Information System for Visual Analyzer Disease Diagnostics

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Abstract. The article is devoted to the problems of construction the recommendation information system for visual analyzer disease diagnostics by electroretinograms. The mathematical electroretinogram model in the form of linear stochastic process is constructed. Method of comparative analysis of electroretinogram angle coefficients as vectors in linear space providing ERG implementation selection before diagnostics is proposed. Angular coefficients and coefficients for orthogonal signal decomposition in the system of basis Chebyshev, Kravchuk, Lager functions are proposed for application. In order to make diagnostic decision the statistical method of hypotheses testing developed on the basis of likelihood ratio logarithm analyses (Neumann-Pearson criterion) is used.

Keywords: visual analyzer, electroretinogram, statistical hypothesis, linear random process

1 Introduction

Nowadays modern information technologies and IoT services have been or are being implemented actually in all healthcare spheres. Due to the information technologies use the doctors are able to carry out objective disease diagnosis, store and use selected information effectively at all stages of direct care. These are the overall information-recommendation systems which make it possible to provide selection processes, storage and processing of information as well as recommendations for proper diagnostic decision-making by doctors on the basis of received information.

2 State of research

The basis of the visual analyzer disease diagnostics is the comprehensive investigation at the early stages of pathology using the latest medical techniques, modern diagnostic equipment for reliable prediction and early treatment.

Despite the large number of examination and diagnostic techniques, visual system treatment, the problem of ensuring the disease accurate diagnosis is still very important. Among the existing diagnostic techniques special attention lately is paid to the method of evoked potentials. [1,2] The essence is to diagnose the disease by analysis of electroretinograms (ERG), each of which is the response to the eye retina irritation in the form of short-time light impulse of a certain intensity, duration and wave length.[1,3,5]

The problem of ensuring the selection and proper statistical processing of biomedical information, recognition and evaluation of informative diagnostic parameters providing registration of changes in the human body is very important in medical eye research practice. The use of computer equipment makes it possible to systemize existing statistical data.

Foreign samples of medical radio-electronic equipment used in Ukraine have several disadvantages: they do not provide complete examination of the visual system, automation of electrophysiological signals analysis, high cost of the above listed diagnostic systems, absence of diagnostic unit providing the diagnosis of visual analyzer disease.

3 Information system

The general schematic structure of information system for eye disease diagnosis developed according to the requirements of International Technical Commission on Electroretinogrphy is shown in (Fig. 1) [8].

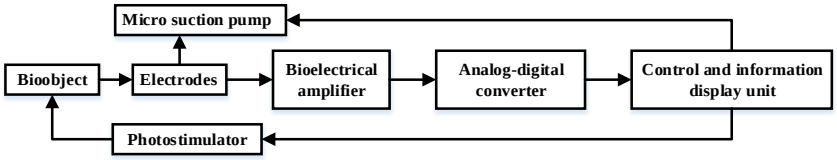

Fig. 1. General schematic structure of IS for eye disease diagnosis

The system consists of special non-polarized electrode for weak signals selection; micro suction pump is designed for sensor holding on eye cornea. Signals amplification and filtering is carried out by highly sensitive amplifier of biopotentials.

Received data processing is performed by specially developed application program package for analysis and diagnosis of patients by means of electroretinograms based on investigations carried out by the authors.

4 Electroretinogram models in the form of linear stochastic process

ERG is the output signal of the visual system where light signals (of various intensity, frequency, duration) are sent to its input. The mechanism of ERG formation makes it possible to consider the visual system as linear one and describe ERG by means of stochastic process

$$\xi(t) = \sum_{k:\tau_k<t} \alpha_k \varphi(\tau_k, t), \quad t \in (-\infty, \infty) \tag{1}$$

where $\varphi(\tau_k, t)$ - impulse response of the visual system,

$\{\tau_{-1} < \tau_0 < \tau_1 < \ldots < t\}$ - time of elementary impulses occurrence,

α_k - random variables characterizing impulse amplitudes.

Generalization of the model (1) is linear stochastic process

$$\xi(t) = \int_{-\infty}^{\infty} \varphi(\tau, t) d\eta(\tau) \tag{2}$$

where $\eta(\tau)$ is the stochastic process with independent increase which growth points coincide with moments τ_k in (1), and jump values are equal

If we assume that the visual system is invariant in time i.e., for its impulse response $\varphi(\tau, t) = \varphi(t - \tau)$, then the ERG model is the stationary linear stochastic process

$$\xi(t) = \int_{-\infty}^{\infty} \varphi(t - \tau) d\eta(\tau) \tag{3}$$

In general case the impulse response depends not only on time variables τ and t but on spatial coordinates. Taking into account mentioned above the EKG model is substantiated in the form of linear random field

$$\xi(t, \bar{r}) = \int_{-\infty}^{\infty} \int_{R_3} \varphi(\tau, t, \bar{s}, \bar{r}) d_\tau d_s \eta(\tau, \bar{s}), \tag{4}$$

where τ, t are time parameters considered in models (1) – (3);

$\bar{s}$ is the point in space R_3, where visual system input is located;

r is the point of output location i.e., the point where ERG is observed;

$\varphi(\tau, t, \bar{s}, \bar{r})$ is the impulse space-time transition function;

$\eta(\tau, \bar{s})$ is nonuniform field with independent increases both in time and space characterizing the input signal intensity.

In case when the visual system is invariant in time its model is linear uniform relatively to spatial variables and stationary in time field.

$$\xi(t, \bar{r}) = \int_{-\infty}^{\infty} \int_{R_3} \varphi(t - \tau, \bar{s}, \bar{r}) d_\tau d_{\bar{s}} \eta(\tau, \bar{s}). \tag{5}$$

Providing that in (4) or (5) the spatial coordinates $\bar{s}$ and $\bar{r}$ are fixed we derive the partial case of these models i.e., linear stationary process (3) or linear process (2) relatively.

When there is no photostimulation the signal received by the sensor is represented as (3). Let us assume that the kernel $\varphi(\tau)$ has finite duration denoted as T_0. When short-term photostimuli with period $\mathrm{T} > \mathrm{T}_0$ are sent the visual system, then the investigated process is represented in the following way

$$\xi(t) = \int_{-\infty}^{\infty} \varphi(t-\tau) d(\eta(\tau) + I(\tau)), \tag{6}$$

where $I(\tau) = I_0 \sum_{n=0}^{N-1} U(\tau - n\mathrm{T})$, I_0 is one stimulus capacity (moreover $I_0 >> \mathbf{D}\eta^{©}(\tau)$),

$U(\tau) = \begin{cases} 1, & t \geq 0 \\ 0, & t < 0 \end{cases}$ is Heaviside function,

T is stimuli feeding period,

N is stimuli amount in one session.

Otherwise (6) is additionally represented as follows

$$\xi(t) = \int_{-\infty}^{\infty} \varphi(t-\tau) d\eta(\tau) + \int_{-\infty}^{\infty} \varphi(t-\tau) dI(\tau), \tag{7}$$

where the second summand in (7) is the stationary linear system response sequence with impulse response $\varphi(\tau)$ and influence of δ-impulse sequence sent to its input.

At the same time $\varphi(\tau)$ is the kernel of linear stochastic process (3) to be estimated.

It is obvious that

$$\mathbf{M}\xi(\mathrm{t}) = m + \int_{-\infty}^{\infty} \varphi(t-\tau) dI(\tau) = m + \sum_{n=0}^{N-1} \varphi(t - n\mathrm{T}) \cdot U(t - n\mathrm{T}) \cdot U((n+1)\mathrm{T} - t) \tag{8}$$

where $m = \mathbf{M}\left[\int_{-\infty}^{\infty} \varphi(\mathrm{t}-\tau) d\eta(\tau)\right] = \kappa_1 \int_{-\infty}^{\infty} \varphi(\tau) d\tau$,

κ_1 is the cumulant of the random variable $\eta(1)$.

Taking into account the fact that during the synthesis of investigated signals registration it is possible to develop the filter intended to filter off the "constant component" of the input signal, let us assume $m = 0$ in (8).

Thus, in order to estimate the process kernel (3) it is sufficient to estimate the mathematical expectation of the process (7) within the interval $[0, \mathrm{T}_0]$.

The following is proposed as estimation

$$m(t)=\frac{1}{N}\sum_{n=0}^{N-1}\xi(t+n\mathrm{T}),\quad t\in[0,\mathrm{T}_0] \tag{9}$$

Thus, the kernel statistical estimate (3) is

$$\hat{\varphi}(t)=m(t),\quad t\in[0,\mathrm{T}_0] \tag{10}$$

Using statistical linearization method the authors investigated the systematic errors of analog-digital conversion of the input stochastic process from quantization and limitation of ADC operating range as well as the system instrument errors.

5 Statistical methods of decision-making in ophthalmology problems

Using statistical approach (Fig. 2) on the basis of ERG model the structural diagram of diagnostic unit (Fig. 3) is developed.

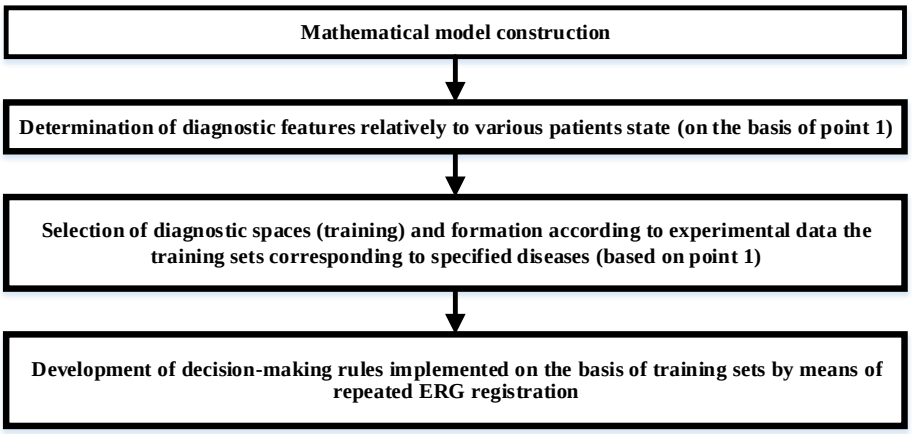

Fig.2. Diagram of the statistical approach to diagnosis

The first stage of the diagram (Fig. 2) – the development of ERG model was implemented in point 1.

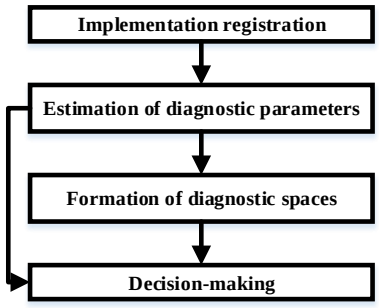

Fig.3. Structural diagram of diagnostic unit

At the next stage new diagnostic features which make it possible to characterize patient's status are determined. The angle between the kernel $\varphi(\tau)$ which estimation technique is described above and certain function $\varphi_0(\tau)$ corresponding HDL for assumed healthy patient is proposed to be used as the first diagnostic feature. More specifically:

$$\psi = \arccos\frac{(\varphi(\tau),\varphi_0(\tau))}{\|\varphi(\tau)\|\,\|\varphi_0(\tau)\|} \tag{11}$$

where $(\varphi(\tau),\varphi_0(\tau))$ is the scalar product of functions $\varphi(\tau)$ i $\varphi_0(\tau)$ (it is considered that these functions are Hilbert space elements); $\|\cdot\|$ is the norm operator.

Angle ψ is also used to determine and consider the registration errors of "screwup".

Besides the angle (11), the expansion coefficient of mathematical expectation estimation $m(t)$ (10) into generalized Fourier series in the system of Chebyshev, Lager and Kravchuk basis functions are proposed to be used as ERG diagnosis features (Fig.4, 5, 6). ($X_{i,1}$ is ERG implementation, ff(i) is approximate function).

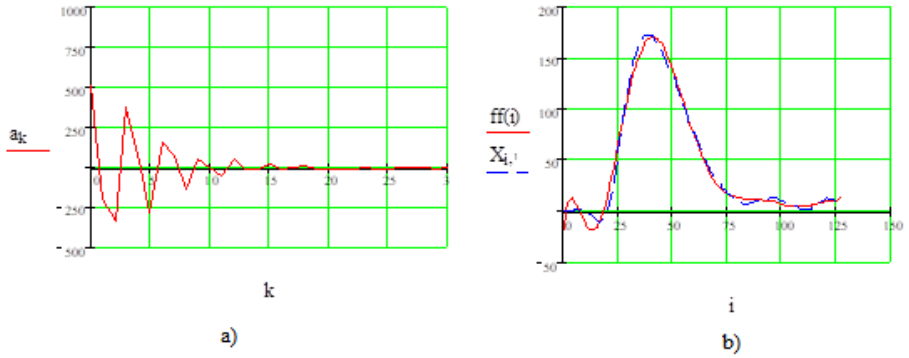

Fig.4.a)spectrum of expansion coefficients in the system of Chebyshev basis functions; b) ERG implementation and approximate function

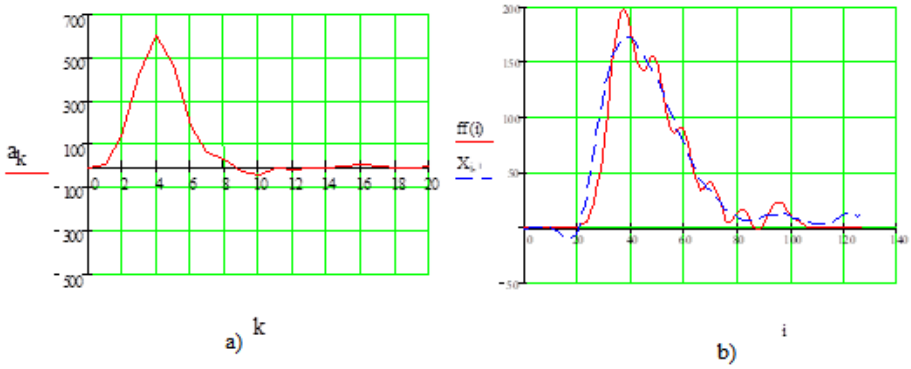

Fig.5.a) spectrum of expansion coefficients in the system of Kravchuk basis functions; b) ERG implementation and approximate function

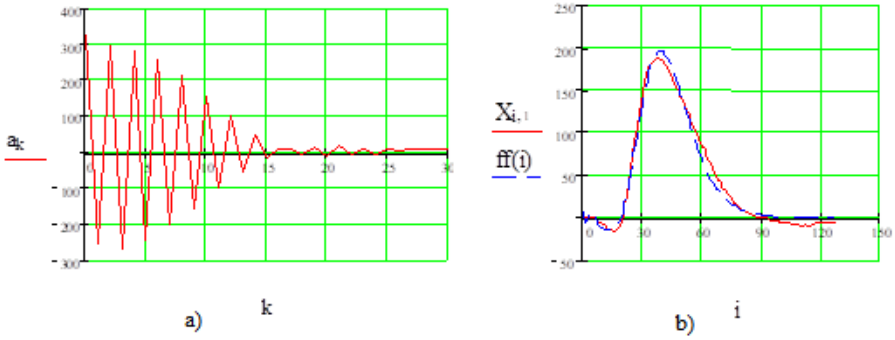

Fig.6. a) spectrum of expansion coefficients in the system of Lager basis functions; b) ERG implementation and approximate function

According to Bessel inequality for Fourier series coefficients

$$\sum_{s=0}^{N-1} a_s{}^2 \le \sum_{i=0}^{L-1} \left(f\left(t_k\right)\right)^2 \tag{12}$$

where a_s is coefficient of expansion into ERG-signal, $f\left(t_k\right)$ is implementation of ERG-signal, i.e., the sum of squared coefficients of expansion into series does not exceed the signal energy. Thus at $s \to \infty$ the expansion coefficient $a_s \to 0$ (see Fig.4,a, Fig.5,a, Fig.6,a) and therefore the main information about the signal are included only by the first series coefficients.

Let us introduce function

$$C\left(N\right) = \frac{\sum_{s=0}^{N-1} a_s}{\sum_{k=0}^{L-1} \left(f\left(t_k\right)\right)^2} \tag{13}$$

$0 < C\left(N\right) < 1$ characterizing energy share carried by coefficients a_s, $s = 0, N-1$, of generalized Fourier series with relatively to the total signal energy.

It is determined that in order to carry not less that 99% of energy by orthogonal expansion coefficients (Fig.7,a), it is sufficient to take 8-10 expansion coefficients into Fourier series using Chebyshev functions system; 35-40 coefficients are required for Lager functions and 45-50 for Kravchuk functions. The number of orthogonal expansion coefficients in Chebyshev system of basis functions appeared to be smaller than in other basis functions (used in the investigation) contributing to total energy (Fig.7,b). Therefore they are selected as diagnosis features of healthy visual analyzer.

It should be noticed that other orthonormal basis were investigated but they showed worse results than Kravchuk functions, particularly def basis.

The obtained results are used in order to carry out the visual system disease diagnosis.

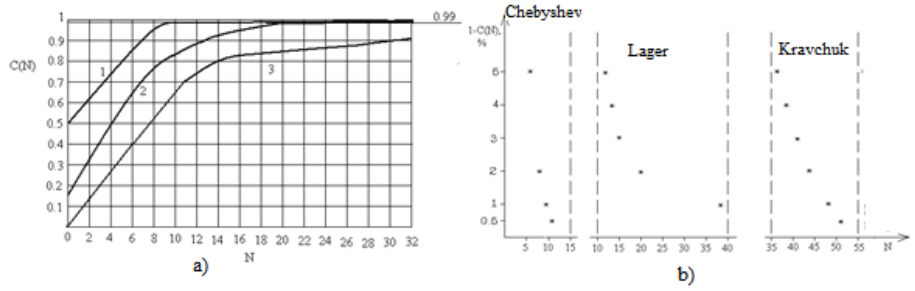

Fig.7. Function dependency graphs $C(N)$:
1- system of Chebyshen basis functions;
2- system of Lager basis functions;
3- system of Kravchuk basis functions.

6 Neumann-Pearson criterion

On the basis of observation and analysis of assumed implementation $x(t)$ it is necessary to decide what values (from the given interval of possible values) accept parameters $l(l_1, l_2, ..., l_n)$, the observer is interested in. That is on the basis of observed implementation processing $x(t)$ it is necessary to measure and estimate the required multidimensional parameter l.

Let us consider the physical phenomenon mathematical model of which represents the stochastic process $\xi(t)$.

Let us formulate incompatible hypotheses $H_0, H_1, ..., H_m$ relatively to the unknown model characteristics. The hypotheses testing task is to accept one of them according to the observed implementation results $x(t)$, $0 \le t \le T$ the stochastic process $\xi(t)$.

Each decision is the result of statistical decisions based on observations. Let us denote by γ_i the decision to accept hypothesis H_i, then $\gamma_i \in \Gamma, i = \overline{0,m}$, where Γ is the decision space.

The decision space Γ coincides with parameters size θ, and elements of set Γ are estimates of the unknown parameter $\gamma = v \in \theta = \Gamma$.

The decision selection rule δ depicts the observation space X on decision space Γ: $X \xrightarrow{\delta} \Gamma$.

In hypotheses testing problem B H_j, $j = \overline{0,m}$ according to sample x with size n each decision section rule δ divides the space into $m+1$ non-overlapping areas:

$$x_j \in X^n, \quad j = \overline{0,m}, \quad x \in X_j, \quad \gamma_j \in \Gamma, \quad \delta \in D$$

D is a set of decision selection rules.

It is obvious the broader knowledge about the signal characteristics of healthy and sick patient the observer has, the easier the diagnosis problem is solved.

The estimated paremeter is random variable for observer. In such situation the most complete information about the possibilitis of parameter value as given by prosterior probability density which is assumed probability dencity of parameter if given implementation $x(t)$ is accepted.

The diagnostics problem can be reduced to hypotheses testing on one parameter or set of one-dimensional or multidimensional distribution function of the observed random value which can be stochastic process parameters.

In order to carry out diagnostics let us introduce the following notations. Для проведення діагностування введемо наступні позначення. Let us denote the random values vector by $\Xi_m = (\xi_1,...,\xi_i,...,\xi_m)$ each component of which $\xi_i, i = \overline{1,m}$ represents the corresponding information parameter. In such a case the vector of implementation Ξ_m is matrix

$$\begin{pmatrix} \xi_1^{(1)},...,\xi_i^{(1)},...,\xi_m^{(1)} \\ ..... \\ \xi_1^{(k)},...,\xi_i^{(k)},...,\xi_m^{(k)} \\ ..... \\ \xi_1^{(n)},...,\xi_i^{(n)},...,\xi_m^{(n)} \end{pmatrix} \tag{14}$$

where $\Xi_m^{(k)}$ is the a priori vector of random values in k-th experiment. $\mathrm{X} = \left\| x_{j,k} \right\|, \ j = \overline{1,m}, \ k = \overline{1,n}$ is implementations matrix (a posterior matrix). Each solution corresponds to one experiment, the amount of lines – to experiments number, the number of columns – to informative parameters amount.

Let us assume that components ξ_i of vector Ξ_m are subjected to the normal distribution law. підлягають нормальному закону розподілу.

Let us denote the average vector Ξ_m value by $\overline{\Theta}$:

$$\overline{\Theta} = (\Theta_1,...,\Theta_i,...,\Theta_m) \tag{15}$$

where $\Theta_i = \mathrm{M}\xi_i$.

Let us denote the correlation matrix of the same vector Ξ_m components by

$$\mathrm{M} = \begin{vmatrix} r_{11},...,r_{1i},...,r_{1n} \\ ..... \\ r_{i1},...,r_{ii},...,r_{in} \\ ..... \\ r_{m1},...,r_{mi},...,r_{mn} \end{vmatrix} \tag{16}$$

where $r_{ij} = \mathrm{M}\left\{ \overset{o}{\xi}_i, \overset{o}{\xi}_j \right\}$.

On the basis of the introduced notations the distribution density Ξ_m is as follows [6]

$$\mathrm{P}(Y)=\frac{|\mathrm{M}|^{-\frac{1}{2}}}{(2\pi)^{m/2}}\exp\left[-\frac{1}{2}(Y-\Theta)^{T}\,\mathrm{M}^{-1}(Y-\Theta)\right] \tag{17}$$

where M is correlation matrix (16);

Y is the argument of distribution density which during specific implementation investigation accepts their values.

While diagnosing specific patients the mathematical expectation of vector Ξ_m accepts specific value actually defining (identifying) the disease.

For normal (healthy) patient let us introduce vector $\overline{\Theta}^{(0)}=\left(\Theta^{(0)},...,\Theta_i^{(0)},...,\Theta_m^{(0)}\right)$. Relatively with a certain disease existence $\overline{\Theta}^{(1)}=\left(\Theta^{(1)},...,\Theta_i^{(1)},...,\Theta_m^{(1)}\right)$.

While examining the patient for disease presence we put forward two hypotheses.

$$\mathrm{H}_0 \text{ - parameter in (3.43): } \Theta=\overline{\Theta}^{(0)}, \tag{18}$$

$$\mathrm{H}_1 \text{ - parameter in (3.43): } \Theta=\overline{\Theta}^{(1)},$$

where $\overline{\Theta}^{(1)}\neq\overline{\Theta}^{(0)}$.

Further we consider hypothesis H_0 as the main one and H_1 as competitive конкуруючою.

To make decision about the correctness of one of the hypotheses we use the theory proposed by Neumann and Pearson based on the analysis of likelihood ratio logarithm The essence of Neumann-Pearson method is the selection of certain restriction C on the set of permissible values for which at given restriction of the probability of the first-order error $\alpha\le\alpha_0$ the value of the second-order error is minimized [6,7].

The function $p(\Xi_m)$ derived from (17) by replacing the nonrandom argument заміною Y with random vector Ξ_m is called the likelihood function [6].

$$l(\Xi_m)=\frac{P\left(\Xi_m,\overline{\Theta}^{(1)}\right)}{P\left(\Xi_m,\overline{\Theta}^{(0)}\right)} \tag{19}$$

It accepts the random values as the function of random vector $\Xi_m^{(k)}$ and depends on the non-random vector parameter Θ, that is why we represent it as $p(\Xi_m,\Theta)=p(\Xi_m)$. Likelihood ratio $l(\Xi_m)$ is called the functions relation at various values Θ defined in hypotheses formulation (18).

Let us denote by $\eta^{(n)}$ the logarithm of likelihood ratio

$$\eta^{(n)}=\ln\left\{\prod_{k=1}^{n}\frac{\mathrm{P}\left(\Xi_m^{(k)},\overline{\Theta}^{(1)}\right)}{\mathrm{P}\left(\Xi_m^{(k)},\overline{\Theta}^{(0)}\right)}\right\}=\sum_{k=1}^{n}\varsigma^{(k)} \tag{20}$$

where

$$\varsigma^{(k)} = \left(\Xi_m^{(k)}\right)^{\mathrm{T}} \mathrm{M}^{-1}\left(\overline{\Theta}^{(1)} - \overline{\Theta}^{(1)}\right) - \frac{1}{2}\left(\overline{\Theta}^{(1)} + \overline{\Theta}^{(1)}\right)\mathrm{M}^{-1}\left(\overline{\Theta}^{(1)} - \overline{\Theta}^{(1)}\right), k = \overline{1,n} \ ;$$

$\mathrm{P}\left(\Xi_m^{(k)}, \overline{\Theta}^{(1)}\right)$ is the likelihood function for hypothesis H_1;

$\mathrm{P}\left(\Xi_m^{(k)}, \overline{\Theta}^{(0)}\right)$ is the likelihood function for hypothesis H_0.

The sequence elements $\varsigma^{(k)}, k = \overline{1,n}$ are Gauss magnitudes each linearly dependent on components of matrix (14). That is $\varsigma^{(k)}, k = \overline{1,n}$ can be considered as discrete white noise or scalar Gauss stochastic process with discrete argument and independent values [6,7].

Decision making connected with the hypothesis selection (18) is characterized by probability of the first and second order errors.

The first order error occurs when the basic hypothesis H_0 is rejected in case if it is true

$$\alpha = \mathrm{P}\left(\mathrm{H}_1 \middle| \mathrm{H}_0\right) \tag{21}$$

where α -is the level of criterion significance.

The second order error– hypothesis H_0 is accepted when hypothesis H_1 is true

$$\beta = \mathrm{P}\left(\mathrm{H}_0 \middle| \mathrm{H}_1\right) \tag{22}$$

where $1-\beta$ is test strength.

The main task in hypothesis acceptance is the selection on the set of permissible process values $e^{\eta^{(n)}}$ of certain threshold C for which at the given value α, fixed sample volume n and the smallest β one can conclude that hypotheses H_0 at $\eta^{(n)} \le \ln C$ and H_1 at $\eta^{(n)} > \ln C$ occur.

Taking into account (19) the criterion of hypothesis H_0 acceptance is as follows

$$\tilde{\Xi}_m \mathrm{M}^{-1}\left(\overline{\Theta}^{(1)} - \overline{\Theta}^{(0)}\right) \le K \tag{23}$$

and hypothesis H_1

$$\tilde{\Xi}_m \mathrm{M}^{-1}\left(\overline{\Theta}^{(1)} - \overline{\Theta}^{(0)}\right) > K \tag{24}$$

where

$$\tilde{\Xi} = \frac{1}{n}\sum_{k=1}^{n}\left(\Xi_m^{(k)}\right)^{\mathrm{T}} = \left(\frac{1}{n}\sum_{k=1}^{n}\xi_1^{(k)}, \ldots, \frac{1}{n}\sum_{k=1}^{n}\xi_i^{(k)}, \ldots, \frac{1}{n}\sum_{k=1}^{n}\xi_m^{(k)}\right) \tag{25}$$

$\xi_i^{(k)}$ is the element of matrix (14).

The formulae for calculation of the threshold value K and sample volume n are given from [6]:

$$K = \frac{k_2\left(U_\alpha - U_\beta\right)}{2\left(U_\alpha + U_\beta\right)} + \frac{1}{2}\left(\overline{\Theta}^{(1)} + \overline{\Theta}^{(0)}\right)\mathrm{M}^{-1}\left(\overline{\Theta}^{(1)} - \overline{\Theta}^{(0)}\right)^T \tag{26}$$

$$n = \frac{\left(U_\alpha + U_\beta\right)}{\kappa_2} \tag{27}$$

where

$$\kappa_2 = \left(\overline{\Theta}^{(1)} - \overline{\Theta}^{(0)}\right)\mathrm{M}^{-1}\left(\overline{\Theta}^{(1)} - \overline{\Theta}^{(0)}\right)^T \tag{28}$$

U_α, U_β are quantiles of normal distribution.

Let us consider the example of the above mentioned approach application for ophthalmodiagnostics based on the parameters of orthogonal decomposition of ERG signal.

The diagnosis is carried out in three stages: at the first stage we determine the diagnostic features corresponding to different patients states; at the second stage we form according to experimental data training sets (images) corresponding to specific matrix patients states; at the third stage we develop diagnostics rules make decisions according to training sets and recorded data.

During the training course ERG of healthy and sick patients (it is not necessary to specify pathology type) were investigated. ERG registration system described in paper [4,8] was used for experiments.

Learning outcomes:

- vector of mathematical expectations of informative parameters foe hypothesis H_0 (healthy patient):

$$\overline{\Theta}^{(0)} = \left(a_1, .. a_{10}\right) =$$
$$= \left(339.5 \quad 55.4 \quad -146.7 \quad -56.1 \quad 57.9 \quad 79.1 \quad 23.9 \quad -46.4 \quad -49.4 \quad -6.9\right)$$

- vector of mathematical expectations of informative parameters foe hypothesis H_1 (sick patient):

$$\overline{\Theta}^{(1)} = \left(a_1^{'}, .. a_{10}^{'}\right) =$$
$$= \left(170.9 \quad 51.7 \quad -105.4 \quad -59.7 \quad 27.8 \quad 665 \quad 32.4 \quad -30.6 \quad -46.5 \quad -12.3\right)$$

Correlation estimates matrix

$$\mathrm{M}=\begin{pmatrix} 120 & 13 & -42 & -3.8 & 8.2 & 7 & -5.4 & -7.8 & -6.1 & 6.3 \\ 13 & 51 & -6.6 & -1.8 & 1.1 & 1.4 & -0.8 & -1.3 & 0.9 & 1.2 \\ -42 & -6.6 & 17 & 1.7 & -3.5 & -2.8 & 2.1 & 2.9 & -2.3 & -2.4 \\ -3.8 & 1.8 & 1.7 & 1.6 & -0.1 & -55 & 0.1 & 0.4 & -0.3 & -0.4 \\ 8.2 & 1.1 & -35 & -0.1 & 1.7 & 3.6 & -1.1 & -0.5 & 0.9 & 0.2 \\ 7 & 1.4 & -2.8 & -5.5 & 3.6 & 1.3 & 0.3 & -1.1 & 0.4 & 0.4 \\ -5.4 & -0.8 & 2.1 & 0.1 & -1.1 & -0.3 & 1.1 & 0.3 & -0.9 & -0.01 \\ -7.8 & -1.3 & 2.9 & 0.4 & -0.5 & -1.1 & 0.3 & 1.2 & -0.4 & -0.6 \\ -6.1 & 0.9 & -2.3 & -0.3 & 0.9 & 0.4 & -0.9 & -0.4 & 1.0 & 0.3 \\ 6.3 & 1.2 & -2.4 & -0.4 & 0.2 & 0.4 & -0.1 & -0.6 & 0.3 & 0.7 \end{pmatrix} \bullet 10^3$$

Setting $\alpha = \beta = 0.05$ according to (26–28) we get $\kappa_2 = 2.48$ $n = 4.38$ (accepting $n = 5$), $K = -5.04$.

On the basis of learning outcomes let us carry out diagnostic experiment.

We get:

$\overline{X}_{10} = (260.8 \quad 25 \quad -139.1 \quad -43.2 \quad 60.7 \quad 60.8 \quad 14.3 \quad -35.8 \quad -36.6 \quad -7.9)$,

where $\overline{X}_{10}$ is implementation;

$\overline{X}_{10}\mathrm{M}^{-1}\left(\overline{\Theta}^{(1)} - \overline{\Theta}^{(0)}\right)^T = -173.6 < K$. Therefore we should accept hypothesis H_0 – the patient is visual.

It should be noted that the considered approach for problems solution related to synthesis of mathematical model of investigated signals with parameters which can be used as diagnostic features, methods of these parameters determination, diagnostic criteria construction are implemented as software package included in the developed information system for ophthalmodiagnosis by electroretinograms.

7 Conclusions

1. The mathematical model in the form of linear stochastic process is substantiated on the basis of physical-chemical processes occurring in the visual system and mechanism of retina biopotentials generation.
2. It is proposed to use the coefficients of orthogonal decomposition of ERG implementations in the system of basis discrete argument functions (Chebyshev, Kravchuk,Lager) as diagnostic features.
3. In order to diagnose the visual analyzer disease the statistical decision-making theory is used. Criteria for decision-making according to informative features of ERG implementations (Neumann-Pearson criterion) is selected.
4. The proposed approach is implemented as application program package.

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