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MATHEMATICAL MODELLING OF THE INFORMATIVE FEATURE CHOICE FOR LIFECYCLE STATE ANALYSIS OF RADIO-ELECTRONIC MEANS PROCESSES

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ABSTRACT

The solution of problems of mathematical modeling of efficiency functions of radio electronic means life cycle processes (REM LC) and selection of informative attributes for REM LC monitoring, by classification of REM states and life cycle processes in attribute space, each of which has a certain significance, that allowed to find a complex criterion and to formalize selection procedures, is given. The cases of insufficient amount of a priori data for correct classification are considered; heuristic methods of selection according to criteria of basic prototypes and information priorities are proposed.

Keywords: informative features, identification of REM states, life cycle monitoring.

1. INTRODUCTION

A distinctive feature of radio electronic means (REMs) is the presence of a large number of monitored parameters. Monitoring, which provides the ability to measure and record the values and rates of change of REM parameters, may have the additional capability to provide insight into the state of the REM under a multitude of parameters as a statistical ensemble. In science the technique is known when the description of behaviour of a micro ensemble of particle parameters gives the possibility to define macro parameters of systems, consisting of them, to create the phenomenological theory and to use for estimation and control of such systems' state. A physical medium consisting of atoms and molecules is an example, microparameters here are coordinates and impulses of these particles, phenomenological theory is thermodynamics, macroparameters are volume, pressure, temperature etc. The observation, in the field of view of which the phase plane on which one can observe decay and mixing of statistical ensemble of REM parameters, gives additional possibilities for monitoring of life cycle of radio electronic means (LC REM).

The functional problem of selecting informative features for LC REM monitoring, as well as reducing their list, and reducing uncertainty can be solved within the methodology of developing a dictionary of features in systems of classification and recognition of the state of objects [1-3]. Here, the goal of selection is to provide optimal recognition.

2. STUDY PROBLEM STATEMENT

In a working dictionary, only the attributes that are, on the one hand, most informative and, on the other hand, affordable (e.g. in terms of costs) for measurement should be used. The definition of a feature dictionary in the context of constraints on the cost of observational hardware has peculiarities.

If the attributes of objects are denoted by δ_j, $j = 1, 2, ..., N$, then each object in the N-dimensional feature space can be represented as a vector $x = (x_1, x_2, ..., x_N)$, with coordinates characterizing the properties of objects.

The metrics for the determination of a measure of proximity or similarity of objects in the N-dimensional feature vector space are introduced. It is possible to use the Euclidean metric

$$d^2(w_{pk}, w_{ql}) = \sum_{j=1}^{N} (x_{pk}^{j} - x_{q_l}{}^{j})^2, \tag{1}$$

$$p, q = 1, 2, ..., m; \quad k = 1, 2, ..., k_p; \quad l = 1, 2, ..., k_q,$$

where x_{pk}^{j} are the values of the j-th attribute of the k-th object of the p-th class, i.e. object of the q-th class, i.e. object w_{ql}.

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As a measure of proximity between objects of a given class $\Omega_p, \quad p=1,\ 2,\ ...,\ m,$ we will use the value

$$S(\Omega_p)=\sqrt{\frac{2}{k_p}\ \frac{1}{k_{p-1}}\sum_{k=1}^{k_p}\ \sum_{l=1}^{k_p} d^2(w_{pk}, w_{pl})}\ , \tag{2}$$

which has the meaning of root mean square scatter of the class or mean square dispersion of objects within the class Ω_p, as a measure of proximity between objects of a given pair of classes Ω_p and Ω_q, $p,\ q=1, ...,\ m,$ the value

$$R(\Omega_p,\Omega_q)=\sqrt{\frac{1}{k_p\, k_q}\sum_{k=1}^{k_p}\sum_{l=1}^{k_q} d^2(w_{pk}, w_{ql})}\ , \tag{3}$$

which has the meaning of the root mean square scatter of objects of classes Ω_p and Ω_q.
The set of features of the objects used in the working dictionary can be described by an N-dimensional vector $\mathrm{A}=(\alpha_1,\alpha_2,...,\alpha_N)$ the components of which take values 1 or 0, depending on whether the corresponding feature of the object is available or not.
Taking into account the α square of the distance between the two objects w_{pk} and w_{ql}

$$d^2(w_{pk}, w_{ql})=\sum_{j=1}^{N}\alpha_j (x^{(j)}{}_{pk}-x^{(j)}{}_{ql})^2\ . \tag{4}$$

Consequently, root mean square scatter of Ω_p class and objects of the classes Ω_p and Ω_q can be written as

$$S(\Omega_p)=\sqrt{\frac{2}{k_p}\ \frac{1}{k_p-1}\sum_{k=1}^{k_p}\sum_{l=1}^{k_p}\sum_{j=1}^{N}\alpha_j (x^{(j)}{}_{pk}-x^{(j)}{}_{pl})^2}\ , \tag{5}$$

$$R(\Omega_p,\Omega_q)=\sqrt{\frac{1}{k_p}\ \frac{1}{k_q}\sum_{k=1}^{k_p}\sum_{l=1}^{k_q}\sum_{j=1}^{N}\alpha_j (x^{(j)}{}_{pk}-x^{(j)}{}_{pl})^2}\ . \tag{6}$$

It can be assumed that the cost of using a feature is proportional to its informativeness, i.e. the number of features of the objects that can be identified using it. This assumption (leaving aside the issue of the accuracy of the observing instruments) is quite general.
Thus, the costs of using the features

$$C=C(\alpha_1,...,\alpha_N)=\sum_{j=1}^{N} C_j\,\alpha_j\ , \tag{7}$$

where C_j are the costs of determining the j-th feature.
As an indicator of the quality or efficiency of the designed recognition system we consider a functional, which in general depends on the function $S(\Omega_p),\ R(\Omega_p,\Omega_p)$ of the decisive rule $L(w,\{w_g\})$

$$I=F[S(\Omega_p);\ R(\Omega_p,\Omega_q);\ L(w,\{w_g\})]\,. \tag{8}$$

Let the value $L(w,\{w_g\})$ be a measure of proximity between a recognizable object w and a class $\Omega_g,\ \ g=1,\ 2,\ ...,\ m,$ given by its objects $\{w_g\}$. As this proximity measure, consider the quantity

$$L(w,\{w_g\})=\sqrt{\frac{1}{k_g}\sum_{g=1}^{k_g} d^2(w,w_g)}\ , \tag{9}$$

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which is the root mean square distance between the object *w* and the objects of the class Ω_p.
The decisive rule is as follows $w \in \Omega_g$, if

$$L(w,\{w_g\}) = extr\ L(w,\{w_i\}) . \qquad (10)$$

It is important to note that decreasing the value $S(\Omega_p)$, "shrinking" the objects belonging to each given class, while increasing $R(\Omega_p,\Omega_q)$, i.e. "diluting" the objects belonging to different classes provides, ultimately, an improvement in the quality of the recognition system. Therefore, improving the performance of the system will be associated with the achievement of the extremum of the functional *I*.
The statement of the research problem can be formulated as follows.
Let the set of objects is subdivided into classes Ω_i, $i = 1, ..., m$, all classes are a priori described in the language of attributes x_j , $j = 1, ..., N$, and funds are allocated to create technical means of observation, the value of which is equal to C_0. It is required, not exceeding the allocated amount of money, to construct a working dictionary of features, which provides the highest possible efficiency of the system.
Thus, the problem is reduced to the finding of conditional extremum of the functional of the form (8), i.e. to the definition of *A* implementing $\underset{\alpha}{extr}\ I = \underset{\alpha}{extr} F\ [S(\Omega_p);\ R(\Omega_p,\Omega_q);\ L(w,\{w_g\})]$

$$C = \sum_{j=1}^{N} C_j \alpha_j \le C_0 . \qquad (11)$$

Possible types of the functional. Let us consider some particular kinds of functional (11). If the required efficiency of the recognition system can be achieved by a more compact arrangement of objects of each class under some conditions with respect to the value of $R(\Omega_p,\Omega_q)$, then the problem is reduced to finding

$$\min_{\alpha}\ \max_{i=1,...,m}\ [S(\Omega_i)] \qquad (12)$$

at

$$\sum_{j=1}^{N} C_j\, \alpha_j \le C_0 \text{ and } R(\Omega_p,\Omega_q) \ge R_0^{(pq)} . \qquad (13)$$

If the required system efficiency can be achieved by "removing" objects belonging to different classes from each other, subject to certain conditions regarding the value of $S(\Omega_i)$, $i = 1,... ,m$, then the problem is reduced to finding

$$\max_{\alpha}\ \min_{p,q=1,...,m}\ [R(\Omega_p,\Omega_q)] \qquad (14)$$

at

$$\sum_{j=1}^{N} C_j \alpha_j \le C_0 \text{ and } S(\Omega_i) \le S_0^i . \qquad (15)$$

If the proper efficiency of the system can only be achieved by increasing the ratio of distances between classes to the rms scatter of objects within the classes, then the problem is reduced to finding

$$\max_{\alpha}\ \min_{p,q=1,...,m} \left[\frac{R^2(\Omega_p\ \Omega_q)}{S(\Omega_p) S(\Omega_q)} \right] \qquad (16)$$

at

$$\sum_{j=1}^{N} C_j \alpha_j \le C_0 . \qquad (17)$$

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3. SOLVING THE PROBLEM OF SELECTING INFORMATIVE ATTRIBUTES CHARACTERISING THE STATE OF THE LC REM PROCESSES

The problem considered above is a generalization of the nonlinear programming problem. The optimality conditions for it can be formulated as follows: for vector C^0 to be an optimal strategy, it is necessary that there exist a scalar $\beta \geq 0$ and a vector $\mu = \{\mu_1, ..., \mu_n\}$ such that

$$\left.\begin{array}{l} \left[\sum\limits_{r=1}^{n} \mu_r \rho_r^j\right] \dfrac{dP_j(C_j^0)}{dC_j} = \beta, \;\; j = 1, ..., N_p; \\ \sum\limits_{j=1}^{N_p} C_j^0 = C_0\,; \\ \sum\limits_{r=1}^{n} \mu_r = 1, \mu_r = 0, if\, \mu = \{\mu_1, ..., \mu_n\} \sum\limits_{j=1}^{N_p} \rho_r^j P_j(C_j^0) > W(C^0). \end{array}\right\} \tag{18}$$

The introduction of a scalar β and a vector μ increases the number of unknowns C_j^0, μ_r and β to the value $N_p + n + 1$. However, the number of equations equals the number of unknowns, since for any r either $\mu_r = 0$, or

$$\sum_{j=1}^{N_p} \rho_r^j \, P_j(C^0{}_j) = W(C^0)\,. \tag{19}$$

Thus, the solution of the system of equations (18) makes it possible to determine the composition of the features of the working dictionary and the optimal allocation of the costs of the observational means of the recognition system, under the assumption of dependency $P_j = P_j(C_j)$ and limitations on the total cost of these means.

With the constraints of being able to use the entire feature vocabulary, the task arises of selecting a limited list (up to 2-3 features). Here we can focus on the location of individual components of the feature vector with respect to the boundaries of the serviceability area of the monitoring objects.

Since at the boundary value of the parameter y_{bd}^j, the end of the vector X must be located at the boundary of the serviceability area, the following equation must be fulfilled

$$x^i{}_{гр} = a_j^i y^j{}_{bd}\,. \tag{20}$$

In statistical estimation, an additional criterion for selection can be the correlation coefficient r_{ij} between the parameters. As the maximum correlation coefficient provides the maximum amount of information

$$J(y^j) = H(y^i) - H(y^j / y^i)\,, \tag{21}$$

contained in the parameter y^i. Here $H(y^i)$ – initial entropy; $H(y^j / y^i)$ – conditional entropy of the object after measurement of the parameter y^i.

The use of binary correlation algorithms makes it possible to formalise and automate the input, processing and recognition of the resulting image with the participation of the decision maker (DM).

4. IDENTIFICATION OF LC REM PROCESSES STATUS

Identification of LC REM implies the existence of rules defining the states of the REM. The attributes to distinguish the states of the monitored object are the performance indicators, which for the allocated state will have a given or extreme value. In order to identify REM states in the monitoring process, it is necessary to check whether the observed parameters are those that provide performance criteria, whether they belong to the set on which the value of

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performance indicators will have set or extreme values. Functional analysis methods can be used to solve state estimation problems [4, 5].

Objects of observation are REM parameters and characteristics can be considered as points of vector and function spaces. For all possible pairs of points on the set Q, there exists a binary relation of comparative efficiency: a point x is more efficient than y if and only if $(x, y \in \Phi)$ or in another notation $x \, \Phi \, y$. In providing LC REM, the problem of selecting the kernel, the set of maximal elements from X by the binary relation $\Phi : X^* = Max\,(Q, \Phi)$. It is assumed that a solution to the problem exists, i.e. the set X^* is not empty. In many problems, it can be assumed that the solution - the set X^* - consists of a single element, and the relationship between the elements is established using functionals $\Lambda(x)$. For example, a point x is more efficient than y when $\Lambda(x) < \Lambda(y)$ or $\Lambda(x) > \Lambda(y)$. It can be shown that in the problems of determining effective points $x_0 \in X^*$ in the presence of constraints $x \in Q_1$, the functional $f = \lambda \Lambda'(x_0)$, where $\Lambda'(x_0)$ is the Frechette derivative at the point x_0, is a reference functional to Q_1, at the point x_0 (i.e. $(f, x_0) < (f, x)$ for all $x \in Q_1$).

Thus, the task of analysing the observation results during monitoring comes down to determining the reference functionals at the observation points, which makes it possible to assess the deviation of the observed points from the effective ones.

In terms of functional analysis: let Q be a set in a linear topological space E, E' – a conjugate space, $x_0 \in Q$ – an outermost point of Q, K_b – a cone of possible directions in Q at the point x_0, K_k – a cone of tangent directions for Q at x_0. If the set of linear functionals supported to Q at the point x_0 denote by Q^*, then $Q^* = f \in E', f(x) \geq f(x_0)$ for all $x \in Q$, i.e., the support functional and the boundary point $x_0 \in Q$ allow us to distinguish the set Q. It can be shown that if Q is a closed convex set. then $Q^* = K_k{}^*$, i.e. forms cones formed by the set of linear functionals supported by Q at x_0. The cone of tangent directions can be defined by the Frechette derivatives of the operators (convex functions) that bind the sets of parameters and performance measures.

Let us consider methods of finding K^* for ways of setting K with different functionals.

Variant 1: For a cone of decreasing directions K_0. A functional $\Lambda(x)$ in linear space E has a derivative $\Lambda'(x_0, g)$ at a point x_0 in the direction g, i.e. there exists

$$\lim_{\varepsilon \to +0} \frac{\Lambda(x_0 + \varepsilon g) - \Lambda(x_0)}{\varepsilon} = f(x_{0,}g). \tag{22}$$

$\Lambda(x)$ satisfies the Lipschitz condition in the region x_0 (for a certain $\varepsilon_0 > 0$ it will be $|\Lambda(x_1) - \Lambda(x_2)| \leq \beta \|x_1 - x_2\|$ at all $\|x_1 - x_0\| \leq \varepsilon_0$, $\|x_2 - x_0\| \leq \varepsilon_0))$ and $\Lambda'(x_0, g) < 0$, then $\Lambda(x)$ – properly descending in x_0, and $K = \{g : \Lambda'(x_0, g) < 0\}$.

Variant 2. For a cone of possible directions. In the case of a set which is not defined by a functional. If Q is a convex set, then the set of decreasing directions K_b at a point x_0 has the form

$$K_b = \{\lambda(Q - x_0), \lambda > 0\},$$

(i.e. $K_b = \{g : g = \lambda(x - x_0),\ x \in Q, \lambda > 0\}$).

Variant 3. For a cone of possible directions. In the case of definition Q by means of affine sets: $E = E_1 \times E_2$, E_1, E_2 are linear topological spaces, the set of efficiency features is defined in E_2, D is a linear operator from E_1 to E_2, $K = \{x \in E,\ \ x = (x_1, x_2) : Dx_1 = x_2\}$, $K^* = \{f \in E', f = (f_1, f_2):\ \ f_1 = -D^* f_2\}$, and as a reference separating function one can use

$$f(x) = (-D^* f_2, x_1) + (f_2, x_2) = -(f_2, D^* x_1 - x_2).$$

The application of this function to partition the sets in the parameter space and to formulate rules that establish a correspondence between the parameter sets and the values of the performance indicators can provide state identification in the LC REM monitoring process.

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Variant 4. For a cone of tangent directions. $P(x)$ - operator from E_1 to E_2, differentiable in the neighborhood of a point x_0, $P'(x)$ is continuous in the neighborhood of x_0, and $P'(x_0)$ maps E_1 to all E_2 (i.e. a linear equation $P'(x_0)g = b$ has a solution g for every $b \in E_2$), the set of tangent directions K to the set $Q = \{x : P(x) = 0\}$ at a point x_0 is a subspace $K = \{g : P'(x_0)g = 0\}$.

Variant 5. For a tangent direction cone is a typical case. Let $x \in R^m$, $Q = \{x : G_i(x) = 0,\ i = 1,...,n\}$, where $G_i(x)$ – functions continuously differentiable in the vicinity of a point x_0, $G_i(x_0) = 0$, $i = 1,...,n$, and vectors $G_i'(x_0)$, are linearly independent. Then $K = \{g \in R^n : (G_i'(x_0), g) = 0, i = 1,...,n\}$. Here $E_1 = R^m$, $E_2 = R^n$, $P(x) = (C_1(x)$, ..., $G_n(x))$, $P'(x_0)$ is a matrix $m \times n$, the *i*-th column of which is equal to $G_i'(x_0)$.

Variant 6. In the process of monitoring, it is necessary to determine whether the effective value of the function characteristic REM $w(z)$, in the simplest case the extreme value of the differentiable target function of one variable, is ensured by checking whether the derivative is equal to zero at the observed value of the parameter. For multivariate target functions and their arguments, this problem can be considered within the framework of set theory and functional analysis.

The formalization in the problem of optimal tuning observation, as one of the LC REM processes, is that it is necessary to evaluate the optimality of the tuning process function $v(z) \in M$ where z is the parameter defining the numerical value of the required characteristic $w(z)$ of the tuning object to provide such a phase trajectory which provides equality $w(0) = c$, $w(Z) = d$, and the extremal value of the integral functional $\int_0^Z \Phi(w(z), v(z), z)dz$, in the presence of the relation given by the differential equation $\frac{dw(z)}{dz} = \varphi(w(z), v(z), z)$.

In problems requiring a maximum fit between the optimised characteristic and some desired one, the criterion of minimum standard deviation is used

$$W_2(X) = \overline{(Y(X) - Y^*)^2}, \tag{23}$$

where Y^* – the desired or required specification value of the characteristic.
For a characteristic defined by a discrete set of points, the target function

$$W_2(X) = \frac{1}{N}\sum_{i=1}^{N} \gamma_i (Y(X, p_i) - Y_i^*)^2, \tag{24}$$

where N – number of sampling points of the independent variable p;
$Y(X, p_i)$ – value of the optimised characteristic at the *i*-th point of the sampling interval;
γ_i – the weighting coefficient of the *i*-th value of the optimised characteristic, reflecting the importance of the *i*-th point compared to the others (as a rule, $0 < \gamma_i < 1$).

In some optimization problems, it is necessary to ensure that the characteristic to be optimized does or does not exceed some given level. These optimality criteria are implemented by the following functions:
- to ensure that a given level is exceeded

$$W_3(X) = \begin{cases} 0 & at \quad Y(X) \geq Y_L^*, \\ (Y - Y(X))^2 & at \quad Y(X) < Y_L^*; \end{cases} \tag{25}$$

- to ensure that the set level is not exceeded

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$$W_4(X) = \begin{cases} 0 & at\ Y(X) \le Y_U^*, \\ (Y(X) - Y_U^*)^2 & at\ Y(X) > Y_U^*, \end{cases} \quad (26)$$

where Y_L^*, Y_U^* – lower and upper limits of the permissible area for the characteristic $Y(X)$.
If it is necessary that the characteristic to be optimised lies within a tolerance zone (corridor), a combination of the two previous optimality criteria is used

$$W(X) = \begin{cases} 0 & at\ Y_L^* \le Y(X) \le Y_U^*, \\ (Y(X) - Y_U^*)^2 & at\ Y(X) > Y_U^*, \\ (Y_L^* - Y(X))^2 & at\ Y(X) < Y_L^*. \end{cases} \quad (27)$$

Where only the shape of the curve needs to be realised, while ignoring the constant vertical displacement, the shift criterion is used

$$W_6(X) = \sum_{i=1}^{N} \gamma_i (Y_i^* - Y(X, p_i) - Y_{av})^2, \quad (28)$$

where $Y_{av} = \frac{1}{N} \sum_{i=1}^{N} (Y_i^* - Y(X, p_i))$.

Important characteristics of the computational process and, first of all, the convergence of the optimization process depend on the type of the target function. Signs of target function's derivatives on controllable parameters do not remain constant in the whole admissible domain, the latter circumstance leads to their ravine character (e.g. circuit design problems), which leads to high computational costs and requires special attention to the choice of optimization method.

Another peculiarity of the target functions is that they are usually multi-extreme and along with the global minimum there are local minima.

Multicriteria optimization problems constitute the general class of problems of identification of the set of efficient solutions. They are characterized by the fact that a binary relation on the set of alternatives from which a choice is to be made is connected with a set of indices - criteria forming a vector efficiency criterion. This binary relation can be generated in various ways. Thus, if

$$W(x) = (W^1(x), \ldots, W^m(x)) \quad (29)$$

vector criterion on set X, then the binary relation may be a Pareto relation or a Slater relation. In other cases, the binary relation on X is given by the DM preference system. It is assumed that the primary source of information is a person who has sufficient information to make a (single) decision. Identification of the DM preference system is one of the major problems in multicriteria problems. Typically, DM preference elicitation procedures are constructed in the language of vector evaluation of alternatives, i.e., based on vector criterion values.

Decision making by DM is facilitated by finding a Pareto set or a Slater set using criterion (29), here methodological problems are largely lost as the notion of solving a multicriteria problem is already well defined. What remains are the computational difficulties typical of extreme problems.

Techniques for solving the task of searching for effective (Pareto-optimal) and weakly effective (Slater-optimal) alternatives are being intensively developed [6-8], and there are programs, software packages and software systems that have been implemented on computers.

The algorithms based on scalarization - reduction to the parametric family of scalar optimization problems - are of great "clarity".

From the convex analysis it follows that if $x_* \in P(X, W)$ – is an effective point in a linear multicriteria problem (with linear criteria in the polyhedron X), then there exists a vector Λ

$$\lambda \in \Lambda = \left\{ \lambda \in E^m / \lambda_i > 0,\ i = 1, \ldots,\ m;\ \sum_{i=1}^{m} \lambda_i = 1 \right\},$$

such that x^* is a solution to a linear and non-linear programming problem

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$$\sum_{i=1}^{m} \lambda_i W^i(x) \to \max_{x \in X} . \qquad (30)$$

Inversely, for any $\lambda \in \Lambda$ solution of problem (30) is an effective point.

It follows that well-developed linear and nonlinear programming methods can be used to find $P(X,W)$ and use the result as an effective set in the process of mapping the situation related to the location of the set of real values of the feature parameters, relative to the set of their effective values in the implementation of LC REM monitoring.

5. CONCLUSIONS

Methods for solving problems of selecting informative features for monitoring LC REM, by classifying the REM states and LC processes in the feature space, each of which has a certain significance, which allowed to find a comprehensive criterion and formalize the selection procedures.

The methods of identification of REM states that interpret them as elements of conjugate linear spaces and set initial sets by linear and non-linear functionals have been improved, making it possible to formulate rules for separation of sets in the space of states and the rules that establish correspondences between the sets of parameters and values of LC REM performance. Application of these rules makes it possible to construct algorithms for optimisation of LC REM performance indicators.

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