Artifact removal from EEG data with empirical mode decomposition

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ABSTRACT

In the paper we propose the novel method for dealing with the physiological artifacts caused by intensive activity of facial and neck muscles and other movements in experimental human EEG recordings. The method is based on analysis of EEG signals with empirical mode decomposition (Hilbert-Huang transform). We introduce the mathematical 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 movement artifacts and show high efficiency of the method.

Keywords: Electroencephalogram, extended setup for EEG electrode system, movement artifacts, empirical mode decomposition, filtration

1. INTRODUCTION

Studying of brain activity is a task of great interest in modern science. It lies in conjunction of many fields of natural science such as neurophysiology, mathematics, biophysics, nonlinear dynamics etc. Main sources of information about brain activity relate to various experimental methods and one of the most common of them is electroencephalogram (EEG). EEG signal represents the sum of electric currents generated by small group of neurons and registered by electrode.[1] Since neuronal network of brain is a quite complex oscillatory system with great number of elements and regimes, EEG is also a complex signal with specific rhythms and patterns that are of interest in various studies: from disorders to cognitive processes.[2]

Tasks of complex signal analysis and oscillatory patterns detection are commonly related to radiophysics and nonlinear dynamics. Number of reliable and effective methods such as windowed Fourier analysis or continuous wavelet analysis[3] were developed for detailed investigation of signals time-frequency structure. Many of these methods find an application in EEG signal analysis.[4] However, analysis of EEG data is commonly complicated by some parasitic oscillatory patterns — noises and so-called artifacts. Noise components in EEG signal are usually caused by some external sources of electric charges and signals such as static charge, bad shielding of recording electrodes, industrial power grid, telephone call etc. Level of noise in EEG signal can be greatly reduced by providing proper experimental conditions including good shielding of recording devices. Physiological artifacts are related to processes that take place in organism and provide generation of some electric charge: eye movement, cardiac rhythms, facial and neck muscle activity, etc.[5,6]

Physiological artifacts are much harder to deal with because their appearance on EEG signal is irrelevant to quality of experimental conditions. Such artifacts usually have high amplitude that exceeds amplitude of most patterns on EEG signal. Moreover, most artifacts are either short bursts with wide frequency range (eye-moving

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and cardiac artifacts) or relatively long oscillations (movement artifacts), and thus they can overlap informative EEG patterns in frequency region (delta, theta and alpha ranges[7,8]) or in time region. 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.[9,10] The method suggests visual (or semi-automated) analysis of EEG time series by experienced neurophysiologist in order to find and locate artifacts. This method requires a lot of time especially in case of routine studies of long-term EEG records and leads to EEG structure distortion due to the procedure of deletion of EEG fragments with artifacts. Other methods are based on analysis of independent components,[11,12] regression analysis[13] and Gram-Schmidt transform.[14] These methods provide decent precision in detection and deletion of artifacts but require additional physiological signal to be recorded and analyzed along with EEG data. This disadvantage is especially noticeable while dealing with muscle-movement artifacts. There are signals that can be recorded relatively easy to aid the detection and the removal of some artifacts: electrooculogram (EOG) and electrocardiogram (ECG) for eye-moving and cardiac artifacts respectively. Electromyogram (EMG) can be used in detection of muscle-movement artifacts, but each electrode records activity only near several small face or neck muscles and thus it is quite difficult to provide proper amount of EMG channels to cover all important muscles.

The task of development of new methods for detection and deletion of noises and artifacts of different types on human EEG is crucial. In present paper we propose the new method that is based on empirical mode decomposition (Hilbert-Huang transform).[15] The method uses clear algorithm and requires no additional experimental signals to be detected besides EEG.

2. HILBERT-HUANG TRANSFORM

Empirical mode decomposition is a part of Hilbert-Huang transform.[15] It is one of the modern methods for time-frequency analysis of complex 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 $e_{max}(t)$,
3. Calculation of low-frequency component of signal (trend) $m(t)$:

$$m(t) = \frac{e_{min}(t) + e_{max}(t)}{2}, \tag{1}$$

4. Extraction of high-frequency component of signal (empirical mode) $d(t)$:

$$d(t) = x(t) - m(t), \tag{2}$$

5. Reiteration of steps 1–4 for trend $m(t)$ for calculation of subsequent empirical mode.

In terms of time-frequency analysis empirical mode decomposition is different from most methods such as Fourier and wavelet transform. Basic functions in empirical mode decomposition are not predetermined 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 frequency ranges of different empirical modes correspond to ranges of different oscillatory patterns on EEG.[16] Thus time-frequency analysis of some specific oscillatory patterns (including artifacts) can be reduced to analysis of one or few individual empirical modes.

3. ARTIFACT REMOVAL ALGORITHM

In the paper we proposed the new method for removing physiological artifacts 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.

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 N 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.

A flowchart of the algorithm is presented in Fig. 1. 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 $f_g = 0.5\,\mathrm{Hz}$ are too short and contain information mostly about noises and background activity so only the modes with frequencies $f_m > 0.5$ ($m = 1, 2, ...M$ is the 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 are analyzed on Step 2 to find the empirical modes with artifacts. Localization of artifacts is performed with continuous wavelet analysis. During Step 2 small fragment of EEG with one or more artifacts is chosen. Wavelet surfaces that provide information about time-frequency structure of signal are constructed an analyzed for this fragment on initial EEG signal and all empirical modes. It is well-known that most artifacts on EEG possess specific time-frequency characteristics such as length, frequency range, main frequency, additional frequencies, waveform, etc. Whole set of these characteristics provides a unique image on wavelet spectrum for each type of physiological artifact. We assume that given empirical mode contains artifacts of given type if its wavelet spectrum demonstrates images of these artifacts.

On Step 3 of the proposed algorithm empirical modes with artifacts are removed and on Step 4 EEG signal is reconstructed. Reconstruction suggests summarizing of the empirical modes $d_i(t)$ that do not content artifacts:

$$X_f(t) = \sum_{i=1}^{N, i \neq n_1, n_2 ...} d_i(t), \tag{3}$$

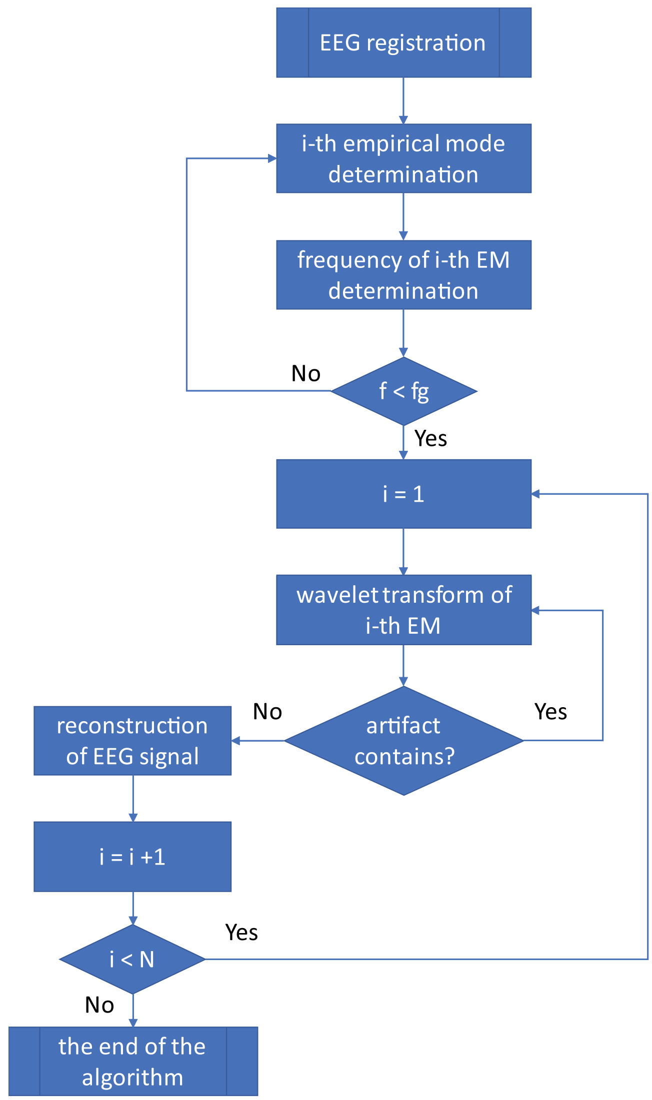

Figure 1. Flowchart of the removing physiological artifacts algorithm

where $X_f(t)$ — reconstructed EEG signal, $d_i(t)$ — 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 artifacts on experimental human EEG signals. Experimental work for recording EEG signals was held in scientific-educational center "Nonlinear dynamics of complex systems" of Saratov state technical university, Saratov, Russia. Experimental design included standard physiological trials such as opening/closing eyes, audio stimulation, photic stimulation etc.[1] along with specially developed trials. Experiments were performed within research of brain mechanisms that are responsible for imagination and performance of limb motions. Special trials included hand/leg real and imaginary movement as a response to visual or sound stimuli.

EEG signals were recorded with use of specific scheme for placing electrodes. This scheme is different from standard International 10-20 system[17] and is illustrated on Fig. 2. Fig. 2 demonstrates schematic image of

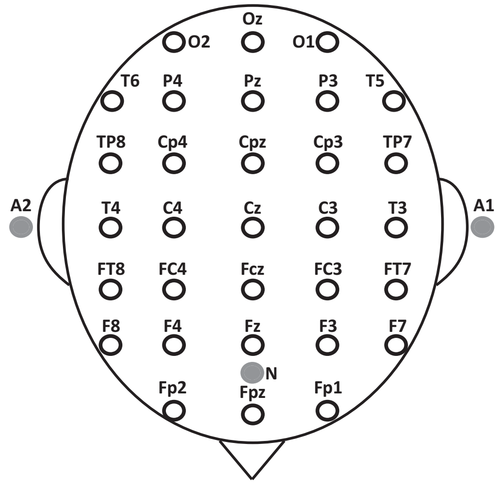

Figure 2. Scheme of extended setup for EEG recording system

human's head (view from above, face down) with 1 neutral electrode (N), 2 referent electrodes (A1 and A2) and 31 electrodes that record EEG signals. Our scheme shares 1 neutral (N) and 2 referent electrodes (A1 and A2) with standard scheme 10-20, but features 31 EEG channels instead of classic 19. Such scheme provides much better spatial resolution of EEG signal over the head which is crucial in case of determination of specific areas of brain responsible for movement processes. As a drawback the scheme requires more resources and is more vulnerable for muscle-movement artifacts because activity of each muscle affects more electrodes at once. Also electrodes are much closer to each other so neighboring EEG signals may interfere when several wires touch each other in case of active movement.

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.

Experiments were held for 20 healthy men and women in age of 18 – 40. Duration of each record was 60-70 minutes.

Most common physiological artifacts that occur on EEG recordings during these experiments were muscle-movement artifacts. Presence of these artifacts can be explained by nature of the research that included a plenty of movement trials. Movement artifacts have significant amplitude (about 1 – 1.5 V) and long duration up to several seconds. These artifacts are frequently found in occipital and temporal channels, which are critical in studies of brain activity related to motions.

Fig. 3 illustrates an example of EEG with episode of muscle-movement activity. Fig. 3 also features wavelet spectrum of EEG signal in log scale. 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. As seen from Fig. 3, movement artifact features long duration and wide frequency range with high energy in low frequency region and some pikes on higher frequencies. Low frequencies correspond to EEG envelope caused by some muscle activity. This envelope breaks zero-mean condition of EEG signal, which is important in time-frequency analysis with some methods. Also the envelope distort very low frequencies ($\sim$1 Hz) that are used in combined neurophysiological studies of brain and heart.

Fig. 4 illustrates the same EEG signal filtered from movement artifact. It can be seen rom Fig. 4, that low frequency envelope was totaly removed while other components of artifact with higher frequencies get their amplitude lowered to the level comparable with average amplitude level of whole EEG signal. Thus, the proposed method can be used for removing muscle-movement artifacts and lower their input during time-frequency analysis of EEG signal.

Statistic analysis of filtering physiological artifacts on EEG recording of all 20 participants showed that proposed method totaly removed or significantly lowered amplitude for 80-85% of movement artifacts. While the

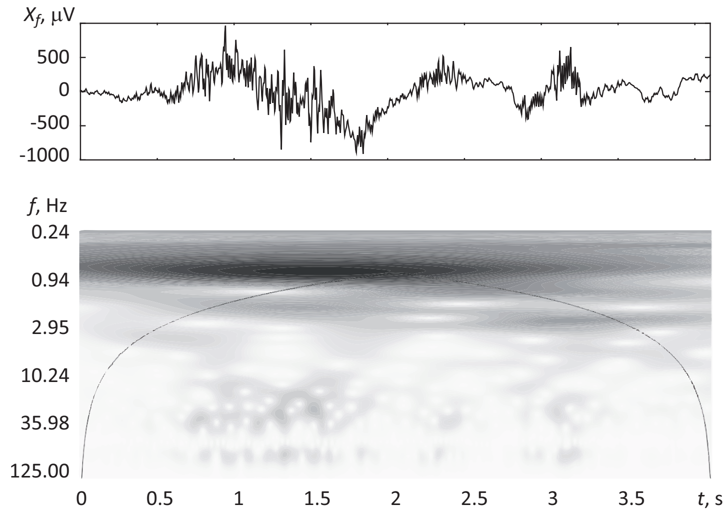

Figure 3. Example of EEG signal with movement artifact; signal is accompanied with corresponding wavelet surface that illustrate time-frequency structure of signal

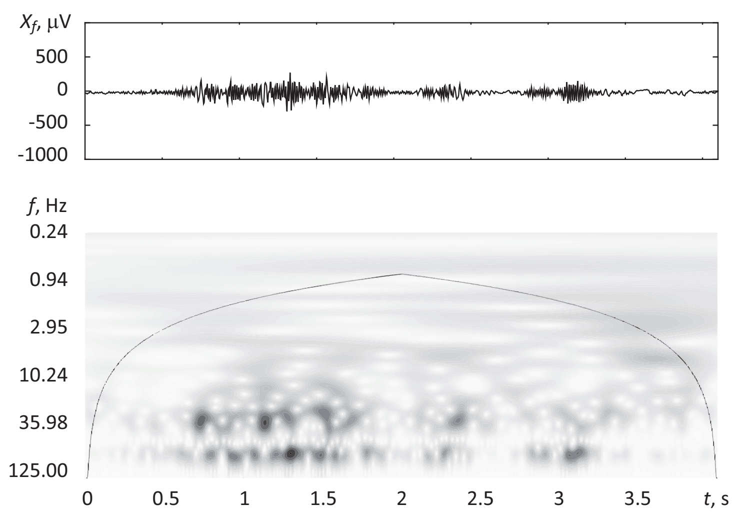

Figure 4. Example of EEG signal, filtered from movement artifact; signal is accompanied with corresponding wavelet surface that illustrate time-frequency structure of signal

method was tested for muscle-movement artifacts its application is not restricted for only this types of artifacts. It also can be used for removing other types of artifacts that have characteristic images on wavelet spectra.

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 muscle-movement artifacts. High efficiency of the method was demonstrated on filtration 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.

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