**International Journal of Innovative Technology and Exploring Engineering (IJITEE)**
**ISSN: 2278-3075, Volume-8 Issue-6S, April 2019**

# Modified Stages of Algorithms for Computing Estimates in the Space of Informative Features

**M.M.Kamilov, A.X.Nishanov, R.J.Beglerbekov**

***Abstract: In the article the tasks of development of the recognition algorithm steps areformulated, based on calculation of estimates using the Fisher's informative criterion in the space of informative features. The problem of optimization for the selection of informative feature sets using the Fisher-type informative criterion in the training sample having objects belonging to only one class is constructed, the proximity function in the space of informative features is constructed. In determining the values of the proximity function, the elements and properties of the Fisher functional are used, the upper and lower boundaries of the proximity function are also defined and the lemmas, properties and assumptions that support them are formulated.***

***Keywords: Use about five key words or phrases in alphabetical order, Separated by Semicolon.***

## I. INTRODUCTION

The study of artificial intelligence systems aimed at solving problems of managing objects, processes and phenomena, forecasting and identification based on the use of recognition algorithms, is one of the most rapidly developing areas that stimulate the development of the theory and the continuous expansion of the fields of application of methods of data mining, including of the image recognition algorithms themselves.

One of the possible directions in the development of recognition algorithms can be the improvement of methods for calculating estimates using the Fisher type informative criteria, which, in contrast to the criteria based on statistics and information theory, are simpler [1, 2, 6]. Despite the simplicity, the Fisher type informative criteria are in some cases the most effective. It is these features that have caused their wide use in solving various practical problems of recognition. At the same time, for each specific task, it is necessary to solve the problem of constructing the corresponding space of informative features. The expediency of such an approach is confirmed by the solution of optimization problems in the formation of sets of informative features using the Fisher type informative criterion of a training sample composed of objects of the same class and constructing a proximity function in the space of such characteristics [2,4,5].

**Revised Manuscript Received on December 22, 2018.**

**M.M.Kamilov,** Department of Software Engineering, Tashkent University of Information Technologies named after Muhammad al-Khwarizmi, Tashkent, Uzbekistan

**A.X.Nishanov,** Department of Software Engineering, Tashkent University of Information Technologies named after Muhammad al-Khwarizmi, Tashkent, Uzbekistan

**R.J.Beglerbekov,** Department of Software Engineering, Tashkent University of Information Technologies named after Muhammad al-Khwarizmi, Tashkent, Uzbekistan

In determining the values of the proximity function, the elements and properties of the Fisher functional are used as rules, and accordingly, the upper and lower bounds of this function are determined [3,4]. It is known that the main step in the computation of estimates in the space of informative features is the determination of the values of the degree of importance (contribution) of a subject of class $X_p$with respect to the class in question.

The approach used in [3] makes it possible to perform calculations with a satisfactory error, and also to obtain the results of estimating the contribution to the formation of a class with simultaneous determination of the degree of importance of the class itself [1-4,6]. In doing so, also evaluate the participation of the objects of the training election $X_p$ in the section of the element of the space of informative signs [5,6].In this paper, we propose the development of the developed approach for solving some of the most urgent problems of the development of recognition algorithms.

### 1. The space of informative signs and the Fisher criterion

Suppose that the training sample of objects is given in the following form: $x_{p1}, x_{p2}, \dots, x_{pm_p} \in X_p, p = \overline{1,r}$, each of which represents the corresponding class and contains objects $x_{pi} = (x_{pi}^1, x_{pi}^2, \dots x_{pi}^N), i = \overline{1, m_p}$, where $x_{pi}^j$ –is the value of the attribute j, measured on the object i, p-th class, r – the number of given classes, $m_p$- number of objects in the class $X_p$.

For the formation of feature sets in the original system of attributes, the N – dimensional vector $\lambda_p = (\lambda_p^1, \lambda_p^2, \dots, \lambda_p^N)$, $\lambda_p \in \{0;1\}, i = \overline{1,N}$ is used for all objects of class $X_p$, whose components take the values 0 or 1 and indicate the absence or presence of the corresponding characteristic in the set in question. The quality criterion corresponding to the $X_p$ class object is denoted by $I(\lambda_p)$ and $\ell_p(\ell_p \ll N$. $Then\lambda p$a set of informative signs is constructed as follows:

$$\Lambda^{\ell_p} = \left\{\lambda_p : \sum_{k=1}^{N} \lambda_p^k = \ell_p, \lambda^{\ell_p} \in \{0;1\}, \qquad p = \overline{1,r}\right\} (1)$$

In [6] the set (1) has been given the special name $\ell_p$ – informative space, respectively, each of its elements$\lambda_p$, $\ell_p$will be an informative vector. The degree of informative character of the characteristic is determined on the basis of the acceptance of the quality criterion$I(\lambda_p)$.

Let's imagine that the quality criterion $I(\lambda_p)$ is represented in the form of a Fisher functional:


*Published By:*
*Blue Eyes Intelligence Engineering*
*& Sciences Publication*

$$I(\lambda_p) = \frac{(a,\lambda_p)}{(b_p,\lambda_p)} \quad (2)$$

In this case, the elements $a = (a^1, a^2, \dots, a^N) b = (b_p^1, b_p^2, \dots, b_p^N)$ are vectors and are considered in the $N$ – dimensional feature space, and their components are calculated as follows:

$$a^j = \sum_{p=1}^{r} \left(x_p^j - \bar{x}_p^j\right)^2, j = \overline{1,N}, \quad b_p^j = \frac{1}{m_p} \sum_{i=1}^{m_p} \left(x_{pi}^j - \bar{x}_p^j\right)^2, j = \overline{1,N}$$

where $\overline{x}_p = \frac{1}{m_p} \sum_{i=1}^{m_p} x_{pi}$, $p = \overline{1,r}$- is the averaged object of the class$X_p$ the symbol in (2) having the form (*, *) – denotes the scalar product of vectors. The above expressions allow us to formulate the problem of optimizing the choice of informative sets of characteristics.

## 2. The choice of informative character sets in $\ell_p$ – informative space

The choice of informative characteristics in data mining tasks represents essentially the transition from the original system of characteristics to the new one, which includes a smaller number of characteristics $(\ell_p \ll N)$. Usually new informative attribute sets are formed in the form of functions from the original features by solving optimization problems.

The problem of optimizing the choice of classes of informative sets of characteristics associated with separability is based on the use of criteria of informativity, with their processing by given functionals.

The set of proposed methods for solving optimization problems [1-4,6] can, in essence, be divided into regular, recurrent and partial search methods. At the same time, the solved optimization problem is formulated as

$$\begin{cases} I(\lambda_p) = \dfrac{(a,\lambda_p)}{(b_p,\lambda_p)} \to \max\limits_{\lambda_p \epsilon \Lambda^{\ell_p}}; \\ \Lambda^{l_p} = \{\lambda_p : \sum\limits_{k=1}^{N} \lambda_p^k = \lambda_p, \lambda^{\lambda_p} \in \{0,1\}, p = \overline{1,r}\} \end{cases} \quad (3)$$

After this, functional extremes are calculated. The solution of the optimization problem is considered to be the value of $\lambda_p$ (3), which corresponds to the maximum value of the function$I(\lambda_p)$.

## 3. The proximity function in the space of $\ell_p$ – informative features

Let two objects, $x_{p1}, x_{p2}$ of class $X_p$ and $\varepsilon = (\varepsilon^1, \varepsilon^2, \dots, \varepsilon^N)$be given, whose vector components take positive small values.

The proximity function $\rho_i(x_{p1,}x_{p2})$ between objects $x_{p1} and x_{p2}$, which in the space $\ell_p$–informative space describes the degree of "similarity" of the corresponding parts of these can be introduced as follows:

$$\rho_i(x_{p1,}x_{p2}, \lambda_p) = \begin{cases} 1 \text{ if } \quad |\lambda_p^i(x_{p1}^i - x_{p2}^i)| < \lambda_p^i \varepsilon^i, i = \overline{1,N}. \\ 0 \text{ else } |\lambda_p^i(x_{p1}^i - x_{p2}^i)| \geq \lambda_p^i \varepsilon^i, i = \overline{1,N}. \end{cases} \quad (4)$$

The first condition expresses the degree of proximity between objects, the second expresses the difference between them, that is, these components are not similar to each other. As a criterion for the separation of two sets of objects, the Fisher functional [6] in the N-dimensional space of the $a = (a^1, a^2, \dots, a^N)$ , $b_p = (b_p^1, b_p^2, \dots, b_p^N)$ vectors, whose components are calculated as follows: $a_p^j = (x_{pi}^j -$ *xpj2, bpj=1mpi=1mpxpij−xpj2, j=1,N.*

Then the proximity functions between the $x_{p1}$ and $x_{p2}$ objects can be entered as follows:

$$\rho_i(x_{pi,}\overline{x_p}, \lambda_p) = \begin{cases} 1, \quad \text{если} \begin{cases} |\lambda_p^i(x_{pi}^i - \overline{x_p^i})| < \lambda_p^i \varepsilon^i, i = \overline{1,N}. \\ \varepsilon^i = \dfrac{a_p^i}{b_p^i} \leq 1 \end{cases} \\ 0, \text{иначе } |\lambda_p^i(x_{pi}^i - \overline{x_p^i})| < \lambda_p^i \varepsilon^i, i = \overline{1,N}. \end{cases} \quad (4')$$

Lemma1. The sum of the value of the proximity function (4) in the $\ell_p$- informative vectors $\lambda_p$, for two objects of class $X_p$ does not exceed the value $\ell_p$. That is, the following inequality holds for all pairs of objects of class $X_p$:

$\sum_{i=1}^{N} \rho_i(x_{p1,}x_{p2}, \lambda_p) \leq \ell_p$.

Proof. On the basis of the definition of the proximity function $\rho_i(x_{p1,}x_{p2})$, as well as the definition of the space $\Lambda^{\ell_p}$ informative features $\lambda_p$ the following holds:

From the definition of the proximity function $\rho_i(x_{p1,}x_{p2}, \lambda_p) = 1$ only when the inequality $|\lambda_p^i(x_{p1}^i - x_{p2}^i)| < \lambda_p^i \varepsilon^i$ is satisfied. This inequality can be satisfied for the values $\lambda_p^i \neq 0$, if $\lambda_p^i = 0$ the inequality is not fulfilled, because both sides of the inequality will be 0. Hence, the inequality is satisfied only for the values of $\lambda_p^i \neq 0$ and only in these cases the value of the proximity function is $\rho_i(x_{p1,}x_{p2}, \lambda_p) = 1$ , in all other cases its value is $\rho_i(x_{p1,}x_{p2}, \lambda_p) = 0$.

4.2.On the other hand, on the basis of the definition $\Lambda^{\ell_p}$ the space $\lambda_p$ of informative features $\sum_{k=1}^{N} \lambda_p^k = \ell_p, \lambda_p^k \in \{0; 1\}, k = \overline{1,N}$, that is, among all $k = \overline{1,N}$ y $\lambda_p$ the value vector $\ell_p$ of the parameters $\lambda_p^k = 1$, the rest $\lambda_p^k = 0$. In conclusion it should be said that the proximity function takes the value $\rho_i(x_{p1,}x_{p2}, \lambda_p) = 1$ if and only if, $\lambda_p^k = 1$, in all other cases the proximity function takes the value $\rho_i(x_{p1,}x_{p2}, \lambda_p) = 0$. Consequently, the number of values of $\lambda_p^k = 1$ for all $k = \overline{1,N}$ is equal to $\ell_p$.


Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

It follows that the number of values of $\rho_i(x_{p1,}x_{p2},\lambda_p) = 1$ for all $k = \overline{1,N}$ does not outweigh $\ell_p$. That is, the following inequality holds:

$$\sum_{i=1}^{N} \rho_i(x_{p1,}x_{p2},\lambda_p) \le \ell_p.$$

We got a statement that had to be proved.

Property. By definition, the function is a proximity – Boolean vector and therefore the sum of the components is bounded from below by zero, and above by $\ell_p$. That is, the inequality:

$$0 \le \sum_{i=1}^{N} \rho_i(x_{p1,}x_{p2},\lambda_p) \le \ell_p.$$

Assumption. If the following equality holds,

$$\sum_{i=1}^{N} \rho_i(x_{p1,}x_{p2},\lambda_p) = \ell_p,$$

then $\rho_i(x_{p1,}x_{p2},\lambda_p) = \lambda_p^i$ holds for all $i = \overline{1,N}$. The proof of the property and the sentence is based on the definition of the proximity function.

### 4. Evaluation of the contribution of the object $x_{pj} \in X_p$ for the formation of the class $X_p$ in the space $\ell_p$ of informative features

The formula for estimating the contribution of the $x_{pj} \in X_p$ object to the formation of the $X_p$ class, in the $\ell_p$ – informative character space is as follows:

$$\Gamma_j(x_{pj,}x_{pk},\lambda_p) = \sum_{\kappa=1}^{m_p}\sum_{i=1}^{N} \rho_i(x_{pj,}x_{pk,}\lambda_p)\,, j = \overline{1,m_p};\ k = \overline{1,m_p};\ j \ne k\,.(5).$$

Lemma 2. The estimate of the contribution (5) to the space of $\ell_p$ – informative attributes is bounded above by the value $(m-1)\ell_p$. That is, the following inequality is true:

$$\Gamma_j(x_{pj,}x_{pk},\lambda_p) \le (m-1)\ell_p\, j = \overline{1,m_p};\ k = \overline{1,m_p};\ j \ne k.$$

Proof. On the basis of the result of Lemma 1: $\sum_{i=1}^{N} \rho_i(x_{p1,}x_{p2},\lambda_p) \le \ell_p$ the following inequality holds

$$\Gamma_j(x_{pj,}x_{pk},\lambda_p) = \sum_{\kappa=1}^{m_p}\sum_{i=1}^{N} \rho_i(x_{pj,}x_{pk,}\lambda_p) \le$$

$$\le \sum_{k=1}^{m_p} \ell_p = (m_p - 1)\ell_p, j = \overline{1,m_p};\ k = \overline{1,m_p};\ j \ne k.$$

Hence it follows that for all objects of class $X_p$and for any $j = 1, m_p$ in the space of $\ell_p$ informative features have the following inequality

$$\Gamma_j(x_{pj,}x_{pk},\lambda_p) \le (m_p - 1)\ell_{p\,,}k = \overline{1,m_p};\ j \ne k.$$

Lemma 2 is proved.

### 6. Evaluation of the contribution of all objects to the formation of the class $X_p$ in the space $\ell_p$ – informative features

Below is a formula for estimating the total contribution of all objects to the formation of a class $X_p$taking into account the degree of proximity of all objects

$$\Gamma_\Sigma(x_{pj,}x_{pk,}\lambda_p) = \sum_{j=1}^{m_p}\sum_{\kappa=1}^{m_p}\sum_{i=1}^{N} \rho_i(x_{pj,}x_{pk},\lambda_p)\,, j = 1,\overline{m_p};\ k = \overline{1,m_p};\ j \ne k\,(6)$$

Here the value of $\Gamma_\Sigma(x_{pj,}x_{pk},\lambda_p)$ means the total contribution of all objects to the formation of the class $X_p$ in the space $\ell_p$ of informative features, and

$$\overline{\Gamma}(x_{pj,}x_{pk},\lambda_p) = \frac{1}{m_p}\sum_{j=1}^{m_p}\Gamma_j(x_{pj,}x_{pk},\lambda_p), j = \overline{1,m_p};\ k = \overline{1,m_p};(7)$$

$j \ne k$

The formula for calculating the average contribution of all objects to the formation of the class $X_p$ in the spaces $\ell_p$ – informative features.

Lemma 3. The estimation of the contribution of all objects to the formation of the class $X_p$ in the space of informative features (6) и (7) is limited to the top by the numbers $\boldsymbol{m_p(m_p-1)\ell_p}$ and $\boldsymbol{(m_p-1)\ell_p}$. That is, the following inequalities hold

$$\sum_{j=1}^{m_p}\sum_{\kappa=1}^{m_p}\sum_{i=1}^{N} \rho_i(x_{pj,}x_{pk},\lambda_p) \le \boldsymbol{m_p(m_p-1)\ell_p}\,, j = \overline{1,m_p};\ k = \overline{1,m_p};\ j \ne k\,.$$

$$\frac{1}{m_p}\sum_{j=1}^{m_p}\sum_{\kappa=1}^{m_p}\sum_{i=1}^{N} \rho_i(x_{pj,}x_{pk},\lambda_p) \le \boldsymbol{(m_p-1)\ell_p}\,, j = \overline{1,m_p};\ k = \overline{1,m_p};\ j \ne k\,.$$

The proof of the inequalities follows from the logical interpretation of the preceding lemmas. These arguments can also be expressed for $\overline{\Gamma}(x_{pj,}x_{pk},\lambda_p)$, that is estimating the average contribution of all objects to the formation of the $X_p$class in the $\ell_p$ space of informative features.

### 7. Decisive rule in the space of $\ell_p$ – informative features

Suppose that a new unknown object is given w=($w^1$,$w^2$,…,$w^N$). Evaluation of the contribution of this object to the formation of the class $X_p$ is made using the formula

$$\Gamma_w(w,x_{pk},\lambda_p) = \sum_{\kappa=1}^{m_p}\sum_{i=1}^{N} \rho_i(w,x_{pk},\lambda_p)\,, k = \overline{1,m_p}. \quad (8).$$

If the inequality $\Gamma_w(w, x_{pk}, \lambda_p) \geq \overline{\Gamma}(x_{pj,} x_{pk}, \lambda_p)$ is fulfilled, then the degree of belonging of the object w=($w^1$,$w^2$,…,$w^N$) to the class $X_p$is considered high, and the contribution to the formation of the class $X_p$ is sufficient.

This algorithm can be applied to all objects of all classes $X_p$, $p = \overline{1, r}$ and it is possible to estimate the degree of belonging of the object to the corresponding class. On the basis of the above proofs of the lemmas and formula (8) of the calculation of $\Gamma_w(w, x_{pk}, \lambda_p)$, it is not difficult to show that its value is bounded from above by the number of maximum voices $\boldsymbol{m_p \ell_p}$.

## II. CONCLUSION

In conclusion, it can be noted that the obtained for all elements in the $\ell_p$ – informative character space and for all objects and classes of the training sample. Of course, in this case, the value of the estimates increases and the results given in [1,5,6] are updated to some extent.

## REFERENCES


1. Juravlev Yu.I. Izbrannie nauchnie trudi. –M:Izdatelstvo Magistr, 1998. -420s.
2. JuravlevYu.I., Kamilov M.M., Tulyaganov SH.E. Algoritmi vichesleniya otsenok i ix primenenie. Tashkent: Fan. 1974 g.-119s.
3. Nishanov A.X. Beglerbekov R.J., Axmedov O.K. Gibridniy algoritm raspoznavaniya v prostranstve informativnix priznakov. Vestnik TUIT, 2017g., №4, 62-69s.
4. Kamilov M.M., Nishanov A.X., Beglerbekov R.J. Primenenie reshayushego pravila dlya vibora informativnix naborov priznakov // Ximicheskaya texnologiya. Kontrol i upravleniya. - Tashkent, 2017, №3. - 82-85s.
5. Nishanov A.X., Samandarov B.S. Assessment model of monitoring and defining the completeness of course elements of information systems. // Journal European Applied Sciences. Germany, 2015, –№5. 56-58 pp.