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Development Algorithm Formation of the System of Support Sets of Signs, Providing Quality and Reliability of Recognition

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ABSTRACT: In this article, the technique of finding the maximumallowable dimensions of the feature space. The principles of formation of the system of support sets based extremely allowable dimension combinations of features on a specific image. The algorithm, which provides the required object recognition for quality and objects..

KEYWORDS: object, attribute, class, reference sample, control sample, the scope of the reference sample, the system of reference sets, the quality and reliability of recognition, the decision rule..

I.INTRODUCTION

There are various methods for establishing criteria for information, allowing you to determine the informative prize or combination of characteristics. It is impossible to give one of them a definite preference. Methods that work better for one of the classes of tasks are less acceptable for another class, however, in many methods, when determining the criteria for the informativeness of characteristics or combinations of characteristics, the volume of the training sample is not taken into account. Based on such considerations, the choice of a certain method with a certain amount of intuition must be performed depending on the actual task and the specific practical possibilities. Moreover, when establishing the criteria for the informativeness of characteristics or combinations of characteristics, one should not disregard such important parameters as the quality and reliability of recognition.

To ensure high quality of recognition, you need to know the characteristics of the objects in which you want to work, the recognizing system, and the training sequence should be chosen so that the characteristics of objects are fully reflected in that sequence [1-3].
Thus, the recognition system must possess not only a given quality, but also the reliability of its achievement. The task of constructing a recognition system is reduced to the fact that in the process of learning the learning sequence has been reached a certain quality, the achievement of which would be ensured with reliability not lower than the preset.

In order to achieve a certain quality of the recognition systems, a preliminary reduction in the dimension of the training sample is made. From the original alphabet of characteristics only a few of the most informative signs or combinations of features are selected. The reduction in the dimensionality of the feature space seems useful in two aspects: first, the amount of computation decreases, and secondly, with the removal of nonessential attributes from the reference sample, the reliability of recognition increases [1-3]. Simultaneously, by reducing the volume of the master sample, the volume decreases, which often leads to a decrease in the reliability of recognition in general. In other words, the volume of the reference sample should be within reasonable limits.

II.LITERATURE SURVEY

Although the Vapnik-Chervonenkis (VC) learning theory [3, 8, 14] has been justly acclaimed as a major conceptual breakthrough, applying its essential theorems to practical problems often yields very loose bounds. In the case of the

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pattern recognition problem, the theorems provide distribution–independent uniform bounds on the deviation between the expected classification error and the empirical classification error. Their derivation reveals many possible causes for their poor quantitative performance:
I)Practical data distributions may lead to smaller deviations than the worst possible data distribution.
II)Uniform bounds hold for all possible classification functions. Better bounds may hold when one restricts the analysis to functions that perform well on plausible training sets.
III) Asymmetrization lemma translates the main combinatorial result into a bound on the deviation between expected and empirical errors. This lemma is a conser-
vative inequality.
IV)The combinatorial characterization of the Vapnik-Chervonenkis capacity is a conservative upper bound.

Duda R., Hart P. and AL Gorelik,Skripnik."Methods of recognition".The classical methods of recognition of objects and phenomena are analyzed. The main tasks when creating the recognition system are highlighted. Parametric and nonparametric methods are considered, such as the method of maximum likelihood, Baussian criterion, histogram, Parzen method, the rule of the nearest neighbor. On the basis of the analysis of classical methods, the necessity and formulation of the problem of recognition in the mode of real-time objects on the video is formulated. In the framework of the identification stages, an iterative method of separating a mixture of normal distribution, based on histogram evaluation is considered.[13-15]

Vapnik VN, ChervonenkisA.Ya. "Theory of Pattern Recognition". Statistical learning theory was introduced in the late 1960's. Until the 1990's it was a purely theoretical analysis of the problem of function estimation from a given collection of data. [1,8,12,]
In the middle of the 1990's new types of learning algorithms (called support vector machines) based on the developed theory were proposed. This made statistical learning theory not only a tool for the theoretical analysis but also a tool for creating practical algorithms for estimating multidimensional functions.
This article presents a very general overview of statistical learning theory including both theoretical and algorithmic aspects of the theory. The goal of this overview is to demonstrate how the abstract learning theory established conditions for generalization which are more general than those discussed in classical statistical paradigms and how the understanding of these conditions inspired new algorithmic approaches to function estimation problems. A more detailed overview of the theory (without proofs) can be found in Vapnik (1995). In Vapnik (1998) one can find detailed description of the theory (including proofs).

In connection with the foregoing circumstance, the creation for each of the most common criteria of informativeness of "one's own" optimization method, which takes into account the mathematical features of a particular criterion, acquires a very relevant and timely sense.

In work [1-3] theoretical results are obtained, which make it very cautious to treat most known recognition methods that do not pay special attention to the formation of a feature space in which decisive rules are built in the learning process. These results are based on relationships that relate parameters such as the number of objects and attributes of the training sample, the quality and reliability of recognition [1,3]. In these papers it was shown that the simpler the decision rule and the lower the dimensionality of a recognized space, the less the probability of erroneous answers that arise during the operation of the recognition system.

These conclusions can be consi. Statement of the problemdered as a rationale for the main purpose of this article.

III. STATEMENT OF THE PROBLEM

The theoretical result is obtained in [3], the meaning of which is that if one is selected on the sample of N decision rules, which unequivocally separates the standard sample of length m , then with probability $(1-\eta)$ it can be asserted that the probability of error when recognizing objects with this rule will be less than ε , where

$$\varepsilon = \frac{\ln N - \ln \eta}{m} \qquad (1)$$

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It follows from (1) that the simpler the decision rule and the lower the dimension of a recognized space, the less the probability of erroneous answers arising from the operation of the recognition system.

It was shown in [4, 5] that the systems of support sets Ω_A are constructed as follows:

a) $\Omega_A = \{\Omega : |\Omega| = k\} = C_n^k$;

b) $\Omega_A = \{\Omega\}, \Omega \subseteq \{1,2,..., n\} = C_n^1 + C_n^2 + ... + C_n^n = 2^n$

In case a) the value of k is found from the solution of the learning problem (model optimization) or is determined by the expert.

In case b) the method of choosing a system of support sets, as of all possible subsystems {1,2, ..., n}, is "averaging" the first and does not require finding an appropriate value of the parameter k.

In this article, in contrast to [4, 5], in the construction of the system of support sets Ω_A not all combinations are used, but only $C_n^{n_0}$ $(n_0 = 1; n_0 = 2;...; n_0 = k; (k < n))$ combinations of features. Here, $n_0\,(n_0 < n)$ is predetermined with regard to the required quality and reliability of recognition for a given volume (the number of features and objects) of the reference sample, i. E. $n_0 = f(\varepsilon, \eta, n, m)$, where ε - the probability of error, η - the reliability of recognition, n - the number of features, m - the number of objects. This leads to a sharp reduction in the system of reference sets Ω_A and allows for the recognition of objects to use combinations of features included in $\Omega_A = C_n^{n_0}$.

Thus, for the successful solution of any recognition problem in algorithms for computing estimates [4, 5], it is necessary to strive to minimize the system of support sets Ω_A, reduce (with in n_0) the dimension space of feature combinations and simplify the class of decision rules (within Ω_A). Therefore, from the master sample, it is necessary to form such support set systems Ω_A that provide the required quality and reliability of recognition.

Let the reference sample of objects $S_{j1}, S_{j2}, \ldots, S_{jm_j} \in K_j,\ j = \overline{1, l}$ be given, where each object S_j is a n-dimensional vector of numerical characteristics, i.e. $S_j = (x_{j1}, \ldots\ldots x_{jn}), j = \overline{1, m}\,(m = m_1 + m_2 + ... + m_l)$.

Suppose that for images $K = K_1,..., K_l$, $K_i \cap K_j = \phi, \forall i \neq \forall j$ holds. Let T_{nml} be the reference sample, $T^*_{nm_1}$ the control sample, where n the number of characters is, m is the number of objects, l is the number of classes, and m_1 is the number of control sample objects.

It is required, using the standard sample T_{nml}, to find the maximum permissible dimension of the space of combinations of features n_0, to construct a system of support sets Ω_A from combinations of features $C_n^{n_0}$ and to determine on this set the decisive rules ensuring the required quality and reliability of recognition.

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IV. FORMATION OF A SYSTEM OF SUPPORT SETS

In [4, 5], the system of reference sets from combinations of features in the first case is defined as $\Omega_A = C_n^k$, and in the second case as $\Omega_A = C_n^1 + C_n^2 + ... + C_n^n = 2^n$. If you consider that each object $S_i \in T_{nm_1}^*$ is mapped to each object $S_j \in T_{nml}$ using $C_n^i(i = \overline{1,k}$ либо $i = \overline{1,n})$ on the basis of the rule

$$d(S_i, S_j) = \begin{cases} 1, если \ \tilde{\omega}S_i = \tilde{\omega}S_j \\ 0, если \ \tilde{\omega}S_i \neq \tilde{\omega}S_j \end{cases}, (2)$$

then the results of the match will correspond to one of the variants 2^i, where $\tilde{\omega}S_i$ and $\tilde{\omega}S_j$ are called the -part of the objects S_i and S_j, respectively. Consequently, it follows from [4, 5] that if $\Omega_A = C_n^k$ and 2^i are taken into account in the first case, in the second case $\Omega_A = C_n^1 + C_n^2 + ... + C_n^n = 2^n$ and, 2^i then the number of all possible subsets {1,2, ..., n} of length i and the results of the objects S_i and S_j $N = 2^i C_n^i,\ i = \overline{1,k}$ and $N = 2^i C_n^i,\ i = \overline{1,n}$ respectively.

If in the master sample the number of objects and characteristics is set too much, then the computer for matching objects on the $N = 2^i C_n^i,\ i = \overline{1,n}$ sets requires a lot of time. Therefore, in formula $N = 2^i C_n^i,\ i = \overline{1,n}$ of $i = 1, i = 2, ..., i = n_0, ..., i = n$, you need to find a specific value i (for example, $i = n_0$), and you need to get 2^{n_0} different results when comparing objects in a system of reference sets $\Omega_A = C_n^{n_0}$ equivalent to the results obtained with $N = 2^i C_n^i,\ i = \overline{1,n}$. To achieve this goal, it is required to find a specific value of n_0. [7,9]

If from the master sample T_{nml} a system of reference sets $\Omega_A = C_n^{n_0}$ and all possible variants of results 2^{n_0} matching objects $S_i \in T_{nm_1}^*$ with objects $S_j \in T_{nml}$ are determined, then the number of all possible decision rules will be less than N, where $N = 2^{n_0} C_n^{n_0}$.

Suppose that before the training, the required values of error probability ε and the reliability of recognition η are set in advance, as well as the number of features n and objects m. Then from (1) it is possible to obtain a functional dependence

$$ln N = \varepsilon m + ln \eta \quad (4)$$

In order to find n_0 we logarithm (3)

$$\ln N = \ln 2^{n_0} + \ln C_n^{n_0} \quad (5)$$

Using $C_m^n \leq \dfrac{m^n}{2^n}$ and taking (6) into account (5), we obtain

$$\ln N = n_0 \ln n \quad (6)$$

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If the obtained value of (6) is substituted into the relation (4), then it is possible to obtain a specific functional dependence for n_0

$$n_0 = \frac{\varepsilon m + \ln \eta}{\ln n} \quad (7)$$

The value found from this dependency n_0 guarantees a given error probability ε with a reliability of $(1-\eta)$ for fixed m, n, η .

If we fix η , m , n , ε then from the relation (7) it is possible to find the limiting values of the dimension of the feature n_0 combinations space that satisfy the given error probability ε when recognizing new objects (Table 1). [6]

$\eta = 0.95$, $m = 100$, $n = 50$.					
ε	0,04	0,07	0,12	0,15	0,19
n_0	1	2	3	4	5

An analysis of the data given in Table 1 shows that an increase in the probability of error ε in the recognition of new objects leads to an increase in the dimension of the n_0 combination of features.

If we fix η , n_0 , ε , n then from the ratio (7) we can find the required number of objects $m = \frac{n_0 \ln n + \ln \eta}{\varepsilon}$ that satisfy the given probability of error ε when recognizing new objects (Table 2).
(Table 1).

$\eta = 0.95$, $n = 20$.					
n	1	2	3	4	5
ε	0,02	0,03	0,04	0,05	0,06
m	294	297	298	298	299

Analysis of the data given in Table 2 shows that with an increase in the probability of error ε in the recognition of new objects and the dimension of the space of n_0 feature combinations, the required amounts of objects m increase.

V. ALGORITHM FOR SOLVING THE PROBLEM

Let us consider an algorithm that allows to create a system of reference sets $\Omega_A = C_n^{n_0}$ that define decision rules $F(S_j), (S_j \in T^*_{nm_1})$ in this set that provide the required quality and reliability of recognition.

First, a system of reference sets T_{nml} is formed from the master sample $\Omega_A = C_n^{n_0}$, then in this set each object $S_j \in T^*_{nm_1}$, $j = \overline{1, m_1}$ is mapped to objects $S_1,\ldots,S_{m_j} \in K_j, j = \overline{1,l}$ and, as a result of the total voting (the total degree of proximity of the recognized object S_i to class K_j), each object $S_j \in T^*_{nm_1}$, $j = \overline{1, m_1}$ is

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classified into one of the predefined classes $K_j \in T_{nml}, j = \overline{1,l}$. At the same time, as a result of the classification of new objects $S_j \in T^*_{nm_1}, j = \overline{1,m_1}$, the required ε and η are provided, taking into account the specified n, m.

The algorithm includes the following main steps:

1. Objects $S_1, S_2,..., S_m$, their characteristics $x_1, x_2,..., x_n$ and classes $K_1, K_2,..., K_l$ in the form of a reference sample T_{nml} are entered into the operative memory.

2. Objects $S_1, S_2,..., S_{m_1}$ and their signs $x_1, x_2,..., x_n$ in the form of a control sample $T^*_{nm_1}$ are entered into the operative memory.

3. The limiting value of the permissible dimension n_0 is determined in the form (7), taking into account the specified values of ε and η, as well as for fixed n and m.

4. Form Ω_A of the given n signs to n_0, ie. $\Omega_A = C_n^{n_0}$.

5. $i = 1$. The object $S_i \in T^*_{nm_1}$ is selected from the RAM.

6. $j = 1$. The object is selected $S_j \in T_{nml}$

7. The object $S_i \in T^*_{nm_1}$ is associated with object $S_j \in T_{nml}$ according to rule (2).

8. The object is $S_j \in T_{nml}$ 0 (zero) or 1 (unit), depending on the results of similarity, which is made in the 7-step algorithm.

9. $j = j + 1$. If $j \le m$, then the algorithm proceeds to step 6, otherwise to step 10.

10. A new table T_{Ω_A} is generated based on the system of reference sets $\Omega_A = C_n^{n_0}$.

11. $p = 1$. The class K_p is allocated and the sum of votes $\Gamma_\Sigma(K_p)$ is calculated for this class.

12. $\Gamma_\Sigma(K_p) = 0$.

13. $j = 1$. Select the object. $S_j \in K_p$

14. $\Gamma_{\Omega_A}(S_j) = 0$.

15. $k = 1$.

16. The condition is checked:

a) If $d(\tilde{\omega}S_{ik}, \tilde{\omega}S_{jk}) = 1$, then, and the algorithm proceeds to step 17.

b) If $d(\tilde{\omega}S_{ik}, \tilde{\omega}S_{jk}) = 0$, then the algorithm proceeds to step 17.

17. $k = k + 1$. If $k \le t(t = C_n^{n_0})$, then the algorithm proceeds to step 15, otherwise to step 18.

18. $j = j + 1$. If $j \le m_i$, then the algorithm proceeds to step 13, otherwise to step 19.

19. $p = p + 1$. If $p \le l$, then the algorithm proceeds to step 11, otherwise to step 20.

20. The sum of the votes of the similarity of the recognized object S_i to the class K_p is calculated:

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$$\Gamma_{\Sigma}(S_i \in K_1) = \sum_{j=1}^{m_1}\sum_{k=1}^{t} \Gamma_{\Omega_A}(S_{jk})$$

$$\Gamma_{\Sigma}(S_i \in K_2) = \sum_{j=1}^{m_2}\sum_{k=1}^{t} \Gamma_{\Omega_A}(S_{jk})$$

$$\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots$$

$$\Gamma_{\Sigma}(S_i \in K_l) = \sum_{j=1}^{m_l}\sum_{k=1}^{t} \Gamma_{\Omega_A}(S_{jk})$$

21. To recognize the object $S_i \in T^*_{nm_1}$, a decision rule is used

$$F(S_i):\begin{cases} \mathrm{S_i} \in K_p,\ \textit{если}\ \max\limits_{1\le p\le l}\left\{\begin{matrix}\Gamma_{\Sigma}(S_i \in K_1), \\ \Gamma_{\Sigma}(S_i \in K_2),\ldots, \\ \Gamma_{\Sigma}(S_i \in K_l)\end{matrix}\right\} \\ \mathrm{S_i} \notin K_1, \mathrm{S_i} \notin K_2, \ldots, \mathrm{S_i} \notin K_l \\ \textit{если}\ \ \Gamma_{\Sigma}(S_i \in K_1) = \Gamma_{\Sigma}(S_i \in K_2) = \ldots = \Gamma_{\Sigma}(S_i \in K_l) \end{cases}$$

22. $i = i + 1.$ If $i \le m_1$, then the algorithm proceeds to step 5, otherwise to step 23.

23. Output of results relating Let us consider an algorithm that allows to create a system of reference sets $\Omega_A = C_n^{n_0}$ that define decision rules $F(S_j), (S_j \in T^*_{nm_1})$ in this set that provide the required quality and reliability of recognition.

First, a system of reference sets T_{nml} is formed from the master sample $\Omega_A = C_n^{n_0}$, then in this set each object $S_j \in T^*_{nm_1}, j = \overline{1, m_1}$ is mapped to objects $S_1, \ldots, S_{m_j} \in K_j, j = \overline{1, l}$ and, as a result of the total voting (the total degree of proximity of the recognized object S_i to class K_j), each object $S_j \in T^*_{nm_1}, j = \overline{1, m_1}$ is classified into one of the predefined classes $K_j \in T_{nml}, j = \overline{1, l}$. At the same time, as a result of the classification of new objects $S_j \in T^*_{nm_1}, j = \overline{1, m_1}$, the required ε and η are provided, taking into account the specified n, m .

The algorithm includes the following main steps:

1. Objects $S_1, S_2, \ldots, S_m$, their characteristics $x_1, x_2, \ldots, x_n$ and classes $K_1, K_2, \ldots, K_l$ in the form of a reference sample T_{nml} are entered into the operative memory.

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2. Objects $S_1, S_2,..., S_{m_1}$ and their signs $x_1, x_2,..., x_n$ in the form of a control sample $T^*_{nm_1}$ are entered into the operative memory.

3. The limiting value of the permissible dimension n_0 is determined in the form (7), taking into account the specified values of ε and η, as well as for fixed n and m.

4. Form Ω_A of the given n signs to n_0, ie. $\Omega_A = C_n^{n_0}$.

5. $i = 1.$ The object $S_i \in T^*_{nm_1}$ is selected from the RAM.

6. $j = 1.$ The object is selected $S_j \in T_{nml}$

7. The object $S_i \in T^*_{nm_1}$ is associated with object $S_j \in T_{nml}$ according to rule (2).

8. The object is $S_j \in T_{nml}$ 0 (zero) or 1 (unit), depending on the results of similarity, which is made in the 7-step algorithm.

9. $j = j + 1.$ If $j \le m$, then the algorithm proceeds to step 6, otherwise to step 10.

10. A new table T_{Ω_A} is generated based on the system of reference sets $\Omega_A = C_n^{n_0}$.

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17. $k = k + 1.$ If $k \le t(t = C_n^{n_0})$, then the algorithm proceeds to step 15, otherwise to step 18.

18. $j = j + 1.$ If $j \le m_i$, then the algorithm proceeds to step 13, otherwise to step 19.

19. $p = p + 1.$ If $p \le l$, then the algorithm proceeds to step 11, otherwise to step 20.

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$$\varGamma_{\Sigma}(S_i \in K_1) = \sum_{j=1}^{m_1} \sum_{k=1}^{t} \varGamma_{\Omega_A}(S_{jk})$$

$$\varGamma_{\Sigma}(S_i \in K_2) = \sum_{j=1}^{m_2} \sum_{k=1}^{t} \varGamma_{\Omega_A}(S_{jk})$$

$$\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots$$

$$\varGamma_{\Sigma}(S_i \in K_l) = \sum_{j=1}^{m_l} \sum_{k=1}^{t} \varGamma_{\Omega_A}(S_{jk})$$

21. To recognize the object $S_i \in T^*_{nm_1}$, a decision rule is used

$$F(S_i): \begin{cases} \mathrm{S_i} \in K_p,\ \textit{если} \max\limits_{1 \le p \le l} \begin{Bmatrix} \varGamma_{\Sigma}(S_i \in K_1), \\ \varGamma_{\Sigma}(S_i \in K_2),.., \\ \varGamma_{\Sigma}(S_i \in K_l) \end{Bmatrix} \\ \mathrm{S_i} \notin K_1, \mathrm{S_i} \notin K_2, \ldots, \mathrm{S_i} \notin K_l \\ \textit{если} \ \ \varGamma_{\Sigma}(S_i \in K_1) = \\ \varGamma_{\Sigma}(S_i \in K_2) = \\ \ldots = \varGamma_{\Sigma}(S_i \in K_l) \end{cases}$$

22. $i = i+1.$ If $i \le m_1$, then the algorithm proceeds to step 5, otherwise to step 23.

23. Output of results relating to the object $S_i \in T^*_{nm_1}$ by the sum of votes for classes, to one of the $K_1, K_2,..., K_l \in T_{nml}$ dicating a refusal of recognition for object $S_i \in T^*_{nm_1}$.

5. Software.

A set of programs based on the developed algorithm is created. The general view of the program's interface window is as follows (Figure 1).

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VI.SOFTWARE

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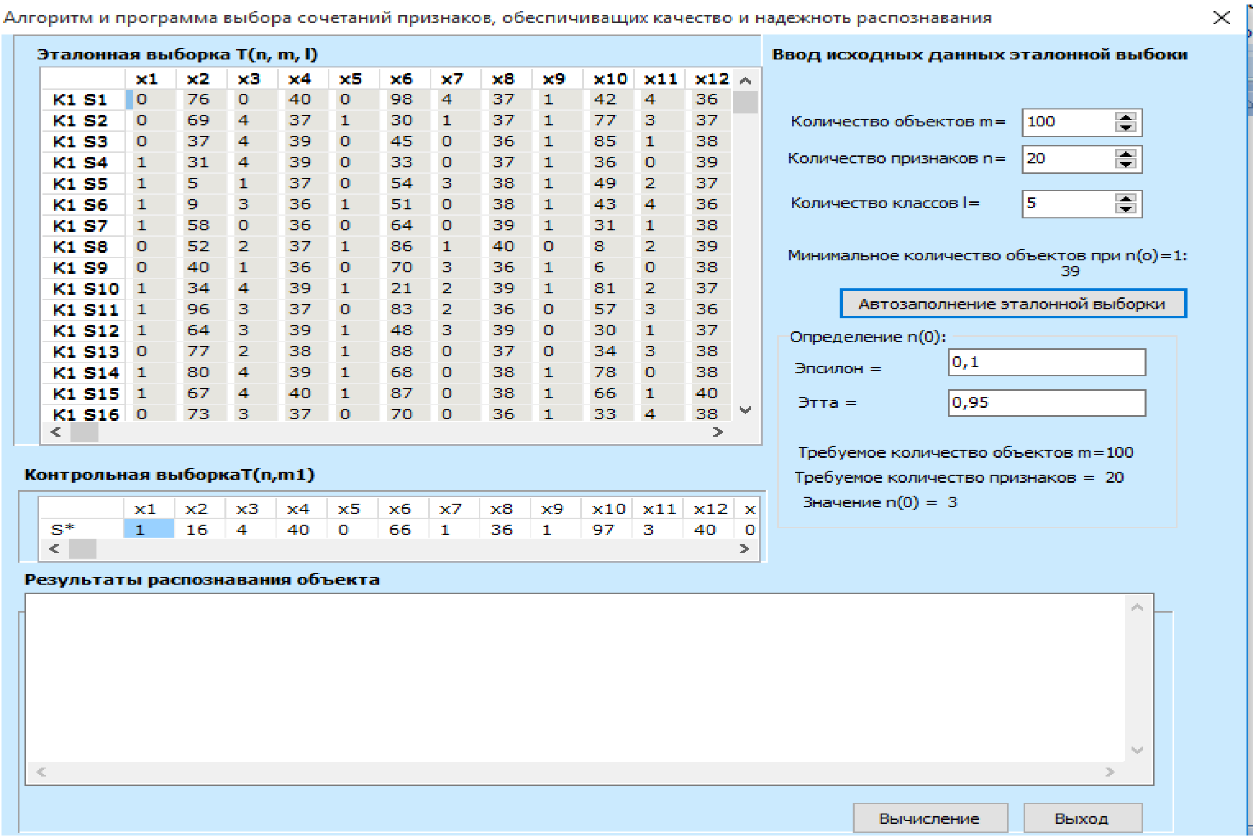

Fig. 1.General view of the interface window.

The calculation module n_0, the system of reference sets $\Omega_A = C_n^{n_0}$ and the recognition of objects a $\Omega_A = C_n^{n_0}$ is shown in Fig. 2.

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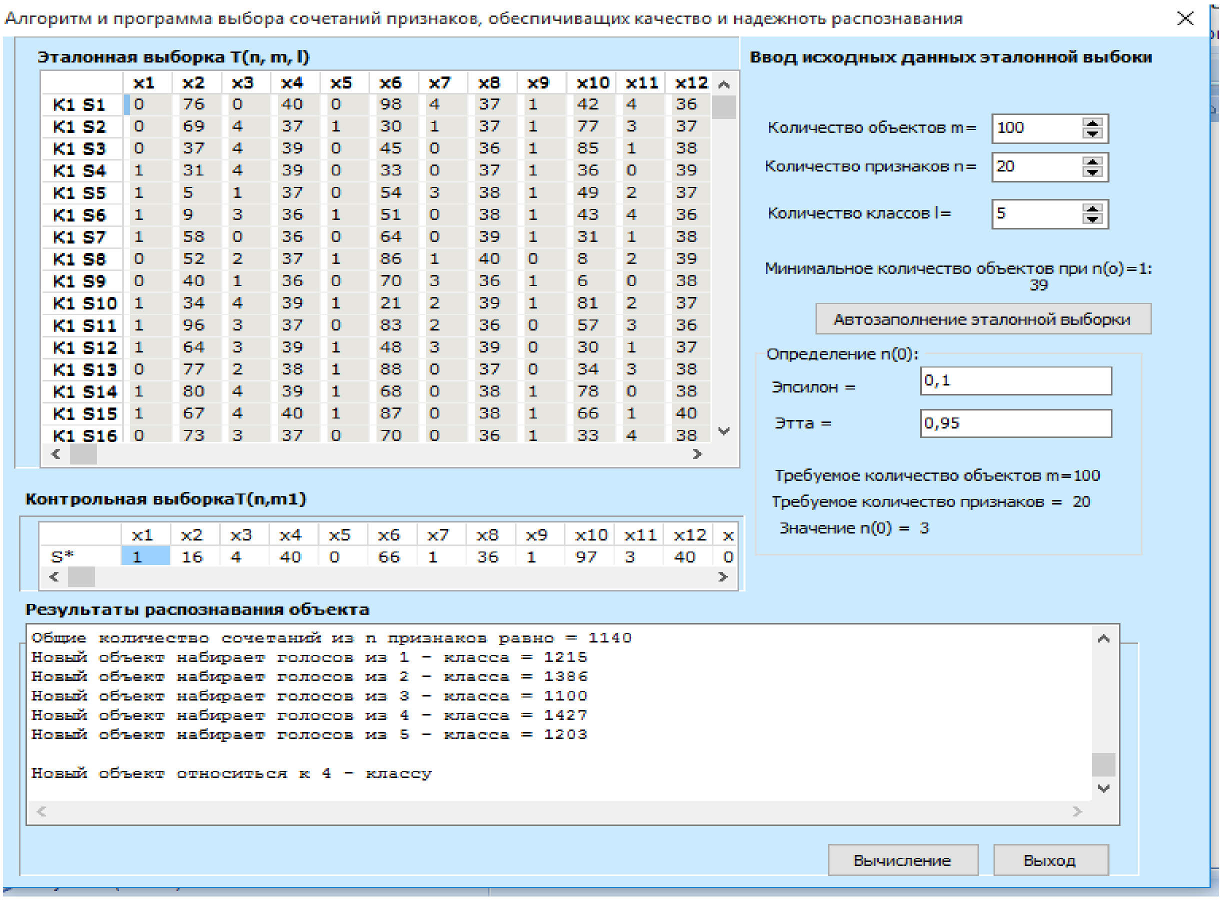

Fig. 2. Results of the computational experiment .

A test was conducted to assess the operability and efficiency of the proposed algorithm and software package for image recognition. The obtained results confirm that the developed algorithm and software complex is applicable for solving practical problems of recognition of objects related to medical, technical, archaeological, hydrogeological, seismological, biological and geological spheres.

VII. CONCLUSION

In contrast to the algorithms given in [4, 5], in this algorithm:

- for given ε and η, and also for fixed n and m, n_0 is determined in the form (7).

- a system of reference sets is formed from the given n signs on n_0, ie. $\Omega = C_n^{n_0}$ $(n_0 \leq n)$;

- $\Omega_A = C_n^{n_0}$ the sum of votes of similarity of $\Gamma(S_j) \in T^*_{nm_1}$, $j = \overline{1, m_1}$ is calculated for each new object $S_j \in T^*_{nm_1}$, $j = \overline{1, m_1}$;

- objects $\Gamma(S_j) \in T^*_{nm_1}$, $j = \overline{1, m_1}$ are classified according to the sum of the voting results, to one of the specified classes $K_j \in T_{nml}$, $j = \overline{1, l}$.

- The amount of computing on the computer is sharply reduced, since $C_n^{n_0} \leq C_n^k$ $(n_0 < k)$ and $C_n^{n_0} \leq C_n^1 + C_n^2 + ... + C_n^n$ $(n_0 < n)$.

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It should be noted that in this algorithm the systems of support sets are greatly reduced Ω_A. The reduction of the system of reference sets Ω_A seems useful in two aspects: first, the amount of computation decreases, and secondly, with the elimination of Ω_A extra combinations of features, the reliability of recognition increases. Simultaneously, due to the reduction of the system of reference sets, the set decreases, which often leads to a decrease in the reliability of recognition as a whole. Therefore, in this algorithm, their functional dependence (5) is considered, so that the quality and reliability of recognition, as well as the volume (number of features and objects) of the master sample is in the required interval.

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