Correction of Ocular Artifacts in EEG Recordings using Empirical Mode Decomposition

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Abstract

EEG recordings are often contaminated with ocular artifacts such as eye blinks and eye movements. These artifacts may obscure underlying brain activity in the electroencephalogram (EEG) data and make the analysis of the data difficult. In this paper, we explore the use of empirical mode decomposition (EMD) based filtering technique to correct the eye blinks and eye movement artifacts in single channel EEG data. In this method, the single channel EEG data containing ocular artifact is segmented such that the artifact in each of the segment is considered as some type of slowly varying trend in the data and the EMD is used to remove the trend. The filtering is done using partial reconstruction from components of the decomposition. The method is completely data dependent and hence adaptive and nonlinear. Experimental results are provided to check the applicability of the method on real EEG data and the results are quantified using power spectral density (PSD) as a measure. The method has given fairly good results and does not make use of any preknowledge of artifacts or the EEG data used.

Keywords: Electroencephalogram, Ocular artifacts, Empirical mode decomposition, Electrooculogram.

1. Introduction

The EEG signal measured from human scalp is very low amplitude signal having low signal-to-noise ratio (SNR). Hence the signal is easily contaminated by different kinds of artifacts such as eye blinks and eye movements. The electrical potentials generated due to the movement and rotation of the electrically charged eye balls are the major sources that affect the sources of EEG signals. Studies have shown that the electric potentials propagate symmetrically on the scalp and frontal channels are largely affected by them [1]. These physiological artifacts are very common in EEG recordings and they complicate the analysis of the EEG data. Hence there is a need to remove these artifacts from the EEG recordings before further analysis of the data.

The most common way of dealing with ocular artifacts is to simply reject the contaminated epochs from the analysis. This may lead to unacceptable loss of data. Another commonly used way of reducing ocular artifacts is to instruct the subject to blink as infrequently as possible and move the eyes as little as possible, i.e. fixating the eyes to a single point. These instructions may create a secondary task changing the initial measurement paradigm.

There are many methods available in the literature dealing with correction of ocular artifacts in EEG recordings [4, 5, 6]. The most commonly used methods for correcting ocular artifacts utilize simultaneously measured EOG signals. The adaptive filtering methods largely make use of these EOG as reference signals. In all the cases it may not be possible to record EOG signals along with the EEG data. Different time-domain and frequency-domain regression methods have been proposed. In regression-based methods EOG and EEG must be uncorrelated. But in practice spread of excitation from eye movements and EEG signals is bidirectional. Since the EOG is also contaminated to a degree with EEG signals, the regression of ocular artifacts has the undesirable effect of removing EEG signals from the data observations. The methods such as those based on principal component analysis (PCA), independent component analysis (ICA) and variants of those deal with multichannel EEG data and assume that the number of sources that are responsible for generating EEG on the scalp is less than the number of observed EEG data channels [2, 3]. But the true number of sources is unknown.

In this paper, we explore the use of empirical mode decomposition based filtering technique in correcting the ocular artifacts (Electro-oculogram, EOG) in single channel EEG recordings. The method is completely data dependent and hence adaptive. The method is explained in the following sections.

2. Empirical Mode Decomposition

Empirical mode decomposition (EMD) is a general signal decomposition technique for analyzing signals and time series data. The EMD was first introduced by N. E. Huang et al. for studying ocean waves [10]. Authors in [8, 9] used the EMD for applications in biomedical engineering studies utilizing it for analyzing esophageal manometric data in gastroesophageal reflux disease. The principle of the EMD technique is to decompose a signal into sum of functions that: (i) have same number of zero crossings and extrema

(or differing at most by one); and (ii) are symmetric with respect to local mean which means that mean value of upper and lower envelopes is equal to zero.

The EMD is a type of adaptive wavelet decomposition whose subbands are built up as needed to separate different components of a signal. The decomposition procedure is adaptive, data driven, therefore highly efficient. The EMD technique adaptively decomposes a signal into oscillating components with which any complicated signal can be decomposed into a definite number of high frequency and low frequency components. The process of decomposition is called sifting and the components are called intrinsic mode functions (IMFs). The EMD picks out the highest frequency oscillation that remains in the signal. Thus locally, each IMF contains lower frequency oscillations than the one extracted just before. This property can be very useful to pick up frequency changes, since a change will appear even more clearly at the level of an IMF.

Consider a signal $x(t)$ between two consecutive local extrema that is two minima occurring at t_- and t_+. We can define local high frequency part as $\{d(t),\ t_- \le t \le t_+\}$ [11, 12, 13]. This detail corresponds to the two minima and passing through the maximum which necessarily exists in between them. Let the corresponding low frequency part or the local trend be $m(t)$. Then $x(t) = m(t) + d(t)$, $t_- \le t \le t_+$. If this is done in some proper way for all the oscillation composing the entire signal, we get what is referred to as intrinsic mode function as well as a residue constituting of all local trends. The procedure can be repeated on the residual considering it as a new signal to be decomposed. Thus successive constitutive components of a signal can be extracted iteratively.

Decomposition of a signal $x(t)$ into IMFs is performed as follows. (i) Identify positive (maxima) and negative (minima) peaks of the original signal. (ii) Construct lower and upper envelopes ($e_{min}(t)$ and $e_{max}(t)$ respectively) of the signal by cubic spline interpolation. (iii) Calculate mean values $m(t) = (e_{min}(t) + e_{max}(t))/2$ by averaging the lower and the upper envelope. (iv) Subtract the mean from the original signal to produce the first intrinsic mode function IMF1, $d(t) = x(t) - m(t)$. (v) Calculate the first residual component by subtracting IMF1 from the original signal $m(t) = x(t) - d(t)$. The residual component is treated as a new signal and is subjected to the process described from step (i) to calculate the next IMF. (vi) Repeat the steps until the final residual component becomes a monotonic function and no more IMFs can be extracted.

The original signal is decomposed as $x(t) = d_1(t) + m_1(t)$ and the first residual $m_1(t)$ itself is decomposed as $m_1(t) = d_2(t) + m_2(t)$. Then $x(t) = d_1(t) + d_2(t) + m_2(t)$. In general $x(t) = \sum_{k=1}^{K} d_k(t) + m_K(t)$. This perfect reconstruction property, together with the spectral interpretation can be used to achieve partial reconstructions only so as to selectively remove fast oscillations leading to denoising of signals and selective removal of slow oscillations corresponding to detrending of signals.

If a signal $x(t)$ to be analyzed contains slowly varying trend superimposed with fluctuating process, the slow varying trend is expected to be captured by IMFs of large indices and the residual. Detrending of $x(t)$ which corresponds to estimation of signal $y(t)$ may be achieved by computing partial fine to coarse reconstruction. Then $\hat{y}_M(t) = \sum_{k=1}^{M} d_k(t)$, where M corresponds to the larger IMF index prior to contamination by the trend. Selection of proper value of M is based on the observation of statistical properties such as empirical mean of $\hat{y}_d(t)$ as a function of test order d and identification for which $d = M$ it departs significantly from zero.

The major advantage of decomposing signals using EMD is that, basis functions are directly derived from signal that is to be decomposed [11]. The analysis is adaptive in contrast to Fourier analysis, where the basis functions are linear combinations of fixed sinusoids. The main drawback of Fourier approaches is that the basis functions are fixed and do not necessarily match varying nature of signals. The EMD can handle both nonlinear and nonstationary signals and is different from Fourier and wavelet transforms because, the Fourier transform is designed to work with linear and stationary signals. The wavelet transform on the other hand is well suited to process nonstationary signals but poor at processing nonlinear signals.

A signal can be decomposed into components each with a distinct time scale. The first component has the smallest time scale which corresponds to the fastest time variation of data and hence more number of zero crossings is present. As the decomposition proceeds, the time scale increases which leads to decrease of frequency and hence the components have small number of zero crossings. It is observed that as the mode number increases the number of zero crossings decrease. This observation motivates us to think EMD to use as general purpose time space filter. The method may help in removing eye blink noise from EEG signals and detects meaningful information that might have been masked by large amount of eye blink noise in the data. In this paper, potential application of EMD for biomedical signal processing tasks especially for filtering of EEG recordings for correcting eye blink artifact is discussed. Here, the idea is to make use of partial reconstructions from the components that are obtained from decomposition. The relevant modes are selected based on their statistical properties.

3. Method

The problem of correcting eye blink artifacts in EEG recordings can be formulated as follows. Consider single channel of EEG recording contaminated with eye blink artifacts. The eye blinks are usually of higher amplitude and low frequency waves when compared with that of EEG signals. The contaminated EEG signal is divided into

epochs of suitable length. The length is selected such that the epoch should satisfy all the conditions so that sifting procedure can be applied on it. The length should be small enough such that the eye blink portion in the epoch of the signal is considered as some kind of trend in the data. Now the problem of removing the eye blink artifact is converted into a problem of removing trend in the signal.

The epoch is subjected to sifting procedure and decomposed into component waves. Since the slow varying trend is of higher amplitude, the effect of it is appeared in the IMFs of higher number. Hence fine to coarse partial reconstruction of the epoch from the component waves can be done. Now the question is to choose the number of modes that can be used in the reconstruction procedure. This is done based on statistical properties of the IMFs such as sample mean. The IMFs for the partial reconstruction of the epochs are selected based on the variation of sample mean as a function of mode number. This partial reconstruction removes the slow varying trend from the epoch and thus eye blink artifact is eliminated. The method is applied to each of the epochs so that entire signal is get cleaned.

4. Results

We have applied the above method to correct eye blink artifacts from the frontal channels of real EEG recordings. The multichannel EEG data is acquired from subjects with a sampling frequency of 200 Hz. The international 10-20 system of electrode placement is used for this purpose. A single channel data of 1000 sample points is selected for experimentation. The signal is segmented into epochs of length 100 samples. Each epoch is subjected to sifting to get component waves. Partial reconstruction of the epoch from the components is carried out to get the clean signal. The results are shown in the Figure 1. From the figure, it is clear that eye blink artifact is cleaned satisfactorily. To quantify the results we plot power spectral densities (PSD) before and after cleaning of the epochs. From the PSD plot in Figure 2, it is clear that most of the information in the delta and theta band of the EEG signal is retained even after the artifact correction.

The method used is completely data dependent and hence adaptive and nonlinear. It does not make use of any preknowledge about the data. The method has given good results in rectifying eye blink artifacts from the EEG recordings. But one should be careful in choosing the length of the epoch to satisfy the conditions to decompose it into component waves. And choosing of IMFs for partial reconstruction of the epochs requires some skill. To apply this method the eye blinks should be of higher amplitude to consider it as a trend in the signal.

5. Conclusions

In this paper, we have carried out a scientific study to use empirical mode decomposition as a tool to correct eye blink artifacts in EEG recordings. The eye blinks are treated as some kind of trend in the signal and detrending property of

EMD is made use of. The method has given satisfactory results in rectifying the ocular artifacts and preserved most of the signal information in the EEG data.
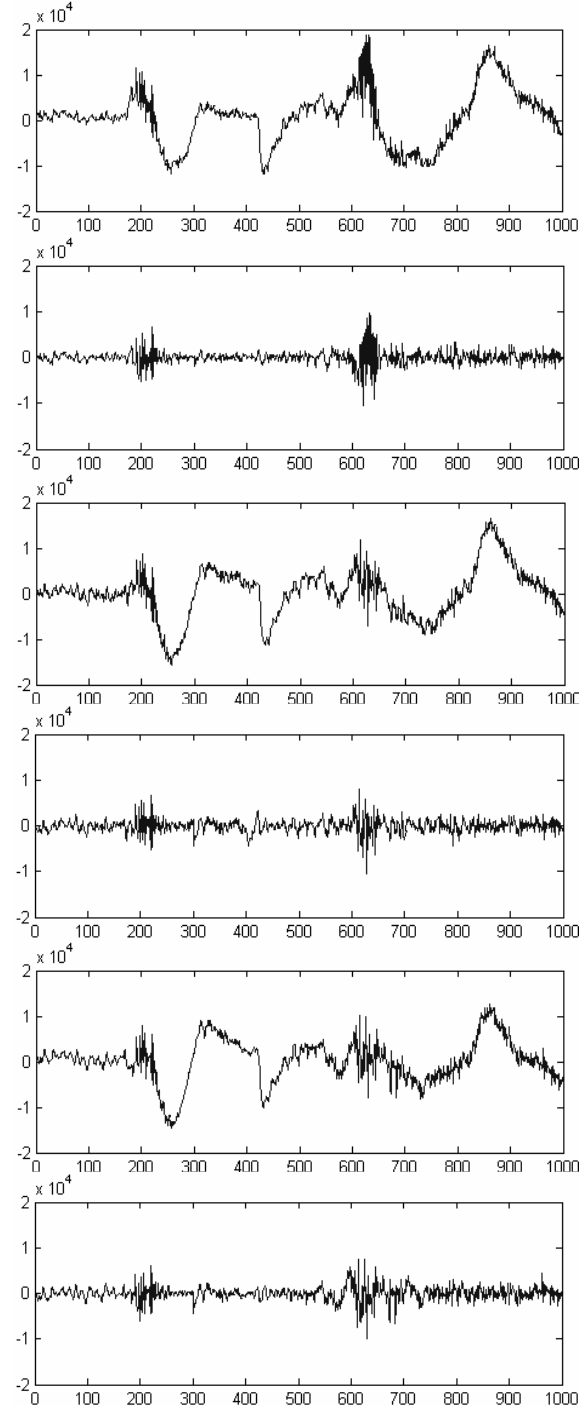

Figure 1: EEG recordings containing eye blink artifacts (odd rows), EEG recordings after eye blink correction (even rows).

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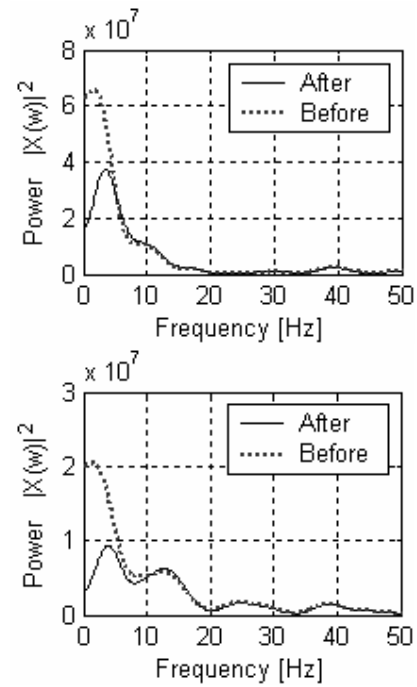
Figure 2: PSD (Blackman-Tukey method) plot of epochs before and after artifact correction. Plots are shown for selected two epochs only.