

Adaptive Filtering of Electroencephalogram Signals Using the Empirical-Modes Method

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Abstract—A new method for the removal of physiological artifacts in the experimental signals of human electroencephalograms (EEGs) has been developed. The method is based on decomposition of the signal in terms of empirical modes. The algorithm involves EEG signal decomposition in terms of empirical modes, searching for modes with artifacts, removing these modes, and restoration of the EEG signal. The method was tested on experimental data and showed high efficiency in the removal of various physiological artifacts in EEGs.

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Currently, a considerable interest in the study of the oscillatory activity in the brain's neural networks is observed. The main sources of information on cerebration are experimental methods of brain-activity registration, for example, electroencephalograms (EEGs) [1]. The EEG signal has a complex composition with a number of characteristic rhythms and patterns that are of interest to researchers in both the study of pathologies (e.g., epilepsy) and in analysis of cognitive processes [2, 3].

In radio-physics, a number of methods of analysis of nonstationary signals have been developed, e.g., window Fourier transformation and continuous wavelet analysis [4], which are very effective in EEG analysis [5, 6]. However, in most cases, studying EEG signals is complicated by the presence of spurious patterns—noises and artifact—which are caused by both external signal sources and processes occurring in the body itself, for example, eye movements, cardiorhythms, the activity of facial and neck muscles, etc. [7, 8].

Most artifacts in EEGs have a significant amplitudes and cover three important EEG low-frequency ranges— δ , θ , and α [1, 2]. The presence of artifacts and their variability complicate the EEG-signal analysis greatly, making preprocessing and filtering an important step of any EEG study.

A number of different methods are used to filter artifacts from EEGs: on the basis of a visual search of artifacts [9, 10], independent-component analysis [3, 11, 12], regression analysis [13], and the Gram–Schmidt transformation [14]. Most methods cause EEG signal distortion [15] or require the joint analysis of EEG with other signals, which may not always be recorded during the experiment.

The development of methods of filtering EEG signals without distorting their structure and requiring the recording of additional physiological signals is an important task. In this paper, a new method for removing artifacts in EEGs based on decomposition in terms of empirical modes (EMs) [16, 17] is presented.

Signal decomposition in EMs is a modern method of time–frequency analysis of nonstationary nonlinear signals and allows us to represent the analyzed signal in the form of a set of amplitude-modulated component with a zero mean—so-called “empirical modes.” In expansion on EMs, basis functions are determined from the signal itself, with their parameters depending directly on the studied signal. This characteristic makes decomposition on EMs a highly adaptive tool for signal analysis. Research has shown [18] that, in many cases, time–frequency analysis and the allocation of specific oscillatory patterns (including artifacts) can be reduced to the analysis of one or more EMs of an EEG signal.

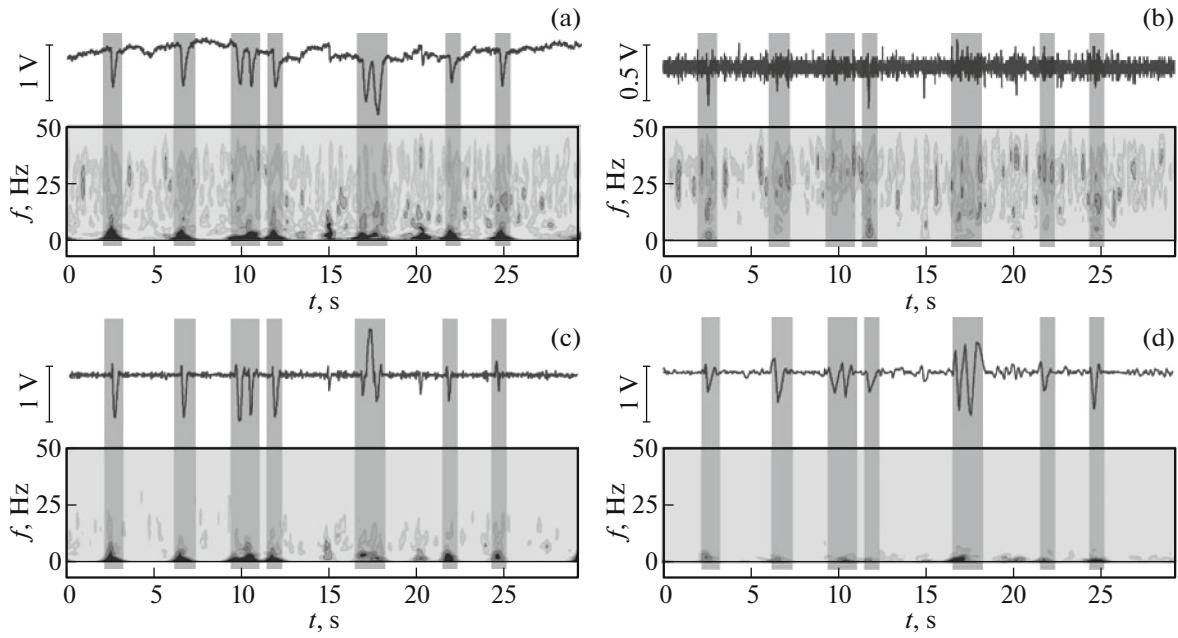


Fig. 1. An example of decomposition in terms of empirical modes: an EEG signal with (a) several oculomotor artifacts and (b, c, d) the first three empirical modes; for each of the signals, a wavelet spectrum that illustrates the frequency–time structure of the signal is given; the artifacts are shown as darkened frames.

This feature is illustrated in Fig. 1, which depicts the experimental signal of human EEG (a) with several oculomotor artifacts, as well as the first three EMs for it (Figs. 1b–1d). Additionally, in Fig. 1, wavelet spectra constructed with Morlet wavelets, which are used to represent a frequency–time signal structure, are shown. On the basis of the wavelet surface in Fig. 1a, it can be seen that the original EEG signal contains various rhythms in the range of 0.5–50 Hz, whereas artifacts occur in the range of 0.5–5 Hz. The wavelet spectrum of the first EM (Fig. 1b) exhibits the highest frequencies, which correspond to the informative components of an EEG signal. Figures 1c and 1d contain the second and third EMs of an EEG signal together with their wavelet spectra, which mainly consist of low frequencies ($\sim 0.5\text{--}5$ Hz) and correspond to the background EEG activity and oculomotor artifacts. Thus, in this case, oculomotor artifacts can be localized in the second and third EMs, while the first EM corresponds to the EEG signal that has been cleaned from artifacts. This localization procedure of an artifact on an EEG was used as a key element in the development of a new method of filtering EEG signals.

The algorithm of the proposed method is as follows.

1. Decomposition of the investigated EEG signal into a set of EMs.
2. Finding EMs containing physiological artifacts.

3. Deletion of EMs containing physiological artifacts.

4. Restoration of the EEG signal from the remaining EMs.

In the first stage of the algorithm, decomposition of the EEG signal on EMs is carried out and the total number of EMs is determined. In the second stage of the algorithm, modes containing artifacts are sought among the EMs under investigation. This is done by comparing the wavelet spectra of the EEG original signal and EMs. From EEG studies, it is known that a large part of physiological artifacts has specific frequency-time characteristics, which collectively create a distinctive image in the wavelet spectrum for each artifact type. In the proposed method, the artifact images are first determined on the wavelet spectrum of the EEG original signal, with the wavelet spectra of each individual EM then being analyzed. In the third stage of the algorithm, all EMs on the wavelet spectra of which artifact images were found are removed from consideration. The fourth stage is EEG-signal reconstruction by summing up of the rest of the EMs. The proposed method results in a restored EEG signal from which physiological artifacts have been removed.

The developed method was tested on the example of removal of the physiological artifacts of two types from the experimental signals of a human EEG. The EEG signals were recorded using the standard scheme

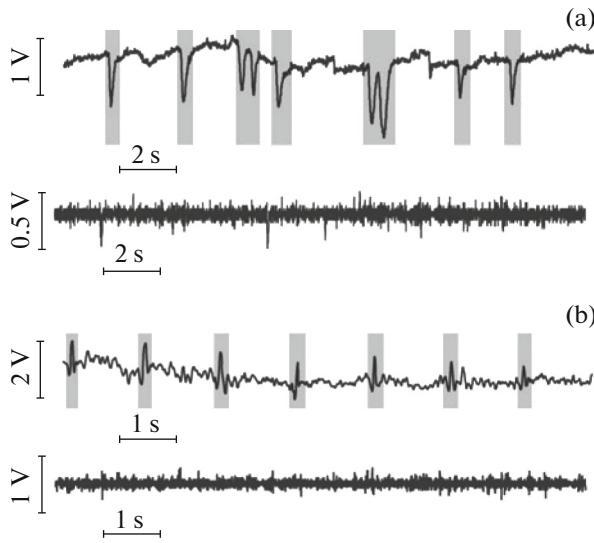


Fig. 2. An example of EEG-signal filtering from the artifacts of two types: (a) oculomotor and (b) cardiorythm artifacts; the EEG signals before filtering are shown on the left part of the figure, the signals after filtering on the right; the artifacts are marked with darkened frames.

of electrode arrangement, the 10–20 international system [19]. All experiments included standard physiological tests and were carried out for 15 healthy men and women 18 to 40 years of age.

During the experiments, two types of artifacts were discovered on the EEG recordings: oculomotor and cardiorythm. Both artifacts are similar in form and appear as short high-amplitude bursts of activity.

An example of the proposed method is shown in Fig. 2, in which the experimental signals of a human EEG containing (a) oculomotor and (b) cardiorythm artifacts are given. Figure 2 also shows the EEG signals after filtering. It is seen that, in each case, both artifacts and the low-frequency envelope of the EEG signal, which does not contain useful information, were removed. Thus, the proposed method can be used not only to remove different types of artifacts in EEGs, but also for filtering the noise component.

The efficiency of the developed method was demonstrated on the example of the removal of oculomotor artifacts from experimental recordings of human EEGs with a duration of 600 s and with 95 artifacts having an amplitude from 1 to 4 V. The criterion for the removal of artifact was its amplitude reduction after filtering to the level of the average amplitude of the EEG signal (in this, case 0.6 V). Eighty-eight artifacts were removed from the EEG recording during filtering, and the accuracy of the developed method was ~92%. In addition, the amplitudes of the artifacts that were not removed

completely were significantly reduced (up to 70% of the original amplitude), which is also useful for EEG-signal filtering.

In the analysis of the method's efficiency, the quantitative characteristic of the signal spectrum distortion was calculated before and after filtration M . For this, the wavelet spectra in the range of $\Delta f = 5$ –15 Hz were calculated for the original and filtered EEG signals and M was calculated as

$$M = \int_{\Delta f}^{\tau} |W(f, t_0) - W_{EM}(f, t_0)| dt df, \quad (1)$$

where $W(f, t_0)$ and $W_{EM}(f, t_0)$ are the wavelet spectrum amplitudes of the EEG signal before and after filtration, respectively, and τ is the EEG-signal length. It was obtained that $M < 10^{-2}$, and, thus, the EEG-signal distortion during artifact removal can be considered negligible.

Thus, in this paper, a new method for filtration and removal of physiological artifacts from experimental EEG signals has been proposed. A method algorithm based on the use of signal decomposition by empirical modes has been developed. The method was tested using the example of the removal of two types of artifacts from EEG signals and showed high efficiency.

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REFERENCES

1. P. L. Nunez and R. Srinivasan, *Electric Fields of the Brain: the Neurophysics of EEG* (Oxford Univ. Press, Oxford, 2006).
2. G. Buzsaki and A. Draguhn, *Science* **304**, 1926 (2004).
3. G. van Luijtelaar, A. Lutjehoann, V. V. Makarov, et al., *J. Neurosci. Methods* **260**, 144 (2016).
4. A. E. Hramov, A. A. Koronovskii, V. A. Makarov, et al., *Wavelets in Neuroscience* (Springer, New York, Dordrecht, London, 2015).
5. A. N. Pavlov, A. E. Hramov, A. A. Koronovskii, E. Yu. Sitenkova, V. A. Makarov, and A. A. Ovchinnikov, *Phys. Usp.* **55**, 845 (2012).
6. S. V. Bozhokin and I. M. Suslova, *Tech. Phys.* **58**, 1730 (2013).
7. J. S. Ebersole, A. M. Husain, and D. R. Nordli, *Current Practice of Clinical Electroencephalography* (Kluwer, Dordrecht, 2014).
8. H. Luders and S. Noachtar, *Atlas and Classification of Electroencephalography* (WB Saunders, Philadelphia, 2000).

9. C. Zhang, L. Tong, Y. Zeng, et al., *Biomed. Res. Int.* **2015**, 720450 (2015).
10. J. A. Uriguen and B. Garcia-Zapirain, *J. Neural Eng.* **12**, 031001 (2015).
11. A. J. Bell and T. J. Sejnowski, *Neural Comput.* **7**, 1129 (1995).
12. C. A. Joyce, I. F. Gorodnitsky, and M. Kutas, *Psychophysiology* **41**, 313 (2004).
13. G. Gratton, *Instrum. Comput.* **30**, 44 (1998).
14. A. A. Koronovskii, A. E. Khramov, O. I. Moskalenko, and V. V. Grubov, RF Patent No. 2560388 (2015).
15. P. A. Merinov and M. G. Belyaev, in *Proceedings of the 39th Interdisciplinary School-Conference of Kharkevich Institute for Information Transmission Problems RAS on Information Technologies and Systems 2015* (Inst. Problem Peredachi Inform. im. A.A. Kharkevicha RAN, Moscow, 2015), p. 313.
16. N. E. Huang, Z. Shen, S. R. Long, et al., *Proc. R. Soc. A* **454**, 903 (1998).
17. A. N. Pavlov, A. E. Filatova, and A. E. Hramov, *J. Commun. Technol. Electron.* **56**, 1098 (2011).
18. V. V. Grubov, E. Yu. Sitnikova, A. N. Pavlov, et al., *Proc. SPIE* **9448**, 94481Q (2015).
19. M. R. Nuwer, C. Comi, R. Emerson, et al., *Electroencephalogr. Clin. Neurophysiol.* **106**, 259 (1998).

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