

Dealing with noise and physiological artifacts in human EEG recordings: empirical mode methods

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ABSTRACT

In the paper we propose the new method for removing noise and physiological artifacts in human EEG recordings based on empirical mode decomposition (Hilbert-Huang transform). As physiological artifacts we consider 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 proposed method with steps including empirical mode decomposition of EEG signal, choosing of empirical modes with artifacts, removing these empirical modes and reconstructing of initial EEG signal. We show the efficiency of the method on the example of filtration of human EEG signal from eye-moving artifacts.

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

1. INTRODUCTION

Analysis of multichannel electroencephalogram (EEG) data is complicated by numerous artifacts of external and internal nature. While some of artifacts are caused by external electrical signals and can be cutoff during experiment, other artifact are of the physiological nature. These artifacts are related to various non-stationary processes in human 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, various cardiac rhythms, etc.^{1,2}

Artifacts irrespective to their nature have significant amplitude on EEG signal that can greatly exceed the amplitude of electrical activity of brain. At the same time, frequency ranges of most artifacts overlap frequency ranges of rhythms that are of interest for the researchers. For example, eye-moving artifacts can be found in 0.5–13 Hz frequency range which is related to the three determined ranges of effective signal — delta, theta and alpha.^{3,4} The presence of artifacts blocks the possibility to use the most widespread methods for routine and scientific analysis of time-frequency structure of EEG signals such as Fourier and Radon transform, wavelet analysis, Hilbert-Huang transform, etc.^{6–8,21} Thus, artifact removing became a standard procedure in modern electroencephalographic studies and development of new efficient methods for artifact filtration is an important problem in EEG analysis.

Nowadays many different methods are used for filtration and pre-processing of experimental EEG signals. One of the most simple and frequently used in routine studies methods is the visual (or semi-automated) search of artifacts with consequent manual or automated deletion of found patterns.^{9,10} EEG fragment that contains artifact is completely deleted as non-informative or replaced with the fragment will null or average EEG signal

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amplitude. This procedure naturally leads to total loss of information about EEG time-frequency structure on chosen signal fragment. In most practical cases EEG filtration with this method comes to routine and subjective procedure that also requires a lot of time and concentration from experienced neurophysiologist. Moreover, the deletion of EEG fragments with artifacts drastically shortens the amount of experimental 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. In case of studying of children EEG or EEG of people with some brain disorders the loss of data can become even more significant. Such 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 very actual and important.

At present time there are few of such methods which based on analysis of independent components^{11,12} and regression analysis.¹³ These methods are widely used in medical practice and scientific researches but they suppose complex transformation of studied EEG signal and provide insufficient precision of artifact detection that not suits for more detailed time-frequency EEG analysis. Another class of methods such as method based on Gram-Schmidt transform¹⁴ provide better performance with more simple algorithms and more precise detection of artifacts. For example, 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 some 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 detecting and removing artifacts of different types on human EEG. The method is based on empirical mode decomposition (Hilbert-Huang transform),¹⁵ it uses clear algorithm and requires no additional experimental signals to be detected besides EEG.

2. EMPIRICAL MODE DECOMPOSITION

Empirical mode decomposition (Hilbert-Huang transform)¹⁵ is one of the modern methods for time-frequency analysis of complex signals of different nature. This method allows to represent the initial signal as a sum of amplitude-modulated components with zero mean (empirical modes). Empirical mode decomposition provides high adaptability in signal analysis because its components — empirical modes — are derived from the analyzed signal.

In terms of time-frequency analysis of signals Hilbert-Huang transform is different from classic Fourier transform or more advanced continuous wavelet transform.¹⁶ While Fourier and wavelet analysis provide time-frequency spectra, empirical mode decomposition offers the set of empirical modes. Each of the empirical modes is characterized by its own frequency range, total number of empirical modes and their frequency ranges are highly dependent on the initial signal. The first empirical mode has the highest frequency, and the latter become lower with the growing number of the mode. Frequency ranges of different empirical modes mostly correspond to different oscillatory patterns on the signal and analysis of specific oscillatory patterns can be reduced to analysis of individual empirical modes. Thus, empirical mode decomposition is a highly adaptive instrument for analysis of local oscillatory patterns on complex signals.

Worth noting that empirical mode decomposition is an effective tool for analysis of amplitude modulated (but not phase modulated) signals. Thus, for signal with a linear growth of the frequency (a linear chirp):

$$x(t) = A \sin[(\omega_0 + \omega_1 t)t] \quad (1)$$

empirical mode decomposition shows a single empirical mode while the classical Fourier analysis detects a full set of frequencies. But since EEG is a signal with sufficient amplitude modulation (along with the phase modulation), we can expect that empirical mode decomposition will be useful in studying the EEG structure.

Algorithm of empirical mode decomposition includes following steps:

1. Finding all extrema on signal $x(t)$

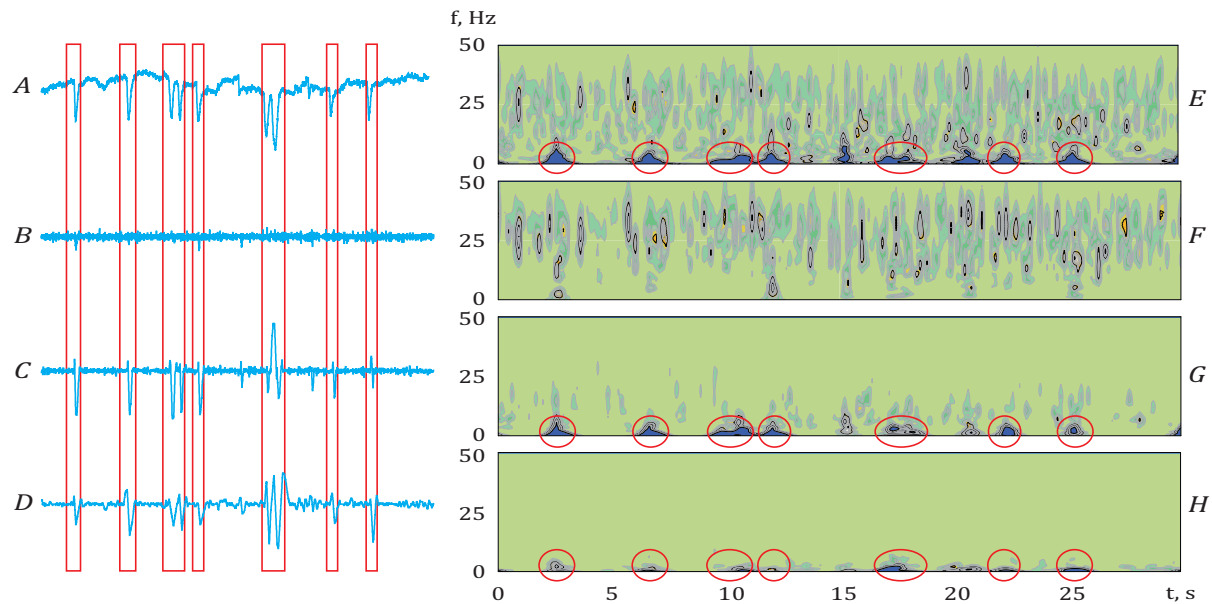


Figure 1. Example of empirical mode decomposition: EEG signal with eye-moving artifacts (A) and three empirical modes (B,C,D), wavelet surfaces for EEG signal (E) and its empirical modes (F,G,H); artifacts are marked with red frames and red ovals

2. Interpolation of signal between minima and maxima and construction of two envelopes: $e_{min}(t)$ and $e_{min}(t)$
3. Calculation of low-frequency component of signal (trend) $m(t)$: $m(t) = \frac{e_{min}(t) + e_{min}(t)}{2}$
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

Example of empirical mode decomposition on EEG signal with artifacts is illustrated on Fig. 1.

Fig. 1 shows 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 (E) and empirical modes (F, G, H). In present paper wavelet transform and its spectra were used only for representation of time-frequency structure of the signals and not for their analysis.

The example EEG signal on Fig. 1A has a number of eye-moving artifacts that are represented by short and high-amplitude oscillatory patterns; artifacts are marked with red frames on Fig. 1A,B,C,D and red ovals on Fig. 1E,F,G,H. Wavelet surface on Fig. 1E shows that initial EEG signal has significant frequencies in the range of 0.5–50 Hz and eye-moving artifacts interfere in the range of ~ 0.5 –5 Hz. Wavelet spectrum for the first empirical mode on Fig. 1F contains information about high-frequency components of EEG signal while wavelet spectra for the second and the third empirical modes on Fig. 1G,H mostly reflect artifact activity in low-frequency range. Thus, it can be concluded that in this case the second and the third empirical modes are referred to eye-moving artifacts and the first empirical mode corresponds to the filtered EEG signal without artifacts.

3. METHOD

In the paper we propose the new method for removing physiological artifacts in human EEG recordings based on empirical mode decomposition (Hilbert-Huang transform). The method is based on the fact that different types of oscillatory patterns on EEG mostly correspond to different empirical modes as it was shown in example in Section 2.

The algorithm of the proposed method is following:

1. Decomposing the studied EEG signal into the set of empirical modes following the algorithm described in Section 2
2. Finding the empirical modes corresponded to the artifacts that should be removed from the EEG signal
3. Removing the empirical modes with artifacts
4. Reconstructing the EEG signal by summarizing the rest empirical modes

The empirical modes acquired after the Step 1 of the algorithm should be analyzed. The task on the Step 2 is to find the empirical modes that contain artifacts. The search of these artifacts can be done in several different ways.

Empirical modes with artifacts can be found with visual search as in classic methods described in Introduction. In case of empirical modes visual search is notably easier because empirical mode decomposition acts as an instrument of adaptive filtration. For example, eye-moving artifacts are seen more clearly on the second empirical mode (see Fig. 1C) than on the initial EEG signal (Fig. 1A) because low-frequency envelope of the signal and some other artifacts gone to other empirical modes.

Another method to determine which empirical modes include artifacts is to compare average signal energy of EEG with artifacts and empirical modes. Signal energy can be calculated as:

$$E(t) = A^2(t), \quad (2)$$

where A — amplitude of the signal. Thus, average energy over some signal can be calculated as:

$$\langle E \rangle = \frac{1}{\tau} \int_{t=0}^{t=\tau} A^2(t) dt, \quad (3)$$

where τ — length of the signal. So fragment of the initial EEG signal with one or few artifacts can be taken and analyzed. Average signal energy should be calculated for this fragment in EEG signal ($\langle E^{EEG} \rangle$) and in all empirical modes ($\langle E_i^{EM} \rangle$, 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:

$$0.85 * \langle E_i^{EEG} \rangle < \langle E_i^{EM} \rangle < 1.15 * \langle E_i^{EEG} \rangle \quad (4)$$

More reliable method to find empirical modes with artifacts is to use instruments of time-frequency analysis such as Fourier analysis or continuous wavelet analysis.

Fourier spectra provides information about significant frequencies in signal, so the spectra of the initial EEG signal and all empirical modes can be constructed. The empirical mode contains given type of artifacts if its Fourier spectrum corresponds to the frequency range of artifacts.

Continuous wavelet analysis introduces wavelet surfaces that give 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). Thus, empirical modes with artifacts can be determined by analyzing its wavelet surfaces.

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

$$U(t) = \sum_{i=1}^{N, i \neq n_1, n_2, \dots} M_i(t), \quad (5)$$

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

Thus, the result of the proposed method is reconstructed EEG signal filtered from artifacts.

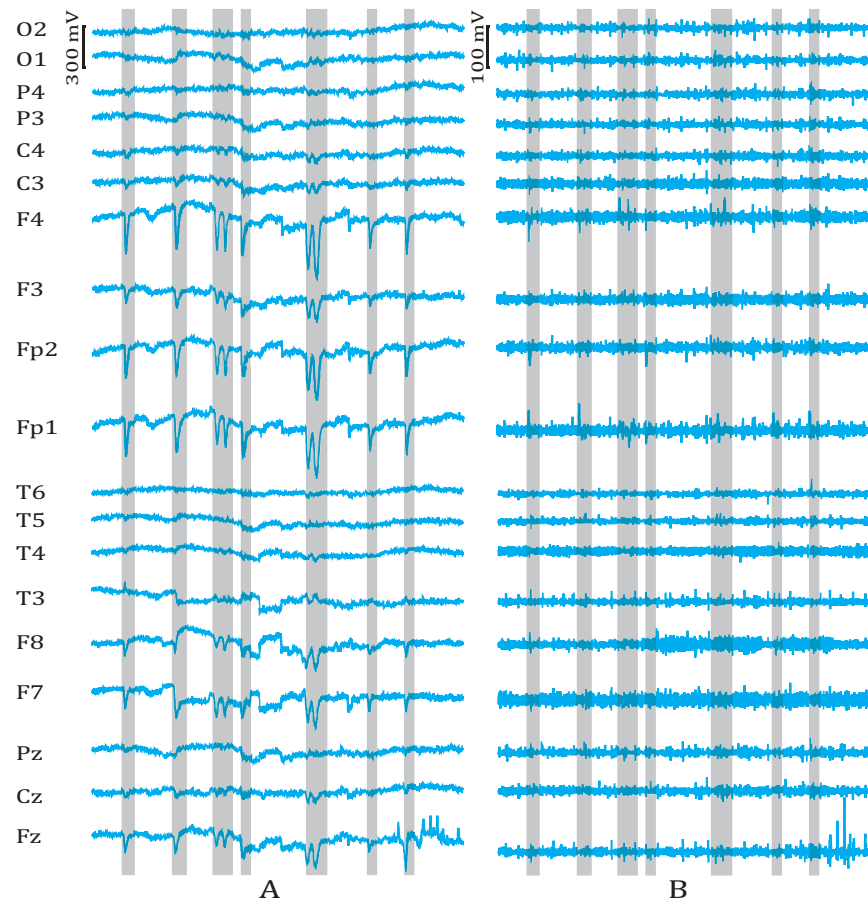


Figure 2. Example of EEG signals filtration: initial experimental EEG signals from multiple channels (A) and filtered signals (B)

4. RESULTS

The proposed method for removing physiological artifacts on EEG signals proposed in the paper was tested on filtering eye-moving artifacts on experimental human EEG signals.

EEG signals were recorded with use of standard scheme for placing electrodes — International 10-20 system.¹⁷ 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 15 healthy men and women in age of 18 – 40. Duration of each record was 25 minutes, which includes standard physiological trials such as opening/closing eyes, audio stimulation, photic stimulation etc.¹⁸ Eye-moving artifacts are quite common for this type of EEG records with high eye activity. These artifacts have significant amplitude (about 1 – 1.5 Hz) and can be found mostly in frontal cortex channels, which are commonly used in studies of cognitive brain activity.

Fig. 2 illustrates an example of filtering EEG signal with the method proposed in the present paper. Fig. 2 shows EEG signals from 19 channels used in International 10-20 system (A) with eye-moving artifacts marked in gray frames and filtered signals for the same channels (B).

During filtration each EEG signal was decomposed into the set of empirical modes. With the help of wavelet analysis 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 second and the third. It can be clearly seen that eye-moving artifacts were filtered from EEG signals. 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 but also for filtering some noise components on EEG signals.

Statistic analysis of filtering eye-moving 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 its application is not restricted for only this type 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, cardia artifacts or artifacts from facial muscle movement.

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 eye-moving artifacts. High efficiency of the method was demonstrated on filtration of eye-moving artifacts 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 analysis.^{16, 19–21}

6. ACKNOWLEDGMENTS

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