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Original Article

Suboptimal Biomedical Diagnostics in the Presence of Random Perturbations in the Data

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Abstract *- The object of this study is medical automatic diagnostic systems, and the subject is automated techniques for diagnosing diseases designed for a countable amount of training and control samples. The necessity to introduce more and more used methods of state assessment and diagnostics of pathological change in research of the human central nervous and cardiovascular apparatus is obvious. The study results make it possible to obtain clinical, functional analysis methods. However, the problem is that they are very complicated in technical execution. This work conducted a set of studies to develop a formal description of methodological approaches to form the image of automated diagnostics of medical and biological systems subjected to random perturbation. This study reviewed current diagnostic methods of the main diagnostic system elements. Research on the development of statistical recognition systems, providing a link of the detection reliability with the necessary constraints to achieve this, is relevant. The study showed that the formation of features using a nonlinear transformation procedure in initial signal spaces and a stochastic coding method of classification of the features is based on calculating the correlation moment using the correlation functions of signs. Given this fact, we propose a methodical solution, which does not imply achieving a clear optimum under an arbitrary distribution of a priori data. This fact helps construct the suboptimal algorithm of the engineering system.*

Keywords *- Biomedical signals, Functional medical diagnostic methods, Recognition methods, Statistical data processing, Stochastic coding.*

1. Introduction

Due to the intensive development and simplifications used in various subject areas and technical systems, their impact on people as an integral part of anthropho-technical systems is increasing. The most sensitive are psychophysical or physical impacts on the human central nervous and cardiovascular systems. That testifies to the necessity of solving complex tasks aimed at introducing more effective methods of state assessment and diagnostics of pathological changes in the functioning of these systems.

The peculiarity of diagnosing such diseases is that symptoms may be difficult to distinguish at the initial stages. In these cases, medical diagnostic techniques rescue, allowing objective analysis of the patient's condition. Methods of technical diagnostics are the most difficult in terms of technical performance but give quite objective results [1]. At the same time, the development of the latest methods strongly depends on the state of medical equipment for their implementation [2]. When developing new diagnostic schemes aimed at working with information regarding functional diagnostics – ECG, EEG, and electromyography, the task of developing algorithms is formed. In addition, new tools are necessary to automate the decision-making process, for example, when analyzing a query "whether the aggregate of an analyzed signal refers to a class of measured signal to a certain condition of an investigated internal organ of a person" [3]-[5].

Thus, signals taken from primary transformations when researching the human cardiovascular system can be considered a class of random vector processes. This fact implies the necessity of research to develop models of medical signals corresponding to actual physiological processes and diagnostic techniques using automatic systems. The latter would allow the implementation of "flexible" algorithms for patient diagnosis or to conduct long-term monitoring of the patient's condition in residential treatment [6], [7]. Here, optimizing temporal and spatial recognition parameters in medical diagnostic systems is particularly important because these parameters, along with a given reliable recognition, have a direct and most favorable effect on the quality and reliability of diagnosis.

There are well-known large-scale algorithms aimed at system analysis of medical data. They are designed to automate diagnostic activities, which are the process of determining whether a selected object belongs to one of the diagnostic classes, detecting, and localizing changes that lead to the transition of the studied object from the "normal" to the "pathology" class [8]-[10].

Thus, it is necessary to develop the following methods:

- Constructing an efficient algorithm for competent recognition of medical biotic pulses;
- Providing a functional technical implementation with time resource limitations in the preparation taken into account and making weighted decisions.

In this connection, developing the listed techniques is relevant and is the goal of the ongoing research. This paper has the following structure:

- In the second section, a review and comparative analysis of existing methods for recognizing biotic signals in diagnostic tasks is performed, the main stages of recognition methods describes, and the need for more in-depth research aimed at developing statistical recognition systems is shown;
- The third section describes the objects and methods of research and substantiates the need to develop approximate non-parametric recognition methods, somewhat inferior to known non-parametric algorithms but at the same time significantly superior to them in terms of simplicity of technical implementation;
- Further, in subsection 3.1, a formalized description of the proposed methodological approach is given, and in subsection 3.2, a description of the results obtained in the form of decision rules based on the principles of minimum distance and hyperspheres is given;
- The fourth section presents an analysis and discussion of the results obtained on the formation of classification features on the principles of measuring correlation moments using sign correlation functions;
- The final sections of the work are conclusions, information about the source of funding and a list of information sources used.

2. Overview of Modern Diagnostic Methods as Base Elements of the Diagnostic System

The working process of a diagnostic system defines according to the human learning ability and the ability to divide the provided objects into classes according to different features. Then, based on comparative analysis of a posteriori information about each incoming object or concept, the a priori class descriptions recognize that the given object belongs to a particular class [11], [12]. The typical, most common functions in a medical diagnostic system are a collection of measurement information, recording as electromagnetic signals, their conversion [13] (preprocessing), quantization, time sampling, elimination of statistically excessive data, a transformation of transmission through communication channels and calibration of measurement paths [14], other and subsequent information processing steps, accumulating information for current processing and long-term storage, interpreting results, and others.

Secondary processing based on pattern recognition methods [15], [16] plays a particular role in the transformation of the initial information within this system, the nature of which is determined by the study objectives and goals, as well as by several specific features, for example:

- The objects under study are usually complex in terms of changing their characteristics in one class;
- Each recognition system is adapted to analyze only certain phenomena and objects, i.e., recognized objects of different classes are initially of one nature;
- A priori information about a class is usually scarce, forcing decisions based on poor information.

An essential feature of actual diagnostic and other recognition tasks is that random perturbations inevitably arise in observations, which stochastic nature affects all stages of processes [17], [18]. Therefore, the range of pattern identification methods that find practical application, including the creation of medical diagnostic systems, is quite broad. It includes methods of determinism based on the use of potential function and algorithms of perceptron recognition and syntactic structural, linguistic recognition [19] as well as statistical [20], logical recognition algorithms based on the calculation of estimates, and algebraic methods [21], [22].

In statistical recognition systems, to determine the dimensionality of the features of the space in the process of optimizing the tasks, the following provisions are used:

- Chernov's upper bound on classification errors [23];
- The total probability of making possible errors in the process of classification by the dimension of symptom space p, the size of the control samples n, and the interclass distances;
- The Mahalanobis distance [24] helps quickly and qualitatively show the potential for monitoring errors through the asymmetry of increasing training and control sample volumes and the importance of features. It is possible to use an expression of error recognition probabilities by the training and control sample volume and distance between classes and an estimate of error classification probabilities by the control sample volume to determine preparation and decision-making time.

To correctly solve the problems of classification of signals of medical and biological optional processes, we use the main developments obtained in the study of the statistical theory. Focusing on the scientific foundations, we can conclude that statistical pattern recognition should be divided into three main stages [25], [26] – detection of spatial features, training of recognition systems, and selecting weighted and accurate solutions reflected in Table 1.

Table 1. The main stages of recognition based on statistical decision theory

The main stages of the statistical recognition process	**The task of the stage**	**The nuances of the solved task**	**Variants of the task solution**
Creating a feature space	Create an initial list of features from the number of available to measure characteristics of the recognized object ($Y_1, Y_2, \ldots, Y_q$) – the most complete and clear reflection of all the most important properties for recognition.	Increasing the feature sizes may be the only way to increase the reliability to the required level. Increasing the feature space increases the computational complexity of the recognition procedure and the overall costs of obtaining the required number of observations. The requirements for the dimensionality of the feature space and minimizing the costs of measurements are contradictory.	Classical formation in conditions of complete a priori information (from primary features $Y_1, Y_2, \ldots, Y_q$ ($p<q$) of a new set of features $Y_1, Y_2, \ldots, Y_q$ optimal by some criterion $J(Y_1, Y_2, \ldots, Y_q)$. This criterion should be interpreted as a "distance" between classes measured by a space feature, or "diameter" or "volume" of the area Ω_m occupied by a class, which uses: the mean square error of approximation of the primary by the new features; the mean inter-class distance; the distance of observations within classes; the entropy of one of the analyzed classes to the other, and others.
Training in the diagnostic system	Overcome a priori uncertainty of the analyzed class, using the information about it contained in the training samples, and creating reference descriptions of classes; applying them in decision rules determines their type.	The possibility of parametric a priori uncertainty of the observed cumulative sample value, by the results of the preliminary analysis on which it turns out possible at least some approximation to establish the form of the distribution law of the sample, here training aims to estimate the parameters of this law. The possibility of non-parametric a priori uncertainty of the observed aggregate sampling value, in the absence of a priori information not only on the parameters but also on the form of their distribution law.	Parametric recognition methods and training methods of normally distributed sampling, due to which the task of parametric education in such conditions is to calculate the characteristics (mean-variance, covariance matrices). The traditional non-parametric recognition method is practically not used to correct the real-world diagnostic systems of random image distributions because it does not consider the stable dependence of the feature in the algorithm. However, this problem can be solved by finding transformations that normalize these distributions. That allows applying parametric recognition methods and optimization effectively, where the detection reliability is expressed analytically through recognizable classes and interclass distances.
Decision-making	Determine a decision rule to evaluate a control set of observations in a class of mutual exclusivity considering the a priori information and parameters extracted during preparation. The choice of the type of solution involves setting the likelihood ratio L and comparing it to a threshold value defined through a qualitative criterion.	Defining likelihood ratio L of conditional common n-dimensional probability densities $\omega_n(x_1, x_2, \ldots, x_n \mid s_j)$ of sample values $x_1, x_2, \ldots, x_n$ under the condition that they belong to class s_j, usually not known a priori.	The decision rule with a particular limit compares not the relative likelihood ratio L, but its estimate $\hat{L}$ obtained in the learning process.

3. Objects and Methods of Research

Although theoretical and practical research on pattern recognition is developing at a high level, the quality of diagnostics depends significantly on the skill and qualification of the specialists involved in solving the problems. That is, medical automatic diagnostic systems, the object of research, are not purely technical but human-machine systems. The process being unformalized, is analyzed by humans. The subject of this study is the automated methods of diagnosing diseases aimed at the final monitoring of the number of training and other samples.

This work solves many problems, applying mathematical techniques and the basics of probability theory, the theory of statistical pattern recognition, and functional diagnosis. They are necessary for forming qualitative feature space and norm resolution for the current recognition systems operating under uncertainty within the distribution of detection signals and a limited number of samples.

If to generalize the situation, the main task of recognition is to form a feature space of dimension p, to train the recognized system using training samples of volume *mk*, and to decide that the control sample of volume *nk* belongs to one of classes *sk*. Recognition errors may occur, with some probability depending on many factors. Minimizing the sum of observations is necessary to provide an automated diagnosis approximated to the optimal engineering solution, which solves the problem.

3.1. Formalized Description of the Methodological Approach

A successful solution to the issue of fixing a random signal directly depends on the correctness of selecting an effective feature system, which depends on the initial system of features.

The technique of nonlinear transformation concerning the primary features provides an opportunity to unilaterally make a deeper description of signals and their classification and demonstrate the initial multidimensional spatial features into one-dimensional ones. Here, it is possible to apply the distribution transformation function of auxiliary processes selected for diagnostic measures within the framework of parallel methodology.

Providing a practical implementation of this approach for constructing a decision rule, clustered samples in conditions of priori dependence is an approximation procedure for creating a likelihood function $\omega^i(\vec{y}) = \omega\,(\vec{y}\,/\,f^i)$ as an unknown function of the input signal f^i, determined by the probability and belonging to the signal space *F*. Calculation of the expansion coefficient $\vec{d}_k^i$ in the Fourier series of a given likelihood function considered according to the accepted orthonormal system $\{e_k(\vec{y})\}$ contributes to fast search and estimation of the functional likelihood applied in the following formula:

$$\hat{\omega}^i(\vec{y}) = \hat{\omega}(\vec{y}\,/\,f^i, \vec{d}^i)\,,\; i = 1, 2, 3, \ldots, M \tag{1}$$

Where the evaluation of the decomposition coefficient d_k^{i*}, given by the training space selection $\vec{y}$, is definable from the expression below:

$$d_k^i = \frac{1}{n_i} \cdot \sum_{\varepsilon=1}^{n_i} e_k\,(\vec{y})\,,\; k = 1, 2, 3, \ldots, Q \tag{2}$$

Thus, for simple loss functions, which require a minimum of average recognition errors, the decision rule is definable in the following form:

$$\omega_i \cdot \omega(\vec{x}\,/\,f^i, \vec{\alpha}^{*i}) \geq \omega_l \cdot \omega(\vec{x}\,/\,f^l, \vec{\alpha}^{*l})\,,\; l = 1, 2, 3, \ldots, M\;.\; l \neq I \tag{3}$$

Here $\vec{\alpha}^*$ is the maximum likelihood value of a random vector parameter $\vec{y}$.

Depending on the expression of the likelihood function estimates, this solution has the following description:

$$\omega_i \cdot \omega(\vec{y}\,/\,f^i, \vec{d}^{i*}) \geq \omega_l \cdot \omega(\vec{y}\,/\,f^l, \vec{d}^{i*}) \tag{4}$$

The quality of approximation of functions $\omega^i(\vec{y})$ using the chosen basic system is connected with the members of group *Q*, more precisely, with their number. However, a significant increase in the signal $\vec{y}$ size significantly increases the labor intensity of operations: one has to study functions $e_k(\vec{y})$ from many parameters.

The most rational approach to implementing such algorithms is to use simple dependencies. They are necessary for the systematic reduction of values of initial class descriptions and at the stage of resolution of the search for the optimal base function system $e_k(\vec{y})$ of interest, providing an opportunity to solve the problem using the least complicated technical implementation.

It is necessary to approximate the likelihood function by the scheme of instant functions, which is currently a sufficiently effective technique for the technical execution of estimates, being stochastic coding. The problem of forming the system of features based on the method of stochastic codes, directed on the distribution of a complex signal, is possible to present as follows. In the process of monitoring to select the symptoms of particular stationary signals $X(t)$ with one-dimensional probability density $\omega_x(X)$ and ergodicity characteristics, we obtain the updated symbolic process:

$$\operatorname{sgn} Z = \begin{cases} 1, & X > H; \\ 0, & X \le H, \end{cases} \tag{5}$$

Here $Z = X - H$; $H(t)$ presents some reference processes $\omega_H(H)$;

At definite X and H, when $X = x$ and $H = \eta$, the dependence takes the following form:

$$\operatorname{sgn} Z = z(t) = \begin{cases} 1, & x(t) > \eta(t); \\ 0, & x(t) \le \eta(t). \end{cases} \tag{6}$$

based on the performed transformations related to revealing the arithmetic expectation sgn$Z$, its conditional expectation is equal $M[\operatorname{sgn}Z|x] = P[\eta<x]$, if the cumulative distribution $F_\eta(x)$ of random variables η is equal to:

$$P(\eta < x) = F_\eta(x) = \int_{-\infty}^{x} \omega_\eta(\eta)d\eta \tag{7}$$

Furthermore, the expression of mathematical expectations of a random process subjected to stochastic coding is as follows:

$$M[\operatorname{sgn} Z] = \int_a^b M[\operatorname{sgn} Z\,|x]\omega_X(x)dx \tag{8}$$

Where $[a, b]$ is the distribution interval of the analyzed signal $X(t)$.

The results obtained after implementing several arithmetic transformations of the example provide an opportunity to conclude the presence of the possibility to determine the average significance of random functions $X(t)$:

$$\hat{M}[X] = \hat{M}[\operatorname{sgn} Z] \tag{9}$$

Now it is clear that by functional varieties, without changing the measuring structure, it is possible to obtain estimates of moments of the most diverse order.

In the active application of stochastic codes, the estimation variance of the measured moments increases noticeably. Here it becomes evident that the positive characteristics are the reduction of the excessive information process $X(t)$ in $\alpha = k/S$, where: K represents the digit of the representation $X(t)$ by the binary code, and S represents the sequence of the definable one-time process function $z(t)$.

It is important to note that in the used mathematical monitoring of the processes $z(t)$ obtained by the stochastic coding technique, the following happens: addition and reduction of characteristics in one way or another correlate with elementary operations. An example is the conjunction and counting of present pulses. We get an opportunity to create a simple probabilistic processor necessary for the statistical operational processing of information to extract effective symptoms.

3.2. Decision Rules Based on the Principles of Minimum Distance and Hypersphere

In any case, it is possible to construct a decision law considering information about the particular form of the law on the distribution of the features or considering the assumption of their normal distribution. For the selected images, the trend occurs in a single cluster formation with the center determined by the vector of mean value and the form determined by the covariance matrix. Here, the contours of equal density represent hyperellipsoids with the direction of the main axes determined by the eigenvectors of the covariance matrix and the length of these axes determined by their eigenvalues.

It is necessary to store the mean vector, the covariance matrix, and the scalar vector to implement a decisive function using information about a particular form of the law of distributions of features. In the framework of statistical theory, the decision class function characteristic is as follows:

$$\mathrm{d}_i(x) = \ln p(\omega_i) - \frac{1}{2}\ln|C_i| - \frac{1}{2}\Big[(x-m_i)'C_i^{-1}(x-m_i)\,,\ i = 1,2,\ldots,M; \tag{10}$$

Where C_i is the covariance matrix and the arithmetic expectation of the first class images, M is a quantitative measure of the classes.

In cases of different covariance matrices, the separating surface is the sum of the linear quadratic terms described by the hyperquadric. If the covariance matrices are the same for each $i = 1,2,\ldots,M$, i.e., $C_i = C$, then:

$$\mathrm{d}_i(x) = \ln p(\omega_i) + x'C^{-1}m_i - \frac{1}{2}\Big[m_i'C_i^{-1}m_i\,, \qquad i = 1,2,\ldots,M \tag{11}$$

This expression has many linear solutions. For implementing this decision rule, it is necessary to keep a mean vector, a covariance matrix for each class, and one scalar matrix.

If $C = I$, then I is a unity matrix. Let us take ω_i as the probability of occurrence of the class, i.e. $p(\omega_i) = 1/M$, then the example for the decision function has the following form:

$$\mathrm{d}_i(x) = x'm_i - \frac{1}{2}m_i'm_i\,, \qquad i = 1, 2, \ldots, M \tag{12}$$

This expression is the decision function of the classifier based on the minimum distance principle, the minimum distance method with a single class reference, in which the vector of the mean value of the images in the corresponding class acts as the reference. Therefore, it is necessary to store only the vector of the mean value of the images and a scalar vector equal to the norm of the expectation vector to store that decision rule in each class.

The implementation based on image gravitation and natural distribution to form clusters of the decision function of the identifier relies on the axiom of compactness of processes. Therefore, the optimal option here is to enter all items from the single class in a particular subset compiled from the total number of related spheres.

If a uniform density contour is a separating surface, it is possible to form this using an appropriate preparation algorithm. In determining this surface, identification involves calculating a density probability option $\omega(\vec{y}|A)$ at the available value $\vec{y}$ in the arsenal and comparing the obtained data with a certain threshold λ.

It is possible to use several application methods to form separating surfaces. However, the most preferred for this solution are approaches based on using the envelope of an elementary figure, especially a hypersphere. The equation of all such surfaces has the following form:

$$\sum (y_i - m_i)^2 = R^2 \tag{13}$$

or

$$\sum |y_i - m_i| = R_j \tag{14}$$

The volume reduction function of one of the areas is allowed for use as an optimality parameter P_G:

$$I = V_G + \lambda\left(\int_G \omega(\vec{y})\,d\vec{y} - P_G\right) \tag{15}$$

Where λ is the Lagrange multiplier.
Let us present the functional I in the following form:

$$I = \frac{2\pi^{n/2}}{\Gamma(n/2)\,n}R^n + \lambda\left(\int_G \omega(\vec{y})\,d\vec{y} - P_G\right) \tag{16}$$

Where $\Gamma(n/2)$ is the gamma function.

Therefore surface division is a secondary feature of efficiency enveloping elementary figures. Let us write the surface of elementary geometries in the form:

$$\sum_{i=1}^{n}\left(\vec{r}_i^{\,*} - m_{ij}^*\right)^2 - \left(R_{ij}^*\right)^2 = 0 \tag{17}$$

Where r_i^* is the estimate of the feature in the first reference distribution (i = 1,2,…,K); m_{ij}^* is an estimate of the arithmetic feature expectation in the first reference distribution for the j-th reference value (j = 1,2,…,M); R_{ij}^* is an estimate of the radius of the hyperbolized sphere.

The necessary characteristics for the future description of the own area look like this: G is the coordinates of the central sphere m_G, and R is the radius. We have these indices in the theoretical and practical mastering of the system detection device. The volume of such class areas predetermines the minimum possible radius $R_{i\ min}$, and the solution of the hyperbolic sphere method is based on getting the detected signal into its class area, marked with a radius $R_{i\,min}$. The whole process in the description and transformation looks like this:

$$\begin{cases} \sum_{i=1}^{n}\left(\vec{r}_i^{\,*} - m_{ij}^*\right)^2 - \left(R_{i\min}^*\right)^2 \le 0,\ x(t) \in \omega_j; \\ \sum_{i=1}^{n}\left(\vec{r}_i^{\,*} - m_{ij}^*\right)^2 - \left(R_{i\min}^*\right)^2 > 0,\ x(t) \notin \omega_j. \end{cases} \tag{18}$$

When overlapping class areas, it is necessary to perform a comparative analysis of the distance between their centers and choose the minimum. Based on the training, data obtain values R_j after estimating m_{ij}^* .

4. Analysis and Discussion of Findings

This paper is a set of studies on the formalization of methodological approaches to forming images with the possibility of effective technical utilization of automated diagnostic systems of biomedical sensors subjected to random perturbation.

The formation process uses the procedure of nonlinear change of the initial spatial pulse and stochastic coding techniques of symptom classification based on the principles of correlation momentum distribution through the option of correlation of signs. One-dimensional power of probability distribution, a variety of correlation possibilities, and an increased efficiency index are endowed with features guaranteeing the occurrence of correlation manifestations of the sign function.

This approach, despite the variance of the estimates of the measured moments increases, makes it possible to minimize the excessive description of the diagnostic processes; easier to implement the detection algorithm through the application of one-digit quantization, which gives the reporting on the situation.

According to the proposed methodological approach, the primary indicator of the quality of the recognized system, i.e., the reliability of its classification, is directly extrapolated to the decision rules by the proposed classification algorithm using the minimum distance method (12) or the hypersphere method (18).

The results of experimental studies related to the dependence of the reliability of the classifications when applying the decision functions (12) and (18) to the features correlation coefficient value show that it is appropriate to build the decision criterion on the minimum distances in the case of a weak correlation between coefficient and sufficiently significant overlap of the own class areas. On the other hand, the hypersphere method is preferable in the case of non-overlapping or minor overlapping of the own class areas.

For preparing an image visualization system with classification based on minimum distance and hypersphere methods, different approaches can be used to find estimates: maximum likelihood methods, method of moments, least squares method, Bayes method, minimum χ^2 method, and others. The presented results may be helpful in further research in developing telemedicine and decision-support systems in medicine [34, 35].

5. Conclusion

If the processing of biomedical signals in real-time is possible, it has to come with the price of considerable hardware and machine time costs. Thus, the practice brings forward the important task of building cost-effective systems to recognize heavy biomedical and other signals. Solving this problem requires investigating the issues of representation and processing of complex biomedical signals, developing promising methods for finding an efficient feature in the recognized signals, and investigating and optimizing algorithms for process and noise recognition.

This paper considers a set of issues on the construction of space features and decision rules in automated diagnostics of medical and biochemical signals and on the analysis of the possibilities of optimization and integration into the realities of individual diagnostic parameters in medicine. Now it is possible to use the results given below.

Analyzing the currently available methods of forming sufficient features for signal classification, the possibility of improving the quality of functioning of automatic diagnostic systems by applying the technique of nonlinear transformation of the primary spatial signal has become apparent. Furthermore, such measures promote the reduction of the excessive description of the received initial signal and time expenses of equipment at the resolution of situations with the classification of signals of biomedical origin.

The work has conducted a set of studies to develop formalized descriptions of methodological approaches to form features based on the stochastic coding method of image signals with the possibility of effective technical implementation of automated diagnostics of biomedical systems subjected to random perturbation.

The presented techniques under the random distribution of a priori information are not a claim for strict optimality. However, it is now possible to construct innovative engineering algorithms close to optimal.

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