MATHEMATICAL MODEL OF THE VARIABILITY OF THE ELECTRICAL ACTIVITY PARAMETERS OF BIOMEDICAL SIGNALS

[1]Abdurashidova K, [2]Kurbonboev Kh, [3]Tuychiev A.
[1]Associated professor Tashkent university of information technologies,
[2,3]Master's student Tashkent university of information technologies
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Abstract. *Biomedical signals such as electrocardiograms (ECG), electroencephalograms (EEG), and electromyograms (EMG) are invaluable sources of information for healthcare and research. Variability within these signals holds rich insights into the functioning of physiological systems. This paper covers the development of mathematical models to understand and exploit the intrinsic variability of electrical activity parameters in biomedical signals.*
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We analyze the variability of several parameters of electrical activity of biomedical signals independently, that is, free component analysis (ECT) - an EEG model based on the division of a multidimensional signal into separate subcomponents (components) that are independent of each other.

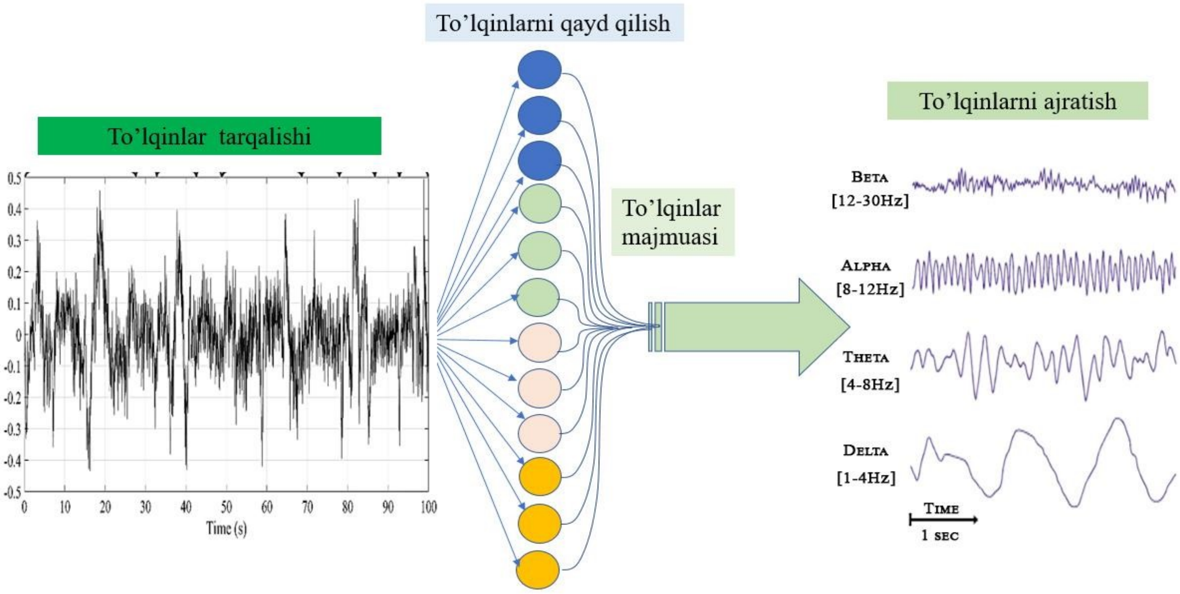
Jenny Herault and Bernard Anse started working on the free component analysis method in 1984, while Christian Jutten continued to work on ECT. The method was fully described by Pierre Caumont in 1994. A year after P.Komon's work, Tony Bell and Terry Sejnovsky created the fastest infomax algorithm, which detects isolated signals by maximizing entropy (a measure of system disorder). Some authors equate this principle with the method of maximum likelihood (value search). population parameter with high probability of the available sample).

The essence of the method is that it can be explained on the example of a mixed batch of ECT (Fig. 1). It can be imagined that, in some cases, it is necessary to perceive and filter several different types of signals, and at the same time, several noisy events.

The task is to separate each signal separately and the noise separately, for this the method of free components is used.

The mathematical expression can be explained as follows: it can be imagined that our sensor (for example, electrodes) receives some signals consisting of several components placed next to each other. In the case of biological waves, these components can be signals transmitted from the brain, environmental noise, etc., for example, in the example of "looking this way or that with the eyes", blinking in the EEG method, eye movements, and the actual bioelectricity of the brain. activity. All signals are mixed and distort overlapping features.

However, it should be noted that despite the overlap, the signals are independent of each other - this is one of the main rules of the free component method. Accordingly, the desired component can be separated from the totality of received signals. For this, signal parameters (amplitude, frequency, spectrum) are recorded as mathematical values in a special table where the elements are connected to each other. Then, with the help of a series of mathematical expressions, regularity and sequential operations are performed, and elements belonging to certain components are separated. These are the division of all sets of values into groups, that is, classification, each of which describes one or another element of the final signal.



1-figure. Principles of free component analysis method

Thus, after separating the recorded signal, we have the opportunity to remove unnecessary elements for ourselves - various noises, as in the example with waves, or in the case of EEG, flashes and other noises are detected. This allows you to clear the record of unnecessary information or highlight specific information.

The mathematical interpretation is based on the fact that the recorded n signals are a linear combination of *m* unknown main signals [4,5]. In the case of signals consisting of free components, i.e. $Z_{n,m}$ is a matrix with dimension (n*m) elements, and $X_j^*(k)$ is a vector consisting of rows, the mathematical model is as follows.

$$X_j^*(k) = \sum_{i=1}^{n} a_{i,j} s_i(k) + \varepsilon_j(k), \quad k = 1,2,\dots,m, \qquad (1)$$

$$X^*(k) = Z s_i(k) + \varepsilon_j(k), \qquad (2)$$

here, $s_i(k) = [s_1^*(k),\ s_2^*(k), \dots,\ s_n^*(k)\ ]^T$ - base free signals,

$\varepsilon_j(k) = [\varepsilon_1(k), \varepsilon_2(k), \dots, \varepsilon_n(k)\ ]^T$ - are additional noises.

$Z_{n,m}$ - the required permutation matrix, $Z_{n,m}$ matrix as well, $s_n^*(k)$ the source vector can also be found in different ways.

Below we will look at the mathematical expressions and algorithms presented for the main amplified signal.

Free component analysis is generally based on two principles:

signal isolation method;

each signal has a non-normal distribution of values.

Each of the ECT algorithms (maximizing information, fast free component analysis and neural network analysis) includes several mandatory parts, such as:

1. centering (subtracting the average vector to simplify free components and creating a variable with an average value of zero);

2. size reduction (using the analysis of dependent components);

3. correlation (getting a new vector of white color with the help of transformations, that is, its components do not correlate with each other and their variances are equal to unity. For this, the spectral decomposition of the matrix is often used);

4. is to filter or clean the signal from artifacts.

One of the most widely used methods is fast free component analysis, which is based on increasing the degree of non-Gaussianity (a distribution other than the normal distribution) and includes a deflation algorithm and a symmetric algorithm one after the other (hence this derivation method) whose general signals are also called a single-element algorithm, and the evaluation of components with symmetric extraction occurs in parallel at the same time. The principle of operation of fast free component analysis is based on the use of the central limit theorem (which states that the distribution of data is close to normal when including a large number of weakly correlated components) and a measure of the order of a non-entropy system.

Within the framework of the proposed model, receptor neurons are, on the one hand, devices that convert analog electrical signals from receptors into a sequence of binary pulses. On the other hand, receptor neurons are dynamic detectors, because they only react to changes in the parameters of signals that come to their input.

Thus, the working model of the receptor neuron is an adaptive discrete-time converter of analog signals (Fig. 2).

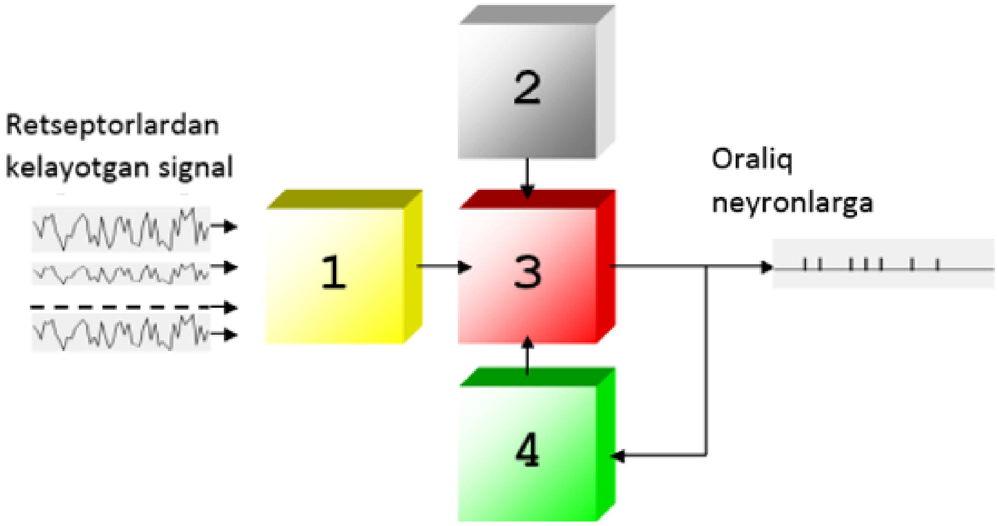


Figure 2. A functional model of a receptor neuron

Block 1 is an integrator, in which the summation of input signals from a set of homogeneous receptors is carried out. The analog signal at the output of the integrator describes the total signal of the receiving field.

Block 2 is a generator of clock pulses, the frequency of which is determined by the neuron itself. The frequency of neuronal spike activity depends on its relative refractory period, which in turn depends on the amplitude of the total signal of the receptive field.

Block 3 is a comparator, in which the comparison of the signals from the integrator 1 and the approximation 4 is carried out at the moments determined by the repetition period of the pulses of the clock frequency generator 2.

At the output of the 3rd comparator, a binary code is formed, determined by the sign of the difference between the approximation function generated in the 4th axiomator and the analog signal coming from the 1st integrator.

According to the principle of such coding, known in communication theory as delta modulation, f(t) is compared with the values of instantaneous values of the original signal function at times t0, t1, t2,..., tn. Depending on the function approximating g(t) and the sign of the difference, a zero or positive pulse is generated. Figure 19 shows the time diagrams of the formation of a binary code in a neuron model.

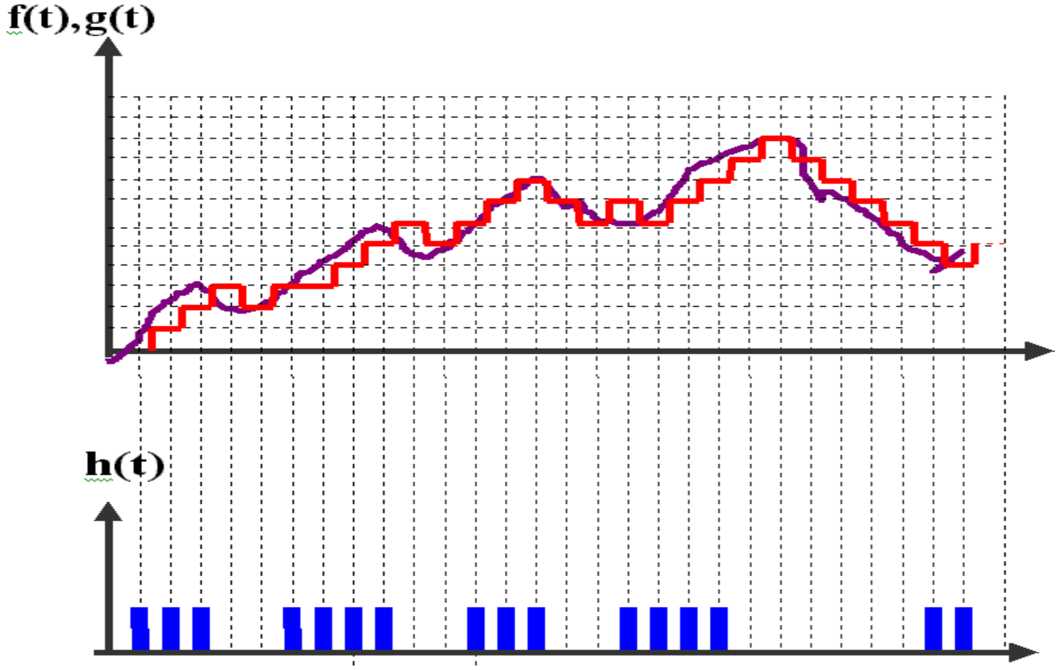


Figure 3. Timing diagram of signal processing in a receptor neuron model.

In this case, the process of forming a sequence of binary pulses can be written in the following form:

$$h_k(t) = \begin{cases} h_1(t), f(t) - g(t) > 0 \\ h_0(t), f(t) - g(t) < 0 \end{cases} \quad (3)$$

here $h_1(t)$ corresponds to the emergence of a positive impulse.
$h_0(t)$ corresponds to the appearance of a zero pulse.

Thus, at the output of the block diagram of the receptor neuron model, a sequence of impulses $h_k(t)$ is formed, which reflects the dynamic properties of the input signal and is identical to the spike activity of individual neurons.

In turn, wavelet free component analysis - TEKT artefact removal method is based on the joint application of discrete wavelet transformation and dependent components. The method is used to remove noise and artifacts in EEG, and the disadvantage of this method is the need to select noisy components in the wavelet substitution results.

There is an automatic version of the TEKT method - ATEKT (automatic wave free component analysis). This method allows for automatic clipping of artifacts from multichannel EEG recordings. It works well with artificially generated EEG recordings and is used to model electrical power artifacts, muscle noise, and eye blinks.

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