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Removing EOG artifacts from EEG Signal Using Noise-Assisted Multivariate Empirical Mode Decomposition

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***Abstract*— Electroencephalogram (EEG) has significant applications on medical diagnosis and Brain Computer Interfacing (BCI). But the main obstacle of analyzing EEG signal is various types of noises to get actual information. Electro-oculogram (EOG) is a vital noise in EEG signal that can be produced by eye movements. De-noising EOG from EEG signal is the key issue in this research. Many research has been done on this purpose mainly Independent Component Analysis (ICA) based EOG separation with reference signal and wavelet based EOG separation. In this research, multivariate Fractional Gaussian noise channel will be used to establish a uniformly distributed reference scale and to derive the energy based threshold to detect the low frequency trends caused by EOG artifact. Avoiding these artifacts, we can get EOG free EEG hoping better results than existing methods.**

Keywords*— *EEG signal; EOG artifacts; Fractional Gaussian Noise channel; Energy based threshold.

I. Introduction

Human brain contains billions of neurons making up a large complex neural network which process signal information of body activity. During the processing of information, neurons change the flow of electrical currents across their membranes. These changing currents generate electric and magnetic fields that can be recorded from the surface of the scalp by attaching small electrodes. The potential difference between electrodes are then amplified and recorded as the electroencephalogram (EEG) signal [1]. EEG signal is used to diagnose various types of diseases like epilepsy, sleep disorder, brain death, Alzheimer etc. But eye blink and eyeball movement causes Electro-Oculogram (EOG) artifacts that is present all over the EEG signal. EOG signals are dominant in nature having higher amplitude. Auditory and mental arithmetic tasks with the eyes closed, leads to strong alpha waves, which are suppressed when the eyes are opened [2]. Thus the desired EEG data becomes noisy which suppress important frequency characteristics. So EEG signal must be noise free for proper analysis and diagnosis of these diseases.

In this research, I have proposed a method of decomposing EEG signal by Noise-Assisted Multivariate Empirical Mode Decomposition (N-A MEMD) [3] and then applying energy based threshold to identify frequency trends of EOG artifacts. For this purpose, a 14-channel EEG data of length 5000 has been used, acquired using international 10-20 electrode placement system [4]. Multivariate Fractional Gaussian noise (fGn) channels will be added as extra channels to the original multivariate EEG signal and then the composite signal will be processed via Multivariate Empirical Mode Decomposition (MEMD) [5]. N-A MEMD method tends to accurately align the common oscillatory modes in corresponding IMFs from multiple channels [3]. This property motivated me to extend the previously proposed method of EOG separation to N-A MEMD.

II. Methods

A. Empirical Mode Decomposition (EMD)

In EMD [6], signal is decomposed as a linear combination of data driven set of basis functions known as the intrinsic mode functions (IMFs). Thus embedded characteristics are revealed. But same index IMFs of different channels are misaligned (mode mixing) e.g. a single IMF containing multiple oscillatory modes and/or a single mode residing in multiple IMFs [3]. It may compromise the physical meaning of IMFs.

B. Multivariate Empirical Mode Decomposition (MEMD)

In recent years, the advances in data acquisition tools have highlighted the need for direct processing of multivariate data. MEMD produces the same number of IMFs for all channels, facilitating direct multichannel modeling and reducing mode mixing problem. But even if it is applied directly, the problem is not completely eliminated. Due to the filter bank property of MEMD, Fractional Gaussian Noise channels which frequency spectrum is correlated to clean EEG, is added to the recorded EEG. Then MEMD is applied to this composite signal, resulting in proper separation of clean EEG and noise [7]. Hence Noise-Assisted MEMD method is introduced in this research.

III. Principle and Algorithm of MEMD

MEMD processes the input signal directly in a multidimensional domain (n-space). Input signal projections are taken directly along different directions in n-dimensional spaces to calculate the local mean. Local mean calculation can be considered as an approximation of the integral of all the envelopes along multiple directions in an n-dimensional space, and the accuracy of this approximation is dependent on how uniformly the direction vectors are chosen, especially for a

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limited number of direction vectors [8]. The default number of directions is chosen to be 64 - to extract meaningful IMFs, the number of directions should be considerably greater than the dimensionality of the signals.

A. Projections of Input Signal in n-Dimentional Spaces

The sampling scheme based on low discrepancy Hammersley sequence is used to project input signal in n-dimensional spaces [8] and hence estimates more accurate local mean. Unlike conventional uniform angular sampling schemes, this scheme belongs to a class of quasi-Monte Carlo methods, and provides relatively more uniform sampling [7].

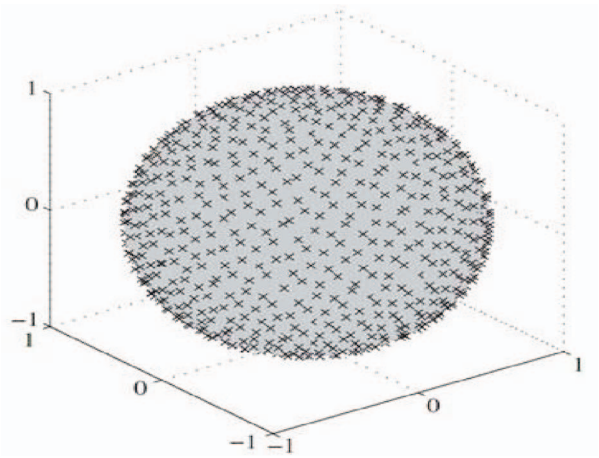

Fig. 1. Direction vectors for taking projections of multivariate signals generated by using a low-discrepancy Hammersley sequence.

The direction vectors in n-dimensional spaces can be equivalently represented as points on the corresponding unit (n-1) spheres. It is necessary since calculation of the local mean, a crucial step in MEMD, is difficult to perform due to the lack of formal definition of maxima and minima in higher dimensional domains [3].

B. Identification of Maxima and Minima

Once the projections along different directions in multidimensional spaces are obtained, their extrema are interpolated via cubic spline interpolation to obtain multiple signal envelopes. Algorithm to identify maxima and minima:

- The value of the current element of the sequence is compared with the preceding and subsequent values.
- If the current value is greater than the preceding and the subsequent values, it is identified as the function maximum.
- If the current value is smaller than the preceding and the subsequent values, it is identified as the function minimum.

Once the extrema are identified, they are connected by cubic spline lines to produce the upper and lower envelopes. These envelopes are then averaged to obtain the local mean. The mean value is further subtracted from the initial sequence. This results in the extraction of the required empirical function in the first approximation. To obtain the final IMF, new maxima and minima are again identified and all the above steps repeated. This repeated process is called sifting. The sifting process is repeated until a certain given stoppage criterion is met. Each multivariate IMF must satisfy two basic conditions:

- In the whole data set, the number of extrema and the number of zero crossings must differ at most by one.
- At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

Algorithm 1: Multivariate Extension of EMD

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

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

- Extract the “detail” *d(t)* using *d(t) = x(t) - m(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)* [3].

Once the first IMF is extracted, it is subtracted from the input signal and the same process (Algorithm 1) is applied to the resulting signal yielding the second IMF and so on. The process is repeated until all the IMFs are extracted and only a residue is left. In multivariate case, the residue corresponds to a signal whose projections do not contain enough extrema to form a meaningful multivariate envelope.

IV. Filter Bank Property of MEMD

Filter banks represent a collection of bandpass filters designed to isolate different frequency bands in the input signal. The IMFs obtained from standard EMD algorithm provide frequency responses similar to that of a dyadic filter bank [11] [12]. The frequency response and the corresponding filter bank property of MEMD were illustrated by applying MEMD on a N = 500 realizations of an eight-channel white Gaussian noise each of length T = 1000; the power spectra of its resulting first fine IMFs (1-9) were then ensemble averaged to yield an averaged power spectra; the stopping criteria used is given in [12], with the value of S = 5; it is then plotted in the top of *Fig. 2*. Next, the same realizations were separately processed via standard EMD and the estimated averaged power spectra of its IMFs are shown in the bottom of *Fig. 2*.

It can be seen that the overlapping of frequency bands of same-index IMFs associated with different channels is much more prominent in the case of MEMD as compared with standard EMD [3].

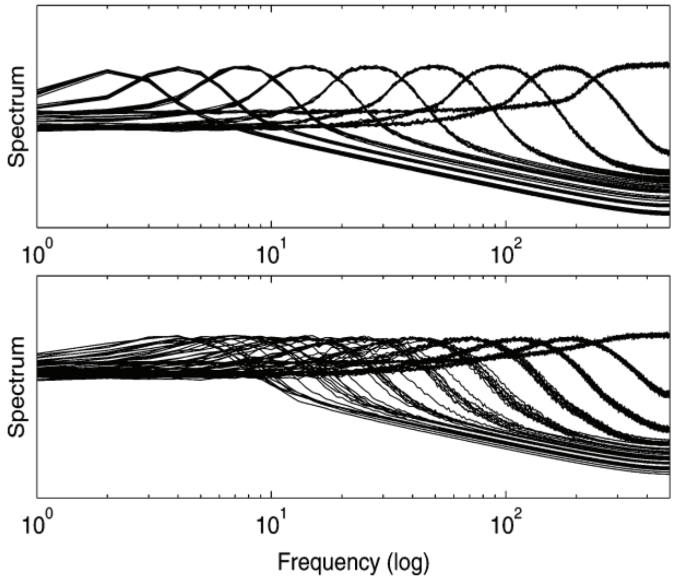

Fig. 2. Averaged spectra of white noise realization via MEMD (top) and standard EMD (bottom)

V. Principle and Algorithm of Noise-Assisted MEMD

N-A MEMD makes use of the quasi-dyadic filter bank properties of MEMD on white noise. An extra channel containing independent multivariate fGn is added to the original multivariate signal, and it is then processed via MEMD. The details of the NA-MEMD method are outlined in Algorithm2:

A. Algorithm 2: Noise-Assisted MEMD

- Create an uncorrelated Fractional Gaussian white noise time-series (*m*-channel) of the same length as that of the input.
- Add the noise channel created in Step 1 to the input multivariate (*n*-channel) signal, obtaining an ($n + m$) channel signal.
- Process the resulting ($n + m$)-channel multivariate signal using the MEMD algorithm listed in Algorithm 1, to obtain multivariate IMFs.
- From the resulting ($n + m$)-variate IMFs, discard the *m* channel corresponding to the noise, giving a set of *n*-channel IMFs corresponding to the original signal [3].

Since required noise free EEG signal resides in similar dyadic frequency spectrum, the method can perfectly separate the frequency bands, hence is able to reduce the EOG artifacts.

VI. Generation of Intrinsic Mode Functions

A multivariate EEG signal with 14-channel of length $T = 5000$ is used. Two uncorrelated fGn channels of same length are added as the 15th and 16th channels to the signal. Now the signal is decomposed using N-A MEMD. The IMFs are shown in *Fig.3.* Higher order IMFs contain lower frequency oscillations than lower order IMFs signal. Thus high frequency neurobiological signals containing valuable information are separated from the low frequency trend of EOG artifacts.

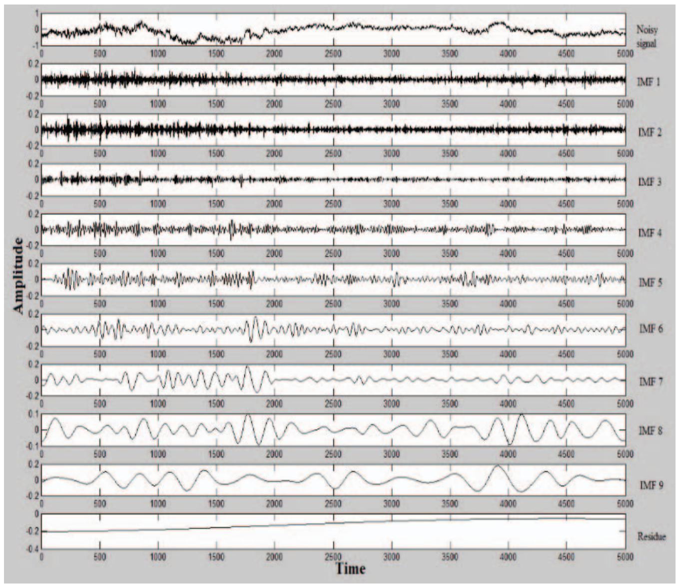

Fig. 3. The waveforms of noisy EEG signal and its first 9 IMFs out of 14 and residue

VII. Principle of Energy Based Threshold

N-A MEMD decomposes all the vectors simultaneously with equal number of IMFs in a perfect filter bank structure. The fGn channel is used here as reference signal to compare the energy to detect the EOG related trends in EEG signal.

Recorded EEG is considered as a superposition of relatively faster oscillating EEG signal and slowly varying EOG artifacts. The energy of the EOG signals is much higher than the EEG signals. Hence EOG signal is treated as the low frequency trend of the recorded EEG signals. I propose a data adaptive detrending method to separate the EOG artifacts from the recorded EEG signals. The trend of EOG is determined by comparing the energy of individual IMF of the EEG channel with the same index IMF of the reference signal (fGn). Higher order IMFs contain the lower frequency components. The high frequency EEG signal of the channel can be easily separated by summing up the lower order IMFs as:

$$\hat{S}_{EEG}^{(n)} = \sum_{j=1}^{C^{(n)}-1} d_j^{(n)}(t) \qquad (2)$$

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

$$\hat{S}_{EOG}^{(n)} = \sum_{j=C^{(n)}}^{J} d_j^{(n)}(t) + r_j^{(n)}(t) \qquad (3)$$

Where $r_j^{(n)}(t)$ is the final residue of the n^{th} channel. The algorithm to find the index $C^{(n)}$ of the threshold IMF for individual EEG channel as:

A. Algorithm 3: Estimating threshold

- Calculate the energies of the IMFs of fGn and its 95% confidence interval (CI).
- Find the index $C^{(n)}$, highest order IMF of an EEG channel that does not exceed the lower limit of CI.

After computing the index $C^{(n)}$ of threshold IMF (for EEG channel), the clean EEG is reconstructed using Eq. (2).

VIII. Identification of Threshold Point

The energy of each IMF of both fGn channel and EEG channels is calculated using the following equation:

$$Energy_i = log_2 IMF_i^2 \quad (4)$$

Where IMF_i is the i^{th} IMF of a channel. Now the 95% confidence interval (CI) for fGn channel is calculated.

The energy of each IMF of an EEG channel is compared to the lower limit of the same index CI value. If the energy exceeds the lower limit, the IMF is an EOG component. Thus the highest order IMF which energy does not exceed the limit is identified and considered as the threshold point $C^{(n)}$. The energy diagram of fGn and channel-1 EEG signal with upper and lower limit CI value is shown as in *Fig. 4.*

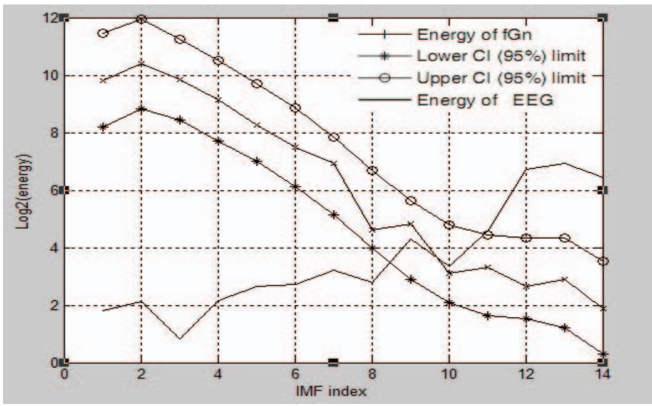

Fig. 4. Selection of threshold IMF index of EEG chan-1. The 6th IMF is selected to as the threshold one

It is visible that the energy line of EEG intersects the lower CI limit near 8. So the 8th IMF is selected as the threshold IMF and index $C^{(n)} = 8$. EEG signal is obtained by adding the IMFs up to the threshold point using Equation (2) and EOG using Equation (3).

IX. Experimental Results

The SNR of noisy EEG signal is:

$$S/N_{Original} = 122.21\ dB$$

The SNR of de-noised EEG signal obtained from both EMD and N-A MEMD method is calculated and the values are:

$$S/N_{EMD} = 134.79\ dB$$

$$S/N_{NAMEMD} = 202.73\ \text{dB}$$

In previous research [13] the decomposition was done using noise assisted EMD. But EMD fails to realize the effect of signals overlapped in multiple channels. Thus in the process of thresholding, some important information is lost. As depicted above the SNR value for N-A MEMD is much higher than ordinary EMD. Hence it is clear that N-A MEMD performs better than EMD to reduce noise from signals.

X. Conclusions

This study is devoted to analyze a method to identify the ocular artifact spike zones in EEG signal applying Noise Assisted Multivariate EMD and energy based threshold. A data driven adaptive threshold method applied only to the ocular artifact zone does not affect the low frequency components and also preserves the shape of the EEG signal in the non-artifact zones which is of very much importance in clinical diagnosis. The proposed method minimizes the complexity of the work and easily identifies the artifact zones for removing the artifacts. Signal to Noise Ratio is used as performance metrics in this paper. Higher SNR value is obtained using this method than the other previously implemented methods, therefore the suppression of ocular artifacts in dB is best. In all cases, artifacts were adequately attenuated, without removing significant and useful information.

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