Filtration of human EEG recordings from physiological artifacts with empirical mode method

Vadim V. Grubov[abc], Anastasiya E. Runnova[abc], Marina V. Khramova[d]

[a] Research and Education Center "Nonlinear Dynamics of Complex Systems", Yuri Gagarin State Technical University of Saratov, Politechnicheskaya Str. 77, Saratov, 410056, Russia;
[b] Department of Automatization, Control and Mechatronics, Yuri Gagarin State Technical University of Saratov, Politechnicheskaya Str. 77, Saratov, 410056, Russia;
[c] Faculty of Nonlinear Processes, Saratov State University, Astrakhanskaya Str. 83, Saratov, 410026, Russia;
[d] Faculty of Computer Sciences and Information Technologies, Saratov State University, Astrakhanskaya Str. 83, Saratov, 410026, Russia;

ABSTRACT

In the paper we propose the new method for dealing with noise and physiological artifacts in experimental human EEG recordings. The method is based on analysis of EEG signals with empirical mode decomposition (Hilbert-Huang transform). We consider noises and physiological artifacts on EEG as specific oscillatory patterns that cause problems during EEG analysis and can be detected with additional signals recorded simultaneously with EEG (ECG, EMG, EOG, etc.) We introduce the algorithm of the method with following steps: empirical mode decomposition of EEG signal, choosing of empirical modes with artifacts, removing empirical modes with artifacts, reconstruction of the initial EEG signal. We test the method on filtration of experimental human EEG signals from eye-moving artifacts and show high efficiency of the method.

Keywords: Electroencephalogram, noise, physiological artifacts, empirical mode decomposition, filtration

1. INTRODUCTION

Studying of brain neuronal networks is an actual and important problem in the modern science. Brain studying is of interest for many researchers from different fields of science: neurophysiology, mathematics, physics, nonlinear dynamics, etc. Information about brain activity is typically obtained by experimental means that include recording of different brain signals. One of the most common brain signals is electroencephalogram (EEG) which represents the sum of electric currents generated by small group of neurons and registered by electrode.[1] Since brain neuronal networks are complex oscillatory systems with great number of elements — neurons, EEG is also a complex signal with number of specific rhythms — oscillatory patterns — that are of interest for researchers.[2–6]

Analysis of complex signals and oscillatory patterns is traditionally related to nonlinear dynamics and radiophysics. There are reliable methods for analysis such as classic Fourier transform or continuous wavelet transform[?,7,9] that allow to investigate time-frequency structure of EEG.[10–12] Nevertheless analysis of EEG data is commonly complicated by the some parasitic specific patterns — noises and so-called artifacts. Some parasitic patterns are caused by external sources of electrical signals such as industrial power grid, static charge, telephone call or by bad connection of EEG electrodes. Most of such artifacts can be cutoff by providing proper EEG electrode connection and shielding during experiment but some patterns with high energy may still take place in EEG signals. Other artifacts are of the physiological nature: they are related to various non-stationary processes in organism during the registration of EEG. There are plenty of activities that can cause artifacts: eye movement, spasms and tension in scalp muscles, muscle activity during jaw movement, cardiac rhythms, etc.[13,14]

Artifacts of external and internal nature commonly have significant amplitude on EEG signals that can greatly exceed the amplitude of electrical activity of brain. Moreover, frequency ranges of most artifacts overlap

Further author information: (Send correspondence to V.V. Grubov)
V.V. Grubov: E-mail: vvgrubov@gmail.com, Telephone: +7 8452 99 88 32

Dynamics and Fluctuations in Biomedical Photonics XIV, edited by Valery V. Tuchin, Kirill V. Larin, Martin J. Leahy, Ruikang K. Wang, Proc. of SPIE Vol. 10063, 1006318 · © 2017 SPIE
CCC code: 1605-7422/17/$18 · doi: 10.1117/12.2250399

frequency ranges of rhythms that are of interest for the researchers. For example, sleep spindles are characterized by frequency range of 10–16 Hz and spike-wave discharges have main frequency of 3–4 Hz with number of harmonics.[15–18] At the same time, eye-moving artifacts, cardiac rhythms, muscle activity can be found in 0.5–15 Hz frequency range which corresponds to the three determined ranges of effective EEG signal — delta, theta and alpha.[19,20] The presence of artifacts along with their variability complicates EEG analysis greatly, thus artifact removing became a standard procedure in modern electroencephalographic studies.

The development of new efficient methods for EEG filtration from artifacts and noises is an important problem in EEG analysis. In present days filtration and pre-processing of experimental EEG signals is performed by number of different methods. The most simple and thus frequently used in routine EEG studies is method based on the visual search of artifacts.[21,22] The method suggests visual (or semi-automated) analysis of EEG time series by experienced neurophysiologist in order to find and locate artifacts. Then artifacts are deleted from EEG signal manually of automatically. Visual analysis requires expert knowledge of EEG signals and takes a lot of time especially in case of routine studies of long-term EEG records. Moreover, the most common way to remove an artifact from EEG signal EEG is to completely delete the whole EEG fragment and replace it with null or average EEG signal amplitude. This procedure naturally leads to total loss of information about EEG time-frequency structure on chosen signal fragment. Such deletion of EEG fragments drastically shortens the amount of informative EEG data for further analysis. For example, in medical practice 10-minute EEG recordings of healthy human can be shortened to 2–3 minutes of filtered signal. The loss of information on EEG inevitably decreases the effectiveness of diagnostic studies and increases costs for data registration. Thus, the development of methods for efficient artifact removal without cutting off EEG data is a very actual and important.

At present time there is number of methods that are widely used for EEG filtration in both medical practice and scientific research. The most used methods are based on analysis of independent components[23,24] and regression analysis.[25] These methods provide decent precision in detection and deletion of artifacts but their algorithms are based on quite complex transforms of EEG signal and require time and high computational power for processing. Another relatively new method is based on Gram-Schmidt transform.[26] The method provides even better precision in artifact detection with more simple algorithm. The method with Gram-Schmidt transform allows relatively quick and accurate detection of eye-moving artifacts, but as a drawback it requires additional EOG signal to be recorded and analyzed along with EEG data. The need for recording of additional signals can increase costs of experimental studies or can make EEG filtration impossible without required equipment. Another disadvantage of the method is the ability to detect only few types of artifacts (eye-moving artifacts in this case), which restricts the sphere of method's use.

In the paper we propose the new method for detection and deletion of noises and artifacts of different types on human EEG. The method is based on empirical mode decomposition (Hilbert-Huang transform),[27,28] it uses clear algorithm and requires no additional experimental signals to be detected besides EEG.

2. EMPIRICAL MODE DECOMPOSITION

Empirical mode decomposition is a part of Hilbert-Huang transform.[27] It is one of the modern methods for time-frequency analysis of nonlinear and nonstationary signals. The method allows to decompose the initial signal into a sum of amplitude-modulated components with zero mean — so-called empirical modes. Empirical mode decomposition suggests that analyzed signal $x(t)$ is determined between two time moments t_- and t_+ and can be presented as sum of low-frequency and high-frequency components. Low-frequency component (or residual) $m(t)$ can be calculated as mean of two envelopes $e_{min}(t)$ and $e_{max}(t)$ constructed from minima and maxima of analyzed signal. High-frequency component (empirical mode) $d(t)$ is calculated as difference between initial signal $x(t)$ and residual $m(t)$. Thus the first empirical mode can be calculated; for calculation of the second empirical mode all steps must be repeated for residual $m(t)$ instead of signal $x(t)$ and so on for subsequent empirical modes.

Algorithm of empirical mode decomposition includes following steps:

1. Finding all extrema on signal $x(t)$
2. Interpolation of signal between minima and maxima and construction of two envelopes: $e_{min}(t)$ and $e_{max}(t)$

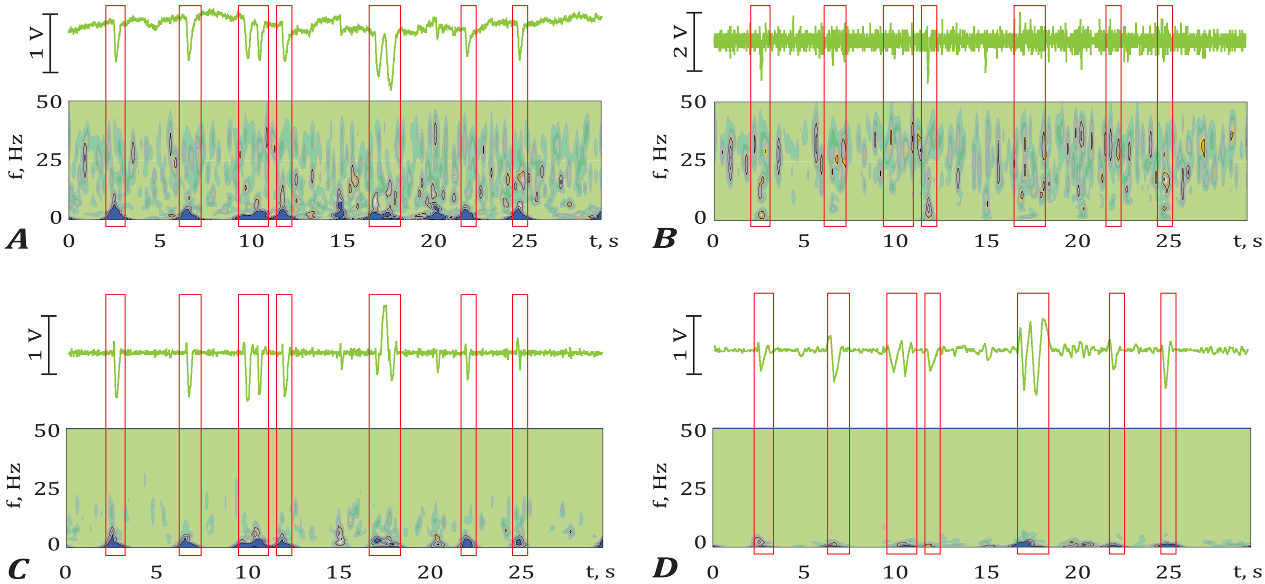

Figure 1. Example of empirical mode decomposition: EEG signal with eye-moving artifacts (A) and three empirical modes (B,C,D); figures are accompanied with corresponding wavelet surfaces that illustrate time-frequency structure of signals; artifacts are marked with red frames

3. Calculation of low-frequency component of signal (trend) $m(t)$: $m(t) = \frac{e_{min}(t)+e_{max}(t)}{2}$
4. Extraction of high-frequency component of signal (empirical mode) $d(t)$: $d(t) = x(t) - m(t)$
5. Reiteration of steps 1-4 for trend $m(t)$ for calculation of subsequent empirical mode

In terms of time-frequency analysis of signals Hilbert-Huang transform is different from classic methods. Basic functions in empirical mode decomposition are not predetermined (as in Fourier or wavelet analysis) but are constructed from analyzed signal itself during decomposition. Time-frequency properties of each empirical mode and total number of empirical modes highly dependent on the initial signal. This feature makes empirical mode decomposition a highly adaptive instrument for signal analysis. The first empirical mode has the highest frequency, and the higher the ordinal number of subsequent mode the lower its frequency. Research shows that in many cases different empirical modes correspond to different oscillatory patterns on EEG.[29] Thus analysis of some specific oscillatory patterns (including artifacts) can be reduced to analysis of one or few individual empirical modes. This feature of empirical mode decomposition is illustrated on following example. Fig. 1 shows empirical mode decomposition of experimental human EEG signal with several eye-moving artifacts.

Fig. 1 shows experimental human EEG signal from frontal cortex with few eye-moving artifacts (A) and three empirical modes for this signal (B, C, D). Fig. 1 also demonstrates wavelet surfaces for corresponding signals: initial EEG and empirical modes. In this case continuous wavelet transform is not used for analysis of EEG signals. Wavelet spectra plays role of instrument for representation and illustrates time-frequency structure of the signals. Eye-moving artifacts are marked with red frames on Fig. 1. These artifacts are represented by short ($\sim$ 300 ms) oscillatory patterns with high-amplitude of 1–1.5 V. Wavelet surface on Fig. 1A shows that initial EEG signal has oscillatory rhythms in wide range of 0.5–50 Hz while eye-moving artifacts interfere in the range of $\sim$0.5–5 Hz. Wavelet spectrum for the first empirical mode on Fig. 1B shows highest frequencies as supposed and thus contains information about most high-frequency and informative components of EEG signal. Fig. 1C,D demonstrate the second and the third empirical modes along with their wavelet spectra. These spectra mostly contain low frequencies ($\sim$ 0.5–5 Hz) that correspond to background and artifact activity. Thus, it can be concluded that in this case eye-moving artifacts can be localized in the second and the third empirical modes while the first empirical mode corresponds to the filtered EEG signal without artifacts. This procedure of localizing of artifacts with in empirical modes can be extended and adapted to other types of artifacts and thus it was used as a core component of the method for EEG filtration developed in the present paper.

3. METHOD FOR EEG FILTRATION

In the paper we proposed the new method for removing physiological artifacts of different types in experimental human EEG recordings. The method is based on procedure of empirical mode decomposition and its property to distribute different types of oscillatory patterns on EEG across different empirical modes as it was shown in example in Section 2.

The algorithm of the proposed method uses elements of empirical mode decomposition, artifacts localization and signal reconstruction. The algorithm includes following steps:

1. Decomposing the studied EEG signal into the set of empirical modes
2. Finding the empirical modes that contain required artifacts
3. Removing the empirical modes with artifacts
4. Reconstructing the EEG signal by summarizing the rest empirical modes

Step 1 suggests empirical mode decomposition of analyzed EEG signal according to algorithm described in Section 2. Total number of empirical modes for given signal is also determined on Step 1. It should be noted that due to different number of minima and maxima in signal some time points are lost during calculation of empirical modes. Each mode is shorter that the initial EEG signal and the higher the ordinal number of subsequent mode the shorter its length. While first few empirical modes loose only insignificant number of time points, this loss becomes more noticeable on modes with higher ordinal numbers. At the same time, most of modes with high numbers are of very low frequency and thus contain no valuable information from EEG signal. Reconstruction of EEG signal on Step 4 uses all chosen modes and the length of reconstructed signal fits the length of the shortest empirical mode. So it is important to choose all modes that contain valuable information of EEG signal and also to take not too many modes that can make resulting filtered signal too short. In case of EEG signal empirical modes with frequencies lower than 0.5 Hz are too short and contain information mostly about noises and background activity so only the modes with frequencies $f_m > 0.5$ ($m = 1, 2, ...M$ - ordinal number of empirical mode) should be analyzed and total number of chosen modes is M.

The empirical modes acquired after Step 1 of the algorithm should be analyzed. The task of Step 2 is to find the empirical modes with artifacts and there are several appropriate ways for this procedure.

Localization of artifacts can be performed with visual search as in classic methods described in Introduction. In case of using empirical mode decomposition visual search is notably easier because expert-neurophysiologist can analyze specific modes instead of the whole signal. Empirical mode decomposition acts as an instrument of adaptive filtration. For example, eye-moving artifacts are seen more clearly on the second and the third empirical modes (see Fig. 1C,D) than on the initial EEG signal (Fig. 1A) because low-frequency envelope of the signal and some other artifacts gone to other empirical modes. Moreover, expert has no need to analyze full EEG recording, he can spot empirical mode with desired artifacts through some small fragment of EEG and be sure that other artifacts of this type are also belong to this mode.

Another method to find empirical modes with artifacts is to analyze average signal energy of initial EEG and each empirical mode. Signal energy $E(t)$ can be calculated as:

$$E(t) = A^2(t), \tag{1}$$

where $A(t)$ — amplitude of the signal. Thus, average energy of some signal over its total length can be calculated as:

$$\langle E \rangle = \frac{1}{\tau} \int_{t=0}^{t=\tau} A^2(t)dt, \tag{2}$$

where τ — length of the signal. Localization of artifacts can be performed by analyzing of a fragment of EEG with several artifacts. Average signal energy should be calculated for this fragment in initial EEG signal ($\langle E^{EEG} \rangle$) and in each empirical mode ($\langle E_i^{EM} \rangle$, where i — number of empirical mode). Energy on each empirical mode is compared with energy on EEG. Empirical mode i contains artifacts if its average energy in given fragment is close to energy of artifact on EEG:

$$0.85 * \langle E_i^{EEG} \rangle < \langle E_i^{EM} \rangle < 1.15 * \langle E_i^{EEG} \rangle \tag{3}$$

More reliable methods to find empirical modes with artifacts are based on Fourier analysis and continuous wavelet analysis.

Fourier spectra is a well-known method for representation of frequency structure of signals. In case of localizing empirical modes with artifacts the spectra of initial EEG signal and all empirical modes can be constructed. Then these spectra should be analyzed and most significant frequencies should be determined. Frequency ranges of most significant physiological artifacts are well-determined in clinical practice. Given empirical mode contains artifacts if most significant frequencies in its Fourier spectrum correspond to the frequency range of artifacts.

Continuous wavelet analysis[9] introduces wavelet surfaces that provide information about time-frequency structure of signal. Time-frequency characteristics of most physiological artifacts are well known, especially their frequency ranges, average lengths and waveforms, which gives a characteristic images for each artifact type on wavelet spectra (for example, see Fig. 1C,D). Thus, empirical modes with artifacts can be determined by analyzing its wavelet surfaces. Empirical mode contains artifacts if its wavelet surface demonstrates images of these artifacts.

On Step 3 of the proposed algorithm empirical modes with artifacts should be removed and on Step 4 EEG signal is reconstructed. Reconstruction suggests summarizing of the empirical modes that do not content artifacts:

$$U(t) = \sum_{i=1}^{N, i \neq n_1, n_2 \ldots} M_i(t), \tag{4}$$

where $U(t)$ — reconstructed EEG signal, $M_i(t)$ — empirical modes, i — number of current empirical mode, N — total number of empirical modes, $n_1, n_2 ...$ — numbers of empirical modes with artifacts.

Thus, the result of the proposed filtration method is reconstructed EEG signal with removed artifacts.

4. RESULTS

Method for removing physiological artifacts on EEG signals was tested on filtering of several types of artifacts on experimental human EEG signals.

EEG signals were recorded with use of standard scheme for placing electrodes — International 10-20 system.[30] Frequency range of EEG records was 0.016 – 70 Hz with band-pass filter on 49.5 – 50.5 Hz to prevent influence of power grid. Amplitude of EEG signals were in range of 0.02 – 2 V with artifacts amplitude about 1 – 1.5 V.

Number of experiments with different designs was performed. First type of experiment included standard physiological trials such as opening/closing eyes, audio stimulation, photic stimulation etc.[1] Another type of experiment suggested movement trials: human subjects performed moves with left and right hands and legs according to demonstrated stimuli. In last type of experiment bistable visual stimuli were demonstrated. All of these stimuli can be percepted as one of two different objects and human subjects decided what kind of object they see in each case. Experiments were held for 15 healthy men and women in age of 18 – 40. Duration of each record was 10, 25 and 30 minutes according to the type of experiment.

Number of physiological artifacts occur on experimental EEG recordings. Eye-moving artifacts are quite common for this type of EEG records with high eye activity. These artifacts have significant amplitude (about

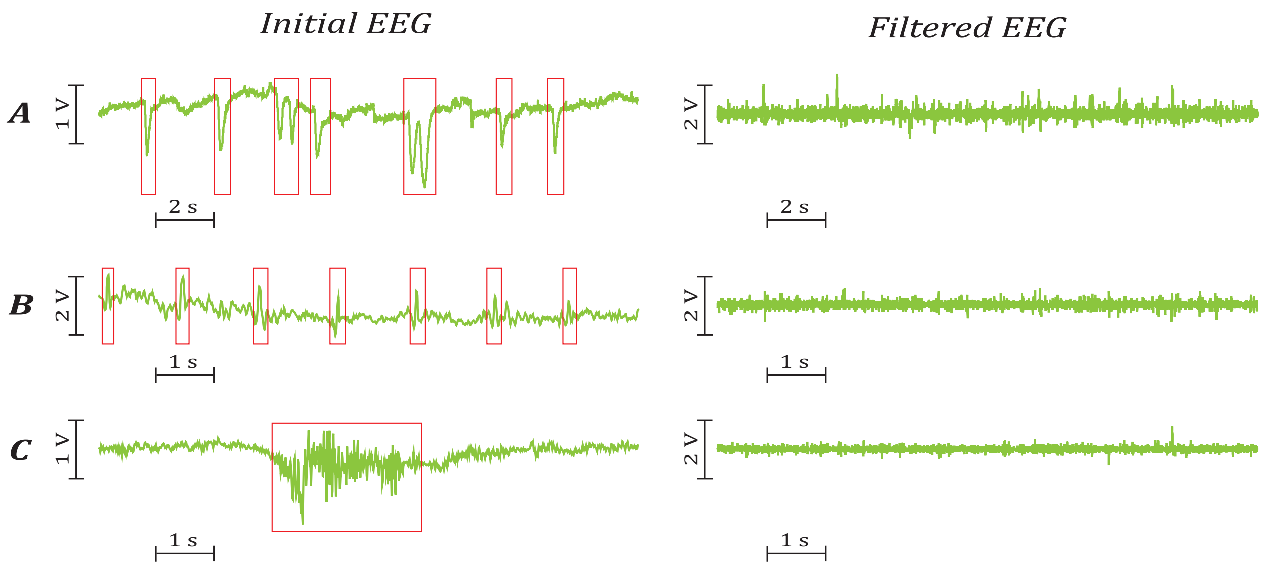

Figure 2. Example of EEG signals filtration on different types of artifacts: eye-moving artifacts (A), cardiac rhythms (B), facial muscle activity (C); each example is illustrated with initial experimental EEG signal (on left) and filtered signal (on right); artifacts are marked with red frames

1 − 1.5 V) and can be found mostly in frontal cortex channels, which are commonly used in studies of cognitive brain activity. Another type of artifacts are associated with cardiac rhythms and commonly interfere in all kinds of EEG recordings. These artifacts also have high amplitude up to 1 V and are characterized by high regularity. Muscle activity also contributes in artifacts on EEG. Mostly it is related to movement of facial and neck muscles and shows up on EEG as high-amplitude bursts (∼1-2 Hz) with wide frequency range. All these types of artifacts interfere in frequency range of 0.5–15 Hz and thus overlap many informative oscillatory patterns on EEG.

Fig. 2 illustrates an example of filtering EEG signal from different types of artifacts with the proposed method. Fig. 2 shows EEG signals before and after filtration from eye-moving artifacts (A), cardiac rhythms (B) and muscle activity (C).

During filtration each EEG signal was decomposed into the set of empirical modes. Then modes with artifacts were determined with the help of wavelet analysis. For example, it was found that the second and the third empirical modes contain eye-moving artifacts (see Fig. 1C,D). Then EEG signal was reconstructed by summarizing all empirical modes except the modes with artifacts. It can be clearly seen that artifacts were filtered from EEG signals in each case for eye-moving artifacts, cardiac rhythms and muscle activity. Moreover, low-frequency envelope of EEG signal that contain no valuable information for analysis was also filtered. Thus, the proposed method can be used not only for removing physiological artifacts of different types but also for filtering some noise components on EEG signals.

Quantitative distortion characteristic of signal spectrum before and after filtration was calculated. For this procedure wavelet spectra were calculated for initial EEG signal and for signal after filtration in frequency range of $\Delta f = 5$–10 Hz. Then quantitative distortion characteristic was found as:

$$M = \int_{\Delta f} \int_0^{\tau} |W(f, t_0) - W_{EM}(f, t_0)| dt df, \quad (5)$$

where $W(f, t_0)$ — amplitude of wavelet spectrum of EEG signal before filtration, $W_{EM}(f, t_0)$ — amplitude of wavelet spectrum of EEG signal after empirical mode filtration, τ — length of EEG signal. Calculation shows that $M < 10^{-2}$ which means that distortion of EEG signal caused by procedure of empirical mode based filtration is insignificant.

Statistic analysis of filtering physiological artifacts on EEG recording of all 15 participants showed that proposed method removed over 95% of all artifacts. While the method was tested for eye-moving artifacts, cardiac rhythms and muscle activity its application is not restricted for only this types of artifacts. It also can be used for removing other types of artifacts that have high amplitude and characteristic frequencies distinct from frequencies on EEG, for example.

5. CONCLUSION

The present work is devoted to the development of the method for removing physiological artifacts from experimental EEG signals. New method based on the empirical mode decomposition (Hilbert-Huang transform) was proposed and tested for filtration of human EEG signals from physiological artifacts. High efficiency of the method was demonstrated on filtration of eye-moving artifacts, cardiac rhythms and muscle activity along with possibility to remove other types of artifacts.

Further research will go towards improvement of the method in order to expand the range of different artifacts and noise components that can be removed with the method. One of possible direction of improvement is combination of the proposed method with some powerful instrument of time-frequency analysis, for example, continuous wavelet transform.

6. ACKNOWLEDGMENTS

This work has been supported by the Russian Foundation of Basic Research (Grant No. 16-29-08221) and Russian Science Foundation (Grant No. 16-12-10100).

REFERENCES

[1] Niedermeyer, E., da Silva, F. L. [*Electroencephalography: Basic Principles, Clinical Applications, and Related Fields*], Lippincot Williams & Wilkins (2004).

[2] Buzsaki, G., and Draguhn, A., "Neuronal oscillations in cortical networks," *Science* **304**, 19261929 (2004).

[3] van Luijtelaar, G., Hramov, A. E., Sitnikova, E. Yu., and Koronovskii, A. A. "Spike-wave discharges in WAG/Rij rats are preceded by delta and theta precursor activity in cortex and thalamus," *Clinical Neurophysiology* **122**, 687-695 (2011).

[4] van Luijtelaar, G., Luttjohann, A., Makarov, V. V., Maksimenko, V. A., Koronovskii, A. A., and Hramov, A. E. "Methods of automated absence seizure detection, interference bystimulation, and possibilities for prediction in genetic absence models," *Journal of Neuroscience Methods* **260**, 144-158 (2016).

[5] Nazimov, A. I., Pavlov, A. S., Nazimova, A. A., Grubov, V. V., Koronovskii, A. A., Sitnikova, E. Yu., Hramov, A. E. "Serial identification of EEG patterns using adaptive wavelet-based analysis," *Eur. Phys. J. Special Topics* **222**, 2713-2722 (2013).

[6] Doron, I., Hulata, E., Baruchi, I., Towle, V. L., Ben-Jacob E., "Time-Invariant Person-Specific Frequency Templates in Human Brain Activity," *Physical Review Letters* **96**, 258101 (2006).

[7] van Vugt, M. K., Sederberg, P. B., Kahana, M. J. "Comparison of spectral analysis methods for characterizing brain oscillations," *Journal of Neuroscience Methods* **162**, 49-63 (2007).

[8] Sitnikova, E., Hramov, A. E., Koronovskii, A. A., and van Luijtelaar, G., "Sleep spindles and spikewave discharges in EEG: Their generic features, similarities and distinctions disclosed with Fourier transform and continuous wavelet analysis," *Journal of Neuroscience Methods* **180**, 304-316, (2009).

[9] Hramov, A. E., Koronovskii, A. A., Makarov, V. A., Pavlov, A. N. and Sitnikova, E. Y. [*Wavelets in Neuroscience*], Heidelberg New York Dordrecht London (2015).

[10] Hramov, A. E., Sitnikova, E., Pavlov, A. N., Grubov, V. V., Koronovskii, A. A., and Khramova, M. V., "Time-frequency dynamics during sleep spindles on the EEG in rodents with a genetic predisposition to absence epilepsy (WAG/Rij rats)," *Proc. SPIE.* **9448**, 94481P, (2015).

[11] Sitnikova, E., Hramov, A. E., and Grubov, V. V., and Koronovskii, A. A. "Time-frequency characteristics and dynamics of sleepspindles in WAG/Rij rats with absence epilepsy," *Brain research* **1543**, 290-299 (2014).

[12] Sitnikova, E., Hramov, A. E., Grubov, V. V., and Koronovskii, A. A. "Rhythmic activity in EEG and sleep in rats with absence epilepsy" *Brain research bulletin* **120**, 106-116 (2016).

[13] Daly, D., Pedley, T., eds., [*Current Practice of Clinical Electroencephalography*], 2nd ed. New York: Raven Press. (1990).

[14] Luders, H., Noachtar, S. [*Atlas and Classification of Electroencephalography*], Philadelphia: WB Saunders Co. (2000).

[15] Ovchinnikov, A. A., Luttjohann, A., Hramov, A. E., van Luijtelaar, G., "An algorithm for real-time detection of spike-wave discharges in rodents," *Journal of Neuroscience Methods* **194**, 172-178 (2010).

[16] Ovchinnikov, A. A., Hramov, A. E., Luttjohann, A., Koronovskii, A. A., and van Luijtelaar, G., "Method for diagnostics of characteristic patterns of observable time series and Its real-time experimental implementation for neurophysiological signals," *Technical Physics* **56**, 1-7 (2011)

[17] Sitnikova, E., Grubov, V. V., Hramov, A. E., and Koronovskii, A. A., "Structure of EEG sleep spindles in rats with genetic predisposition to absence epilepsy (WAG/Rij)," *Journal of higher nervous activity* **62**, 733-744 (2011).

[18] Sitnikova, E., Hramov, A. E., Grubov, V. V., Ovchinnikov, A. A., and Koronovskii, A. A., "On-off intermittency of thalamo-cortical oscillations in the electroencephalogram of rats with genetic predisposition to absence epilepsy," *Brain Research* **1436**, 147-156 (2012).

[19] Tyner, F., Knott, J., and Mayer, Jr. W., [*Fundamentals of EEG technology. Basic Concepts and Methods*], NY: Raven Press. (1983).

[20] Lopes da Silva, F. H., Nunez, P. L., Srinivasan, K. [*Electric fields of the brain: the neurophysics of EEG*], Oxford University Press. (2006).

[21] Zhang, C., Tong, L., Zeng, Y. et al. "Automatic Artifact Removal from Electroencephalogram Data Based on A Priori Artifact Information," *Biomed Res Int.* **720450** (2015).

[22] Uriguen, J. A., Garcia-Zapirain, B. "EEG artifact removal-state-of-the-art and guidelines," *J Neural Eng.* **12**(3), 031001 (2015).

[23] Bell, A. J., Sejnowski, T.J. "An information-maximization approach to blind separation and blind deconvolution," *Neural Comput.* **7**, 1129 (1995).

[24] Joyce, C.A., Gorodnitsky, I.F., Kutas, M. "Automatic removal of eye movement and blink artifacts from EEG data using blind component separation," *Psychophysiology.* **41**, 313-325 (2004).

[25] Gratton, G. "Dealing with artifacts: Behavior Research Methods," *Instruments & Computers* **30**, 44-53 (1998).

[26] Bau, D., Trefethen, L. N. [*Numerical linear algebra*], Philadelphia: Society for Industrial and Applied Mathematics. (1997).

[27] Huang, N.E., Shen, Z., Long, S.R. at al. "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," *Proc. R. Soc. A* **454**, 903 (1998).

[28] Pavlov, A. N., Filatova, A. E., and Hramov A. E., "Digital filtering and time-and-frequency analysis of nonstationary signals on the basis of wavelets and empirical modes," *J. Communication Technology and Electronics* **56**, 1098 (2011).

[29] Grubov, V.V., Sitnikova, E.Yu., Pavlov, A.N., Khramova, M.V., Koronovskii, A.A., and Hramov, A.E. "Time-frequency analysis of epileptic EEG patterns by means of empirical modes and wavelets," *Proc. SPIE* **9448**, 94481Q (2015).

[30] Nuwer, M. R., Comi, C., Emerson, R. et al. "IFCN standards for digital recording of clinical EEG," *Electroencephalogr. Clin. Neurophysiol.* **106**, 259–261 (1998).