Impact Factor:

ISRA (India)	= **6.317**	**SIS** (USA)	= **0.912**	**ICV** (Poland)	= **6.630**
ISI (Dubai, UAE)	= **1.582**	**РИНЦ** (Russia)	= **3.939**	**PIF** (India)	= **1.940**
GIF (Australia)	= **0.564**	**ESJI** (KZ)	= **9.035**	**IBI** (India)	= **4.260**
JIF	= **1.500**	**SJIF** (Morocco)	= **7.184**	**OAJI** (USA)	= **0.350**

SOI: 1.1/TAS DOI: 10.15863/TAS

International Scientific Journal

Theoretical & Applied Science

p-ISSN: 2308-4944 (print) **e-ISSN:** 2409-0085 (online)

Year: 2021 **Issue:** 09 **Volume:** 101

Published: 30.09.2021 **http://T-Science.org**

QR – Issue **QR – Article**

N.I. Juraeva

Karshi branch of Tashkent University of Information Technologies named after Muhammad al-Khwarizmi
Department of Telecommunications Engineering, Uzbekistan
https://orcid.org/0000-0001-7459-003X
nafisa0878@mail.ru

A.F. Khayrullaev

Karshi branch of Tashkent University of Information Technologies named after Muhammad al-Khwarizmi
Department of Telecommunications Engineering, Uzbekistan
Karshi city, Beshkent highway 3 km, Republic of Uzbekistan
alisher.xayrullayev@mail.ru

TECHNICAL MEANS FOR RECOGNITION OBJECTS IN CONDITION OF UNCERTAINTY

Abstract: *This article details the functionally useful criteria for recognizing objects in terms of uncertainty and error correction algorithms.*

A method for analyzing a non-stationary random signal is proposed for obtaining an estimate of the useful signal during information processing under uncertainty conditions. Using the proposed method of estimating the useful signal allows you to get a unified approach to processing.

Key words: *satellite communication, holography, synthesis of recognition systems, vicious, geometric contours, risk, recognition errors, image.*

Language: *English*

Citation: Juraeva, N. I., & Khayrullaev, A. F. (2021). Technical means for recognition objects in condition of uncertainty. *ISJ Theoretical & Applied Science, 09 (101),* 768-772.

Soi: http://s-o-i.org/1.1/TAS-09-101-110 ***Doi***: crossref https://dx.doi.org/10.15863/TAS.2021.09.101.110

Scopus ASCC: *2200.*

Introduction

It is well - known that processed signals in the direction of radio engineering such as radiolocation, radio navigation, space commu-nication, artificial satellite communication, and recently developing holography are mainly visual information.

The signal being processed must give a complete picture of the object. Theoretical and practical experiments show that these signals, during processing due to numerous noise and noise, can give incorrect representations, i.e. processing of the visual signal is carried out under conditions of uncertainty.

The selection of the most informative (useful) signs in the synthesis of recognition systems is one of the most important tasks of the theory and practice of recognition. However, to date there is no corresponding formal formulation of this problem. In the informal formulations of the problem, the definition of informative features follows: 1) reducing to the minimum the number required for describing classes of attributes without significantly increasing the probability of recognition error; 2) the possibility of using relatively simple recognition algorithms; 3) reduce the likelihood of recognition errors. The solution of this problem usually involves issues of simplifying the recognition system and improving the quality of its work. There are two approaches to building an effective feature system.

The first approach is that from the very beginning, the installation is taken to find a small number of signs of great information. However, all the methods used in this case are still based on heuristics and empirics, so there is a choice of signs determined by the intuition, experience and imagination of the developer. However successful the system of features may have been, one cannot prove that it is better than some other one.

The second approach is that out of a large number of initial features, according to a certain criterion of feature effectiveness, the smallest number of features that are most useful for recognizing features is selected. The second approach to building an effective system of signs is more constructive than the first, although it has a significant drawback: with the obligatory presence of a link between the criteria for the effectiveness of signs and the probability of recognition errors, there is no functional dependence between these quantities.[1,2].

1. Statement of a problem

It is not possible to reliably estimate the change in the probability of recognition errors after minimizing the description, thereby leaving doubts about its effectiveness. The aggravating factor here is the fact that the probability of errors is determined not only by the system of signs, but also by the adopted decisive rule, and depends on the errors that occur in the real recognition system. This explains the lack of winners of the use of criteria for the effectiveness of signs in the practical implementation of recognition systems. Based on the second approach to the selection of useful traits, it is possible to functionally associate the criterion of the effectiveness of the traits with the probability of recognition errors.

2. The concept of the problem decision

The utility of some feature in the initial set of n features will be determined by the increment of the total probability of errors ΔP_m with the exception of this feature from the original set:

$$\Delta P_m = P_m - P'_m \qquad (1)$$

where P_m is the total probability of recognition errors of classes A_1 and A_2 for the initial set of n features; P'_m is the total probability of recognition of classes A_1 and A_2 with the exception of the k-th feature from the initial aggregate.

Depending on the sign of the increment of ΔPm, the following cases may occur:

- $P_m < 0$ - the sign k is useful, since its exclusion from the original description leads to an increase in the probability of error;
- $P_m = 0$ - the sign k is useless, since its exclusion from the original description does not change the probability of error;
- $P_m > 0$ - the sign k is harmful, because without it the probability of recognition error decreases.

Such an approach to the determination of the criteria for the utility of attributes implies the use of a specific decision rule, since it is only within its framework that a recognition error makes sense.

If the existence of useful or useless signs does not cause any doubts, since a large number of easily controversial examples confirms it, then the concept of “harmfulness” of signs seems at first glance to be controversial. However, it does not contradict the statement that harmful information does not exist. Information about the harmfulness of the trait is useful information; the whole question is whether it is properly used.

The difficulty of perception and awareness of the concept of harmfulness of a trait lies in the fact that it arises in its pure form only when distinguishing two classes. In the case of a larger number of classes of “absolute” harmfulness of a trait, as a rule, there is no harm: the harmfulness of a trait in distinguishing certain pairs of classes is opposed to its usefulness in distinguishing other pairs.

The “disappearance” of harmful signs when distinguishing more than two classes is only apparent. It occurs due to averaging of the effectiveness of signs over all pairs of classes under the conditions of the prevailing number of useful signs. The negative effect of signs harmful for distinguishing one or another class does not disappear and is expressed in an increase in the probability of recognition error of these classes, and, consequently, of the total recognition error [3,4].

When recognizing more than two classes, a “vicious” circle may arise the inclusion of some attribute in the description of classes will be useful for distinguishing one pair of classes, but harmful for distinguishing others, the exclusion of this feature from the descriptions of classes on the contrary will prove harmful for distinguishing the first classes and useful for distinguishing the second. The consequence of this contradiction is the obligatory increase in the number of recognition errors with an increase in the size of the alphabet of classes for any decision rules that use one standard per class.

Only based on the analysis of the utility, uselessness or harmfulness of a sign when each of the pairs of classes of a given alphabet is divided can the alternative of including or excluding this sign from the original description be solved from the point of view of minimizing recognition errors.

3. Realization of the concept

After the implementation of the contour preparation algorithm, it is necessary to recognize the types of selected simply connected geometric contours and to determine some of their geometric parameters (sizes). It is convenient to divide the procedure for recognizing contours and determining their geometrical parameters from arriving at the input of a pictorial image system to issuing simply connected contours to the system and determining their geometrical characteristics into three stages.

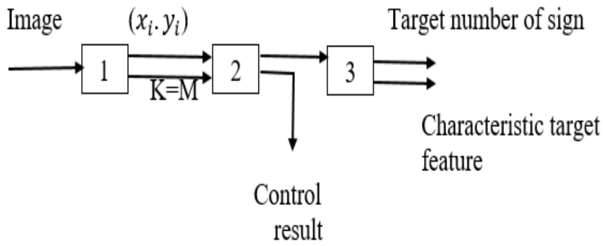

Figure 1. Contour recognition stages:
1 - Preliminary preparation of images; 2 - contour recognition; 3 —recognitions target traits

Consider the steps of the contour recognition algorithm.

Stage 1. At this stage, preliminary preparation of graphic information is carried out (block 1). At the output of block 1 (Figure 1), sets of points $(x_i, y_i, B_i)_k$ where k are formed (where k = 1, 2, 3... is the number of a simply connected contour) of separate simply connected contours, which are the initial data for the block 2

Stage 2. At this stage, the shapes of geometric contours are recognized (block 2). Each recognized contour is assigned a sequence number.

The recognition algorithm works on the principle of coincidence or non-coincidence of the area of an unknown figure, found in two different ways. The first method allows you to determine the area of the shape of the existing coordinates of its points, using, for example, the formula of a triangle or a trapezoid. The area of the figure found in this way is called integral and denoted by S_i. The area of the same figure can be found by the second method through the system of geometric parameters of the figure, characterizing its size, elongation and compactness.

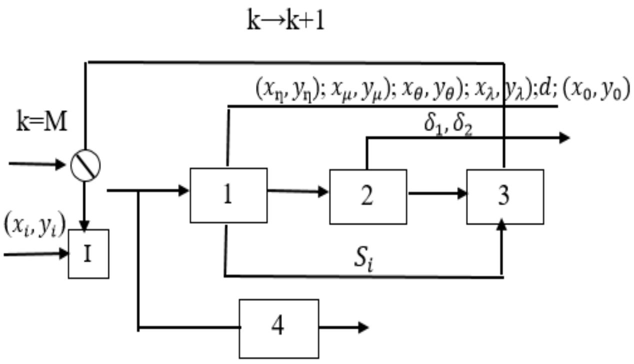

Figure 2. Outline recognition step procedures: 1 - normalization; 2 - determination of parameters δ_i; 3 - contour analysis; 4 - output points of contours on teletype

The area of the shape found by this method is called geometric and denoted by S_g.

Stage 3. At this stage, the formation of features characterizing the intended purpose of the classified objects occurs, and the numerical values of their geometric parameters are determined (block 3).

Error detection of object recognition

The statistical classification methods are based on the assumption that the probability density function $f\ (x)$ for any of the distinguished classes is nonzero on the entire set of feature values. That is, any vector x can appear in any of the classes, but with a different probability. Since we are inevitably forced to strictly define the boundaries between classes in the space X, there is always a chance that a certain number of points from any class fall into the others. This error is called *the first kind error (α)*. On the other hand, a certain number of points from other classes can get into this class. This error is called *the second kind error (β)*. The total error probability of selecting each class is thus p (α) p (β). The errors arising from the classification into N classes are usually described as a table (error matrix):

Table 1.

Veritable\result	K_1	K_2	…	K_N
K_1	σ_{11}	σ_{12}	…	σ_{1N}
K_2	σ_{21}	σ_{22}	…	σ_{2N}
…	…	…	…	…
K_N	σ_{N1}	σ_{N2}	…	σ_{NN}

The rows of this matrix correspond to the fraction of images from the K_i class to the K_j class. Thus, the diagonal of the matrix is the proportion of correctly classified images, that is, they fall into their class [4].

The sum of all other values on the line is the proportion of images that fell to other classes, that is, the error of the first kind. The sum of all other values in a column is the proportion of images that fall into this class from other classes, that is, the error of the second kind. Naturally, we cannot ensure with such a formulation of the problem a decision with a minimum error for each individual image. However, with a large number of images, as in the case of the classification of image pixels, we can try to minimize the average error probability $p\,(\alpha) + p\,(\beta)$ with repeated decision-making.

For this purpose, the concept of "risk" is introduced, that is a fee for each error, and a condition is determined that corresponds to the minimum of the average risk. For a pair of classes K_i and K_j, it has the following form:

$$\frac{P_i f_i(x)}{P_i f_i(x)} = 1 \text{ or in logarithmic form } ln\frac{P_i f_i(x)}{P_j f_j(x)} = 0 \quad (2)$$

Since we are looking for a minimum risk with repeated decision making, expression (2), besides probability density functions, also includes a priori probabilities P_i and P_j. We can say that these probabilities characterize the frequency of appearance of each class on the analyzed set of images, which is proportional to the fraction area under this class.

The second expression from (2) corresponds to the already known form of the separating function for a pair of classes: $d_{ij}(x)$= 0. That is, if $P_i f_i(x) \geq P_j f_j(x)$, then we decide in favor of the class K_i, otherwise we decide in favor of the class K_j. The ratio (2) is called the likelihood ratio, and the functions in the numerator and denominator are called likelihood functions. In another way, we can say that at each interval we decide in favor of the class whose total probability within a given set of images for a specific value of x is maximum. This decision rule is called the maximum likelihood principle.

In the case when the entire set of images must be broken down exactly into N classes, the maximum likelihood principle is often written using the Bayes formula for a complete system of N statistical hypotheses. In such a system, it is assumed that the probability of the implementation of at least one of the N hypotheses is one. In our case, the hypothesis is the belonging of the image of x to a certain class K. Then for each concrete implementation of x, the probability of the implementation of the k-th hypothesis is

$$P\left(\frac{K_k}{x}\right) = \frac{P_k p(x/K_k)}{\sum_{i=1}^{N} P_i p(x/K_i)} \qquad (3)$$

The value of P (Kk / x) is called the posterior class probability for a particular image x, that is, the probability obtained on the basis of an experiment in which we know the probability of the appearance of the image x in each class. In fact, this is the same likelihood function, expressed in fractions of the total probability of the occurrence of a particular x on a given set of images. Therefore, the classification rule remains the same: the decision is made in favor of the class for which the a posteriori probability is maximum.

Conclusion

It should be noted that the problem of recognition of optical images is one of the urgent problems of information technology and is solved with the help of optical - electronic systems with some elements of artificial intelligence. Currently developed for optical - electronic recognition systems based on the use of statistical, structural and other methods of image recognition, as well as some methods that are a combination of the above. Such machine vision systems are widely used in a number of areas of technology and, above all, for visual inspection of industrial products.

References:

1. Milenkiy, A. V. (1975). *Klassifikatsiya signalov v usloviyax neopredelennosti. Statisticheskiye metodi samoobucheniya v raspoznavanii obrazov)*. (p.328). Moscow: ≪Sov. Radio≫.

2. Anisimov, B.V., Kurganov, V.D., & Zloban, V.K. (1983). *Raspoznavaniye i sifrovaya obrabotka izobrajeniy:* Ucheb.posobiye dlya studentov vuzov. (p.295). Moscow: Vissh. shk..
3. Butakov, YE.A., Ostrovskiy, V.I., & Fadiyev, I.L. (1986). *Obrabotka izobrajeniy na EVM.* (p.250). Moscow: Radiosvyazi.
4. Jurayeva, N.I., Khayrullaev, A.F., & Hamraev, J.X. (2020). *Analysis of the energy efficiency of wireless communication when receiving a data stream*. International Conference on Recent Advancements in Engineering and Management (ICRAEM-2020). https://doi.org/10.1088/1757-899X/981/3/032007
5. Jurayeva, N.I., & Khayrullaev, A.F. (2021). *Analysis of energy consumption and data transmission control in modern mobile communication systems*. II International Conference on Advances in Materials Science and Technology -CAMSTech-II-2021. https://conf.domnit.ru/ru/materialy/camstech-2021/
6. Baccelli, F., & Foss, S. (1995). On the saturation rule for the stability of queues. *J. Appl. Prob*.-Vol. 32, pp.494-507.
7. Baek, S., Son, J., & Choi, B. (2009). *Performance Analysis of Sleep Mode Operation, for IEEE 802.16m Advanced WMAN*. Proc. of the ICC 2009, pp.1-4.
8. Blondia, C. (1993). A discrete-time batch Markovian arrival process as B-ISDN traffic model. *Belgian Journal of Operations Research, Statistics and Computer Science*, Vol. 32, pp. 3-23.
9. Blondia, C., & Casals, O. (1992). Statistical multiplexing of VBR sources: a matrix-analytic approach. *Performance Evaluation*, Vol. 16, pp. 5-20.
10. Boxma, O., & Groenendijk, W. (1988). Waiting times in discrete-time cyclic-service systems. *IEEE Trans, on Comm.*, T. 36, № 2, pp. 164-170.