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Bispectral Analysis of Electroencephalogram Using Neural Networks to Assess the Depth of Anesthesia

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The article reviews algorithms of bispectral analysis of the electroencephalogram (EEG) signal of a patient to determine the level of brain activity during sedative-assisted treatment. The proposed algorithms are based on construction of multiple convolutions of complex amplitudes of the EEG signal, combined into so-called bispectra. Artificial neural networks (ANNs) are used to perform bispectral analysis and form a conclusion on the degree of patient brain activity. The article also shows individual results of functioning of the algorithms on real EEG signals and compares these results with expert judgments of doctors (anesthesiologists and neurophysiologists).

The efficiency of current sedative-assisted treatment methods essentially depends on the optimal dosage of these drugs. As a rule, the optimal dose means the minimum dose that ensures the safety and efficacy of treatment. The requirement of the minimum dose is usually due to two main points. On the one hand, it ensures quicker emergence of a patient from anesthesia while minimizing complications, and on the other hand, it saves expensive drugs. The optimal dose can be estimated in several ways, for example, by calculation taking into account the analysis of the patient's hemodynamics (heart rate, blood pressure, oxygen consumption, etc.). A well-known drawback of this approach is the fundamentally ambiguous relationship between the hemodynamic parameters of the patient and the depth of anesthesia. Currently the most effective method of determining the depth of anesthesia is direct evaluation of patient brain activity by analysis of the EEG signal, which is typically obtained with three electrodes fixed in the frontotemporal region of the head (left or right). The patient brain activity can be quantitatively indicated by a relative index of brain activity, the activity index (AI), the values of which vary from 0 to 100 [1]. A value of 0 corresponds to complete electrical silence of the brain, i.e., actual absence of any tangible (marked) electrical interaction between neurons. A value of 100 corresponds to the active wakefulness of the patient. A value of 50 characterizes the middle of the operation stage. Calculation of the AI in the range from 40 to 100 is of particular interest in view of the large number of cases. Calculation of the AI by analysis of the EEG signal [2] is a difficult and time-consuming task that so far has no simple solutions. The reasons for this are many; the major ones are as follows:

– the absence of a single model of functioning of the brain or any of its major subsystems;

– the presence of interference in the EEG signal;

– the wide and quite rich spectrum of the EEG signal;

– an EEG signal has both a frequency and a spatial structure;

– severe restrictions on the area of mounting and number of electrodes;

– use of dissociative anesthetics;

– the EEG signal can show pronounced patient characteristics, as well as patient state and diagnosis.

In the frequency domain in the EEG signal, as a rule, a number of frequency ranges are identified, five of which are of particular interest in the bispectral analysis of brain activity in the band up to 40 Hz: the δ range (0.2-4 Hz), θ range (4-8 Hz), α range (8-14 Hz), β_1 range (lower beta range, 14-25 Hz), and β_2 range (upper beta range, 25-40 Hz).

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To overcome the above-mentioned features (problems) that arise in EEG signal analysis, it is proposed to use an algorithm based on bispectral analysis using artificial neural networks (ANNs) [3-5]. The choice in favor of such an approach can be explained by two reasons. On the one hand, application of bispectral conversion, which is a set of signal convolutions, allows for integrated and statistical evaluation of the spectral characteristics of the signal. Such an approach can be effective when dealing with noise-like signals. On the other hand, the application of ANNs for bispectral processing enables both clustering of results and building of complex multidimensional dependences enabling assessment of the specific AI value. The proposed algorithms consistently process the EEG signal coming from the electrodes to the input of the ADC module for assessment of the depth of anesthesia.

Preprocessing of the EEG uses filters to suppress various kinds of interference related to the electromagnetic environment expected during operation. One of the most widespread examples of interference is interference generated by an electrical network with a fundamental frequency of 50 Hz. To eliminate the influence of noise on the useful part of the signal spectrum, a rejection filter with a Q factor of 50 is used. After signal filtering a discrete Fourier transform on a sliding time interval is performed; the length of the interval is ca. 7 s. If necessary, the spectrum is adjusted at the upper limit of the useful range of 40 Hz. Complex amplitudes $C_n[k]$ (where k is the window index and n is the harmonic index) obtained by the Fourier transform are used to construct bispectra based on discrete convolutions of the form

$$B^p(i,j) = \frac{1}{N_k}\sum_{k=1}^{N_k} F_b^p\left(C_i[k], C_j[k]\right);$$

$$B^a(i,j) = \frac{1}{N_k}\sum_{k=1}^{N_k} F_b^a\left(C_i[k], C_j[k]\right),$$

where N_k is the size of the convolution window (number of FFT windows), i and j are harmonic indices, and F_b is a function of two complex variables that determines the method of bispectrum construction. Convolutions are calculated for all pairs of values i, j of a predetermined frequency band. F_b are functions enabling assessment of the correlation between the different phases and amplitudes of harmonics within the signal spectrum. This selection of functions F_b is associated with the assumption that correlation between the harmonics of the signal may indicate the existence of links between different systems of the brain with their own characteristic frequencies. The absence of correlations can be seen as evidence of breakage of connections between individual brain subsystems, as well as the actual suppression of these subsystems. The expressions for F_b are as follows:

$$F_b^p\left(C_i[k], C_j[k]\right) = \\ = \left[\arg\left(C_i[k]\right) - m_i^p\right]\cdot\left[\arg\left(C_j[k]\right) - m_j^p\right];$$

$$F_b^a\left(C_i[k], C_j[k]\right) = \left(\left|C_i[k]\right| - m_i^a\right)\cdot\left(\left|C_j[k]\right| - m_j^a\right);$$

$$m_i^p = \frac{1}{N_k}\sum_{k=1}^{N_k}\arg\left(C_i[k]\right); \quad m_i^a = \frac{1}{N_k}\sum_{k=1}^{N_k}\left|C_i[k]\right|.$$

Figure 1 shows examples of bispectra $B^p(f_i, f_j)$ and $B^a(f_i, f_j)$ of the EEG signal after normalization at a convolution of all FFT windows using the functions F_b^p and F_b^a respectively. The convolution window size for the construction of a bispectrum is ca. 20-80 s. The exact value depends on the need to identify fast changes in brain states. The bispectra in Fig. 1 show a two-dimensional dependence of the correlation coefficient between the respective harmonics. The result of the bispectral conversion is a large array of information, which, according to the assumption, suggests the presence of functioning of and interaction between the brain systems.

The total bispectrum cannot be used for further analysis of the patient's anesthetic depth for two main reasons: on the one hand, due to the high requirements for computational resources necessary for its complete processing, and, on the other hand, due to the necessity of averaging the assessment of activity and interactions of the brain subsystems operating in the given frequency ranges (δ, θ, α, β_1, and β_2). Therefore, further processing was aimed at reducing the amount of data by averaging the correlation coefficients of the frequency ranges. As a result of this averaging, histograms were obtained, which are shown in Fig. 2. The obtained histograms respectively represent two 15-dimensional vectors P and A, which are used for calculation of the AI. The total data dimension is 30 items. In fact, already on the basis of these two vectors it is possible to obtain specific AI values using a certain ANN-implemented multidimensional function. However, studies show that there are several different two-vector sets that characterize patient states identical or similar in terms of the brain activity. In this regard, according to available EEG records, it is necessary to preidentify sets corresponding to the same state as that defined by the doctor expert, i.e., it is necessary to solve the problem of clustering in a 30-dimensional space. It is proposed to solve this problem using modified ANN structures of the winner-take-all (WTA) type. In a modified structure, in contrast to the classical, instead of a sin-

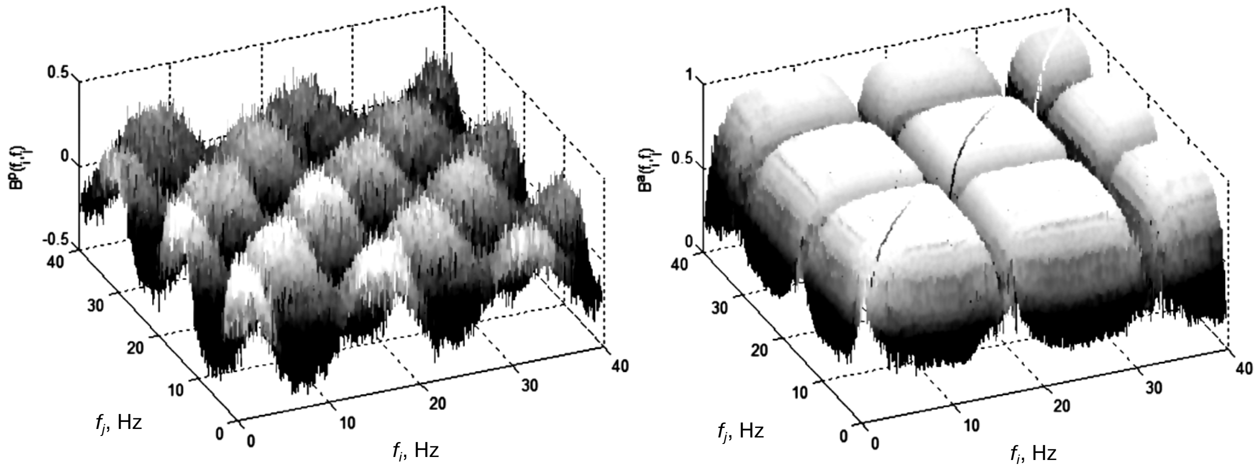

Fig. 1. Examples of bispectra $B^p(f_i, f_j)$ and $B^a(f_i, f_j)$ of the EEG signal.

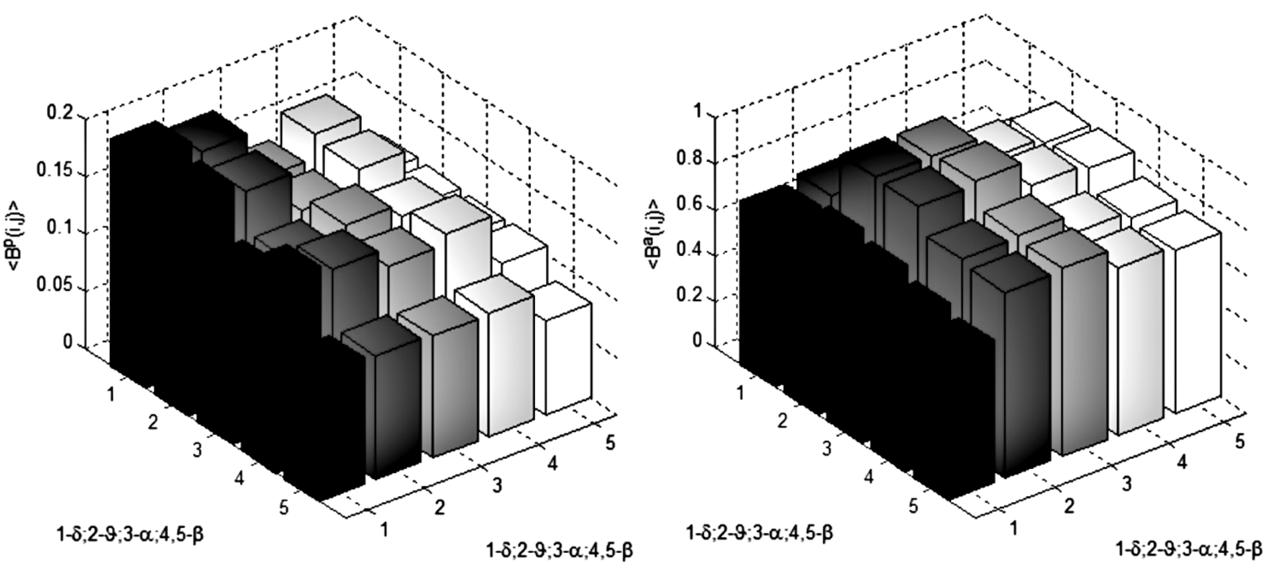

Fig. 2. Histograms obtained by bispectrum averaging in the appropriate ranges.

gle neuron responsible for one cluster having 30 inputs, a block of three neurons is used, as shown in Fig. 3a.

Polarizer inputs of all neurons are considered to be zero. The block in Fig. 3a shows three outputs: the first (μ_Σ) characterizes the degree of membership of input vectors P and A in a current cluster; the second (μ_P) shows the magnitude of the projection of the vector P on the vector of weights $w^{(1)}_{1,\,l-15}$, and the third (μ_A), of the vector A on the vector of weights $w^{(1)}_{2,\,l-15}$. An ANN designed to solve the problem of clustering is shown in Fig. 3b and consists of *N* parallel-connected blocks shown in Fig. 3a. The weights of the second layer of each block are constants and do not change during the learning process. The weights of the first layer of each of the blocks change in accordance with the rules of WTA training, while the output μ_Σ of each of the blocks is used for identifying the winning neuron for the next iteration. During training the ANN it is also necessary to determine the number of blocks, which must be such that all available EEG signal recordings are classified and the number *N* is as small as possible. To speed up the training, recordings with close, according to experts, states are preliminarily grouped together. The training set consisted of more than 1,500 5-min fragments of EEG signal recordings. As a result of training the network, five basic brain states were identified, each of which corresponds to three to six sets of two vectors, which will be called basis vectors:

1) wakefulness – six pairs of basis vectors;

2) superficial sedation (first stage) – four pairs of basis vectors;

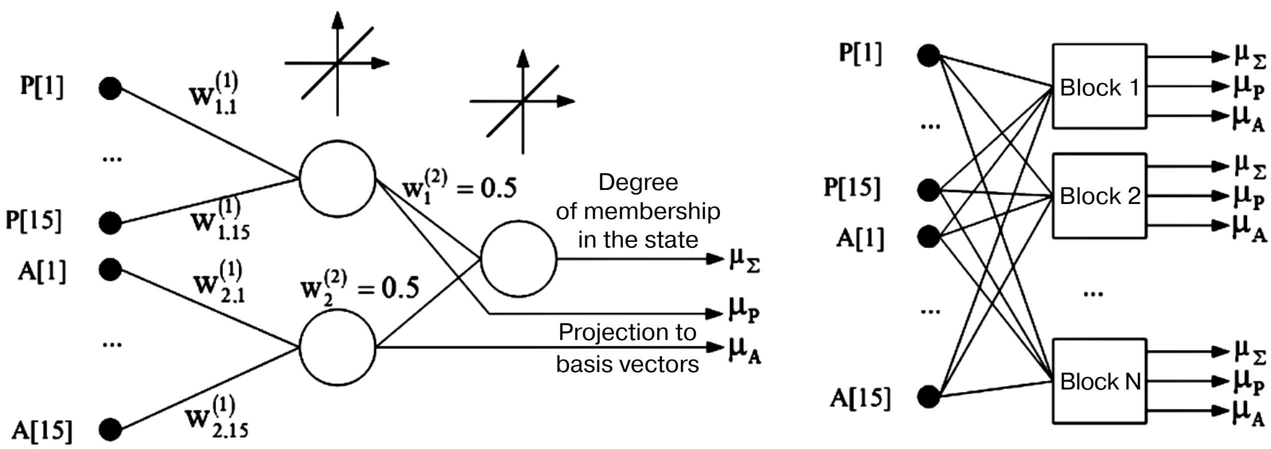

Fig. 3. Structure of ANN for clustering of brain states: (a) structure of a standard block; (b) structure of a WTA network.

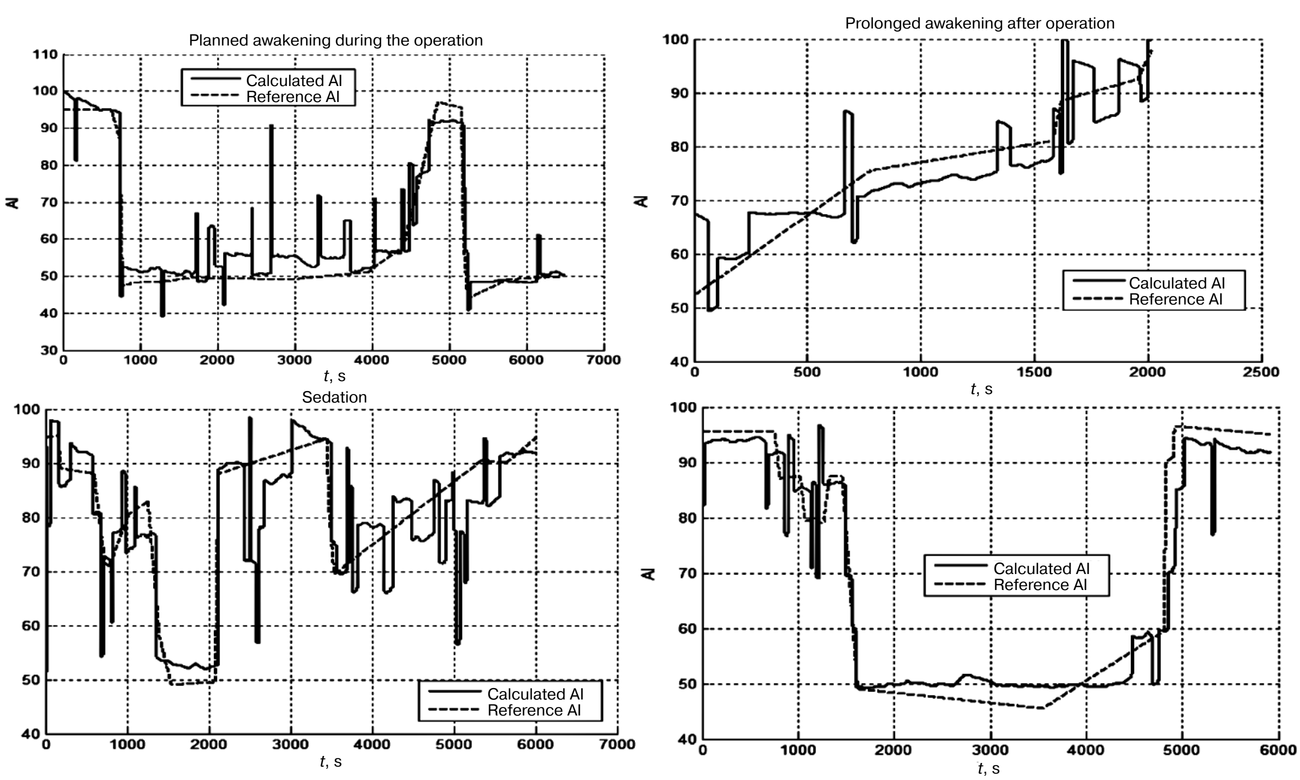

Fig. 4. Results of the algorithm.

3) deep sedation (second stage) – three pairs of basis vectors;

4) operating stage (third stage) – six pairs of basis vectors;

5) operating stage (third stage) using ketamine – three pairs of basis vectors.

After the training the coordinates of the basis vectors are determined by the weights of neurons of the first layer of each of the blocks: $w^{(1)}_{1,\,l-15}$ for vectors P and $w^{(1)}_{2,\,l-15}$ for vectors A. As a result, the total number of training units in the network is 22. Thus, supplying the network with the input vectors P and A, at the output a set of 22 values μ_{Σ}, μ_{P}, and μ_{A} is obtained.

To calculate the AI the ANN is used as a universal approximator of complex multidimensional relationships. Prior to the construction of the network, a procedure of reducing the dimension of the input data is performed, similar to the procedure of accumulation used for fuzzy inference. As the basis of the ANN a three-layer network with a direct signal propagation is adopted. The first layer contains 30 neurons with smooth activation functions, Gaussian or hyperbolic tangent. The third layer is comprised of one neuron with a linear activation function. Training of the ANN to calculate the AI was conducted separately from the ANN performing clustering of brain states. The volume of the training sample was about 60 full intraoperative records, containing typical and characteristic states of the patient. ANN training was conducted by the Levenberg–Marquardt method. As a result of training the MSE was about 0.4%. A check with all records (over 150 records) showed good generalization ability of the ANN.

Figure 4 presents the results of the proposed algorithm for calculating the AI with an indication of the reference AI values formed by the experts. The results shown in Fig. 4 indicate generally good agreement of the reference AI values with the calculated values. The advantages also include a sufficiently small reaction time to change in the state of the patient. An obvious drawback is a rather high lability of indications, which most likely can be explained by the higher sensitivity of the algorithm, i.e., lack of resistance with respect to interference and characteristics of the particular patient.

The proposed algorithm is being tested as part of the Triton MGA-06 depth of anesthesia monitor, which would allow identifying complex situations that have not been taken into account in the ANN training and expanding the set of basis vectors to cover most of the possible cases in actual practice.

It is also worth noting that the obtained results can be used to confirm the connection of the correlation picture of the interaction of individual brain subsystems observed in the bispectrum with the activity of the patient's brain.

The proposed method of synthesis of EEG signal analysis algorithms enables effective use of, on the one hand, the possibility of submission of bispectral signals using correlation analysis and, on the other hand, the capabilities of ANNs in terms of learning, clustering, approximating and generalizing the results.

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