The Removal of EOG Artifacts from EEG Signals using Multivariate Empirical Mode Decomposition

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ABSTRACT

The recorded electroencephalography (EEG) signals are usually contaminated by electrooculography (EOG) artifacts. In this project, the multivariate empirical mode decomposition (MEMD) method will be proposed to remove EOG artifacts (EOAs) from multichannel EEG signals. Firstly, the EEG signals will be decomposed by the MEMD into multiple multivariate intrinsic mode functions (MIMFs). The EOG-related components will then be extracted by reconstructing the MIMFs corresponding to EOAs. This method is used to eliminate EOG signals from the contaminated EEG signals. This method will be simulated using MATLAB. The improvement of this method will be based on two parameters, signal-to-noise ratio (SNR) and mean square error (MSE) after removing ocular artifacts. The results will be compared with any other existing techniques like empirical mode decomposition (EMD).

KEYWORDS: EEG, EOG, MIMF, SNR, MSE.

INTRODUCTION

Electroencephalography (EEG) signal is an electrophysiological monitoring method to record electrical activity of the brain. It is typically noninvasive, with the electrodes placed [1] along the scalp, although invasive electrodes are sometimes used in specific applications. EEG measures voltage fluctuations resulting from ionic current within the neurons of the brain. In clinical contexts, EEG refers to the recording of the brain's spontaneous electrical activity over a period of time, as recorded from multiple electrodes placed on the scalp. Diagnostic applications generally focus on the spectral content of EEG, that is, the type of neural oscillations (popularly called "brain waves") that can be observed in EEG [2] signals. Most of the cerebral signal observed in the scalp EEG falls in the range of 1–20 Hz. Waveforms are subdivided into bandwidths known as alpha, beta, theta, and delta to signify the majority of the EEG used in clinical practice. The alpha waves have the frequency spectrum of 8-13 Hz and can be measured from the occipital region in an awake person when the eyes are closed. The frequency band of the beta waves is 13-30 Hz; these are detectable over the parietal and frontal lobes. The delta waves have the frequency range of 0.5-4 Hz and are detectable in infants and sleeping adults. The theta waves have the frequency range of 4-8 Hz and are obtained from children and sleeping adults. EEG signals have small amplitudes and strong randomness so they can be very easily contaminated with various artifacts. One of the most common artifacts influencing the quality of EEG signals are electrooculography (EOG) activities whose magnitude is usually much higher than that of EEG signals. EOG has a burst of high energy in low frequency, which seriously affects the EEG waves, like theta waves and delta waves.

In order to reduce the interference of EOAs, subjects are asked not to blink for a long time or to blink as infrequently as possible, which causes eyes uncomfortable. Especially for some specific patients, such as children with attention deficit hyperactivity disorder (ADHD), it is difficult to obey it. Hence, many EOAs often appear in EEG signals. The common clinical practice is to directly reject EEG segments with eye artifacts. However, it may lead to some loss of important EEG information. Therefore, it is very essential to effectively remove EOAs from EEG signals and preserve underlying brain activity signals with little
distortion in the preprocessing of EEG signals.

MULTIVARIATE EMPIRICAL MODE DECOMPOSITION:

A. EMPIRICAL MODE DECOMPOSITION

EMD [3] is a fully data-driven method for the multiscale analysis of nonlinear and non-stationary real-world signals [4]. It decomposes the original signal into a finite set of amplitude and/or frequency-modulated (AM/FM) components, termed IMFs, which represent its inherent oscillatory modes. More specifically, for a real-valued signal x(k), the standard EMD finds a set of N IMFs and a monotonic residue signal r(k).

1. Find local minima and maxima of s(n).
2. Form upper, eu(n), and lower, el(n), envelopes by cubic splines interpolation.
3. Find the mean, m(n) = (eu(n)+el(n))/2.
4. If h(n) = s(n)−m(n) is not an IMF, go to step 1 using h(n) instead of s(n). Else, $h(n) = IMF_k(n)$.
5. If the residue, $r(n) = s(n) - IMF_k(n)$ has more than a zero cross, go to step 1 and find next IMF. Once IMFk(n) are extracted, the signal can be expressed as:

$$s(n) = \sum_{k=1}^{M} IMF_k(n) + r(n)$$

B. MULTIVARIATE EMD

Empirical mode decomposition (EMD) is a fully data adaptive technique to decompose any signal into a finite set of band-limited basis functions called intrinsic mode functions (IMFs). Each IMF is considered as both amplitude and frequency modulated oscillatory component. The multivariate EMD [5] (MEMD) is a more generalized extension of the EMD suitable for dealing with direct processing of multivariate data for real-world applications. To extend general idea of multivariate signals for MEMD, input data are straightforwardly processed in n-dimensional spaces to generate multiple n-dimensional envelopes by taking signal projections along different directions in n-dimensional spaces. The calculation of the local mean can be considered an approximation of the integral of all the envelopes along multiple directions in an n-dimensions space. This step is complex to perform due to the lack of formal definition of maxima and minima in n-dimensional domains in general EMD. The sampling based on low discrepancy Hammersley sequence is used to generate projections of input signal. Once the projections along different directions in multidimensional spaces are obtained, their extrema are interpolated via cubic spline interpolation to obtain multiple signal envelopes. Thus, obtained envelopes are then averaged to obtain the local mean of the multivariate signal.

Consider a sequence of n-dimensional vectors $\{v(t)\}_{t=1}^{T}$ which represents a multivariate signal with n components, and $x^\theta = \{x_1^\theta, x_2^\theta, \ldots, x_n^\theta\}$ denoting a set of direction vectors along the directions given by angles $\theta^k = \{\theta_1^k, \theta_2^k, \ldots, \theta_n^k\}$ on an (n−1) sphere. Then, the proposed multivariate extension of EMD suitable for operating on general nonlinear and non-stationary n-variate time series is

1. Choose a suitable point set for sampling on an (n − 1)-sphere.
2. Calculate a projection, denoted by $\{p^\theta k\}_{k=1}^{K}$ of the input signal $\{v(t)\}_{t=1}^{T}$ along the direction vector $X_k^\theta$, for all k, giving $\{p^\theta k\}_{k=1}^{K}$ as the set of projections.
3. Find the time instants $\{t^\theta i\}$ corresponding to the maxima of the set of projected signals $\{p^\theta k\}_{k=1}^{K}$.
4. Interpolate \[ \left[ t_i^{(k)}, v_i^{(k)} \right] \] to obtain multivariate envelope curves \[ \left\{ e_{\theta k} \right\}_{k=1}^K \].

5. For a set of K direction vectors, the mean \( m(t) \) of the envelope curves is calculated as

\[
m(t) = \frac{1}{K} \sum_{k=1}^{K} e_{\theta k}(t)
\]

6. Extract the ‘detail’ \( d(t) \) using \( d(t) = x(t) - m(t) \). If the ‘detail’ \( d(t) \) fulfils the stoppage criterion for a multivariate IMF, apply the above procedure to \( x(t) - d(t) \), otherwise apply it to \( d(t) \).

EOAs are characterized by abnormal burst of high-energy in low-frequency. Time-frequency evolution pattern of EOAs is observable in artifact-contaminated EEG recordings. Therefore, the time-frequency similarity \[6\] between two signals was used for the selection of artifact-linked MIMFs. Because the amplitudes of real EOG signals were greater than those of EEG signals, the channel with maximum amplitude was chose from EEG signals as the EOG reference. Because the spectrum of EOAs is often concentrated in the frequencies below 10 Hz, the time-frequency representation (TFR) of EOG reference between 0 and 10 Hz was computed by using wavelet transformation \[7\]. For each MIMF, the TFR between 0 and 10 Hz was also obtained by averaging the wavelet transformation of all channels of signals. Then, the correlation coefficients between EOG-TFR and each MIMF-TRF were calculated. Because the frequency bands of MIMFs were ranked from high frequency to low frequency, correlation coefficients were sorted ascendingly. The critical MIMF was determined by searching the maximum difference between adjacent correlation coefficients. If the jth MIMF satisfied the above condition, the EOG-related signal could be calculated by summing all artifact-linked MIMFs, which was denoted

\[
u(t) = \sum_{j=1}^{\infty} MIMF_j(t)
\]

At the same time, the retained EEG signal without EOAs was obtained by other MIMFs, namely

\[
v(t) = \sum_{i=1}^{j-1} MIMF_i(t)
\]
RESULTS:

Fig 2: Recorded EEG signals at various electrode positions

Fig 3: Extracted clean EEG signal using MEMD algorithm
Fig 4. Removed EOG artifacts from input signal

Table 1. Comparison between EMD and MEMD

<table>
<thead>
<tr>
<th>Parameter</th>
<th>EMD</th>
<th>MEMD</th>
</tr>
</thead>
<tbody>
<tr>
<td>SNR</td>
<td>3.452</td>
<td>3.845</td>
</tr>
<tr>
<td>MSE</td>
<td>0.009824</td>
<td>0.000169</td>
</tr>
</tbody>
</table>

CONCLUSION:
In this study, the MEMD method was proposed to remove EOAs from artifact-contaminated EEG signals. The performance of the proposed method was evaluated by simulated and real EEG signals. The simulation results indicated that the proposed method could successfully eliminate EOAs from simulated EEG signals and preserve useful EEG information with little noise.

REFERENCES: