# MULTIVARIATE EMD BASED APPROACH TO EOG ARTIFACTS SEPARATION FROM EEG

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**ABSTRACT**

Measured electroencephalography (EEG) signals can be contaminated with other electrophysiological signal sources. This contamination decreases accuracy of neuroengineering applications such as brain computer interfaces. This paper focuses on the removal of electrooculography (EOG) that strongly appears in frontal electrodes EEG. To develop an EOG removal algorithm, we propose to utilize recently developed a multivariate extension of empirical mode decomposition (EMD) called MEMD. MEMD decomposes a multichannel signal into a set of intrinsic mode functions (IMF), and the number of IMFs is identical among the channels. We establish a criterion for choosing IMFs to separate an EOG-related component from the observed signal. Numerical examples confirm the proposed approach extracts EOG component better comparing to conventional blind source separation methods.

***Index Terms—*** EEG, EOG, fractional Gaussian noise, multivariate empirical mode decomposition.

## 1. INTRODUCTION

Electrophysiological signals captured non-invasively from a surface of human body are contaminated by external interferences (e.g. electromagnetic radiation sources) which cause inductive currents in cables connecting a subject with bio-amplifiers. This interference is easy to remove knowing those signals characteristics. The problem arrises with separation of multiple non-linearly and non-stationary mixed interference sources (EMG, ECG, EOG, etc.) generated within human body. Those mixing processes are serious obstacles in neuroscience experiments (ERP detection, slow wave synchronization/desynchronization, etc., in application for BCI/BMI) [1, 2]. Our paper focuses on removal of eye movement related artifacts, which carry significant power in form of EOG contaminating much lower in power EEG.

Traditional frequency filtering does not work well to remove these artifacts, since they are nonlinearly generated signals and are oscillated with time-varying frequency. Independent component analysis (ICA) or blind source separation (BSS) has been known to be promising for EOG removal [3]. In particular, BSS methods based on the second-order statistics such as AMUSE and the recent WASOBI are applicable to extract an EOG-related component, and they are used in the application of brain computer interfacing (BCI) as a preprocessing. However, a major drawback of BSS is that the result of separation highly depends on parameters, and EOG-related component can appear in multiple independent components (see Fig. 6). To tackle these problems, an EOG removal method that uses a bivariate extension to empirical mode decomposition (BEMD) [4] has been proposed. BEMD is a technique to decompose pairs of signals for which one is introduced as a reference. This method successfully exploits the BEMD, and the main method consists of a two-step BEMD with different reference signals first to filter pure EOG signal and next to use such filtered EOG to remove this muscle interference from EEG channels one-by-one. The limitation of this method is that BEMD can deal with only two signal channels simultaneously, while in brain applications, EEG is recorded with more than two channels

Fortunately, the BEMD has been extended to multivariate EMD (MEMD) [5]. This motivates us to extend the previously proposed method for EOG removal with BEMD to that with MEMD. The aim of this paper is to introduce a novel computational framework based on MEMD, convenient for simultaneous data conditioning and information separation for neuorophysiological signals with known interference sources, in particular, to separate eye movements from EEG signals.

## 2. METHODS

To this end, experiments were conducted in the Advanced Brain Signal Processing Laboratory of RIKEN Brain Science Institute, Japan. Six subjects participated in affective empathy inducing experiments with visual facial stimuli. The EEG electrodes were connected to the 64 head channels as in extended 10/10 EEG recording systems and sampled with 2048Hz using BIOSEMI amplifiers. The electrode impedance was kept below 5k$\Omega$. The experimental paradigm caused the subjects to move eyes frequently and unconsciously, causing ocular interference in EEG. For this reason, as a reference channel, EOG signals were recorded capturing eye movements and blinks.

### 2.1. Multivariate EMD

Empirical mode decomposition (EMD) is 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 [6]. The multivariate EMD (MEMD) is more generalized extension of the EMD suitable for dealing with direct processing of multivariate data for real world applications [5]. 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

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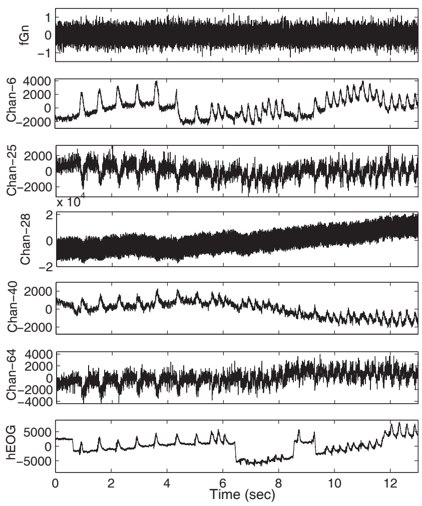


**Fig. 1**. Different signals of a typical data matrix for MEMD.

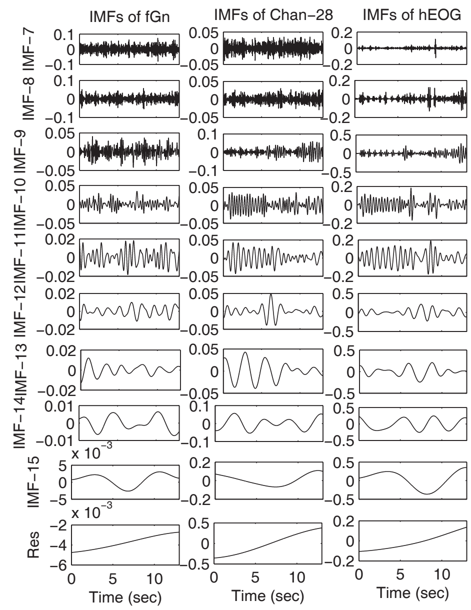


**Fig. 2**. The results of MEMD on the data matrix shown in Fig. 1. The IMFs ($7-15$ and residue) of only three variables fGn (left), Chan-28 (middle) and hEOG (right) are illustrated.

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 in [5]. 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. The following algorithm proposed in [7] is employed here to decompose signal $s(t)$ into a set of IMF components.

1. Generate the pointset based on the Hammersley sequence for sampling on an $(n-1)$-sphere [8];
2. Calculate a projection, denoted by $\{p^{\theta_k}(t)\}_{t=1}^{T}$ of the input signal $\{s(t)\}_{t=1}^{T}$ along the direction vector $X^{\theta_k}$, for all $k$ (the whole set of direction vectors), giving $\{p^{\theta_k}(t)\}_{k=1}^{K}$ as the set of projections;
3. Find the time instants $\{t_i^{\theta_k}\}_{k=1}^{K}$ corresponding to the maxima of the set of projected signals $\{p^{\theta_k}(t)\}_{k=1}^{K}$;
4. Interpolate $[t_i^{\theta_k}, s(t_i^{\theta_k})]$, for all values of $k$, to obtain multivariate envelope curves $\{e^{\theta_k}(t)\}_{k=1}^{K}$;
5. For a set of $K$ direction vectors, calculate the mean $\mu(t)$ of the envelope curves as:

$$\mu(t) = \frac{1}{k}\sum_{k=1}^{K} e^{\theta_k}(t) \tag{1}$$

6. Extract the "detail" $d(t)$ using $d(t) = X(t) - \mu(t)$. If the "detail" $d(t)$ fulfills the stoppage criterion for a multivariate IMF, apply the above procedure to $X(t) - d(t)$, otherwise apply it to $d(t)$.

Consider a time sequence of $N$-dimensional vectors denoted by $s(t) = [s_1(t), s_2(t), \ldots, s_N(t)]^T$ representing a multivariate signal with $N$ components, and $X^{\theta_k} = \left\{x_1^k, x_2^k, \ldots, x_N^k\right\}$ denoting a set of direction vectors along the directions given by angles $\theta^k = \left\{\theta_1^k, \theta_2^k, \ldots, \theta_{N-1}^k\right\}$ on an $(n-1)$-sphere. Once the first IMF is extracted, it is subtracted from the input signal and the same process is applied to the resulting signal yielding the second IMF and so on. In the multivariate case, the residue corresponds to a signal whose projections do not contain enough extrema to form a meaningful multivariate envelope. The stopping criterion for MEMD of IMFs is similar to standard EMD [6], the difference being that the condition for equality of the number of extrema and zero crossings is not imposed, as extrema cannot be properly defined for multivariate signals. Filter banks represent an array of band-pass filters designed to isolate input signal into different frequency bands.

### 2.2. EOG Suppression from EEG

Multivariate EMD decomposes all the vectors simultaneously with equal number of IMFs. The fractional Gaussian noise (fGn) is used here to compare the energy to detect the trend in the EEG signals. The analyzing signal of MEMD includes the known reference signal (fGn), the desired channels, the reference EOG (vEOG or hEOG) denoted as rEOG. Then the $(N+2)$-variate data $s(t)$ can be defined and decomposed with MEMD as:

$$\begin{aligned} s(t) &= [\underbrace{s^{(0)}(t)}_{\text{fGn}}, \underbrace{s^{(1)}(t), \ldots, s^{(N)}(t)}_{N\text{ EEG channels}}, \underbrace{s^{(N+1)}(t)}_{\text{rEOG}}]^T \\ &= \sum_{j=1}^{J} d_j(t) + r_J(t), \end{aligned} \tag{2}$$

where $s^{(0)}(t)$, $s^{(i)}(t)$ $(i = 1, \ldots, N)$, and $s^{(N+1)}(t)$ denote fGn, the channel-$i$ EEG signal, and rEOG, respectively. The different signals of a typical data are shown in Fig. 1. The EOG effects are prominent in Chan-6, whereas, the other EEG channels are noisy and the presence of EOG effects is not clearly visualized, and hence, it is difficult to make separated.

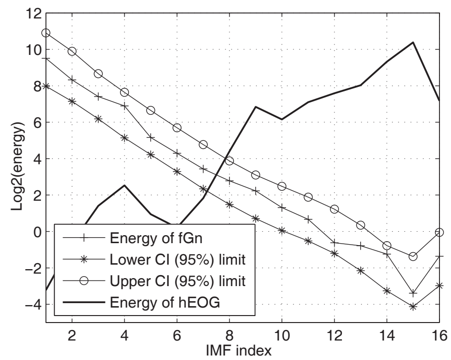


**Fig. 3**. Selection of threshold IMF index of hEOG. The $8^{th}$ IMF is selected to determine the high frequency limit of EOG suppression.

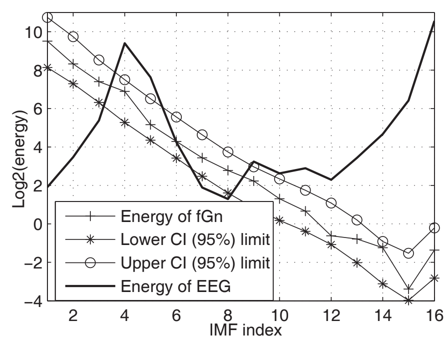


**Fig. 4**. Selection of threshold IMF index of EEG Chan-28. The $9^{th}$ IMF is selected to as the threshold one.

After applying MEMD, the overall IMF space for all channels is obtained as $Q(n, j, t)$; where $n = 0, 1, \ldots, N + 1$ are the channel indexes, $j = 1, 2, \ldots, J$ represents the IMF indexes for any channel, and $t = 1, 2, \ldots, T$ are the time indexes of any vectors (the length of all vectors are same). Recorded EEG is considered as a superposition of relatively faster oscillating EEG signal and slowly varying EOG artifacts. It is well known that the energy of the EOG signals is much higher than that of the EEG signals. Hence EOG signal is treated as the low frequency trend of the recorded EEG signals. We propose a data adaptive detrending method to separate the EOG artifacts from recorded EEG signals. The trend of EOG is determined by comparing the energy of individual IMF with the reference signals (fGn). Higher order IMFs contain the lower frequency components. We can easily separate the high frequency EEG signal of the channel by summing up the lower order IMFs as:

$$\hat{s}^{(n)}_{EEG}(t) = \sum_{j=1}^{C^{(n)}-1} d^{(n)}_j(t), \tag{3}$$

where $d^{(n)}_j(t)$ is the $j^{th}$ IMF of the $n^{th}$ channel. Here the subject is to find the critical (threshold) IMF with index $C^{(n)}$ such that the IMFs of indices $C^{(n)}, C^{(n)} + 1, \ldots, J$, are responsible for the low frequency EOG artifacts. Then the EOG can easily be separated as:

$$\hat{s}^{(n)}_{EOG}(t) = \sum_{j=C^{(n)}}^{J} d^{(n)}_j(t) + r^{(n)}_J(t), \tag{4}$$

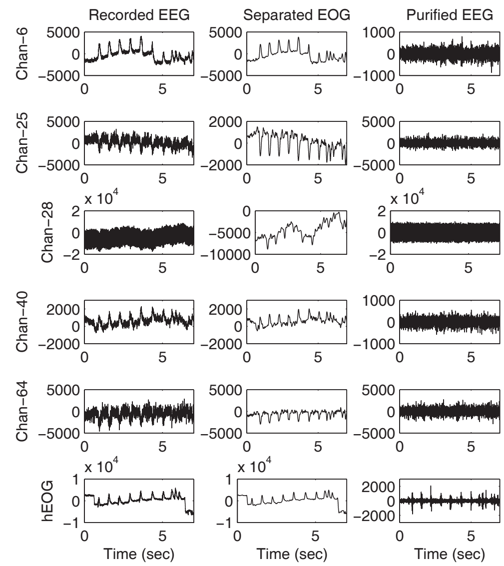


**Fig. 5**. Separation of EOG from recorded EEG for selected six channels only.

where $r^{(n)}_J(t)$ is the final residue of the $n^{th}$ channel. A novel algorithm is proposed herewith using MEMD to find the index $C^{(n)}$ of the threshold IMF for individual EEG channel as:

1. Calculate the energies of the IMFs of fGn and its 95% confidence interval (CI).
2. Find the lowest order IMF of rEOG channel exceeding the upper limit of CI, say it is the $p^{th}$ IMF. Compute the mean period $\tau_m$ of $p^{th}$ IMF of fGn.
3. For any $n^{th}$ EEG channel, calculate the mean periods $\sigma^{(n)}_j$ for $p \leq j \leq J$ of the IMFs exceeding the upper limit of CI.
4. Find the threshold IMFs index $C^{(n)}$ of the $n^{th}$ channel such that $|\tau_m - \sigma^{(n)}_j|$ is minimum for $j = C^{(n)}$.

After computing the index $C^{(n)}$ of threshold IMF (for EEG channel), the EEG and EOG of that channel is separated using Eq. (3) and Eq. (4) respectively. It is noted that before applying MEMD to data $x(t)$, the amplitude of all the vectors are normalized. The scaling factors of normalization are stored to get back the original amplitude of individual channel after separating EOG and EEG. If $\lambda_n$ is the scaling factor of normalization for $n^{th}$ channel, the separated EOG and EEG with original scale are obtained as: $s^{(n)}_{EOG} = \lambda_n \hat{s}^{(n)}_{EOG}$ and $s^{(n)}_{EEG} = \lambda_n \hat{s}^{(n)}_{EEG}$ respectively.

## 3. EXPERIMENTAL RESULTS

All the desired EEG channels as well as fGn and reference EOG (rEOG) are decomposed together using MEMD yielding same number of IMFs for each vector. The MEMD has the ability to align the common scale present within the multivariate data. Each common scale is manifested in the common oscillatory modes in all variates within the multivariate IMF [5]. Such mode alignment property helps to make use of similar scales in different data sources and hence can be very much useful for the analysis of EEG data to separate EOG artifacts. The MEMD is applied on the multivariate data

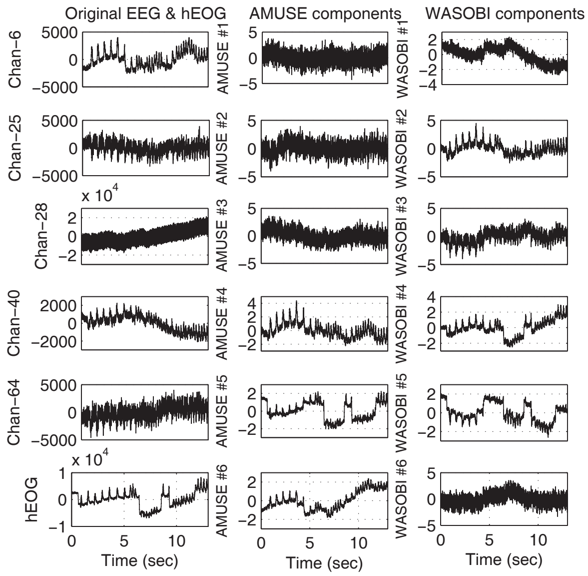


**Fig. 6**. Unsuccessful separation of EOG from EEG using BSS (AMUSE [3] - middle column; WASOBI [9] right column) due to several components carrying still the artifacts.

shown in Fig. 1. The selected three-variate IMFs (fGn, Chan-28, hEOG) are shown in Fig. 2. Out of 15 IMFs, only the higher order 9 IMFs ($7-15$) and the residue are presented here.

The IMFs of the fGn are used here as the energy threshold to detect the low frequency trend caused by EOG artifact. The reference EOG signal is used to determine the upper frequency limit of the separated EOG from EEG channels. Although in EMD based application, no basis function is used to realize the frequency response, the IMFs of fGn can be used as data driven bases. Thus we can obtain proper frequency tracing from fGn part of MEMD application. The energies of the IMFs of hEOG are compared with the upper confidence limit of fGn energies. The lowest order IMF of hEOG exceeding the confidence limit is the first one of the low frequency trend i.e. the EOG interference of the recored EEG. Figure 3 illustrates the IMF's energies fo hEOG and fGn with its confidence limits. The $8^{th}$ IMF of hEOG is the starting IMF of purified EOG artifact obtained by using Eq. (4). The mean period ($\tau_m$) of the $8^{th}$ IMF of fGn is taken as the upper frequency limit of EOG signal.

To separate the EOG artifact from any EEG channel, the energies of the IMFs of that channel are compared in the similar way as in Fig. 3. The energy comparison of EEG Chan-28 with fGn is presented in Fig. 4. The next step is to find the index of the IMF from which the EOG artifact will be started. The beginning IMF is selected from the set of IMFs exceeded the upper confidence limit with the mean period closest to $\tau_m$. In Fig. 4, the $9^{th}$ IMF satisfies the both condition and taken as the beginning point of separating EOG artifact from Chan-28. If classical EMD is used, the $5^{th}$ IMF will be selected because there is no way to synchronize the mean period when the signals (fGn and EEG of Chan-28) are decomposed separately, only the energy comparison is performed. The mean period of the $8^{th}$ IMF of Chan-28 is closest to $\tau_m$. With BEMD [4], the $8^{th}$ IMF will be selected because no energy comparison is performed for individual EEG channels. Only the mean period is taken into consideration whereas, the energy of the $8^{th}$ IMF does not exceed the confidence limit. If the EOG is separated starting from the $8^{th}$ IMF, it will include some energy of pure EEG part. In all cases, the proposed MEMD based approach is able to make the effective separation of EOG artifacts. The separation results of EOG and purified EEG of all the channels of Fig. 1 are illustrated in Fig. 5. Another potential multivariate approach, a BSS using well-known AMUSE [3] or a recent WASOBI [9] are also applied to separate the EOG interference as shown in Fig. 6. It is observed that the separation of EOG is not perfect and it is difficult to identify the component which represents only the EOG signal. Thus it is problematic to separate the EOG contamination from the other channels.

## 4. CONCLUSIONS

A data driven adaptive method has been implemented to separate the EOG artifacts from recorded EEG signals. The newly developed multivariate EMD method has been employed together with proposed, by the authors of this paper, the criterion to successfully label IMFs for further separation of the recorded brain signals into clean EEG and the interference to be discarded (EOG in the presented case). The proposed MEMD extension is a step forward in automatic data driven electrophysiological signals separation leading to successful removal of EOG artifacts from contaminated EEG. Comparison with contemporary blind source separation methods supports the strength of the developed approach.

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