .., a_n)$. t should be noted that recognition models deal only with objects in the feature space, so we will not distinguish between S and $\mathcal{I}(S)$.

Consider the set of admissible objects $\mathbb{S}$, which consists of l subsets (classes) $\mathcal{C}_1, \dots, \mathcal{C}_j, \dots, \mathcal{C}_l$:

$$\mathbb{S} = \bigcup_{j=1}^{l} \mathcal{C}_j,\ \mathcal{C}_i \cap \mathcal{C}_j = \emptyset, i \neq j, i, j \in \{1, 2, \dots, l\}. \tag{1}$$

n this case, it is assumed that the partition (1) is not completely determined, and there is only some initial information I_0 about the classes $\mathcal{C}_1, \dots, \mathcal{C}_j, \dots, \mathcal{C}_l$. Usually I_0 is defined as classified objects. To determine I_0 select m objects from $\mathbb{S}$: $\tilde{S}^m = \{S_1, \dots, S_u, \dots, S_m\}$. We introduce the following notation: $\tilde{\mathcal{C}}_j = \tilde{S}^m \cap \mathcal{C}_j$, $\tilde{\mathcal{D}}_j = \tilde{S}^m \backslash \tilde{\mathcal{C}}_j$. Then the initial information I_0 can be represented as a set of pairs consisting of S_u and $\tilde{\alpha}(S_u)$:

$$I_0 = \{S_1, \tilde{\alpha}(S_1), \dots, S_u, \tilde{\alpha}(S_u), \dots, S_m, \tilde{\alpha}(S_m)\}, \tag{2}$$

where $\tilde{\alpha}(S_u) -$ object information vector S_u ($S_u \in \Xi$): $\tilde{\alpha}(S_u) = \; \alpha_{u1}, \dots, \alpha_{uj}, \dots, \alpha_{u\ell})$. Here $\alpha_{uj} -$ value of the predicate of the following form:

$$\mathcal{P}_j \; S_u) = \begin{cases} 1, if \;\; S_u \in \tilde{\mathcal{C}}_j; \\ 0, if \;\; S_u \notin \tilde{\mathcal{C}}_j. \end{cases}$$

The set of information vectors corresponding to the objects $\tilde{S}^m$, forms the information matrix $\left\|\alpha_{uj}\right\|_{m \times l}$.

It is known [1, 2] that an arbitrary recognition algorithm can be represented as a sequential execution of the operators $\mathfrak{B}$ (recognizing operator) and $\mathfrak{C}$ (decision rule):

$$\mathfrak{A} = \mathfrak{B} \circ \mathfrak{C}. \tag{3}$$

From (3) it follows that each recognition algorithm $\mathfrak{A}$ can be divided into two successive stages. At the first stage, the discriminating operator $\mathfrak{B}$ converts a valid object S_u into a numerical estimate represented by a vector b_u :

$$\mathfrak{B}(S_u) = \tilde{\mathfrak{b}}_u, \tag{4}$$

where $\tilde{\mathfrak{b}}_u = (b_{u1}, \dots, b_{uv}, \dots, b_{u\ell})$.

At the second stage, by numerical estimation, b_{uv} decision rule $\mathfrak{C}$ determines the belonging of the object S_u to the classes $\mathcal{C}, \dots, \mathcal{C}_j, \dots, \mathcal{C}_l$:

$$\mathfrak{C}(b_{uv}) = \begin{cases} 0, if \; b_{uv} < \mathfrak{c}_1; \\ \Delta, if \; \mathfrak{c}_1 \leq b_{uv} \leq \mathfrak{c}_2; \\ 1, if \; b_{uv} > \mathfrak{c}_2, \end{cases} \tag{5}$$

where $\mathfrak{c}_1, \mathfrak{c}_2$ – decision rule parameters. In this case, the b_{uv} estimate is calculated using the recognition operator (4).

3. Statement of the problem

Let given sets of m objects $\tilde{S}^m$. It is known that it can be represented as l subsets of$\tilde{C}_1, \dots, \tilde{C}_j, \dots, \tilde{C}_l$. On the basis of these objects, the initial information I_0 is defined, represented as a set (2). It is required for information I_0 and descriptions of given objects $\mathcal{I}(S_u)$ $(S_u \in \tilde{S}^m)$ to construct such a recognizing operator $\mathfrak{B}$ (see formula 4), which, using the decision rule $\mathfrak{C}$ (see formula 5), allows to calculate the predicate values $\mathcal{P}_j$ $S_u)$ $\mathcal{P}_j$ $S_u) = "S_u \in \mathcal{K}_j", u = \overline{1, m})$:

$$\mathfrak{B}(\tilde{S}^q) = \|\mathfrak{b}_{uv}\|_{m\times l}, \mathfrak{C}(= \|\mathfrak{b}_{uv}\|_{q\times l})=\|\beta_{uv}\|_{m\times l}, \beta_{uv} \in \{0,1,\Delta\}.$$

Here β_{ij} is interpreted as follows. If $\beta_{ij} = \Delta$, then it is considered that algorithm A could not determine the value of the predicate $\mathcal{P}(S_i')$. Else β_{ij} $\beta_{uv} \in \{0,1\})$ is the value of the characteristic function on a valid object S_i, calculated by the algorithm $\mathfrak{A}$:

$\beta_{ij} = 1$ – object S_i is in class $\mathrm{C_j}$,

$\beta_{ij} = 0$ – object $\mathrm{S_i}$ not in class C_j.

It should be noted that the distinctive feature of this task is that the number of signs (n), involved in the description of recognition objects is quite large [4, 5]. Under these conditions, most signs are interrelated, which makes it difficult to use many recognition algorithms. The development of recognition operators is carried out precisely in conditions of high dimensionality of feature space.

4. Proposed approach

A new approach to solving the formulated problems is proposed. The basis of this approach is the model of modified recognition operators based on the calculation of estimates [1-3]. Distinctive features of the developed recognition model are the result of identifying independent subset interrelated features and highlighting the preferred model of intermediate decision making. Note that the proposed approach is a logical continuation of the works of Academician Yu.I. Zhuravleva and his students.

Recognizing operators based on the definition of basic reference objects in the initial two stages do not differ from the corresponding stages of the modified recognition operators described in [4, 5]. Therefore, only the next 10 stages, starting with the third, are considered below. However, for purposes of completeness, these steps are listed.

1. Selecting subsets of tightly coupled features.

2. Determination of representative traits.

3. Selecting subsets of tightly coupled objects. At this stage, m' "independent" subsets of tightly bound objects are defined. The formation of subsets of tightly bound objects is performed based on an assessment of the proximity of the subsets of tightly bound objects. According to this method, the studied set of tightly bound objects are combined into one subset if they are close enough (in a sense) to each other. Otherwise, they belong to different subsets of objects.

Let $\mathbb{V}$ - all kinds of non-intersecting subsets of the set of learning objects $\{S_1, \dots, S_i, \dots, S_m\}$. At this stage it is determined m' subsets of tightly coupled objects $\mathbb{V}_{\mathfrak{B}}$ based on pairwise comparison of these objects according to predetermined criteria:

$$\mathbb{V}_{\mathfrak{B}} = \{V_1, \dots, V_q, \dots, V_{m'}\}, \mathbb{V}_{\mathfrak{B}} \subset \mathbb{V},$$

$$\bigcap_{q=1}^{m'} V_q = \emptyset; \bigcup_{q=1}^{m'} V_q = \mathbb{V}_{\mathfrak{B}}; m' = |\mathbb{V}_{\mathfrak{B}}|.$$

Depending on the method of specifying the measure of proximity between the subsets of tightly bound objects (V_{p} and $\mathrm{V_q}$) the separation quality functional, you can get various recognizing operators for selecting independent sets of tightly bound objects.

4. Formation of a set of representative objects. The main idea of choosing representative objects is to select a set of the most typical representatives of each class from the objects of the training sample. In the process of forming a set of representative objects, it is required that each selected object should be close to the objects of its own subset of tightly bound objects. As a result of this stage, we get a set of reference objects whose power is much less than the original $m' < m$). Further, the formed set of reference objects is denoted by $\mathbb{E}_0$ $\mathbb{E}_0 = \mathcal{S}_1, \ldots, \mathcal{S}_{m'})$).

5. Determination of proximity function $d_u(S_p, S_q)$ between objects S_p and S_q in a two-dimensional subspace of representative features. At this stage, a function is defined that characterizes the similarity of objects S_p and S_q in a two-dimensional subspace of representative features $\mathfrak{D}$ $\mathfrak{D} = \mathcal{D}_1, \ldots, \mathcal{D}_u, \ldots, \mathcal{D}_n)$, $\mathcal{D}_u = (x_{u_1}, x_{u_2}), x_{u_1}, x_{u_2} \in X'$). The distances between these objects in the subspace of the representative features $\mathcal{D}_u$ are determined as follows [6]:

$$d_u^2(S_p, S_q) = \sum_{i=1}^{2} w_{1u_i} \; a_{pu_i} - a_{qu_i})^2, \tag{6}$$
$$w_{1u_1} + w_{1u_2} = 1,$$

where w_{1u_i}– recognizing operator, parameter used when constructing a distance function in a two-dimensional subspace of representative features.

Then, using (3), we introduce the notion of a first-level proximity function. The first level proximity function is a threshold function defined in a two-dimensional subspace of representative features $\mathcal{D}_u$:

$$\mu_{1u}(S_p, S_q) = \begin{cases} 1, if \; d_u^2(S_p, S_q) \leq \varepsilon_{1u}^2, \\ 0, if \; d_u^2(S_p, S_q) > \varepsilon_{1u}^2, \end{cases}$$

where ε_{1u} – recognizing operator, parameter used when constructing the first level proximity function. The second level proximity function is a threshold function defined in a subspace of representative features $\mathcal{D}_u$ and $\mathcal{D}_v$:

$$\mu_{2u}(S_p, S_q) = \begin{cases} 1, if \; w_{2u} d_u^2(S_p, S_q) + \; 1 - w_{2u}) d_v^2(S_p, S_q) \leq \varepsilon_{2u}^2, \\ 0, if \; w_{2u} d_u^2(S_p, S_q) + \; 1 - w_{2u}) d_v^2(S_p, S_q) > \varepsilon_{2u}^2, \end{cases}$$
$$w_{2u} + w_{2v} = 1,$$

where w_{2u}, ε_{2u} – parameters of the discriminating operator used in constructing the second level proximity function.

*6. Selection of subsets of tightly coupled pairs of elements in a subspace of representative features***.** At this stage, a system of "independent" subsets consisting of strongly connected elements is determined. Each element of this subset consists of a pair of signs. As a result of this stage, a system of n' "independent" subsets of tightly bound $\mathcal{D}_u$ ($u = \overline{1, n'}$). The power of the subsets $\mathcal{D}_u$ depends on the input data, the functions of proximity of each level and the parameter n' are considered. By assigning different proximity functions and different values to the n' parameter, you can get different recognition operators.

Depending on the method of specifying the measure of proximity between subsets of tightly coupled pairs of features ($\mathcal{D}_u$ and $\mathcal{D}_v$) and the quality functional of the classification analysis, you can get various procedures for selecting independent subsets of tightly coupled feature pairs.

*7. Formation of a set of representative elements in a subset of tightly coupled pairs of features***.** At this stage, a set of representative elements is formed of subsets of tightly coupled pairs of features, each of which is a typical representative of a selected subset of tightly coupled feature pairs [4].

8. Setting the system of support sets. Let $\mathcal{H}_{\widetilde{\omega}}$- all sorts of subsets $\{\mathcal{D}_1, \ldots, \mathcal{D}_u, \ldots, \mathcal{D}_n\}$. The set of all such subsets is denoted by Ω. At this stage the system of support sets is specified Ω_B ($\Omega_B \subseteq \Omega$)).

9. Setting the proximity function between objects. Consider valid objects S_p and S_q. At this stage, the proximity function $\mu_{\widetilde{\omega}}(S_p, S_q)$ between S and S_q objects in the $\widetilde{\omega}$- part of the space $\mathfrak{D}$.

10. Calculation of estimates for objects of a fixed reference set. At this stage of the task of the modified recognition operators based on the calculation of estimates, the numerical characteristic $\Gamma_{\widetilde{\omega}}(S_p, S_q)$, called the estimate, is calculated. The assessment is determined by the value of the proximity function by objects in the selected subspace of features

$$\Gamma_{\tilde{\omega}}(S_p, S_q) = \lambda_p \mu_{\tilde{\omega}} \ S_p, S_q),$$

where λ_p– operator's parameter.

11. Calculating the grade for a class on a fixed support set. Let the values be calculated $\Gamma_{\tilde{\omega}}(S_p, S_q)$ $S_p \in \tilde{K}_j$). The grade for the class is determined as follows

$$\Gamma_{\tilde{\omega}}(S_p, K_j) = \begin{cases} 1, if \sum_{S_p \in \tilde{K}_j} \Gamma_{\tilde{\omega}}(S_p, S_q) \geq \delta_j; \\ 0, else \end{cases}$$

here δ_j– operator's parameter.

*12. Estimate for the class K_j by the system of support sets***.** Let each vector $\tilde{\omega}$ correspond to a numerical parameter $\tau_{\tilde{\omega}}$. Evaluation of the reference set system Ω_A is

$$\Gamma(S_p, K_j) = \sum_{\tilde{\omega} \in \Omega_B} \tau_{\tilde{\omega}} \Gamma_{\tilde{\omega}}(S_p, K_j).$$

Thus, we have defined a class of modified recognition operators based on the evaluation of estimates. Any recognizing operator B from this model is completely determined by setting a set of parameters $\tilde{\pi}$. The set of all recognition operators from the proposed model is denoted by $B(\tilde{\pi},\ S)$. The determination of the best recognition operator in the framework of the considered model is carried out in the parameter space $\tilde{\pi}$. The best recognizing operator $B(\tilde{\pi}_0,\ S)$ is selected based on the search for the minimum value of the quality functional of the recognizing operator:

$$\mathfrak{R}(\tilde{\pi},\ \tilde{S}^m) = \Theta\left(B(\tilde{\pi},\ \tilde{S}^m)\right)/\mathfrak{m},$$

$$\Theta\left(B(\tilde{\pi},\ \tilde{S}^m)\right) = \left(\sum_{S \in \tilde{S}^m} \mathfrak{Q}(\|\tilde{\alpha}(S) - \mathfrak{C}(B(\tilde{\pi}, S))\|)\right),$$

$$\mathfrak{m} = |\ \tilde{S}^m|,\ \ \mathfrak{Q}\ x) = \begin{cases} 1, when\ x = 0; \\ 0, when\ x \neq 0, \end{cases}$$

where ||·|| – boolean vector rate.

To test the performance of the considered model of recognizing operators, it is necessary to conduct experimental studies. The following is a description of the experimental studies.

5. Experiment and Results

In order to verify the operability of the considered operator model, functional schemes of recognition programs have been developed. The software implementation of the developed operators is implemented in C ++. An experimental study of the performance of the proposed model of recognizing operators is carried out on the example of solving a model and practical problem.

5.1. Model problem

The source data of recognizable objects for a model task is generated in the space of dependent attributes. The number of classes in this experiment is two. The size of the initial sample is 800 implementations (400 implementations for objects of each class). The number of features in the model example is 140. The number of subsets of tightly coupled features is 6.

As test models of recognizing operators were selected.:

1) classical model of recognizing operators, based on the calculation of estimates ($\mathfrak{B}_1$);
2) model of modified recognition operators based on the calculation of estimates ($\mathfrak{B}_2$);
3) model of recognizing operators proposed in this paper ($\mathfrak{B}_3$).

Comparative analysis of the listed models of recognition operators when solving the considered problem was carried out according to the accuracy of recognition of objects of the control sample.

Let the initial sample be given $\mathfrak{V}$. To calculate the specified criteria when solving the considered problem, in order to exclude successful (or unsuccessful) splitting of the initial sample $\mathfrak{S}$ into two equal parts $\mathfrak{V}_t$ and $\mathfrak{V}_c$ ($\mathfrak{V} = \mathfrak{V}_t \cup \mathfrak{V}_c$, $\mathfrak{G}_t$ – is a sample for training, $\mathfrak{V}_c$ – is a sample for control), the method is used sliding control [7]. In this method, the initial sample of objects $\mathfrak{V}$ is randomly divided into k blocks and forms sets $\mathbb{V}$:

$$\mathbb{V} = \{\mathfrak{V}_1, \dots, \mathfrak{V}_u, \dots, \mathfrak{V}_k\}.$$

The elements of the set $\mathbb{V}$ are assumed to satisfy the following simple conditions:

1) $\Xi_u \cap \Xi_v = \emptyset, u, v \in \{1, \dots k\}, u \neq v,$
2) $|\Xi_1| = \dots = |\Xi_k|,$
3) $|\mathbb{V}| = |\Xi_1| + \dots + |\Xi_u| + \dots + |\Xi_k|,$
4) $|\Xi_1 \cap C_j| = \dots = |\Xi_u \cap C_j| = \dots = |\Xi_k \cap C_j|,$
5) $|\Xi_u| = |\Xi_u \cap C_1| + \dots + |\Xi_u \cap C_j| + \dots + |\Xi_u \cap C_l|,$

where k – natural number (in our experiment $k = 20$).

The sliding control process for these blocks involves several steps. At each step, choose k' where $k' = 0.9 * k$) from k blocks as a training sample, and on this sample, recognition operators with the given parameters are trained. A discriminating operator trained in this way is checked for the remaining $(k - k')$ blocks (control sample). Quality assessment of recognition operators is carried out on training and control samples according to the specified criteria. As a result of each test, the quality assessment of recognition operators on the control sample is determined and accumulated. In the process of executing each next step, one block is selected from the control and training samples and they are interchanged. In this case, the blocks attached from the control sample are fixed accordingly, and they do not participate in the procedure for selecting candidates in the formation of the next sample of control objects. Data process is repeated k times. After all the repetitions of the quality assessment procedure for recognizing operators, the recognition accuracy is determined as averages over all control samples. The experiments were performed on a Pentium IV Dual Core 2.2 GHz computer with 2 Gb RAM.

As noted earlier, the model problem was solved using the model of recognizing operators $\mathfrak{B}_1$, $\mathfrak{B}_2$ and $\mathfrak{B}_3$. The recognition accuracy in the learning process for $\mathfrak{B}_1$ is 98,8%, for $\mathfrak{B}_2$ – 99,1%, for $\mathfrak{B}_2$ – 99,6%. The results of solving the problem under consideration with the use of various recognition operators in the monitoring process are (respectively): 81,7; 92,3; 97,8.

Comparison of these results shows that the proposed model of recognizing operators $\mathfrak{B}_3$ has improved the accuracy of recognition of objects described in the space of interrelated features (more than 15% higher than $\mathfrak{B}_1$ and more than 5% relative to more than 15%). This is explained by the fact that in the $\mathfrak{B}_2$ model it does not use basic reference objects in the recognition of objects, it does not form subsets of tightly coupled pairs of features, it does not define representative pairs of features. In addition to these drawbacks, the model $\mathfrak{B}_1$ does not take into account the interrelatedness of signs.

It should be noted that the developed operators differ from traditional recognizing operators such as calculating estimates in that they not only take into account the large dimension of the feature space, but also reduce the size of the training sample. Therefore, it is advisable to use these operators not only in cases when the dimension of the feature space is large enough and some dependence is detected between the signs, but also when the size of the training sample is large. As the results of the above experimental studies show, when a sufficiently strong dependence is found between the signs of all the objects under consideration, the signs repeating the same information are eliminated in the process of forming a set of representative signs (described in the first and second stages) representing all those attributes that are not contained in this set. Similarly, the size of the training sample is reduced.

The results of the experimental study show that the proposed model of recognizing operators allows one to solve the pattern recognition problem more precisely under conditions when the training sample size and the dimension of the feature space are large enough.

5.2. Practical tasks

As a practical example, consider the problem of biometric identification of a person by a signature image. It is known that existing methods and algorithms for biometric identification of a person by

signature are divided into two large groups [8-10]: 1) methods aimed at solving a signature recognition problem online; 2) methods oriented to solving signature recognition tasks offline.
The methods of the first group operatively generate information on the change of dynamic signs (position coordinates, speed, acceleration or pressure on the tablet surface) characterizing the signatures. The methods of the second group can operate only with information about the form of the signature obtained as a result of the analysis of the images of the signature. It should be noted that in many applications related to the processing of various official documents (for example, bank checks, statements of cash payments, receipt, power of attorney), methods of identification of individuals are required that are adapted to work in offline mode and provide sufficiently high accuracy in identifying individuals by signature image.
As a source of data was given a set of 1500 images of the signature. The number of possible classes is 25. At the same time, the power of each subset is the same: $|\widetilde{\mathrm{K}}_{\mathrm{j}}| = 60$. All considered images are normalized and have different sizes.
Of these images, 80% were selected (in this experiment, 1200 images) to form a training sample, the remaining 20% were control samples.
The recognition accuracy in the control process for $\mathfrak{B}_1$ is 82,4%, for $\mathfrak{B}_2$ – 91,3%, for $\mathfrak{B}_2$ – 96,9%. C Comparison of these results shows that the proposed model of recognition operators has improved the accuracy of recognition of objects described in the space of high dimensionality of signs of large dimensionality (approximately 5-10 percent higher than using the model $\mathfrak{B}_1$ and $\mathfrak{B}_2$). Experimental studies have shown that the proposed model provides higher accuracy in solving the problem of recognition of personality by signature. At the same time, it is necessary to note the fact that the time spent on training the discriminating operator has increased, since building an optimal recognition operator requires more computation than when using the traditional model of recognition operators $\mathfrak{B}_1$.

Conclusion

1. Analysis of the existing literature sources showed that many methods and algorithms are mainly focused on solving applied problems of object recognition with independent features. However, in the majority of applied recognition problems encountered in science, technology and production, the considered images are characterized by interrelated features. When solving such problems, the assumption of independence of signs is often not fulfilled. Although various algorithms were developed to solve such recognition problems, they turned out to be ineffective in terms of accuracy and computational complexity. Despite this, the development of recognition algorithms under conditions of interconnectedness of signs has not been studied sufficiently.
2. A new approach has been proposed for constructing a model of recognizing operators, and on the basis of this approach a model of modified recognizing operators has been constructed, such as calculating estimates. The application of the proposed recognition operators allows to improve the accuracy of recognition of objects described in a space of large dimension, and to expand the scope of application for solving applied problems. The proposed new approach allows you to: expand the models of recognizing operators such as calculating estimates; improve the accuracy of recognition of objects described in the space of large dimension; increase the scope of recognizing operators such as calculating estimates when solving applied problems.
3. The results of solving a model problem showed that the proposed model of recognizing operators improves the accuracy and significantly reduces the number of computational operations by recognizing an unknown object specified in the space of interrelated signs. At the same time, the time spent on training the operator has increased. This circumstance is explained by the fact that in the proposed model rather complicated optimization procedures are used than in the traditional model of recognizing operators. The developed recognition operators can be used in medical and technical diagnostics, geological forecasting, biometric identification and other areas where it is possible to solve the problems of classifying objects defined in the space of large dimension signs.

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