A Procedure for a Choice of the Operating Feature Dictionary for Recognition of Radiation Sources with Means of Radar Monitoring

Kalyuzhniy N.M., Galkin S.A., Nikolaev I.M., Kolesnik V.I.

Abstract – **Approaches to a choice of the most informative combinations of signal features are considered. The procedure for a choice of the operating feature dictionary is proposed. Probabilities of true recognition and are estimated**.

Keywords – **recognition, radiating sources, operating feature dictionary, probability density function**.

I. INTRODUCTION

One of the most important problems of radio monitoring means is recognition of radiating sources [1]. The recognition implies the decision making as for attribution of the detected radiation to one of predetermined classes on the basis of the analysis of some combination of its measured parameters (a vector of features). Frequency, time and spatial parameters of radiations and their sources are used as the features.

When developing recognition means and algorithms of their functioning in radio monitoring systems, there arises a problem of estimation of the potentiality for specified class objects recognition by specified feature combinations, and of a choice, on the basis of this estimate, of the operating feature dictionary providing recognition of radiations and (or) their sources with the error probabilities being not worse than the specified ones.

II. MAIN PART

An alphabet of source classes and a combination of their radiation parameters that could be used as features for recognition of sources and (or) their radiations are given. A decision as for attribution of the recognition object to one of the specified alphabet classes is being made by results of some feature vector processing according to a recognition algorithm. Features are considered independent. An algorithm of decision making is considered known.

It is needed to choose those parameters of their specified combination whose use as features will provide the best probabilities of true recognition and recognition errors for the specified algorithm. Measurement errors for feature values are assumed to be zero. The chosen parameter combination will be considered the operating feature dictionary.

The known approach to the problem solution.

1. Synthesizing algorithms of decision making for possible feature combinations each.

2. Estimating the recognition error probability of the prescribed class alphabet for feature combinations each.

3. By results of the error probability estimation, a choice of that feature combination for which the recognition error probabilities are smallest. This feature combination should be

Kalyuzhniy, N. M., Galkin S.A., Nikolaev I.M., Kolesnik V.I.

Kharkov National University of Radio Electronics,

14 prospekt Lenina, Kharkov, Ukraine

E-mail: rmorti@gmail.com

considered the operating feature dictionary.

In order to explain the difficulties that occur when solving the problem according to the described approach, consider the statement of the decision-making rule problem and ways of quality assessment for recognition algorithms synthesized in accordance with an approach being applied when testing statistical hypothesis by the maximum likelihood method.

The statement of the recognition problem in terms of testing statistical hypothesis.

Given are the class alphabet and the operating feature dictionary. The reference description of classes each in metrics of features s_i each is specified by the onedimensional probability distribution density $w_{1ki}(s_i)$ where $k = 1...K$ is the class number; $i = 1...I$ is the feature number. Under assumption of features to be independent, the reference description of the *k* -th class can be presented as a product of one-dimensional probability densities $W_{1ki}(s_i)$:

 $\binom{\mathbf{r}}{\mathbf{s}} = \prod_{i=1}^{I} w_{1ki}(s_i)$ W_{lk} **(S)** = $\prod_{i=1}^{l} W_{1ki}(s_i)$. Under testing is the complicated hypothesis H_k ($k = 1...K$) that the recognition object with a vector of measured feature values *T* $\mathbf{X} = \begin{bmatrix} x_1 & x_2 & \dots & x_I \end{bmatrix}^T$ belongs to the *k*-class, versus one of complicated alternatives being in the recognition object belonging to other class j ($j \neq k$) of the class alphabet. The *a posteriori* probability density function of the vector of rife *a posterior* probability density function of the vector of measured values **x** is assumed to be known and presented as: $\left(\mathbf{\bar{x}} | \mathbf{\bar{s}} \right) = \prod_{i=1}^{I} W_{1i} \left(x_i | s_i \right)$ $=$ \int_0^I *i* $W(\mathbf{\dot{x}}|\mathbf{\dot{s}}) = \prod W_{1i}(x_i|s_i)$ 1 $\mathbf{x}|\mathbf{s}$) = \prod $W_{1i}(x_i|s_i)$.

It is necessary to optimally determine disjoint domains \mathbf{X}_k of space **Х** of possible values for measured parameter vector **x**
 x so that, when $\mathbf{x} \in \mathbf{X}_k$, the decision that the recognition object belongs to the k -class ($k = 1...K$) is made. A decision-making rule being optimal by the *a posteriori* probability maximum criterion looks like [2]:

$$
H_k : \max_{k} \left(\frac{p_k \prod_{i=1}^{I} \int_{S_k} w_{1ki}(s_i) \cdot W_1(x_i|s_i) ds_i}{\sum_{j=1}^{K} p_j \prod_{i=1}^{I} \int_{S_j} w_{1ji}(s_i) \cdot W_1(x_i|s_i) ds_i} \right) \tag{1}
$$

When developing algorithms for recognition of radiations and their sources, the reference descriptions of classes in metrics of features $W_{1ki} (s_i)$ each are assumed to be uniformly distributed at a specified interval, whereas the *a*

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posteriori probability density functions of measured values of feature $W_{1i}(x_i | s_i)$ to be normally (by Gaussian law) distributed with the expectation s_i and the dispersion s_i . According to the described assumptions, the decision-making rule, by the *a posteriori* probability maximum criterion, can be presented as:

$$
H_k : \max_{k} \left(p_k \prod_{i=1}^{I} \frac{1}{b_{ki} - a_{ki}} \cdot \frac{1}{2} \cdot \left[erf \left(\frac{b_{ki} - x_i}{\sqrt{2 \cdot s_i^2}} \right) - erf \left(\frac{a_{ki} - x_i}{\sqrt{2 \cdot s_i^2}} \right) \right] \right) (2)
$$

where p_k is the *a priori* probability of the *k*-class recognition object occurrence at the recognition system input; a_{ki} , b_{ki} are, respectively, the origin and the end of a section whereat a value of feature s_i for the k -class is uniformly distributed; S_i is the dispersion of the feature x_i measurement error; $erf(y) = \frac{2}{\sqrt{D}} \cdot \int \exp(-t^2) dt$ *y* $erf(y) = \frac{2}{\sqrt{t}} \cdot |\exp(-t^2)dt$ 0 $\frac{2}{\sqrt{2}} \cdot \int \exp(-t^2)$ *p* . Notice that expression (2) determines such domain \mathbf{X}_k of space \mathbf{X} that, when the vector of measured feature values $\overrightarrow{\mathbf{x}}$ hits it, hypothesis H_k (decision making that the recognition object

under consideration belongs to the *k* -class) should be taken.

Probabilities of true recognition *a* and recognition errors *b* are defined from the expressions [2]:

$$
a = \sum_{k=1}^{K} p_k \cdot \int_{X_i} \left(\prod_{i=1}^{I} \frac{1}{b_{ki} - a_{ki}} \cdot \frac{1}{2} \cdot \left[erf \left(\frac{b_{ki} - x_i}{\sqrt{2 \cdot s_i^2}} \right) - erf \left(\frac{a_{ki} - x_i}{\sqrt{2 \cdot s_i^2}} \right) \right] dx
$$
\n
$$
b = \sum_{k=1}^{K} p_k \cdot \left(\int_{X \in X_i} \left(\prod_{i=1}^{I} \frac{1}{b_{ki} - a_{ki}} \cdot \frac{1}{2} \cdot \left[erf \left(\frac{b_{ki} - x_i}{\sqrt{2 \cdot s_i^2}} \right) - erf \left(\frac{a_{ki} - x_i}{\sqrt{2 \cdot s_i^2}} \right) \right] \right) dx
$$
\n
$$
m
$$

The analysis of expressions (2), (3), (4) shows realization complexity of the described approach to a choice of the most informative set of attributes. This complexity consist that:

1. If *N* possible features are considered, then it is necessary to consider $2^N - 1$ decision-making algorithms, what requires a long time.

2. Estimation of error probabilities is reduced to computation of multiple integrals (expressions (3) and (4)) over the domain defined by expression (2). It is rather complicated to analytically compute these integrals, so it is necessary to use numerical integration methods.

A procedure developed by the authors enables one to choose the most informative feature combination. Its essence consists in the following.

1. For each feature of possible pair of classes each, under assumption of the null dispersion ($S_i = 0$) of the feature measurement error, the simplified decision making rule is defined as: the decision is being made for that class for which a value of the probability density w_{1ki} (s_i) at a point of the measured value of feature x_i is greater.

2. To estimate the decision-making errors probability for each pair of classes of a given alphabet for each feature. For clarity, these probabilities can be summarized in the table. The number of rows and columns is equal to the total number of classes of the reference database. Recorded in each table cell are estimates of the probability that the object class defined by a row number is recognized as a class corresponding to a column number. The number of such tables is equal to the total number of features. We shall call the table built in a described way the matrix of recognition errors (e.g., the recognition error matrix by the "carrier frequency" feature).

3. An element of the matrix of recognition errors by any of possible feature combinations can be obtained by multiplication of corresponding elements of error matrices by features entering the specified combination.

4. As a measure of the feature combination informativeness P , we take the error probability which can be estimated by the expression:

$$
P = \sum_{j=1}^{K} p_j \cdot \sum_{i=1}^{K} p_i \cdot Q_{ij}
$$
 (5)

where $p_{j(i)}$ is the *a priori* probability of occurrence of the *k*-class recognition object at the recognition system input; Q_{ii} is the error matrix **Q** element by features being part of the specified combination. The proposed procedure enables one to range feature combinations by their informativeness.

For testing an adequacy of the proposed procedure, the mathematical simulation of the recognition algorithm by a criterion of maximum *a posteriori* probability was carried out.

For chosen feature combinations, decision making rules, being optimal by the maximum *a posteriori* probability criterion, were formed. Probabilities of true recognition and recognition errors were estimated with a method of statistical simulation. Chosen feature combinations were ranged both by informativeness in accordance with the given method and by recognition error probabilities as a result of statistical simulation. The results of ranging with both methods coincide.

III. CONCLUSION

It is shown in the paper that the use of the proposed procedure of choosing the operating feature dictionary for assessment of different feature combination informativeness is possible. This is confirmed by comparison of results of statistical simulation and calculations carried out in accordance with the proposed procedure. The proposed procedure can be used for operating feature dictionary optimization by «a system effectiveness of recognition not worse than the specified ones» criterion at the minimal receiving expenses of features.

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