



ISSN: 2350-0328

**International Journal of Advanced Research in Science,  
Engineering and Technology**

**Vol. 7, Issue 6 , June 2020**

# **The Formation of Signs Subsystems for Recognition of Objects When Crossing the Classes of the Reference Sample**

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**ABSTRACT:** The article poses and solves the problems of constructing mixed decision rules consisting of a complex of an incomplete set of individual attributes and combinations of properties, each of which individually is not an attribute inherent in a particular class when the classes of the reference sample intersect in the space of original properties. The procedures for finding the value of the limiting dimension of feature spaces, the selection of individual features, and the combination of properties inherent in a particular class are presented, which together satisfy the established error in separating the classes of the reference sample and ensure the error probability and its reliability when recognizing new objects. In the found space, mixed decision rules are constructed for recognizing the objects on the basis of a joint set of selected separate features and combinations of properties, each of which individually is not an attribute inherent in a particular class. The conclusion of the study as a whole are presented.

**KEYWORDS:** reference sample, control sample, error probability, reliability, limit dimension of feature space, error value, 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. [6, p.1; 9]

## **II. LITERATURE SURVEY**

In recent years, a lot of methods and algorithms have appeared that somehow solve the problem of pattern recognition. These methods and algorithms differ in approaches to solving the recognition problem, in mathematical tools used and the complexity of the learning algorithms.

In [1, p. 95] theoretical results were obtained that do not consider the synthesis of feature spaces in which decision rules are built in the learning process. These results are based on relationships linking parameters such as quality, reliability, dimension of feature space with the length of the reference sample.

The method of ultimate simplifications (MUS) is described in [2, pp. 12-17; 3, pp. 76-83]. The concepts of an attribute and a semi-attribute are introduced and defined. A rule is given for constructing homogeneous and mixed spaces, consisting of both attributes and semi-attributes. Using this method, a linear decision rule is constructed that unmistakably separates the reference sample in a space of small dimension in the case when the classes do not intersect.

The authors of the article [4, pp. 714-717] have developed the recognition algorithms based on the calculation of estimates using the Fisher informative criterion in the space of informative features. The problem of optimizing the choice of sets of informative features by an informative criterion of the Fisher type in the reference sample is constructed.

In [5, pp. 671-678] the issues of constructing a model of recognition algorithms aimed at classifying the objects under conditions of a large dimension of the feature space are discussed.

The algorithms for the sequential formation of the feature space were proposed in [6, pp. 6215-6226; 7, pp. 74-79; 8, pp. 24-38; 9, pp. 9-13; 10, pp. 22-36]; they ensure the quality and reliability of new objects recognition when the classes of the reference sample in the original feature space do not intersect.

### III. STATEMENT OF THE PROBLEM

One of the main issues in solving the recognition problem is finding individual characteristics or their combinations inherent in a particular class. Moreover, when finding them, such important parameters as the quality and reliability of recognition could not be neglected. In connection with the above circumstance, finding individual features or combinations of properties (which separately are not a feature inherent in the class) taking into account the volume (number of objects and number of features) of the reference sample, as well as the quality and reliability of recognition, is currently one of the most urgent problems of pattern recognition.

Let a reference sample  $(V = V_1, \dots, V_l \ (V_q \cap V_p \neq \emptyset \text{ at } \forall q \neq \forall p))$ , be given, where each object  $X_\gamma \in V \ (\gamma = \overline{1, m})$  is  $n$ -dimensional vector of numerical features, i.e.  $X_\gamma = (x_{\gamma 1}, \dots, x_{\gamma n}) \ (\gamma = \overline{1, m}; i = \overline{1, n})$ , and a control sample is  $V^* = X_\gamma^* (\gamma = \overline{1, m^*})$ . Denote by  $V_q$  - any class  $V_j \in V$ , i.e.  $V_q = \forall V_j$ , and by  $V_p$  all other  $(m-1)$  classes except  $V_q$ , i.e.  $V_p = V \setminus V_q$ , where  $V_q \cup V_p = V$ .

It is required to determine the limiting values of the dimension of the attribute space  $n_0 = f(m, n, \nu, \varepsilon, \eta)$  before training, taking into account  $m$ -number of objects  $X_\gamma$ ,  $n$ -initial properties  $x_i$  and  $\nu$  - the predetermined error rate when separating  $X_\gamma \in V_q$  from  $X_\gamma \in V_p$ , and also  $\varepsilon$  - the pre-fixed values of the error probability and  $\eta$  - its reliability when recognizing new objects  $X_\gamma^* (\gamma = \overline{1, m^*})$ . In this case, it is necessary in the process of training:

- to choose from  $x_i (i = \overline{1, n})$  separate characteristics of the  $t$ -th type  $x_i^{(t)q} (t = \overline{2, 3})$  inherent in  $V_q$ ;
- to form a reference set  $\Omega_q$  from a combination of properties  $x_i (i = \overline{1, n_1}; n_1 \leq n)$ , each of which is not separately an attribute of  $t (t = \overline{2, 3})$ -th type  $x_i^{(t)q}$  inherent in  $V_q$ ;
- to determine from  $\Omega_q$  the attributes of the  $n_0^{(t)}$ -th rank of the  $t (t = \overline{2, 3})$  th type  $I_h^{(t)q}$  inherent in  $V_q$ ;
- to choose among  $I_h^{(t)q} (t = \overline{2, 3})$  those that are included together with types  $x_i^{(t)q}$  in space  $n_0$ .
- to build from the selected  $t$ -th type  $x_i^{(t)q}$  and  $I_h^{(t)q}$  mixed decision rules  $R_q^{(t)}(X)$  that satisfy the set  $V$  at separation  $X_\gamma \in V_q$  from  $X_\gamma \in V_p$  in  $V$  and provide the error probability  $(\nu + \varepsilon^2)$  and  $\eta$  at recognition  $X_\gamma^* (\gamma = \overline{1, m^*})$ .

### IV. METHODS FOR SOLVING THE PROBLEM

Suppose that the properties  $x_i (i = \overline{1, n})$  are given on  $V$  and  $V^*$ . Each value of  $x_i$  can be logical or numeric. For binarization of  $x_i$ , the rules given in [8, pp. 26-27] are used.

Note that in [1, p. 95] theoretical results were obtained that do not consider the synthesis of feature spaces in which  $R_q(X)$  are built in the learning process. One of them, rephrased, states that if in the  $n$ -dimensional binary space of attributes  $x_i(i = \overline{1, n})$  the decisive rule  $R_q(X)$  makes mistakes with a frequency  $\nu$  when separating  $X_\gamma \in V_q$  from  $X_\gamma \in V_p$ , then it can be stated with reliability  $(1-\eta)$  that the probability of erroneous recognition  $X_\gamma^*(\gamma = \overline{1, m^*})$  with  $R_q(X)$  will be less than  $\nu + \varepsilon$ , where

$$\varepsilon = \sqrt{\frac{\ln N - \ln \eta}{2m}} \tag{1}$$

Using (1) determine  $n_0$  which is contained in (6), provided that  $m, n$  are predefined and  $\nu, \varepsilon, \eta$  are stated. To find the value of  $n_0$ , the following can be obtained from (1)

$$\ln N = (\nu + \varepsilon^2)2m + \ln \eta \tag{2}$$

Depending on the composition of a random and independent sample  $V$ , the learning process may stop at any  $n_0$ . If the erroneous separation  $X_\gamma \in V_q$  from  $X_\gamma \in V_p$  with the error frequency  $\nu$  occurred in  $n_0$ , and if these  $n_0$  attributes  $x_i(i = \overline{1, n_0})$  are selected from  $n$  properties  $x_i(i = \overline{1, n})$ , then the number  $N$  of all possible  $R_q(X)$  will not exceed  $N$ , where

$$N = 2^{n_0} C_n^{n_0} \tag{3}$$

Finding the logarithm (3) we get

$$\ln N = \ln 2^{n_0} + \ln C_n^{n_0} \tag{4}$$

If consider that  $C_n^{n_0} \leq n^{n_0}$  then from (4)

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

Substituting (5) into (2) a concrete value of  $n_0$  can be determined

$$n_0 = \frac{(\nu + \varepsilon^2)2m + \ln \eta}{\ln 2 + \ln n} \tag{6}$$

Setting concrete values of  $m, n, \eta, \nu, \varepsilon$  from (6) concrete values of  $n_0$  can be presented in the form of table (Table 1).

Table 1.

$\eta=0,95; m=300; n=50.$					
$\nu$	0,01	0,03	0,05	0,07	0,1
$\varepsilon$	0,01	0,03	0,05	0,07	0,1
$n_0$	1	4	7	10	14

From table 1 we can draw the following conclusions:

- with increase in  $\nu$  and  $\varepsilon$ ,  $n_0$  greatly increases at given  $m$  and  $n$ ;
- to increase  $n_0$  at fixed values of  $\nu$ ,  $\varepsilon$  and  $\eta$ , it is necessary to increase  $m$  or decrease  $n$ .

In [9, p. 1-5] three types of features are defined and the procedures for creating a space of the homogeneous features are gdescribed that lead to the linear separation of classes in the case when the classes of the reference sample do not intersect. However, for those cases when, from a given set of initial properties, it is not possible to obtain the number of

attributes necessary for separating classes, performing logical operations on properties that are not separately the attributes defined in [9, pp. 1-5] it is possible to obtain new properties, using which, together with individual attributes, it is possible to achieve separation  $X_\gamma \in V_q$  from  $X_\gamma \in V_p$  with the error when the classes of the reference sample intersect in the space of the original properties.

Consider the procedure for constructing mixed  $R_q(X)$ , allowing us to use the  $h$  - e combination of properties of the  $t$  ( $t = \overline{2,3}$ ) - type  $I_h^{(t)q} = \langle x_{h_1}, \dots, x_{h_{n_0^{(t)}}} \rangle$  together with the attributes of the  $i$ - type  $x_i^{(t)q}$  inherent in  $V_q$  (if  $t = 2$  - the second type and if  $t = 3$  - the third type), defined in [9, pp.1-5]. In contrast to [9, pp. 1-5], in this case,  $R_q(X)$  should satisfy the set  $\nu$  when separating  $X_\gamma \in V_q$  from  $X_\gamma \in V_p$  and to ensure  $(\nu + \varepsilon^2)$  and  $\eta$  at recognition  $X_\gamma^*(\gamma = \overline{1, m^*})$ , since according to the statement of the problem  $V_q \cap V_p \neq \emptyset$  at  $\forall q \neq \forall p$  is performed for  $V_j (j = \overline{1, l})$ .

Before building  $R_q(X)$ , attributes of type  $I_h^{(t)q}$  are first determined. In [9, p. 10] individual features of the  $t$  ( $t = \overline{2,3}$ )-th type  $x_i^{(t)q}$  are determined from the initial properties  $x_i (i = \overline{1, n})$  on the basis of special requirements and those properties  $x_i$  that do not satisfy these requirements are excluded from further consideration. Further, only such properties  $x_i$  are considered, and from them the type attributes  $I_h^{(t)q}$  inherent in  $V_q$  are determined.

Suppose that from  $x_i (i = \overline{1, n})$ ,  $n_q^{(2)}$  number of attributes types  $x_i^{(2)q}$  and  $n_q^{(3)}$  number of attributes type  $x_i^{(3)q}$  according to the ratios given in [9, pp. 1-5] are selected, but they are not enough to satisfy the stated  $\nu$  at separation  $X_\gamma \in V_q$  from  $X_\gamma \in V_p$  in space  $n_0$ . Then learning can be continued by an additional set of remaining properties  $x_i (i = \overline{1, n_1}) (n_1 \leq n)$ , where  $n_1$  is calculated as

$$n_1 = n - (n_q^{(2)} + n_q^{(3)}) \tag{7}$$

Now  $x_i (i = \overline{1, n_1})$  is checked individually. If for  $x_i$

$$[(\exists X_\gamma \in V_q : x_{\gamma i} = 1) \wedge (\exists X_\gamma \in V_q : x_{\gamma i} = 0) \wedge (\exists X_\gamma \in V_p : x_{\gamma i} = 1) \wedge (\exists X_\gamma \in V_p : x_{\gamma i} = 0)] = 1 \tag{8}$$

is satisfied then it is not considered a separate attribute inherent in  $V_q$ .

Suppose that from  $x_i (i = \overline{1, n})$ ,  $n_q^{(t)}$  number of features of  $t$  ( $t = \overline{2,3}$ ) th type  $x_i^{(t)q}$  is selected. Then from the properties  $x_i (i = \overline{1, n_1})$  each of which satisfies relation (8)  $\Omega_q^{(t)} (t = \overline{2,3})$  are constructed taking into account  $\beta_q^{(t)} = C_{n_1}^{n_0^{(t)}}$  in the form

$$\Omega_q^{(t)} = \left\{ I_1^{(t)q} = \langle x_{1_1}, \dots, x_{1_{n_0^{(t)}}} \rangle, \dots, I_{\beta_q^{(t)}}^{(t)q} = \langle x_{\beta_{q1}^{(t)}}, \dots, x_{\beta_{q n_0^{(t)}}^{(t)}} \rangle \right\} \tag{9}$$

Here,  $n_0^{(t)}$  is calculated taking into account  $n_0$  found in the form (6) and the number  $n_q^{(t)}$  of selected features of the type  $x_i^{(t)q}$ , inherent in  $V_q$ , i.e.

$$n_0^{(t)} = (n_0 - n_q^{(t)}), (t = \overline{2,3}). \tag{10}$$

If we take into account (10), then from (9) it can be seen that at  $t = 2$ , the set  $\Omega_q^{(t)}$  is constructed from a combination,  $\beta_q^{(2)} = C_{n_1}^{n_0^{(2)}}$ , and at  $t = 3$  accordingly  $\beta_q^{(3)} = C_{n_1}^{n_0^{(3)}}$ . At  $t = 2$  each  $I_h^{(t)q} \in \Omega_q^{(t)} (h = \overline{1, \beta_q^{(t)}})$  in (8) is presented by

$$I_h^{(t)q} = \bigvee_{i=1}^{n_0^{(t)}} x_{h_i} (h = \overline{1, \beta_q^{(t)}}; n_0^{(t)} \leq n_0), \tag{11}$$

at  $t = 3$  accordingly

$$I_h^{(t)q} = \bigwedge_{i=1}^{n_0^{(t)}} x_{h_i} (h = \overline{1, \beta_q^{(t)}}; n_0^{(t)} \leq n_0). \tag{12}$$

If at  $t = 2$  for  $I_h^{(t)q}$  given in (11) is satisfied

$$[(\forall X_\gamma \in V_q : I_{qh}^{(t)} = 1) \wedge (\exists X_\gamma \in V_p : I_{qh}^{(t)} = 0) \wedge (\exists X_\alpha \in V_p : I_{qh}^{(t)} = 0)] = 1 \tag{13}$$

or at  $t = 3$  for  $I_h^{(t)q}$  given in (12) is satisfied

$$[(\exists X_\gamma \in V_q : I_{qh}^{(t)} = 1) \wedge (\exists X_\alpha \in V_q : I_{qh}^{(t)} = 0) \wedge (\forall X_\gamma \in V_p : I_{qh}^{(t)} = 0)] = 1 \tag{14}$$

then  $I_h^{(t)q}$  is considered an attribute of  $n_0^{(t)}$ -th rank of the  $t$ -th type inherent in  $V_q$ .

Similarly, at  $t = 2$  and  $t = 3$  each  $I_h^{(t)q} \in \Omega_q^{(t)} (h = \overline{1, \beta_q^{(t)}})$  is represented in the form (11) and (12), respectively, and among them those attributes of the  $n_0^{(t)}$  th rank  $I_h^{(t)q} (h = \overline{1, \mu_q^{(t)}}; \mu_q^{(t)} \leq \beta_q^{(t)})$  inherent in  $V_q$  are selected which satisfy (13) and (14), respectively, where  $\mu_q^{(t)}$  is the number of attributes of the  $n_0^{(t)}$  th rank of the type  $I_h^{(t)q}$  selected from  $I_h^{(t)q} (i = \overline{1, \beta_q^{(t)}})$ .

Further, for each  $t$ -th type  $I_h^{(t)q} \in \Omega_q^{(t)} (t = \overline{2,3}; h = \overline{1, \mu_q^{(t)}})$  to be determined in the form of (13) or (14) together with the selected  $n_q^{(t)}$  number of features of the  $t$ -th type  $n_q^{(t)}$  to satisfy  $\mathcal{V}$  at separation  $\forall X_\gamma \in V_q$  from  $\forall X_\gamma \in V_p$ , and to ensure  $(\nu + \varepsilon^2)$  and  $\eta$  at recognition of  $X_\gamma^* (\gamma = \overline{1, m^*})$ , it is necessary to calculate the error value of each selected  $I_h^{(t)q}$ . The error value of each  $I_h^{(t)q}$  at separation  $\forall X_\gamma \in V_q$  from  $\forall X_\gamma \in V_p$  is determined in the form

$$f(I_h^{(t)q}) = \rho_h^{(t)q} / m \quad (t = \overline{2,3}; h = \overline{1, \mu_q^{(t)}}), \tag{15}$$

which shows that  $0 < f(I_h^{(t)q}) < 1$ . Here  $\rho_h^{(t)q}$  - is the number of erroneously classified  $X_\gamma \in V$  using  $I_h^{(t)q}$ .

Suppose that according to the relations given in [9, pp. 1-5],  $n_q^{(t)} (n_q^{(t)} < n_0) (t = \overline{2,3})$  number of features of the  $t$ -th type  $x_i^{(t)q}$  was selected, but they are not enough to satisfy the stated  $\mathcal{V}$ . Then, to increase the space  $n_q^{(t)}$  up to  $n_0$ , the attributes of type  $I_h^{(t)q}$  inherent in  $V_q$  defined in the form (13) and (14) together with the accumulated  $n_q^{(t)}$  number of attributes of type  $x_i^{(t)q}$  can be used. If we take into account  $n_0^{(t)}$  defined in (10), then the maximum permissible error value for each  $I_h^{(t)q} \in \Omega_q^{(t)}$  at separation  $X_\gamma \in V_q$  from  $X_\gamma \in V_p$  can be estimated in the form

$$f(I_h^{(t)q}) \leq n_0^{(t)} / n_0, (t = \overline{2,3}; h = \overline{1, \mu_q^{(t)}}). \tag{16}$$

Among  $I_h^{(t)q} \in \Omega_q^{(t)} (h = \overline{1, \mu_q^{(t)}})$  for which (16) are selected, else excluded from further consideration. Among  $I_h^{(t)q} \in \Omega_q^{(t)} (h = \overline{1, \mu_q^{(t)}})$  for which (16) holds, they are chosen, otherwise they are excluded from further consideration. Each of the selected t-th type  $I_h^{(t)q} (h = \overline{1, \lambda_q^{(t)}}; \lambda_q^{(t)} \leq \mu_q^{(t)})$  satisfying (16) can participate as an applicant for inclusion in  $n_0$  for sharing with the accumulated attributes of the t-th type  $x_i^{(t)q} (i = \overline{1, n_q^{(t)}})$ .

Assume that for the selected type attributes  $x_i^{(t)q} (i = \overline{1, n_q^{(t)}})$  in [9, p. 10] the following is performed

$$(V_q \setminus M_1^{(t)} = \phi) \wedge (M_1^{(t)} \cap V_p \neq \phi) = 1 \text{ at } t = 2, \tag{17}$$

$$(V_q \setminus M_2^{(t)} \neq \phi) \wedge (M_2^{(t)} \cap V_p = \phi) = 1 \text{ at } t = 3. \tag{18}$$

Here  $M_1^{(t)} = \bigcap_{i=1}^{n_q^{(t)}} U_i^{(t)}$  and  $M_2^{(t)} = \bigcup_{i=1}^{n_q^{(t)}} U_i^{(t)}$ ,  $U_i^{(t)}$  - is the subset  $\{\exists X_\gamma : x_i^{(t)q} = 1\} \in V$ .

Given relations (16) - (18), we can continue to build up space  $n_q^{(t)}$  to  $n_0$  by additional selection of an attribute type  $I_h^{(t)q}$  satisfying the relation

$$(V_q \setminus E_1^{(t)} = \phi) \wedge (E_1^{(t)} \cap (V_p \setminus M_v^{(t)}) = \phi) = 1 \text{ at } t = 2, \tag{19}$$

$$((V_q \setminus M_v^{(t)}) \setminus E_2^{(t)} = \phi) \wedge (E_2^{(t)} \cap V_p = \phi) = 1 \text{ at } t = 3. \tag{20}$$

Here  $E_1^{(t)} = M_1^{(t)} \cap W_h^{(t)}$  and  $E_2^{(t)} = M_2^{(t)} \cup W_h^{(t)}$ ,  $W_h^{(t)}$  - is the subset  $\{\exists X_\gamma : I_h^{(t)q} = 1\} \in V$ ,  $M_v^{(t)}$  - a subset  $\{\exists X_\gamma\} \in V$ , which correspond to  $v$ . At  $t = 2$  to a set  $M_v^{(t)}$  correspond such  $v$  number  $X_\gamma \in V_p$  for which  $x_i^{(t)q} = 1$  and  $I_h^{(t)q} = 1$ , and at  $t = 3$  accordingly  $X_\gamma \in V_q$  for which  $x_i^{(t)q} = 0$  and  $I_h^{(t)q} = 0$ .

It can be seen from (19) and (20) that the set of objects correctly classified by type attributes  $x_i^{(t)q}$ , together with the union of sets of objects correctly classified by type attributes  $I_{qh}^{(t)}$  should cover  $V_p$  with account for  $v$  at  $t = 2$  and accordingly  $V_q$  at  $t = 3$ . Then for each  $X_\gamma \in V_q (\gamma = \overline{1, l})$  at  $t = 2$  and  $t = 3$  with account for  $h = \overline{1, \lambda_q^{(t)}}$  is checked respectively

$$R_q^{(t)}(X_\gamma) = \begin{cases} 1, \text{ if } R_q^{(t)}(X_\gamma) = \bigwedge_{i=1}^{n_q^{(t)}} x_{\gamma i}^{(t)q} \wedge I_{\gamma h}^{(t)q} = 1, \\ 0, \text{ else.} \end{cases} \tag{21}$$

$$R_q^{(t)}(X_\gamma) = \begin{cases} 1, \text{ if } R_q^{(t)}(X_\gamma) = \bigvee_{i=1}^{n_q^{(t)}} x_{\gamma i}^{(t)q} \vee I_{\gamma h}^{(t)q} = 1, \\ 0, \text{ else.} \end{cases} \tag{22}$$

For convenience, denote the array of selected attributes of the t-th type  $x_1^{(t)q}, x_2^{(t)q}, \dots, x_{n_q^{(t)}}^{(t)q} (t = \overline{2, 3})$  by  $P_q^{(t)}$ . Then the error value of each joint set  $I_h^{(t)q}$  and  $P_q^{(t)}$  at separation  $\forall X_\gamma \in V_q$  from  $\forall X_\gamma \in V_p$  is calculated as

$$f(P_q^{(t)}, I_h^{(t)q}) = \rho_q^{(t)} / m \quad (h = \overline{1, \lambda_q^{(t)}}; t = \overline{2, 3}) \tag{23}$$

taking into account the quantity  $R_q^{(t)}(X_\gamma) = 0$  determined from (23) and (24), respectively, where  $\rho_q^{(t)}$  is the quantity of  $X_\gamma \in V$  for which  $R_q^{(t)}(X_\gamma) = 0$ .

Assume that in the learning process,  $\lambda_q^{(t)}$  number of type attributes  $I_h^{(t)q}$  inherent in  $V_q$  was chosen from (9), which are used in conjunction with  $P_q^{(t)}$ , and their  $\lambda_q^{(t)}$  number  $f(P_q^{(t)}, I_h^{(t)q})$  is calculated in the form of (23). Then, for each  $f(P_q^{(t)}, I_h^{(t)q})$ , the inequality is checked

$$f(P_q^{(t)}, I_h^{(t)q}) \leq \nu \quad (h = \overline{1, \lambda_q^{(t)}}; t = \overline{2, 3}). \tag{24}$$

Using (24), among the  $\lambda_q^{(t)}$  number of type attributes  $I_h^{(t)q}$ , such  $\sigma_q^{(t)}$  quantities  $I_h^{(t)q}$  are selected for which together with  $P_q^{(t)}$  (24) is satisfied. Relations (21) and (22) at  $t = 2$  and  $t = 3$ , respectively are checked for each selected joint set  $(P_q^{(t)}, I_h^{(t)q})$ .  $R_q^{(t)}(X_\gamma, V_q)$  is constructed for recognition  $X_\gamma$  taking into account  $R_q^{(t)}(X_\gamma) = 1$  determined from (21) and (22) at  $t = 2$  and  $t = 3$ . Then  $R_q^{(t)}(X_\gamma, V_q)$  has the form

Using (24) are selected among  $\lambda_q^{(t)}$  the number of features of the type  $I_h^{(t)q}$  is selected, such  $\sigma_q^{(t)}$  the number  $I_h^{(t)q}$  for each of which together with  $P_q^{(t)}$  performed (24).

$$R_q^{(t)}(X_\gamma, V_q) : \begin{cases} X_\gamma \in V_q, & \text{if } R_q^{(t)}(X_\gamma) = 1, \\ X_\gamma \notin V_q, & \text{if } R_q^{(t)}(X_\gamma) = 0. \end{cases} \quad (\gamma = \overline{1, m}; t = \overline{2, 3}) \tag{25}$$

Note that if (24) is not satisfied, the joint set  $(P_q^{(t)}, I_h^{(t)q})$  is excluded from further consideration.

Similarly, using relations (7) - (24) for each  $V_q \in V(q = \overline{1, l})$ ;  $R_q^{(t)}(X_\gamma, V_q)$  ( $\gamma = \overline{1, m}; q = \overline{1, l}; t = \overline{2, 3}$ ) is constructed in the form of (25), used in recognition of  $X_\gamma^* \in V^*(\gamma = \overline{1, m^*})$ .

Now we consider the recognition procedure for each new  $X_\gamma^* \in V^*(\gamma = \overline{1, m^*})$  based on (25). The error probability  $\psi = \nu + \varepsilon^2$  which provides in recognition  $X_\gamma^*(\gamma = \overline{1, m^*})$  is calculated. First,  $X_\gamma^* \in V^*$  is selected and from its initial properties  $(x_1, \dots, x_n)$  only those properties  $(x_1, \dots, x_{n_q^{(t)}}, x_{(n_q^{(t)}+1)}, \dots, x_{n_0^{(t)}})$  ( $n_q^{(t)} + n_0^{(t)} = n_0; n_0 \leq n$ ) are selected that correspond to a joint set of selected  $P_q^{(t)}$  and  $I_h^{(t)q}$  for which (24) is satisfied. Then, relations (21) and (22) are checked for  $X_\gamma^*$ , and as a result, the membership of  $X_\gamma^*$  to each  $V_q (q = \overline{1, l})$  in the form of (25) is determined.

It should be noted that  $X_\gamma^*$  will belong to  $V_q$  if two (at  $t = 2$  and  $t = 3$ ) sets are found among  $(x_1, \dots, x_n)$  of the object  $X_\gamma^*$  that correspond simultaneously to two (at  $t = 2$  and  $t = 3$ ) types of a joint set of deleted attributes  $P_q^{(t)}$  and  $I_h^{(t)q} \in \Omega_q^{(t)}$  inherent in  $V_q$  for each joint set for which (24) is satisfied. Similarly, using the above procedure, with (25), the rule is checked for each  $X_\gamma^* \in V^*(\gamma = \overline{1, m^*})$

$$O_{q\gamma} = \begin{cases} 1, & \text{if } R_q^{(2)}(X_\gamma) \wedge R_q^{(3)}(X_\gamma) = 0, \\ 0, & \text{else.} \end{cases} \quad (q = \overline{1, l}; \gamma = \overline{1, m^*}) \quad (26)$$

Given (26), the number of erroneously recognized  $X_\gamma^*$  to each  $V_q$  is calculated in the form

$$S_q = \sum_{\gamma=1}^{\hat{m}_q} O_{q\gamma} \quad (O_{q\gamma} = 1), \quad (q = \overline{1, l}; \hat{m}_q \leq m^*). \quad (27)$$

The portion of erroneously recognized  $X_\gamma^*$  from  $m^*$  accounting for (27) is calculated in the form

$$H_q = S_q / m^* \quad (q = \overline{1, l}). \quad (28)$$

If among  $V_q \in V(q = \overline{1, l})$  there exists such  $V_q$  for which  $H_q \leq \psi$  is satisfied, the recognition process  $X_\gamma^*(\gamma = \overline{1, m^*})$  is considered completed.

Thus, if  $R_q^{(t)}(X_\gamma)$  is built on the basis of a joint set of type attributes  $P_q^{(t)}$  and  $I_h^{(t)q}$  and is satisfies  $\nu$  at separation  $X_\gamma \in V_q$  from  $X_\gamma \in V_p$  in space  $n_0$ , then it provides the error probability  $\psi$  and its reliability  $\eta$  in recognizing new  $X_\gamma^* \in V^*$ .

### V. CONCLUSION

In the process of solving the problem, the following can be concluded:

- 1) before the start of the learning process,  $n_0 < n$  taking into account the given values  $m, n$  and  $\nu, \varepsilon, \eta$  in the form were calculated (6), where  $R_q^{(t)}(X_\gamma, V_q)$  satisfying the stated error  $\nu$  is sought at separation  $X_\gamma \in V_q$  from  $X_\gamma \in V_p$ ;
- 2) the selected number  $n_q^{(t)}$  of type attributes  $x_i^{(t)q}$  were used that were not enough to meet the stated  $\nu$  at separation  $X_\gamma \in V_q$  from  $X_\gamma \in V_p$  in space  $n_0$ ;
- 3) learning process was continued with an additional set of combinations of properties in the form (9), each of which is not separately a type attribute  $x_i^{(t)q}$ ;
- 4)  $\sigma_q^{(t)}$  number of type attributes  $I_h^{(t)q}$  inherent in  $V_q$  is selected from  $\Omega_q^{(t)}$  for each of which (13), (14), (16) are fulfilled and with type attributes  $P_q^{(t)}$ , (24) is fulfilled which leads to a sharp reduction in  $\Omega_q^{(t)}$ ;
- 5)  $R_q^{(t)}(X_\gamma, V_q)$  are constructed from  $\sigma_q^{(t)}$  number of type attributes  $I_h^{(t)q}$ , each of which together with  $P_q^{(t)}$  satisfies  $\nu$  at separation  $X_\gamma \in V_q$  from  $X_\gamma \in V_p$  in the form (25).
- 6) on the basis of  $R_q^{(t)}(X_\gamma, V_q)$  new  $X_\gamma^* \in V^*$  recognized in the form of (26) - (28).
- 7) the volume of calculations on the computer is sharply reduced due to the exclusion from further consideration of those  $I_h^{(t)q}$  for which (13), (14), (16) and (24) are not satisfied.





ISSN: 2350-0328

# International Journal of Advanced Research in Science, Engineering and Technology

Vol. 7, Issue 6, June 2020

Thus, in the proposed methodology, the  $n$  number of initial properties  $x_i$  is reduced initially to  $n_1$  ( $n_1 \leq n$ ) due to the selected type attributes  $P_q^{(t)}$ , and then the  $\beta_q^{(t)}$  number of property combinations  $I_{qh}^{(t)q} \in \Omega_q^{(t)}$  is reduced to  $\sigma_q^{(t)}$  ( $\sigma_q^{(t)} \leq \beta_q^{(t)}$ ) due to the selected type attributes  $I_{qh}^{(t)q}$ .

This reduction seems to be useful in two aspects: firstly, the amount of computation is reduced, and secondly, with the removal of unnecessary  $x_i \in V$  and  $I_{qh}^{(t)q} \in \Omega_q^{(t)}$  the recognition reliability is increased. At the same time, due to reduction in  $x_i \in V$  and  $I_{qh}^{(t)q} \in \Omega_q^{(t)}$  the quantity  $R_q^{(t)}(X_\gamma, V_q)$  is also reduced, which often leads to a decrease in the recognition reliability as a whole. Therefore, in this model and algorithm, a functional dependence  $n_0$  is considered in the form (6) so that,  $\nu, \varepsilon, \eta$ , and  $m, n$  are in the established limit interval.

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