Selecting classifiers to ensure the quality and reliability of pattern recognition at class intersection

D K Bekmuratov

Department of Computer Systems, Tashkent University of Information Technologies named after Muhammad al-Khwarizmi, Shokhrukh Mirzo 41, Samarkand, Uzbekistan

E-mail: bekmurodov_d@mail.ru

Abstract. The article poses and solves the problem of selecting classifiers for the case when the given classes intersect in the space of initial properties of objects. The value of the limiting dimension of the classifier space is determined, taking into account the volume of the learning sample, the probability of errors made when separating classes and recognizing new objects. Procedures are given for determining the classifiers of three types and selecting among them the ones that satisfy the predetermined error when separating classes, and the predetermined error probability and reliability when recognizing new objects. An algorithm and software were developed based on the proposed procedures. Computational experiments on a computer and the results were presented in the form of decision rules used for object recognition.

1. Introduction

There are various methods and algorithms for pattern recognition learning. These methods and algorithms differ in approaches and selection of criteria for informativeness in determining attributes. In most of them, when determining the informativeness of attributes, the size of the learning sample (the number of objects and attributes), which affects the quality and reliability of recognizing new objects, is not taken into account.

In [1, 2], algorithms for calculating estimates (ACE) are presented. In these algorithms, the degree of similarity of objects is calculated in the process of comparing all possible combinations of attributes included in the description of objects. Consequently, ACE allows us to take into account the differences in the information content of individual attributes and their combinations.

In [3], algorithms of partial precedence (APP) are proposed. Based on these algorithms, allowable elementary logical classifiers (AELC) are distinguished with respect to reference objects. The selected AELCs lead to an error-free separation of the reference sample classes in the case when the classes do not intersect in the space of initial properties.

In [4, 5], theoretical results are obtained based on relationships connecting such parameters as the probability of error and reliability with the complexity of decision rules when recognizing new data.

The method of limiting simplifications (MLS) is presented in [6, 7]. This method is used to construct a linear decision rule. This rule unmistakably separates the reference sample in a small dimension space when the classes do not intersect in the space of initial properties. In MLS algorithms, the dimension of some hypothetical space is determined before learning, and a linear separating function completely defined in this space is also determined. The space itself in the learning process is constructed from attributes that lead to an error-free separation of classes.
The authors of the article [8] developed a pattern recognition algorithm based on the calculation of the estimate using Fisher's informative criterion in the space of informative attributes. The problem of optimizing the selection of informative attributes by the Fisher-type criterion is solved. A proximity function is constructed based on the elements and properties of the Fisher functional in the space of informative attributes.

The study in [9] discusses issues related to the construction of a pattern recognition model, focused on the classification of objects of high dimension of the attribute space. A new approach to the construction of a model of recognition operators based on the construction of multilevel proximity functions is proposed. A distinctive feature of the proposed model is the determination of a suitable set of threshold functions when constructing extreme recognition operators.

In [10], the issues of constructing a model of pattern recognition algorithms aimed at classifying objects in conditions of high dimension of the attribute space are considered. The main advantage of the proposed algorithms is the choice of preferable models of elementary threshold rules with the subsequent calculation of the estimates of object membership. These algorithms provide a significant reduction in the number of computational operations when recognizing unknown objects.

In [11], the problems of determining representative attributes are considered when constructing an algorithm for recognizing extreme patterns, defined in a multidimensional attribute space. The main advantage of the proposed procedures is to improve the accuracy of the results of the subset selection. These subsets are closely related by objects that appear when constructing a pattern recognition algorithm under conditions of high dimension of attribute space.

The reference [12] proposes the problem of forming an attribute space, used in object recognition. In the process of learning objects, the initial properties of objects are first selected and informative attributes are formed based on a decrease in the dimension of the space of initial properties.

The reference [13] considers the problem of constructing a model of pattern recognition algorithms in conditions of high dimensions of attribute space. A distinctive feature of the proposed model and algorithms is the determination of a suitable set of elementary threshold rules. These rules are related within the preferred combinations of representative attributes with the construction of approximation functions based on the sets of attributes combinations.

In [14], a method is proposed for selecting informative interrelated attributes based on informative heuristic criteria. As informative heuristic criteria, we use the criteria associated with assessing the separability of given classes on the basis of the fundamental hypothesis of compactness of recognition, which states that with an increase in the distance between classes, their separability improves.

In articles [15, 16], algorithms for the formation of the space from three types of attributes and from r-th rank complex features for each class, respectively, are proposed. These algorithms ensure the quality and reliability of pattern recognition with error-free separation of the classes of the reference sample in the case when the classes of the reference sample do not intersect.

In [17], the problem of identifying individual attributes from uninformative properties of objects and of minimizing the generated subsystems of features is solved when the classes of the reference sample do not intersect.

In this article, in contrast to the above studies, the problem of learning and object recognition is solved when the classes of the reference sample intersect in the space of initial properties. Before the learning process, the limiting values of the dimension of the classifier space are found. This dimension is determined taking into account the number of specified objects and properties, the preset error values when dividing the classes of the reference sample, as well as the value of the error probability and its reliability when recognizing new objects. In the found space, decision rules are constructed from classifiers of two types, each of which is generated with respect to reference objects. On the basis of constructed decision rules, new objects are recognized with the assurance of the established quality and reliability.
2. Formulation of the problem

Let a reference sample \( V = V_1, ..., V_l \) (\( V_q \cap V_p \neq \emptyset \) at \( \forall q \neq \forall p \)) be given, where each object
\[ X_i \in V (\gamma = 1, m) \] is \( n \)-dimensional vector of numerical features, i.e. \( X_i = (x_{i1}, ..., x_{in}) \) when recognizing new objects \( X_{ij} \in V_p, \gamma = 1, m, i = 1, n \), and control sample \( V^* = X_{ij} (\gamma = 1, m) \). We denote any class \( V_j \in V \), i.e. \( V_q = \forall V_j \) by \( V_q \), and all other classes \((m - 1)\) except \( V_q \), i.e. \( V_p = V \setminus V_q \), where \( V_q \cup V_p = V \) by \( V_p \).

It is required to determine the limiting values of the dimension of the classifier \( W_i^{\gamma} \) of space \( n_0 = f (m, n, \nu, \epsilon, \eta) \) before learning, taking into account the number of \( m \)-objects \( X_j, n - \)the initial properties of \( x_i, \nu - \)the predetermined error frequency when separating \( X_j \in V_q \) from \( X_j \in V_p \), and \( \epsilon - \)the predetermined value of the error probability and \( \eta - \)the reliability of the probability of errors made when recognizing new objects \( X_{ij} (\gamma = 1, m) \).

3. Methods for solving the problem

Let us assume that properties \( x_i (i = 1, n) \) are set on \( V \) and \( V^* \). The values of each \( x_i \) can be logical or numeric.

We note that in [3] theoretical results were obtained that relate to the construction of \( R_q(X) \) from the features of a reference sample. One of the authors, in a paraphrased form, asserts that if in \( n \)-dimensional binary space of features \( x_i (i = 1, n) \) the decision rule \( R_q(X) \) makes errors with frequency \( \nu \) when separating \( X_j \in V_q \) from \( X_j \in V_p \), then with certainty \( (1 - \eta) \) it can be argued that the probability of erroneous recognition \( X_{ij} (\gamma = 1, m) \) using \( R_q(X) \) will be less than \((\nu + \epsilon)\), where:

\[
\epsilon = \sqrt{(\ln N - \ln \eta)/2m}.
\] (1)

Using (1) we define \( n_0 \), contained in (6), provided that \( m, n \) are predetermined and \( \nu, \epsilon, \eta \) are set. In order to find the value of \( n_0 \), we can obtain the following from (1):

\[
\ln N = (\nu + \epsilon^2)2m + \ln \eta.
\] (2)

Depending on the composition of random and independent sample \( V \), the learning process can stop at any \( n_0 \). If the erroneous separation of \( X_j \in V_q \) from \( X_j \in V_p \) with the frequency of errors \( \nu \) occurred with the classifier \( W^\gamma \) including \( n_0 \) properties, and if \( x_i (i = 1, n) \) is selected from \( n \) properties \( x_i (i = 1, n) \) with respect to \( m \) reference objects \( Z_j = \forall x_j \), then the number \( N \) of all possible decision rules \( R_q(X) \) will not exceed \( N \), where:

\[
N = m 2^{n_0} C_n^{n_0}.
\] (3)

Taking the logarithm of (3), we obtain:

\[
\ln N = \ln m + \ln 2^{n_0} + \ln C_n^{n_0}.
\] (4)

Considering that \( C_n^{n_0} \leq n^{n_0} \) from (4) we have:

\[
\ln N = \ln m + n_0 \ln 2 + n_0 \ln n = \ln m + n_0 (\ln 2 + \ln n).
\] (5)

Substituting (5) to (2), we can find a specific value of \( n_0 \):

\[
n_0 = ((\nu + \epsilon^2)2m + \ln \eta - \ln m) / (\ln 2 + \ln n).
\] (6)

Thus, as follows from (6), if one or more decision rules \( R^\gamma(X) \) are selected from \( N \), corresponding to the selected \( W^\gamma \) inherent in \( V_q \) and they separate \( X_j \in V_q \) from \( X_j \in V_p \) in \( V \), with error \( \nu \), then
when recognizing new \( X'_\lambda \in V (\gamma = 1, m) \), the error probability will not exceed \((\nu + \varepsilon)\) and its reliability will meet \((1 - \eta)\).

Let the system of support sets \( \Omega_A = \{ \Omega : |\Omega| = n_0 \} = C_{n_0}^{n_0} \) be defined with (6). Then \( \Omega_A \) can be represented in the form:

\[
\Omega_A = \{ I_k = < x_{11}, \ldots, x_{1m} >, \ldots, I_k = < x_{\lambda k}, \ldots, x_{\lambda m} > \}, \tag{7}
\]

where \( \lambda = C_{n_0}^{n_0} \).

Let us assume that a certain reference set \( I_k \in \Omega_A \) is given, and that the reference object \( Z_q^q = z_{11}, z_{12}, \ldots, z_{kn_0}, Z_q^2 \in V_q \) and the system of comparison rules \( d_1^k, d_2^k, \ldots, d_n^k \) are fixed in it.

The following is used as \( d_i^k \):

\[
d_i^k(Z_q^q, X_\gamma) = \begin{cases} 1, & \text{if } |z_{nu} - x_{ai}| \leq \delta_i \\ 0, & \text{else} \end{cases}
\]

where \( \delta_i \) is the given or defined threshold.

Let us denote a subset of objects \( X_\gamma \in V \) by \( U_{1i}^k \) for which the following holds:

\[
W_{1i}^Z = \wedge_{i=1}^{n_0} d_i^k(Z_q^q, X_\gamma) = 1,
\]

and a subset of objects \( X_\gamma \in V \) by \( U_{2i}^k \) for which the following holds:

\[
W_{2i}^Z = \wedge_{i=1}^{n_0} d_i^k(Z_q^q, X_\gamma) = 0.
\]

Then \( W_{1i}^Z \) is the classifier inherent in \( V_q \) if for \( U_{1i}^k \) and \( U_{2i}^k \), generated by (8) or (9) one of the relations (11) - (13) is satisfied:

\[
(V_q \subseteq U_{1i}^k) \wedge (U_{1i}^k \cap V_p = \phi) \wedge (V_p \subseteq U_{2i}^k) \wedge (U_{2i}^k \cap V_q = \phi) = 1, \tag{11}
\]

\[
(V_q \subseteq U_{1i}^k) \wedge (U_{1i}^k \cap V_p \neq \phi) \wedge (U_{2i}^k \subseteq V_p) \wedge (U_{2i}^k \cap V_q = \phi) = 1, \tag{12}
\]

\[
(U_{1i}^k \subseteq V_q) \wedge (U_{1i}^k \cap V_p \neq \phi) \wedge (V_p \subseteq U_{2i}^k) \wedge (U_{2i}^k \cap V_q \neq \phi) = 1. \tag{13}
\]

Therefore, if for \( U_{1i}^k \) and \( U_{2i}^k \) (11) is fulfilled, then \( W_{1i}^Z \) is a classifier of the first type \( W_{q1}^{(1)Z} \), if (12) is fulfilled, then \( W_{2i}^Z \) is a classifier of the second type \( W_{q2}^{(2)Z} \), if (13) is fulfilled, then \( W_{1i}^Z \) is a classifier of the third type \( W_{q3}^{(3)Z} \) inherent in \( V_q \).

As seen from (11), each sampled \( W_{q1}^{(1)Z} \) unmistakably separates \( \forall X \in V_q \) from \( \forall X \in V_p \) and therefore independently participates in object recognition. If we take into account the formulation of the problem \( V_q \cap V_p \neq \phi \) at \( \forall q \neq \forall p \), then the type classifier \( W_{q1}^{(1)Z} \) does not exist in the reference sample and therefore, in further considerations, we will consider only classifiers of the types \( W_{q2}^{(2)Z} \) and \( W_{q3}^{(3)Z} \), which make errors when separating \( \forall X \in V_q \) from \( \forall X \in V_p \).

Let by sequential viewing \( I_k \in \Omega_A (k = 1, \lambda) \) classifiers of the \( t \)-th type (if \( t = 2 \), then of the second type; if \( t = 3 \), then of the third type) be selected inherent in \( V_q \) according to (12) and (13):

\[
W_q^{(t)} = W_{q1}^{(1)Z} \cup W_{q2}^{(2)Z} \cup W_{q3}^{(3)Z} (t = 2, 3; \lambda_i \leq \lambda). \tag{14}
\]
If in the formulation of the problem we take into account $V_q \cap V_p \neq \emptyset$ at $\forall q \neq \forall p$, each sampled $W_q^{(i)Z} \in W_q^{(i)}$ of the $n_0$-th rank makes some errors when separating $\forall X \in V_q$ from $\forall X \in V_p$. Therefore, a specific error value is calculated for each selected $W_q^{(i)Z} \in W_q^{(i)}$ in the form:

$$f(W_q^{(i)Z}) = \rho_k^{(i)}/m,$$  

(15)

where $\rho_k^{(i)}$ is the number of incorrectly classified objects $X$ using $W_q^{(i)Z}$. This relation shows that $0 \leq f(W_q^{(i)Z}) \leq I$.

Further, among $W_q^{(i)Z} \in W_q^{(i)}$ ($t = 2,3; k = 1, \lambda, \lambda \leq \lambda_i$) such $W_q^{(i)Z}$ are selected for which the following is fulfilled:

$$f(W_q^{(i)Z}) \leq \nu$$  

(16)

and they are included in $R_q^{(i)}(X)$, otherwise excluded from further consideration and the learning process is considered complete for one $V_q$.

Similarly, using the above relations (8) or (9) and (9) - (16) for each $V_q \in V(q = 1,l)$ the classifiers of the $n_0$-th rank are found:

$$W_q^{(i)Z} \in W_q^{(i)} \quad (q = 1, l; t = 2,3; k = 1, \lambda, \lambda \leq \lambda_i).$$  

(17)

Taking into account (17), $R_q^{(i)}(X)$ ($k = 1, \lambda_i$) is constructed for each $V_q$ ($q = 1, l)$, satisfying (16) when separating $X \in V_q$ from $X \in V_p$ in the form:

$$R_q^{(i)}(X) = \begin{cases} X \in V_q, & \text{if } W_q^{(i)} = \frac{n_0}{{\sum}}_{i=1}^n d_i^q(Z_i, X) = 1 \quad (q = 1, l; t = 2,3; k = 1, \lambda_i) \quad \text{(18)} \\ X \notin V_q, & \text{else.} \end{cases}$$

Now we consider the recognition pattern for $X^* \in V^*(q = 1, m^*)$ based on (17) and (18). First, $X^* \in V^*$ are selected, and only such properties of $X^* = (x_1, ..., x_m)$ ($n_0 \leq n$) are selected from its initial properties $X^* = (x_1, ..., x_m)$ that correspond to such $W_q^{(i)Z} \in W_q^{(i)}$ for $f(W_q^{(i)Z})$ which meet (18).

Then the similarity between $X^*$ and $Z^q \in V_q$ is calculated by selected $W_q^{(i)Z} \in W_q^{(i)}$ in the following form:

$$R_q^{(i)}(X*, W_q^{(i)Z}) = \begin{cases} 1, & \text{if } R_q^{(i)}(X^*, W_q^{(i)Z}) = \frac{n_0}{{\sum}}_{i=1}^n d_i^q(Z_i, X^*) = 1 \quad (q = 1, l; t = 2,3; k = 1, \lambda_i) \\ 0, & \text{else} \end{cases}$$  

(19)

From (19) it follows that if $R_q^{(i)}(X^*, W_q^{(i)Z}) = 1$ then $X^*$ and $Z^q \in V_q$ are considered similar in the selected $W_q^{(i)Z}$, otherwise they are considered not similar.

According to (19), the sum of the similarity between $X^* \in V^*$ and $\exists Z^q \in V_q$ considering $R_q^{(i)}(X^*, W_q^{(i)Z}) = 1$ for each $V_q (q = 1,l)$ is calculated in the form:

$$G_q^{(i)} = \sum_{W_q^{(i)Z} \in V_q} R_q^{(i)}(X^*, W_q^{(i)Z}), \quad (q = 1, l; t = 2,3; k = 1, \lambda_i).$$  

(20)

Based on (20), a decision rule $R_q^{(i)}(X^*)$ is constructed for recognizing new $X^* \in V^*$ in the form:
Thus, if each selected classifier \( W_{qk}^{(i)} \in W_q^{(i)} \) satisfies (16) when separating \( \forall X_\gamma \in V_q \) from \( \forall X_\gamma \in V_p \), then each \( R_{qk}^{(i)}(X_\gamma^*, W_{qk}^{(i)}) \) constructed in the form (19) provides \( V + \varepsilon \) and \( \eta \) in the recognition of \( X_\gamma^* \in V^*(\gamma = 1, m^*) \).

4. Algorithm for solving the problem
Let us consider an algorithm for constructing \( R^{(i)}(X) \) from classifiers \( W_{qk}^{(i)} \in W_q^{(i)} (t = 2, 3, k = 1, \lambda, \lambda \leq \lambda) \).

The algorithm includes the following main stages:

1. Initial measures \( l, m, n \) and \( m^* \) for \( V \) and \( V^* \), respectively, and the values \( V, \varepsilon, \eta \) are introduced.

On the basis of the specified measures, classes \( V_j \in V(j = 1, l) \), objects \( X_\gamma \in V(\gamma = 1, m) \), \( X_\gamma^* \in V^*(\gamma = 1, m^* \), and the values of their properties \( x_1, x_2, \ldots, x_n \) are introduced.

2. Classes \( V_q = \forall V_j \) and \( V_p = V \setminus V_q (p \neq q) \) are set.

3. \( n_q \) is calculated in the form (6).

4. The system of support sets \( \Omega_A \) is determined in the form (7).

5. A certain support set \( I_k \in \Omega_A \) is considered.

6. The reference object \( Z_k^* \in V_q \) is set.

7. Comparisons of objects \( X_\gamma \in V \) and \( Z_k^* \in V_q \) in the form (8).

8. The classifier \( W_k^Z \) is determined using (9) and (10).

9. The type of classifier \( W_{qk}^{(i)}(t = 2, 3) \) is determined in the form (11) - (13).

10. Repeating steps 5-9, \( W_{qk}^{(2)} \) and \( W_{qk}^{(3)} \) are formed in the form (14).

11. For each \( W_{qk}^{(i)} \in W_q^{(i)} \), an erroneous value is calculated in the form (15), when separating \( \forall X_\gamma \in V_q \) from \( \forall X_\gamma \in V_p \).

12. Condition (16) is checked for each \( W_{qk}^{(i)} \in W_q^{(i)} \). If (16) is fulfilled then go to step 14, otherwise go to step 13.

13. \( W_{qk}^{(i)} \in W_q^{(i)} \) is excluded from further consideration and go to step 11.

14. \( W_{qk}^{(i)} \in W_q^{(i)} \) is saved and a corresponding decision rule \( R_{qk}^{(i)}(X_\gamma) \) in the form (18).

15. \( X_\gamma^* \in V^* \) is selected and the similarity between \( X_\gamma^* \) and \( Z_k^* \in V_q \) is calculated in the form (19).

16. The sum of the similarity between \( X_\gamma^* \in V^* \) and \( \exists Z_k^q \in V_q \) is calculated in the form (20).

17. Recognition of \( X_\gamma^* \) is made in the form (21).

18. End of the algorithm.

5. Software package and computational experiment
The software was created and a test was conducted to assess the performance and efficiency of the proposed algorithm in relation to pattern recognition (Figure 1).
Figure 1. Results of the computational experiment

The algorithm and the program were tested on a reference \( V(m = 300, n = 30, l = 3) \) and control \( V' (m = 8, n = 30) \) sample with given values of \( \nu = 0.03, \epsilon = 0.03, \eta = 0.95 \). According to the calculation data, \( n_0 = 5 \) was obtained according to (6). On the basis of \( n_0 = 5 \), a system of support sets \( \Omega_A \) was formed, where each \( I_k \in \Omega_A \) consists of 5 properties according to (6). With (13), (14) and (18), the classifiers used for the recognition of 8 new objects, were selected. It was found that out of 8 new objects, 4 belong to the first class and 4 belong to the second class.

Further, setting specific values of \( m, n, \eta \) and increasing the values of \( \nu \) and \( \epsilon \) in (6), we can present the dynamics of changes in \( n_0 \) value (see Table 1).

| \( V \) | 0.01 | 0.02 | 0.03 | 0.04 | 0.05 | 0.06 | 0.07 | 0.08 | 0.09 | 0.1 |
|---|---|---|---|---|---|---|---|---|---|---|
| \( \epsilon \) | 0.01 | 0.02 | 0.03 | 0.04 | 0.05 | 0.06 | 0.07 | 0.08 | 0.09 | 0.1 |
| \( n_0 \) | 1 | 3 | 5 | 7 | 9 | 11 | 13 | 15 | 17 | 19 |

The following conclusions can be drawn from Table 1:
- with an increase in \( V \) and \( \epsilon \), \( n_0 \) sharply increases with fixed \( m \) and \( n \);
- to decrease \( n_0 \) at fixed values of \( V \), \( E \) and \( \eta \), it is necessary to increase \( m \) or to decrease \( n \).

6. Conclusions
In the course of solving the above problem, the following main indications can be noted:
- the maximum allowable dimension of the space of classifiers \( n_0 \) is indicated that should not be exceeded in the learning process with given \( V \), \( E \), \( \eta \) and fixed \( m \) and \( n \);
- relationships for the definition of classifiers and their types were obtained;
- the conditions for the selection of classifiers were determined, which led to a noticeable reduction in their number;
- it was established by numerical calculations that any increase in the dimension of the classifier space led to a noticeable decrease in the reliability and quality of recognition of new objects;
- it was established by computational experiments that the volume of computations on a computer was sharply reduced due to the exclusion from further consideration of classifiers that do not satisfy (12), (13) and (16).

Thus, in the proposed procedures and algorithm, the system of support sets \( \Omega_A \) was noticeably reduced, as well as the number of selected classifiers \( W_{qk}^{l^2} \in \Omega_A \), which led to a decrease in the amount of computations and ensured the quality and reliability of recognition.

References
[1] Zhuravlev Yu I, Kamilov M M, Tulyaganov Sh E 1974 Algorithms for calculating estimates and their applications (Tashkent: Fan)
[2] Zhuravlev Yu I, Ryazanov V V and Senko O V 2006 Recognition. Mathematical methods. Software system. Practical applications (Moscow: Fazis) 65-69
[3] Abdukarimov R T, Kamilov M M, Kondratyev A I 1984 Informational recognition systems of partial precedence (Tashkent: FAN)
[4] Vapnik V N, Chervonenkis A Y 1974 Theory of Pattern Recognition (Moscow:Nauka) 416-418
[5] Vapnik V N 1999 Complete Statistical Theory of Learning. Automation and Remote Control 80 (11) 1949–1975
[6] Vasilyev V I 1991 Pattern Recognition and Image Analysis: USSR (USA) 1 23-32
[7] Vasiliev V I, Bekmuratov K A 1992 Synthesis of properties by the learning sampling in the problems of pattern recognition learning Journal of Automation 1 76-83
[8] Kamilov M M, Nishanov A X, Beglerbekov R J 2019 Modified stages of algorithms for computing estimates in the space of informative features 8 (6) 714-717
[9] Kamilov M, Fazilov Sh, Mirzaeva G, Gulyamova D, Mirzaev N 2020 AMSD-2019. Journal of Physics: Conference Series 1441 012142, doi:10.1088/1742-6596/1441/1/012142
[10] Fazilov Sh Kh, Mirzaev N M, Mirzaeva G R 2019 Modified recognition algorithms based on the construction of models of elementary transformations 150 671-678
[11] Fazilov S K, Mirzaev N M, Radjabov S S, Mirzaeva G R. Journal of Physics: Conference Series Mechanical Science and Technology Update 1260 (10)
[12] Fazilov Sh, Mamatov N 2019 Formation an informative description of recognizable objects. AMSD 2018. IOP Conf. Series: Journal of Physics: Conf. Series 1210 012043 doi:10.1088/1742-6596/1210/1/012043
[13] Fazilov Sh, Khamdamov R, Mirzaeva G, Gulyamova D, Mirzaev N 2020 Models of recognition algorithms based on linear threshold functions. AMSD-2019. Journal of Physics: Conference Series 1441 012138 doi:10.1088/1742-6596/1441/1/012138.
[14] Mamatov N, Samijonov A, Yuldashev Z 2019 Selection of features based on relationships. Mechanical Science and Technology Update. IOP Conf. Series: Journal of Physics: Conf. Series 1260 102008 doi:10.1088/1742-6596/1260/10/102008
[15] Bekmuratov K A, Akhatov A R, Bekmuratov D K 2019 Formation of complex attribute spaces
of the r-th rank, ensuring the quality and reliability of recognition Problems of Computational and Applied Mathematics 1 (23) 24-38

[16] Bekmuratov K A, Bekmuratov D K and Akhatov A R 2019 Synthesis of feature spaces ensuring the quality and reliability of recognition 2019 Dynamics of Systems, Mechanisms and Machines (Dynamics) 1-5 eISSN: 2644-2760. (PoD) ISSN: 2381-7593. doi:10.1109/Dynamics47113.2019.8944721

[17] Bekmuratov K 2019 Determination of attributes inherent in classes from non-informative properties of reference sample objects. Problems of Computational and Applied Mathematics. 6 (24) (Dec 2019), Pp 22-36. ISSN 2181–8460 (Print), eISSN 2181–046X (Online)