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BIOMEDICAL PHYSICS

Adaptive Filtration of Physiological Artifacts in EEG Signals in Humans Using Empirical Mode Decomposition

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Abstract—A new method for adaptive filtration of experimental EEG signals in humans and for removal of different physiological artifacts has been proposed. The algorithm of the method includes empirical mode decomposition of EEG, determination of the number of empirical modes that are considered, analysis of the empirical modes and search for modes that contains artifacts, removal of these modes, and reconstruction of the EEG signal. The method was tested on experimental human EEG signals and demonstrated high efficiency in the removal of different types of physiological EEG artifacts.

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INTRODUCTION

At present, the study of the oscillatory activity in neural networks of the brain attracts much interest. This problem is at the intersection of many fields of sciences: neurophysiology, medicine, biophysics, nonlinear dynamics, mathematics, etc. The main sources of information on the brain functioning are experimental methods including recording different brain signals. The electroencephalogram (EEG), which is the sum of electrical currents that are generated by a small group of neurons and recorded using an electrode, is one of the most widespread brain signals that are used in research [1]. Since the neural network of the brain is a very complicated oscillatory system, the EEG signal also has a very complex spectral structure with a few frequency ranges (delta, alpha, beta, gamma, etc.), different characteristic rhythms, and oscillatory patterns that attract interest of researchers both during the study of different pathologies (e.g., epilepsy) and during analysis of different functional tests and cognitive processes [2–5].

The problem of analysis of complex signals and characteristic oscillatory patterns in an EEG is traditionally referred to radiophysics and nonlinear dynamics. There are many effective methods for studying the time-frequency structure of signals that are developed in this field, e.g., windowed Fourier transform or continuous wavelet transform [5]. Many of these methods are also quite effective for analysis of EEG signals [6, 7]. Nevertheless, in most cases the application of these methods for investigation of EEG signals is impeded by the presence of different parasitic processes (patterns), noises, and so-called artifacts. When the EEG is recorded, the resulted signal is affected not only by the electrical activity of the neural ensemble of the brain, but also by the external sources of the electrical signal and different electrophysiological processes in the body. Noise in the EEG signal can be caused by different external sources of the electrical signal, e.g., by an industrial network, accumulated static charge, poor contact between the recording electrodes, etc. The presence of noise components in the EEG signal can be significantly reduced by providing a good contact between the electrodes and shielding the recording equipment. The artifacts in the EEG signal are usually of the physiological origin and most often caused by nonstationary processes that occur in the body during EEG recording beside brain activity. These processes can be eye movements, cardiac rhythms, activity of face and neck muscles, etc. [8, 9].

Most EEG artifacts have a significant amplitude that in many cases exceeds the amplitude of the carrying electrical activity of the ensemble of brain neurons. In addition, the frequency ranges of many artifacts coincide with the ranges of patterns that are of interest for investigation. For example, spike-wave discharges that are actively studied and connected with manifestation of absence seizures in humans have the dominant frequency of 3–4 Hz and the well pronounced second harmonic with a frequency of 6–8 Hz; sleep spindles that are also analyzed to study sleep disorders and the mechanisms of the brain functioning have the frequency of 12–14 Hz. At the same time, eye movement artifacts, cardiac rhythms, and muscle activity can be detected within the entire range of 0.5–15 Hz, which includes the three highly informative low-frequency EEG ranges, delta, theta, and alpha [1–3]. Thus, the presence of artifacts and their high variability significantly complicate the time-frequency analysis of EEG signals, which makes the preliminary processing and filtering of EEG signals an important stage of any EEG analysis.

At present, different methods are used to filter the EEG from artifacts. One of the simplest and most widespread methods is based on the visual search for artifacts [10, 11]. The method implies visual (or semiautomatic) analysis of the EEG time series and search for artifacts by an experienced neurophysiologist. The identified artifacts are removed from the signal manually or automatically. It should be noted that this method requires expert knowledge of the structure of EEG signals and significant time costs, especially when long EEG recordings are processed. Moreover, the main method for removal of the artifacts in this case is complete removal of an EEG interval that contains the artifact or setting the signal amplitude within this interval to zero. This procedure inevitably results in the distortion of the EEG signal or complete loss of the information on the time-frequency structure of the signal within this interval [12]. The reduction of EEG data for investigation is critical under the conditions of limited data. For example, the artifact removal by the described method can reduce a 10-minute EEG recording of a healthy human to 2–3 min. The reduction of the EEG recording for investigation decreases the effectiveness of the diagnostics and increases the cost of the experimental work.

Other methods for removal of artifacts are based on different signal decomposition and transformation methods, e.g., on independent component analysis [4, 13, 14], regression analysis [15], and the Gram–Schmidt process [16]. These methods have sufficiently high accuracy of the artifact selection and small distortion of the structure of the EEG signal. However, the algorithms of most of these methods are based on combined analysis of EEG and other physiological signals that contain information on certain types of artifacts, e.g., the electrooculogram (EOG) contains eye movement artifacts, the electrocardiogram (ECG) contains cardiac rhythms, etc. To use these methods, it is necessary to provide recording of additional signals, which is not always possible due to the absence of necessary equipment or investigation of signals that have been recorded beforehand. The application of these methods is also limited by the possibility of removal only of certain types of artifacts (e.g., eye movement artifacts in the case of the Gram–Schmidt process).

Thus, the development of methods for filtering EEG signals that do not distort the structure of the EEG signal and at the same time do not require recording of additional physiological signals is an important problem.

A promising method for processing EEG signals and removal of physiological artifacts is an empirical mode decomposition [17, 18]. Methods that employ empirical modes have been already developed to remove eye movement artifacts [19] and to select cortical patterns of the beta activity in an EEG [20]. These studies demonstrated the prospects of the empirical mode decomposition; however, the results that were obtained cover a sufficiently narrow field, the removal of artifacts only of a certain type (eye movements), or selection of a very specific type of EEG activity.

The present study generalized the approach to filtering EEG signals using empirical modes and proposed a new method for removal of a wide spectrum of physiological artifacts. The suggested method does not require recording of additional physiological signals (EOG, ECG, MEG), which distinguishes it among most classical methods for artifact removal and offers a simple and unified algorithm for EEG filtering, the structure of which does not depend on the type of artifacts that are removed and at the same time makes it possible to remove artifacts of different types in contrast to the approaches in [19, 20].

1. EMPIRICAL MODE DECOMPOSITION

The empirical mode decomposition is a part of the Hilbert–Huang transform and one of the modern methods of the time-frequency analysis of nonlinear nonstationary signals [17–21]. This method allows one to represent a studied signal in the form of a set of amplitude–modulated components with a zero mean, so-called empirical modes.

When experimental data are analyzed, one of the stages of the preliminary processing is reduction of the signal to the zero-mean level, which makes it possible to avoid problems that are connected with erroneous determination of the instantaneous frequency of the empirical modes. However, it is not always possible to implement for nonstationary signals (e.g., EEG), the mean value of which can change in time and be different from zero within local regions [22, 23]. To correctly determine the empirical modes and their instantaneous frequencies by this method, the following conditions should be met:

(1) The local mean value of each empirical mode should be zero.

(2) The number of zero-level crossing for the plot of each empirical mode and the number of local maxima (or minima) of this mode should coincide or differ no more than by 1.

The procedure of the empirical mode decomposition of the signal $x(t)$ implies the following algorithm:

(1) Finding all the extrema (the minima and maxima) of the signal $x(t)$.

(2) Interpolation of the signal between the minima and maxima and construction of the two corresponding envelopes, $e_{\min}(t)$ and $e_{\max}(t)$.

(3) Calculation of the low-frequency component of the signal (trend) as a mean between the two envelopes

$$m_1(t) = \frac{e_{\min}(t) + e_{\max}(t)}{2}.$$

(4) Calculation of the high-frequency component of the signal as a difference between the initial signal and the trend, $d_1(t) = x(t) - m_1(t)$.

If the above-mentioned conditions are satisfied for $d_1(t)$, then it can be considered the first empirical mode $c_1(t)$ of the signal, i.e., $c_1(t) = d_1(t)$.

Otherwise, if the mean value of $d_1(t)$ is not zero, the iteration procedure should be performed

$$d_{11}(t) = d_1(t) - m_{11}(t),$$
$$d_{12}(t) = d_{11}(t) - m_{12}(t),$$
$$\dots$$
$$d_{1k}(t) = d_{1(k-1)}(t) - m_{1k}(t),$$

where $m_{1k}(t)$ is the trend that is calculated for the signal $d_{1(k-1)}(t)$. The iteration procedure ends, when $d_{1k}(t)$ becomes a signal with a zero mean. In this case, $d_{1k}(t)$ becomes the first empirical mode, i.e., $c_1(t) = d_{1k}(t)$.

(5) Subtracting the first empirical mode $c_1(t)$ from the initial signal $x(t)$ and obtaining the residue $r_1(t)$, $r_1(t) = x(t) - c_1(t)$.

To find the second empirical mode, the procedure in (1)–(4) is repeated for the signal $r_1(t)$ instead of the initial signal $x(t)$ and the new value $r_2(t)$ is obtained, which is then used to find the third empirical mode, etc.

An example of the algorithm functioning and a process of finding the first empirical mode are demonstrated in Fig. 1, which gives an initial test EEG signal from the occipital area of the human brain (the O1 electrode, when the 10–20 international system of electrode placement is used) (Fig. 1a) and the results of the consequent steps of the algorithm (Fig. 1b, the extrema in the considered signal; Fig. 1c, the two envelopes with respect to the maxima and minima; Fig. 1d, the low-frequency component (trend) of the signal; Fig. 1e, the high-frequency component of the signal, which is the empirical mode). Figures 1b–1e denote the initial signal by a gray color and the results of each of the algorithm steps by a black color.

According to the time-frequency analysis, the empirical mode decomposition significantly differs from most methods for analysis of signals. The basis functions, with respect to which the decomposition is carried out, in this case are not known beforehand (as, e.g., in the Fourier or wavelet transform), but determined during the decomposition of the signal itself. The total number of empirical modes and the time-frequency characteristics of each individual mode directly depend on the signal that is studied. This property makes the empirical mode decomposition a

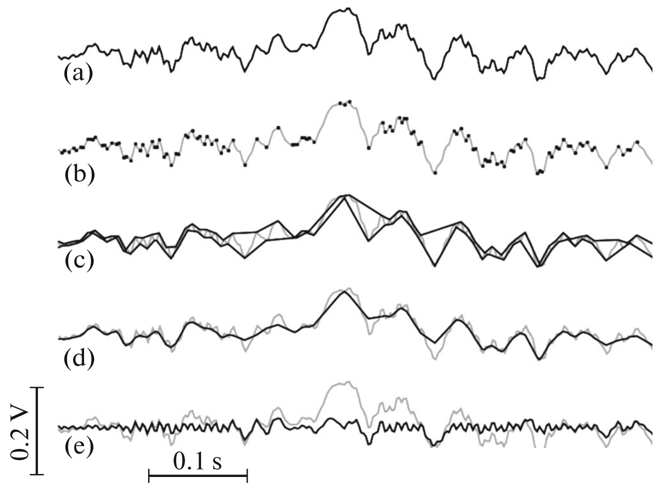

Fig. 1. Stepwise demonstration of the procedure of finding the first empirical mode: an initial EEG signal (a), the found extrema of the signal (denoted by dots) (b), the two envelopes that are constructed using the maxima and minima (c), the calculated signal trend (d), the calculated empirical mode (e).

highly adaptive tool for analysis of signals. The first empirical mode in the decomposition has the highest frequency and the higher the ordinal number of the empirical mode, the lower its dominant frequency. It is shown in [24, 25] that in many cases the frequency structure of different empirical modes corresponds to characteristic oscillatory patterns in EEG signals. Thus, the time-frequency analysis and selection of certain oscillatory patterns (including artifacts) can be reduced to the analysis of one or several modes of the EEG signal.

This property of the empirical mode decomposition is illustrated in Fig. 2, which gives an experimental EEG signal that is recorded from the frontal lobe electrode Fp1 (Fig. 2a) in a human using the 10–20 system and contains several eye movement artifacts and three empirical modes for the considered EEG signal (Figs. 2b–2d). In addition, Fig. 2 demonstrates wavelet spectra that are constructed using the basis Morlet wavelet with the central frequency of 2π [5] for the initial EEG signal and for the three first empirical modes. In this case, the wavelet analysis is used not as an independent tool for analysis of signals, but as clear demonstration of the time-frequency structure of the signal. The eye movement artifacts in Fig. 2 are denoted by dark gray bands. These artifacts are short (~300 ms) oscillatory patterns with a high amplitude of 1–1.5 V. It can be seen from the wavelet spectrum in Fig. 2a that the initial EEG signal contains different rhythms and patterns within a wide range of 0.5–50 Hz, while the eye movement artifacts occur within 0.5–5 Hz. The wavelet spectrum of the first empirical mode (Fig. 2b) demonstrates the highest frequencies in accordance with the procedure of the empirical mode decomposition; therefore, this mode contains

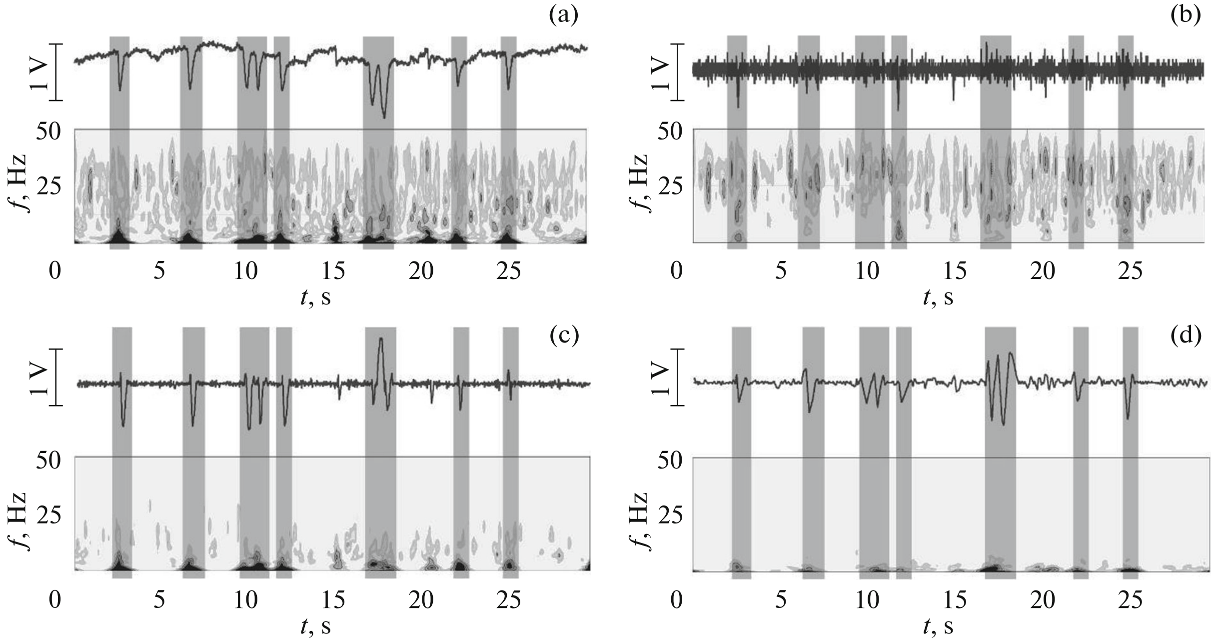

Fig. 2. Example of the empirical mode decomposition: an EEG signal with several eye movement artifacts (a) and its first three empirical modes (b–d); each of the signals has the wavelet spectrum given, which demonstrates its time-frequency structure; the artifacts are denoted by dark boxes.

high-frequency and informative components of the EEG signal. Figures 2c and 2d contain the second and the third empirical modes of the EEG signal together with their wavelet spectra. These spectra mainly contain low frequencies (~0.5–5 Hz), which correspond to the background EEG activity and eye movement artifacts. Thus, in this case eye movement artifacts can be localized in the second and third empirical modes, while the first empirical mode corresponds to the EEG signal without the artifacts. This procedure of localization of artifacts in EEG using empirical modes was broadened to separate artifacts of other types and used as a key element in the development of a new method for filtering EEG signals.

2. METHOD FOR REMOVAL OF ARTIFACTS IN EEG SIGNALS

This study proposes a new method for filtering EEG signals from artifacts using the empirical mode decomposition. The algorithm of the developed method is the following:

(1) Empirical mode decomposition of an EEG signal.

(2) Finding empirical modes that contain physiological artifacts.

(3) Removal of empirical modes that contain physiological artifacts.

(4) Reconstruction of the EEG signal using the remaining empirical modes.

The first stage of the algorithm is empirical mode decomposition of an EEG signal and determination of the total number of empirical modes that are considered.

It should be noted that during the decomposition of the EEG signal each empirical mode is shorter than the initial signal and the preceding mode. This occurs when the signal trend is calculated, since the unequal number of the minima and maxima results in one of the envelopes, $e_{\min}(t)$ or $e_{\max}(t)$, being shorter than the other and some points of the other envelope needing to be removed for the calculation of the trend according to the formula $m(t) = \frac{e_{\min}(t) + e_{\max}(t)}{2}$. At the same time, the higher the ordinal number of the empirical mode, the lower its dominant frequency, which leads to the highest empirical modes having extremely low frequencies. The first several empirical modes lose an insignificant amount of points, when compared to the initial signal; however, as the ordinal number of the mode increases, the losses become more noticeable.

This peculiarity of the empirical modes is demonstrated in Fig. 3, where a typical EEG signal (Fig. 3a), its first empirical mode (Fig. 3b), and its fifth empirical mode (Fig. 3c) are given. In addition, Fig. 3 gives the logarithmic Fourier spectra for the EEG signal and its empirical modes. It can be seen from Fig. 3b that the first empirical mode contains different frequencies with a peak near 3 and 25 Hz and the length of the signal in this case almost does not differ from the length of the initial EEG signal. It can be seen

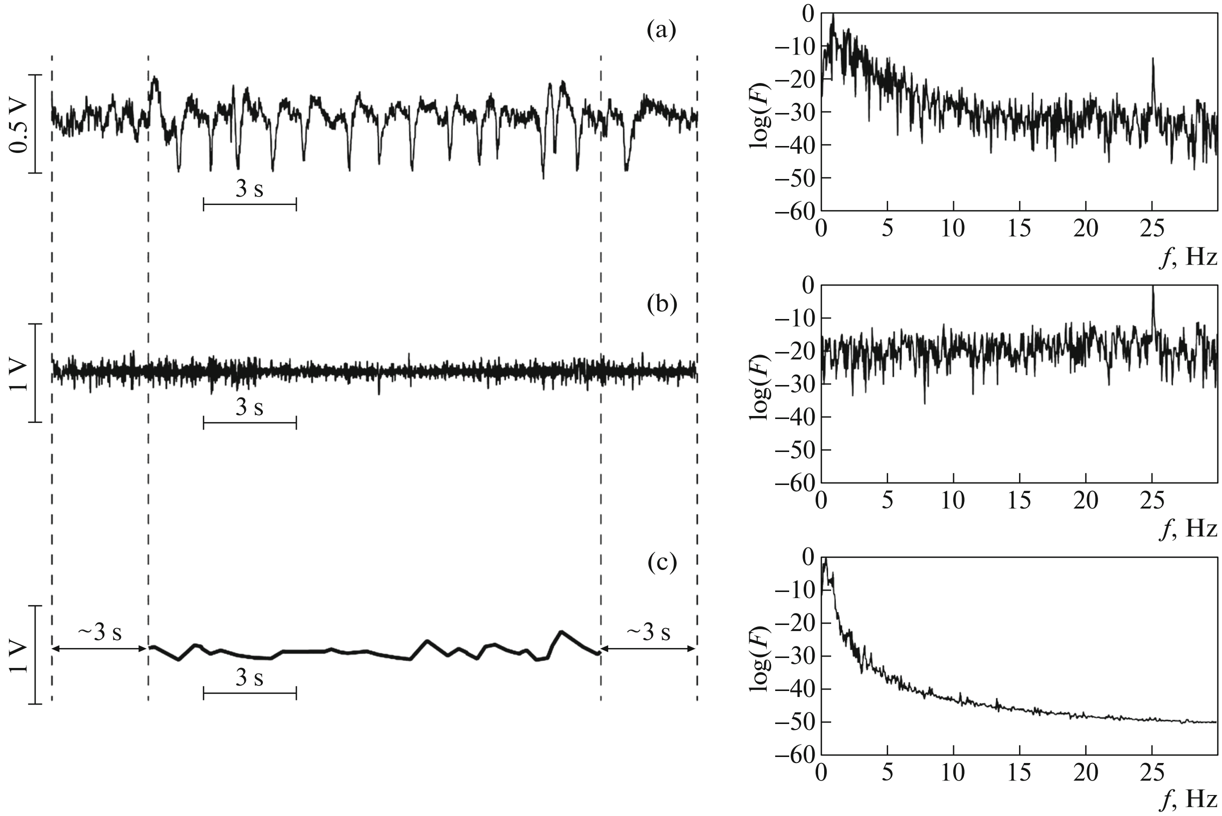

Fig. 3. Example of comparison of characteristics of the lower and higher empirical modes: an EEG signal (a), the first empirical mode (b), and the fifth empirical mode (c); for each of the signals the logarithmic Fourier spectrum is given, which demonstrates the frequency composition of the signal.

from the Fourier spectrum of the fifth empirical mode (one of the highest, Fig. 3c) that it contains low frequencies ~0.5 Hz, which correspond to the slow-wave activity and different noises in EEG that are usually not analyzed neither in clinical practice nor in cognitive research, and, thus, this mode does not contain useful information. We also note that the fifth empirical mode is shorter than the initial EEG signal. This difference can be up to several seconds, which is not important for long EEG recordings, but can be of importance, when short EEG intervals are studied or brain activity is analyzed in real time (e.g., for creation of brain-computer interfaces) [26, 27].

The peculiarity of the algorithm of the offered method is that the reconstruction of the EEG signal at the last stage of the algorithm is carried out by the summation of all the remaining empirical modes and, therefore, the reconstructed signal has the length of the shortest mode from this sum. Thus, during analysis it is necessary to select the optimum number of empirical modes for consideration in order to take into account the maximum number of modes with useful information, on one hand, and, on the other hand, not to take too many high modes, which would have resulted in a significant reduction in the length of the filtered signal due to the boundary effects. Studies demonstrate that in the case of EEG signals in humans, frequencies that are lower than 0.5–1 Hz are mainly background activity and noise (Fig. 2c). Thus, the algorithm of the suggested method considers only empirical modes with the dominant frequency $f_m >$ 0.5 Hz ($m = 1, 2, ..., M$ is the ordinal number of the empirical mode) and the total number of the considered modes is M. When the sampling rate of the EEG recording is 250 Hz, the number of empirical modes that are analyzed usually does not exceed five.

At the second stage of the algorithm, search for modes that contain physiological artifacts is carried out among the considered modes. This procedure is performed using continuous wavelet transform. For this, the same small interval that contains one or several desired artifacts is selected both in the initial EEG signal and in all empirical modes. Then, for this interval in the EEG signal and empirical modes, the corresponding wavelet spectra are constructed and analyzed. It is known from clinical practice and EEG studies that most physiological artifacts have specific time-frequency characteristics, such as frequency range, dominant frequency, duration, waveform, etc. The combination of these properties creates a characteristic pattern in the wavelet spectrum for each artifact type. For example, in the case of eye movement

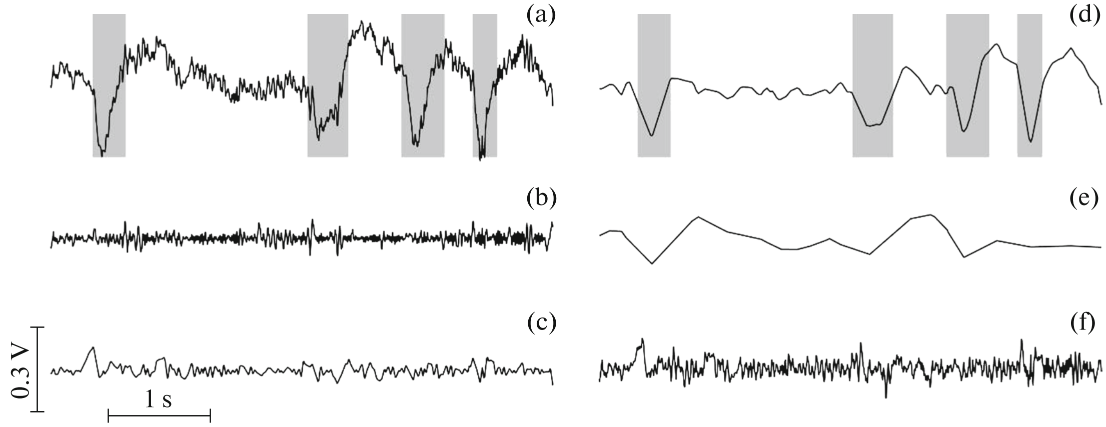

Fig. 4. Example of functioning of the method for filtering EEG signals from artifacts: an EEG signal with several eye movement artifacts (denoted by dark boxes) (a), four empirical modes of the EEG signal (b–e), and the reconstructed signal (f).

artifacts the wavelet spectrum has a sharp increase in the wavelet energy within 0.5–5 Hz during ~300–500 ms (Fig. 2). In the suggested method, the artifact patterns are first determined using the wavelet spectrum of the initial EEG signal and, then, the wavelet spectra of each individual empirical mode are analyzed. It is believed that the empirical mode contains a desired artifact, if its wavelet spectrum contains the pattern of this artifact.

At the third stage of the algorithm, all the empirical modes that have artifacts are removed from the consideration. At the fourth stage, the EEG signal is reconstructed. For this, the remaining empirical modes that do not contain artifacts are summed up

$$U(t) = \sum_{i=1}^{N, i \neq n_1, n_2 \ldots} M_i(t), \quad (1)$$

where $U(t)$ is the reconstructed EEG signal, $M_i(t)$ is the empirical modes, i is the number of the current mode, N is the total number of the empirical modes, and n_1, n_2, ... are the numbers of empirical modes that contain artifacts.

The result of the proposed method is the reconstructed EEG signal with the physiological artifacts being removed.

An example of the functioning of the method is given in Figs. 4 and 5. Figure 4 gives a small interval of an EEG signal from a T4 channel that contains several eye movement artifacts (highlighted by dark boxes) (Fig. 4a), four empirical modes of the EEG signal (Figs. 4b–4e) that are calculated at the first stage of the algorithm, and the result of filtration, the reconstructed EEG signal after summing up the empirical modes (Fig. 4f). Figure 5 contains the wavelet spectra that correspond to the signals in Fig. 4. It can be seen from Figs. 4b–4d and the corresponding spectra in Figs. 5b–5d that the first three empirical modes have predominantly high frequencies, while the fourth empirical mode (Figs. 4e and 5e) has a frequency lower than 1 Hz. Thus, in this case only the first three empirical modes are considered. Then, according to the second step of the algorithm, artifacts are localized in one of the modes. In the wavelet spectrum in Fig. 5a, a dark box denotes the pattern of the considered artifact; the same pattern is observed in the wavelet spectrum of the third empirical mode in Fig. 5d. In this case, artifacts were found in the third empirical mode, which was removed according to the third stage of the algorithm. After this, only the first and the second empirical modes that were summed up at the fourth step of the algorithm resulting in the reconstructed EEG signal (Fig. 4f) remained. It can be seen from Fig. 5f that the wavelet spectrum of the reconstructed signal corresponds to the spectrum of the initial EEG signal (Fig. 5a), but does not contain patterns of the considered artifacts.

Though the above-mentioned example is given for removal of eye movement artifacts, the developed method can also be applied to remove artifacts of other types. In Section 3, we describe examples of removal of cardiac rhythms and artifacts of muscle activity; however, this list can be widened. The developed algorithm can remove other types of artifacts, if these artifacts have a pronounced pattern in the wavelet spectrum and their corresponding empirical modes can be identified.

3. RESULTS

The developed method was tested on the removal of physiological artifacts of several types from experimental human EEG signals. The EEG signals were recorded using an Entsefalan-19/26 encephalograph (Medikom-MTD, Taganrog, Russia) using the 10–20 international system of electrode placement [28]. The signals were filtered by the recording devices within the frequency range of 0.016–70 Hz with a bandpass filter of 49.5–50.5 Hz to remove mains hum. The design of the experiments included standard physio-

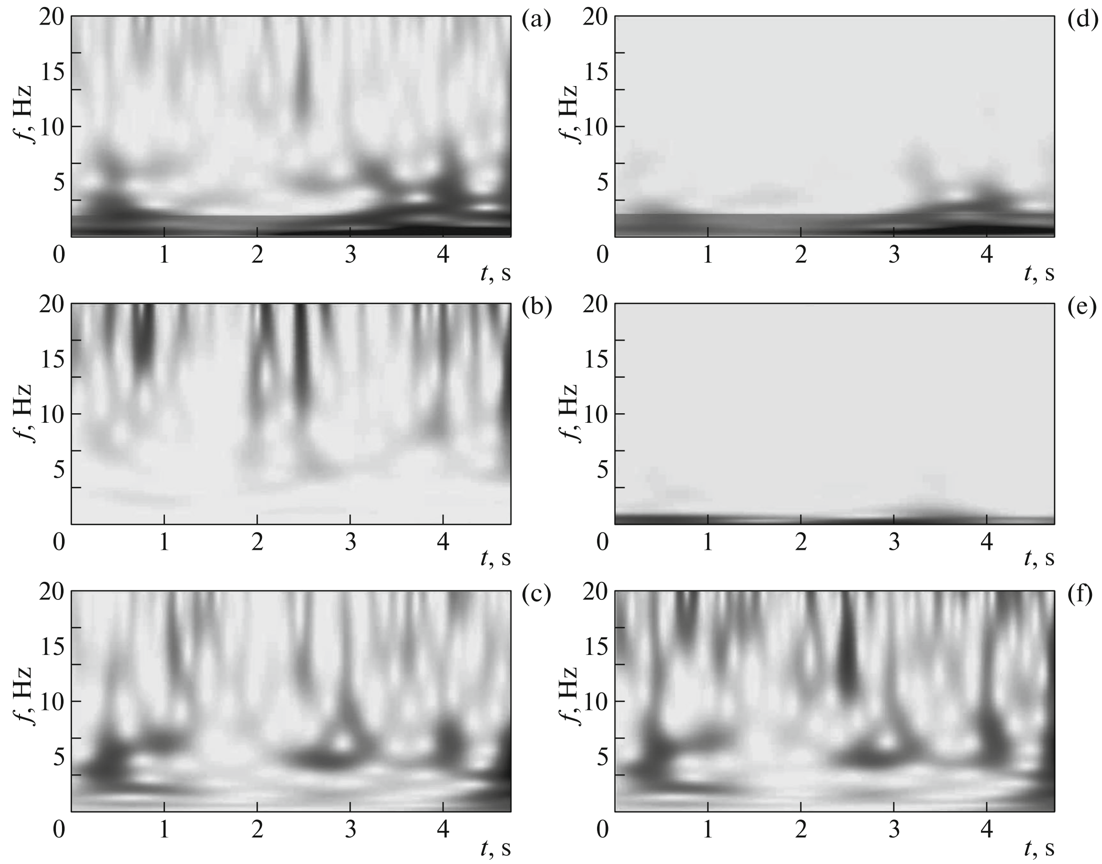

Fig. 5. Example of functioning of the method for filtering EEG signals from artifacts: wavelet spectra that are calculated for an EEG signal with several eye movement artifacts (the artifact pattern in the spectrum is highlighted by a dark box) (a), four empirical modes of the EEG signal (b–e), and the reconstructed EEG signal (f).

logical tests. All the experiments were carried out for 15 healthy men and women at an age of 18–40 years. All the experiments were approved by the ethics committee of the Gagarin State Technical University of Saratov.

During the experiments, the EEG recordings were found to have several types of artifacts, eye movements, cardiac rhythms, and muscle artifacts, each of which were observed within a frequency range of 0.5–15 Hz and, thus, coincided with the range of informative patterns in the EEG signals; therefore, filtration of these artifacts is an important problem.

The results of the proposed method are given in Fig. 6, which show experimental human EEG signals that contain eye movement artifacts (Fig. 6a), cardiac rhythms (Fig. 6b), and artifacts of muscle activity (Fig. 6c). The right part of Fig. 6 also demonstrates the EEG signals after filtration by the suggested method. It can be seen that in each of the cases the artifacts were removed by filtration. In addition, it should be noted that the low-frequency envelope of the EEG signal that did not contain useful information was also removed after application of the developed method. Thus, the suggested method can be used not only for elimination of different types of physiological artifacts in EEG, but also for filtration of several noise components.

The effectiveness of the developed method was demonstrated on an example of the removal of eye movement artifacts from an experimental human EEG recording. A recording with a duration of 600 s was considered with 95 artifacts that had an amplitude from 1 to 4 V being found. The criterion of the removal of the artifact was a reduction in its amplitude after filtration to the mean amplitude of the EEG signal. The mean amplitude of the EEG signal was calculated according to the amplitude of the background activity and different informative patterns, but not artifacts; the mean amplitude in this case was 0.6 V. During filtration of the EEG recording, 88 artifacts were removed, and the accuracy of the developed method was ~92%. Similar results were obtained for the other subjects. Moreover, artifacts that were not removed completely had a significant decrease in the amplitude (a decrease was up to 70% of the initial amplitude), which was also useful for filtration of the EEG signal.

When the effectiveness of the method was analyzed, the quantitative characteristic of the distortion

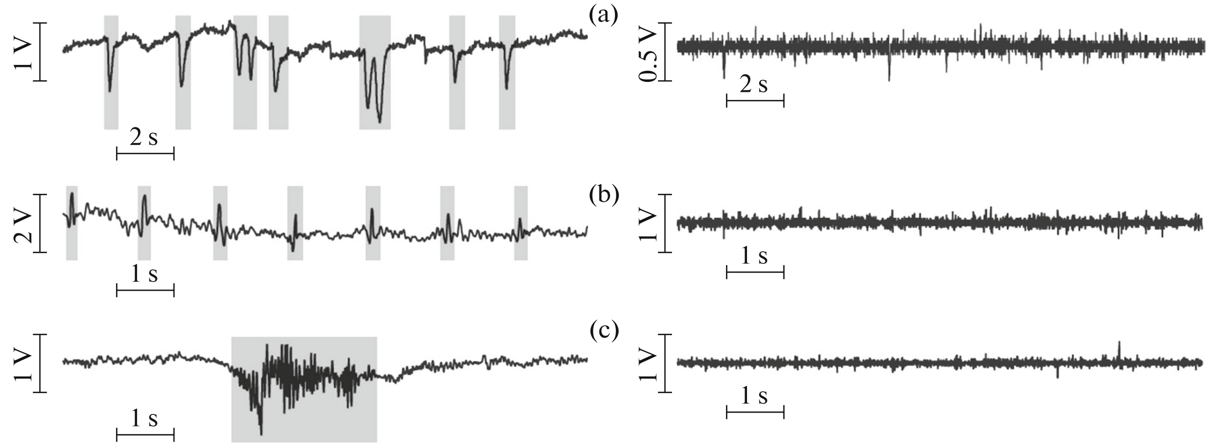

Fig. 6. Results of the filtering of an EEG signal from three types of artifacts: eye movements (a), cardiac rhythms (b), and muscle activity (c); EEG signals before filtration are given in the left part of the figure, the signals after filtration are given in the right part of the figure, the artifacts are denoted by dark boxes.

of the signal spectrum before and after filtration by the developed method was calculated. For this, the wavelet spectra within the frequency range $\Delta f = 5–15$ Hz were calculated for the initial and filtered EEG signals. Then, the quantitative characteristic of the distortion was calculated as

$$M = \frac{1}{E}\int_{\Delta f}\int_{0}^{\tau}|W(f,t) - W_{\mathrm{EM}}(f,t)|dtdf, \qquad (2)$$

where $W(f, t)$ is the amplitude of the wavelet spectrum of the EEG signal before filtration, $W_{\mathrm{EM}}(f, t)$ is the amplitude of the wavelet spectrum of the EEG signal after filtration by the developed method, and τ is the length of the EEG signal; normalization was carried out with respect to the mean amplitude of the wavelet spectrum of the initial signal

$$E = \int_{\Delta f}\int_{0}^{\tau}|W(f,t)|dtdf. \qquad (3)$$

The calculations have resulted in $M < 10^{-2}$ and, thus, the distortion of the EEG signal that is induced by the empirical mode decomposition and removal of the artifacts can be considered insignificant.

CONCLUSIONS

Thus, the present study proposed a new method for filtering EEG signals and removal of physiological artifacts of different types. The universal algorithm of the method that is based on signal decomposition by empirical modes has been developed. The peculiarities of the method that include selection of the empirical modes for consideration and search for modes that contain physiological artifacts by the continuous wavelet transform have been discussed. It has been demonstrated that the developed algorithm is universal for removal of artifacts of different types. The functioning of this method has been discussed on an example of the removal of the three types of artifacts, eye movements, cardiac rhythms, and muscle activity. The method demonstrated a high accuracy (~90%). The calculation of the quantitative characteristics of the distortion of the signal has been performed, which has demonstrated that the distortions that have been introduced into the signal due to the removal of physiological artifacts are insignificant.

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