Separation of Ocular Artifacts from EEG Signal using Noise Assisted Bi-variate Adaptive Filtering

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Abstract

This paper focuses ocular artifacts separation of EEG signals using Noise Assisted Bi-variate adaptive based filtering. In order to facilitate clinical diagnosis and/or implement so-called brain computer interface (BCI), detecting the rhythmic activity from EEG data recorded in a noisy environment is crucial. The pre-processing of EEG signal is mandatory due to highly interference with the EEG signal. Electro-oculogram (EOG) is the most important interference that misinterpret significantly of the EEG signal for brain activity measurements. To suppress EOG data, we have used a newly developed model with empirical mode decomposition (EMD) named as noise assisted EMD (NEMD). Because the complex signals have a mutual dependence between the real and imaginary parts, so it is possible to analyses both parts simultaneously using NEMD. Here, the EEG signal and white Gaussian noise (reference signal) are combined to produce complex signal which is decomposed using NEMD to extract complex intrinsic mode functions (IMFs). Then the low frequency trend (EOG) and high frequency components (purified EEG) of recorded EEG signals are obtained partial reconstruction on the basis of the energy distribution of their intrinsic mode functions. The experimental results show that the NEMD based data adaptive filtering technique performs better.

Keywords: *ocular artifacts, source separation, electroencephalograph (EEG), Noise assisted Empirical Mode Decomposition (NEMD)*

1. Introduction

The most familiar example of source separation problem in acoustics named as ‘Cocktail Party Problem’ where a listener attempting to pay attention to one speaker in a party environment. A similar problem appears in the context of an experimenter recording electromagnetic signals emitted by a neural source in a human brain. An electroencephalogram (EEG) represents complex signals is a sum of the large number of neurons potentials that measures and records the electrical activity in the brain. Special sensors are attached to the scalp surface by wires and the brain's electrical activity represents complex irregular signals that may provide information about neural activities in the brain [1]. EEG is a very popular brain activity test and analysis tool for many applications in Neuroscience. EEG signals are recorded from the head are contaminated by external interferences such as electric power or electromagnetic radiation. This interference is usually easy to separate from EEG signals based on signals electrical characteristics. Moreover, human body contains multiple electrophysiological signals which are non-linear in nature and their spectral properties can be correlated may exhibit a time-varying non-stationary response. These processes are serious obstacles to many neurological problem detection and identifications [2].

In cognitive neuroscience research, researchers are motivated in recovering signals associated with ocular activity from specific brain regions. To separate EOG interference features from recorded EEG signals, method based on frequency analysis and statistical signal processing using independent component analysis (ICA) have been proposed [3]. But the frequency domain filtering makes spectral distortion while separating EOG interference. However, recently a number of researchers [4-6] have turned to ICA aiming to decompose the recorded EEG data into independent components utilizing higher order statistics but main problem is that the extracted components do not confirm the original scale and sequences. Knuth in [7] demonstrated that the Bayesian methodology provides a natural and logically consistent means by which prior information can be incorporated into a specific neuroelectromagnetic separation problem.

In this paper, a fully data adaptive technique named noise assisted empirical mode decomposition (NEMD) is employed. The basis functions of NEMD called intrinsic mode functions (IMFs) are derived directly from the recorded raw EEG data without any prior information [8]. Recently, it is shown that NEMD approach is the best for non-linear signal analysis and provides more efficient results than others. The fractional Gaussian noise (fGn) has interesting characteristics with EMD [9]. The EMD on fGn acts as dyadic filterbanks [10]. The energies of the IMFs decrease almost linearly with increasing their order. It implies that the higher frequency IMFs contain more energies than that of the lower frequencies. The fGn is used as the reference signal to implement different applications of NEMD. The analyzing EEG signal and fGn are decomposed together with NEMD in which fGn is used as the reference signal. Several tuning parameters are selected from some previous experiments on fGn and are used to separate the fGn type noise to extract the trend in the signals. We use fGn in a different way to fix the energy reference to extract the trend. In NEMD two signals (EEG and fGn) are decomposed simultaneously based on their rotating properties. The trend of EEG signal is detected by comparing the energy of individual IMF with that of the reference signal. In this paper we have successfully implemented the scheme of separation of EEG signal using EMD and NEMD approaches.

This paper is organized as follows: the Noise assisted EMD on EEG signal is described in Section 2, the NEMD based time domain filtering is explained in Section 3, different types of experimental results are illustrated in Section 4 and finally Section 5 contains some concluding remarks.

2. Noise Assisted EMD of Signal

The empirical mode decomposition (EMD) decomposes a signal into waveforms modulated in both amplitude and frequency *i.e.*, at the scale of its local oscillation. The idea behind is a signal with high frequencies superimposed on low frequencies. In order to handle bivariate time series, the ordinary EMD is extended to complex EMD is called bivariate EMD [11] here we named as noise assisted EMD (NEMD). In NEMD, two variables are decomposed simultaneously (without losing mutual dependency) based on their rotating properties. The algorithm of the NEMD, as proposed in [11], is as follows:

1. Let the complex signal is $s(n)$

2. For 1 <*m*<*M*
   (a) Projectionsof *M* signal in direction of φ_m is given by $\{p\varphi_m\}_{m=1}^{M}$, so project the complex signal *s*(*n*) by using a unit complex number $e^{-j\varphi_m}$ in the same direction is given by

$$p\varphi_m(n) = R\left(e^{-j\varphi_m}s(n)\right), \quad m = 1,2, \dots \dots, M$$

where *R*(.) is the real part of the complex signal
   (b) Find the locations $\{n_j^m\}_{m=1}^{M}$ corresponding to the maxima of $\{p\varphi_m(n)\}_{m=1}^{M}$;
   (c) Interpolate between the maxima points $[n_j^m, s(n_j^m)]$, to obtain the partial envelope curve in direction φ_m named $\{e_{\varphi_m}(n)\}_{m=1}^{M}$;
3. Compute the mean of all tangents: $e(n) = {}^{2}/_{M} \sum_m e_{\varphi_m}(n)$,
4. Subtract the mean from input signal to obtain $d(n) = s(n) - e(n)$,
5. Test if *d*(*n*) is an IMF;
   (a) If yes, repeat procedure from the step (1) on the residual signal,
   (b) If no, replace *s*(*n*) with *d*(*n*) and repeat the procedure from step (1).

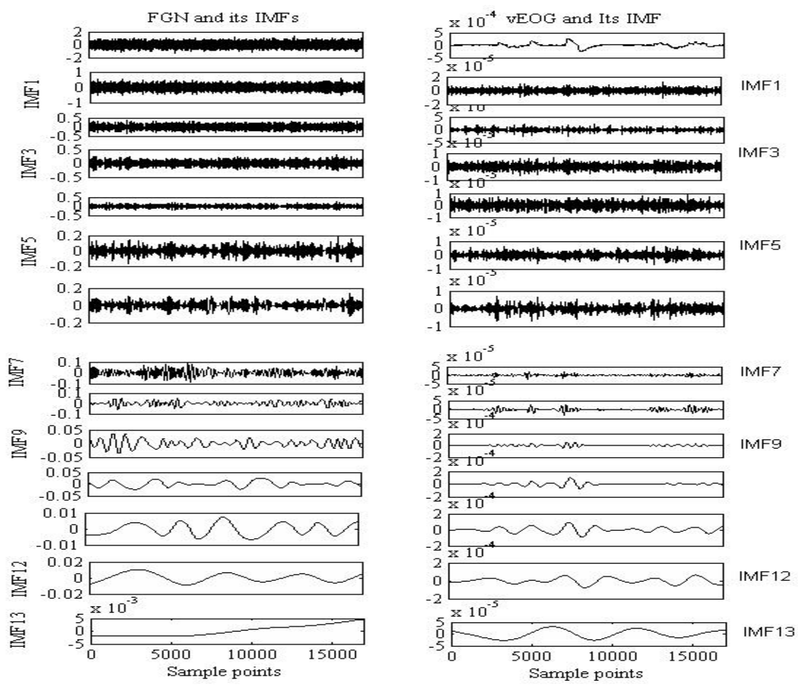

Figure 1. Noise Assisted Empirical Mode Decomposition of Recorded EEG Signal

Once the first IMF is derived, define $d_1(n)=s(n)$, which is the smallest temporal scale in *s*(*n*). The rest of the IMF components are generated the residue $r_1(n)$ of the data by subtracting $d_1(n)$ from the signal *s*(*n*) as: The sifting process will be continued until the final residue is a constant which is a monotonic function means a function with only one maxima and one minima from which no more IMF can be derived. The subsequent basis functions and the residues are computed as

$$r_2(n) = r_1(n) - d_2(n), \cdots, r_M(n) = r_{M-1}(n) - d_M(n) \quad (1)$$

where $r_M(n)$ is the final residue. At the end of the decomposition the signal $s(n)$ is represented as:

$$s(n) = \sum_{m=1}^{M} d_m(n) + r_M(n) \tag{2}$$

where $d_m(n)$ is the m^{th}IMF and $r_M(n)$ is the final residue which can be either the mean trend or a constant, and functions $d_m(n)$ are nearly orthogonal to each other, and all have zero means. In NEMD, $s(n)$ is modeled as a complex $s(n) = x(n) + j\eta(n)$ [11], where $j = \sqrt{-1}$, $x(n)$ and $\eta(n)$ represents EEG signal and fGn respectively. The fGn is generated on the basis of overall noise level estimated from the EEG signal. The fGn is a versatile model of homogeneously spreading broadband noise without any dominant frequency band although it is a generalization of ordinary white noise. Its statistical properties are entirely determined by its second –order structure, which depends solely upon one single scalar parameter and Hurst exponent [12]. The decomposition produces two separate sets of IMFs (real and imaginary) corresponding to individual signals as shown in Figure 1.

3. NEMD based Time Domain Filtering

The Noise assisted empirical mode decomposition (NEMD) based data adaptive filtering is implemented to separate the high frequency part (purified EEG) and low frequency trend (EOG interference) of the analyzing EEG signal. The original EEG signal $s(n)$ is decomposed into IMFs using NEMD. The decomposition produces two separate sets of IMFs (real and imaginary) corresponding to individual signals as shown in Figure 1. It is noted that $s(n)$ consists of slowly varying trend superimposed to a high frequency fluctuating process y(n). The trend is expected to be captured by IMFs of large indices (plus the final residue). A process of de-trending $s(n)$, which corresponds to estimating $y(n)$, may therefore relate to compute the partial, fine-to-coarse reconstruction as

$$h(n) = \sum_{k=1}^{D} d_k(n) \tag{3}$$

where D is the largest IMF index prior the remaining IMFs representing signal trend contamination. For the IMFs $d_k(n)$; k =1,2,...,D a rule of thumb, so the choice of D is based of observation of the evolution of the $h(n)$ energy as a function of a test order k. The optimized k=D is chosen when the energy index departs significantly from the energy of the reference signals [11].

A toy example of the NEMD approach to separate EOG interference from EEG signal in the case of an oscillatory low frequency waveform embedded in Gaussian noise (fGn) is shown in Figure 2. This Figure suggests that a dual strategy can be used for detrending fGn type noise process by computing the complementary partial reconstruction based on only those IMFs whose energy is below the threshold. The 95% confidence interval (CI) is used as the boundary limit of the energy based detrending technique. The 6^{th} IMF is selected as the starting point of low frequency component. All the lower order IMFs (of recorded EEG signal) starting from the obtained lower limit up to the residue are summed up to construct the low frequency trend $y(n)$ representing the EOG artifacts. The high frequency components *i.e.*, the original EEG signal $h(n)$ is obtained as

$$h(n) = s(n) - y(n) \tag{4}$$

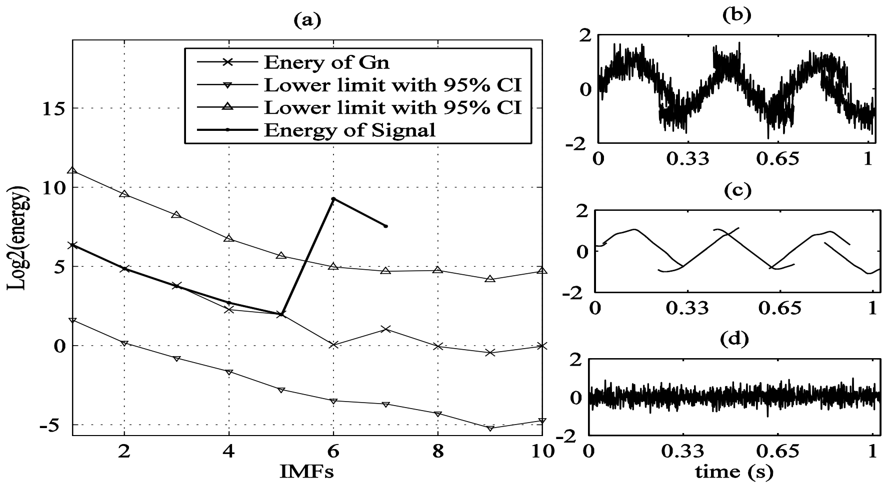

Figure 2. Amplitude Modulated Low Frequency Oscillation Embedded in Gaussian Noise (fGn) is Plotted in (b). The Estimated Energies of the 7 IMFs are Plotted in (a) together with the "Noise Only" Model and the 95% Confidence Interval. The Partial Reconstruction obtained by Adding the Residual and IMFs 6 to 7 is Plotted in (c). The Partial Reconstruction of IMFs 1 to 5 is Plotted in (d) Yeilding the fGn

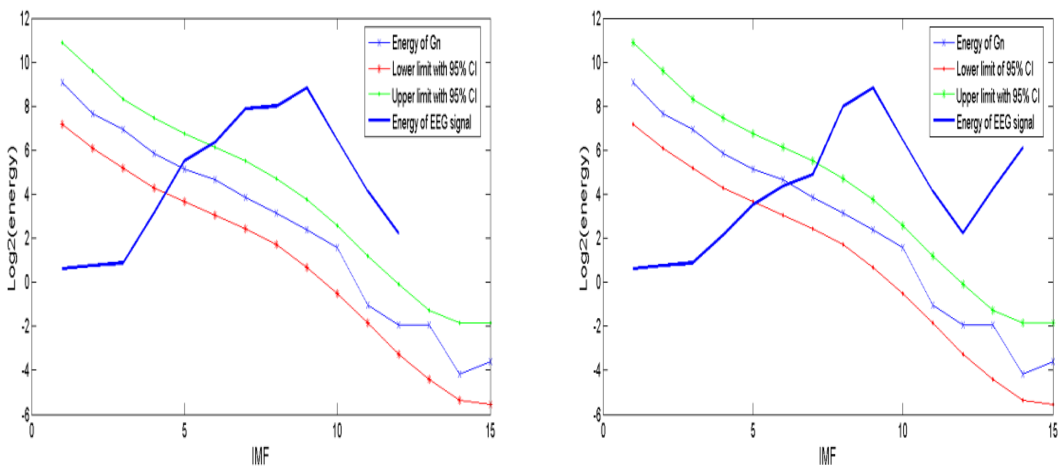

Figure 3. The Selection of Starting IMF (the 8th IMF) to Extract the Low Frequency Component of Recorded EEG Signal. Its Energy exceeds the Upper Limit (95% of CI) of the IMFs' Energies of fGn, using EMD (left) and NEMD (right)

The limit of the IMF to separate the trend (EOG) *i.e.*, the low frequency components (EOG) of the recorded EEG signal is determined by comparing the IMF (real) energy with that of the reference (imaginary) signal. The Gaussian noise (fGn) is used here as the reference signal which is estimated from the imaginary IMFs. When the energy of any IMF of EEG signal exceeds the upper limit of 95% confidence interval of the fGn, that IMF is selected as the lower limit of the low frequency trend (EOG) of EEG as shown in Figure 3.

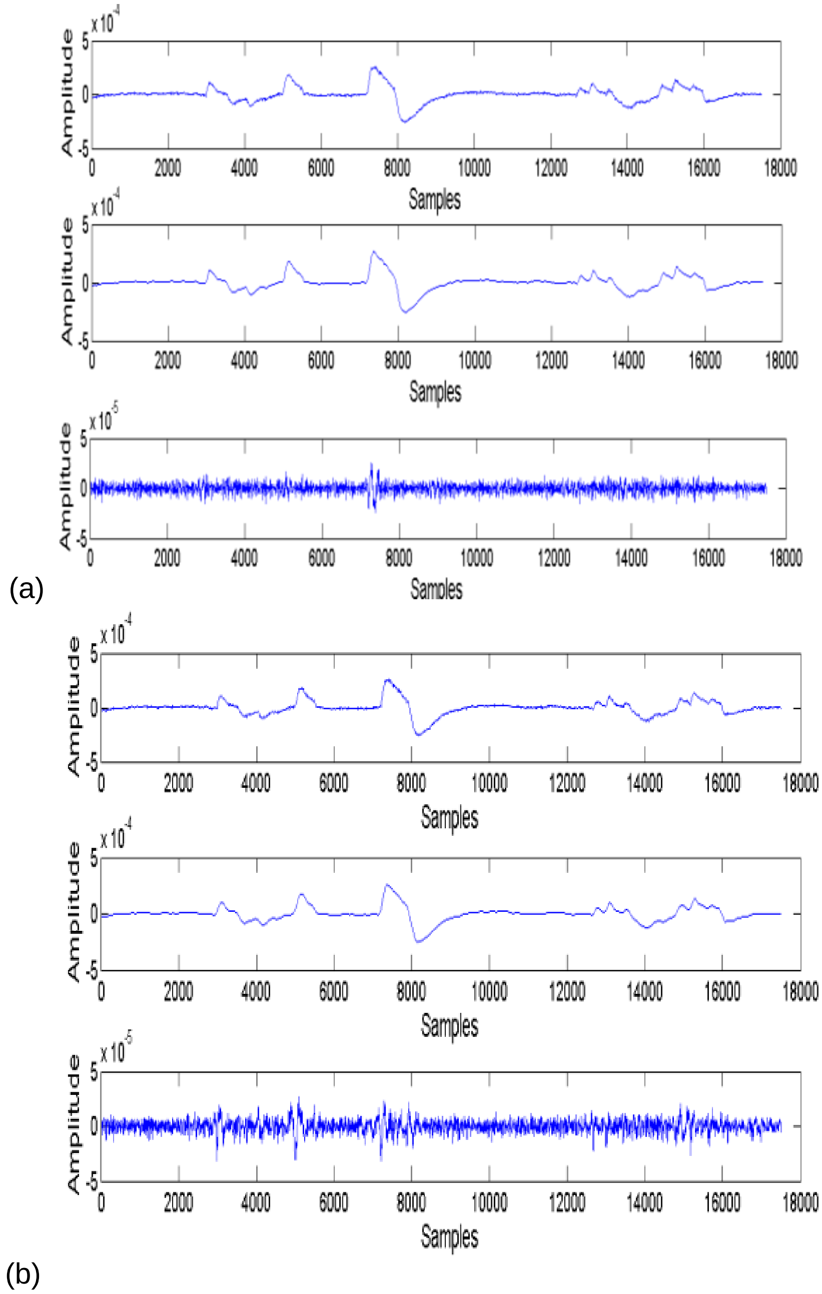

Figure 4. Separation of EOG Artefact (top) and the EEG Signal (bottom) using EMD (a) and NEMD (b) Based Data Adaptive Method

The proposed NEMD based algorithm for EOG separation is given bellow:

1. EEG signal and Gaussian noise (fGn) are combined producing complex signal $s(n)$. Both of the signals are normalized in amplitude
2. Apply NEMD on the complex signal.
3. Compute Log energy of individual imaginary fGn IMF and its upper and lower bound with 95% confidence interval.

4. Compute the Log energy of the real IMF. Find the real IMF with energy exceeding the upper limit of 95% confidence interval derived in step 1 say it m^{th} IMF. The selected m^{th} (in Figure 4, m=9) IMF is the starting index of constructing EOG signal. The EOG effect is separated by summing up the IMFs starting from m^{th} up to the residue of the NEMD of EEG signals.

4. Experimental Results and Discussions

The first step of the experiment is to separate EOG artifacts from recorded EEG signals using EMD and NEMD based time domain filtering method. To evaluate the performance of the proposed approaches, we analyzed 13 channels (12 EEG channel and 1 reference EOG channel termed as vEOG) of EOG data.

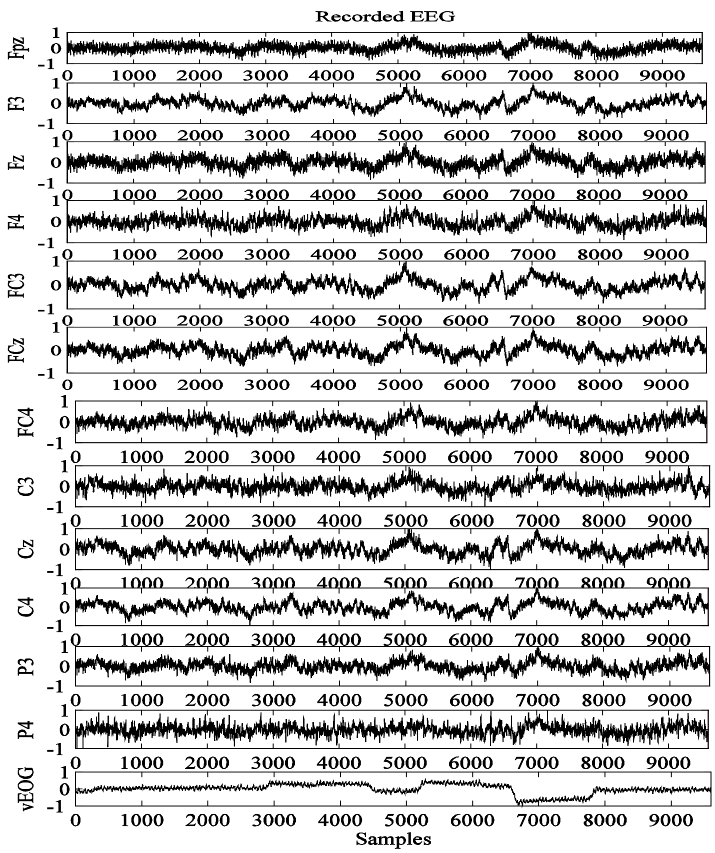

Figure 5. Recorded EEG Signal for 13 Channels (12 EEG Channel and 1 ref. vEOG) of EOG Data

In the first step, this article presents two procedures for separating successfully EOG interference from multiple channel EEG recordings-using data adaptive de-trending approach where a mixing model was not trivial as it is presented in Figure 5. The EEG signals are recorded (at the Advanced Brain Signal Processing Laboratory, RIKEN, Japan) from head surface and electrodes were connected to the appropriate head channels and sampled with 2.4kHz frequency using bio signal amplifier.

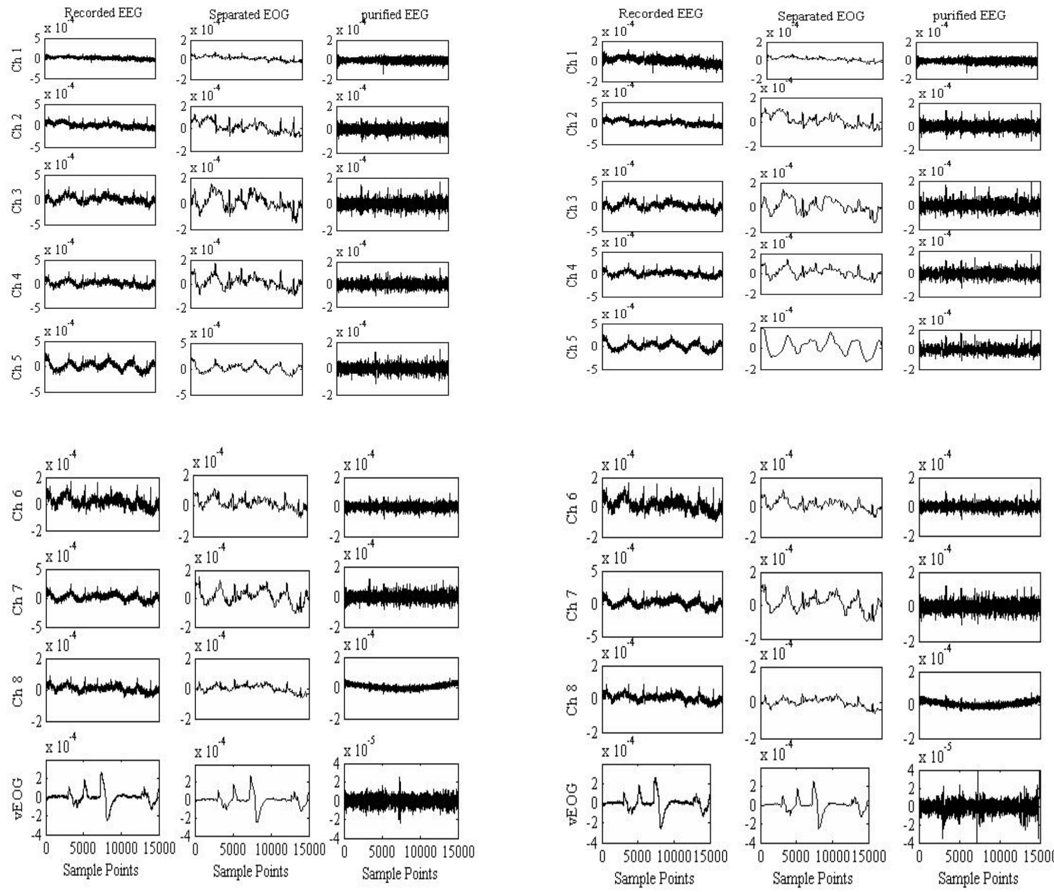

Figure 6. The Result of EMD (left) and NEMD (right) Approach to the Recorded EEG (left), Separated EOG (middle) and Purified EEG (right) of 9 Channels

The results of separated purified EOG and EEG signals using EMD are shown in Figure 6 (left). The reference EOG signal extracted from the reference channel vEOG is demonstrated in the figure. The reference EOG is used to determine the spectral limits of the EOG artifacts contaminating other EEG signals. From the experiments it is clear that the contamination of any EEG channel with EOG artifact also depends on the spatial distribution of the channels. The EOG and EEG separation results using NEMD for the mentioned 9 channels are also shown in Figure 6 (right).

In order to compare the performance of EMD with NEMD, experiments are conducted on the recorded EEG signals of size 9600 at different noise levels. The power spectrum results for separated EOG signal by EMD and NEMD approaches for 9 channels are illustrated in Figure 7.

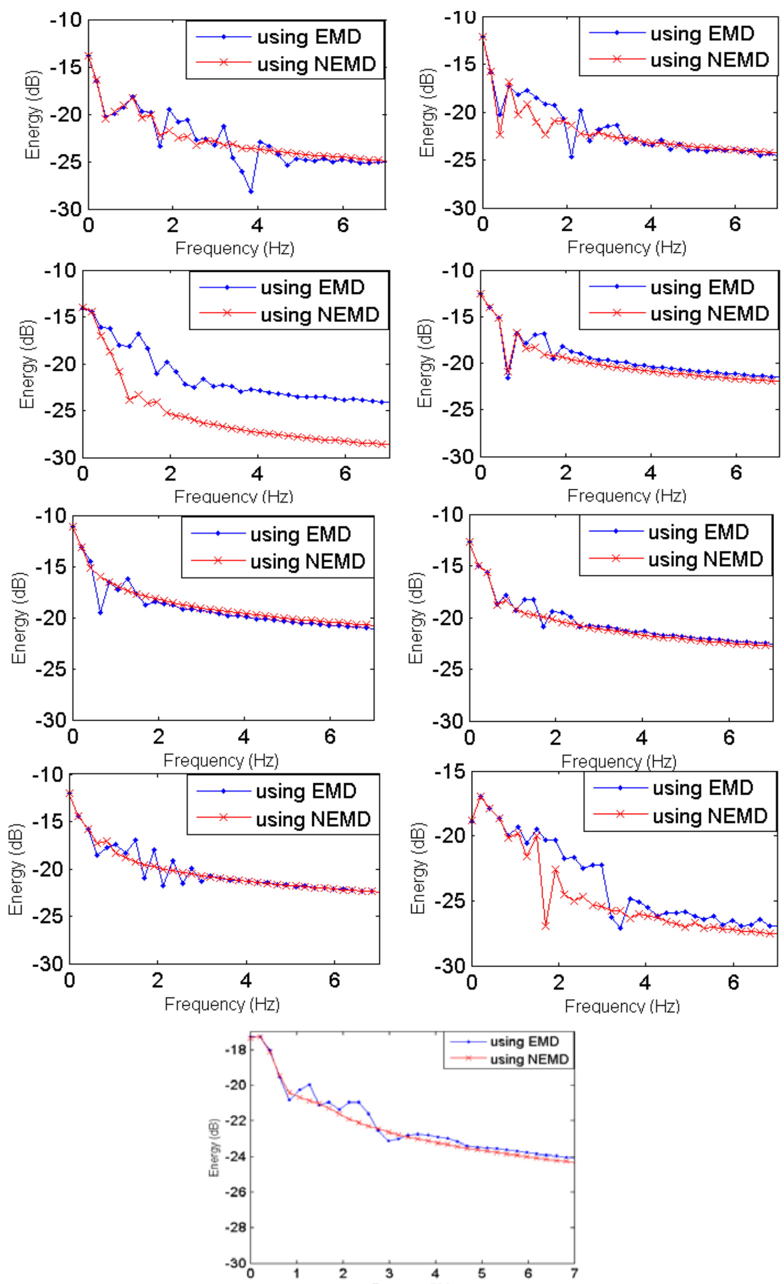

Figure 7. Separation of EOG for 8 Channels (except vEOG). The Circle Line Spectra Represent Interferences were removed by EMD while the Cross Lines by NEMD

From these figures, it is shown that in EMD approach, there are many higher frequencies signals components superimposed on lower frequency signal, that is, still remain information about neural activities in the brain with EOG signal which occur serious problem for neuroscience application or medical diagnosis. The main strength of the EOG below 0 to 0.8 Hz range are understandable overlapping of both spectra is very common in all 9-channels and after that range, whereas in NEMD approach, no neural activities in the brain correlated with EOG artifacts. It is important to stress by analyzing frequency domain-analysis in figure

6 and visualizing time-domain signal that NEMD method separates very strong EOG interference more perfectly from broad frequency content of neuro physiological signals and so it is an efficient technique for improving the quality of EEG signals in biomedical analysis.

5. Conclusion

Empirical Mode Decomposition is an emerging new technique of signal decomposition having many interesting properties. In particular, EMD can be applied to non-linear; non-stationary noisy signals and does not require any prior knowledge on the nature and number of modes embedded in a signal. Vocalization and cranial muscle movement artifacts are similar to EOG artifacts and thus also can be removed by adapting the present techniques. The resulting separated “purified” EEG and slow wave signals are very easy to visualize in time domain. The separation of ocular artifacts by EMD and NEMD based time domain filtering are demonstrated where NEMD performed better, without removing significant and useful information and produces a smooth denoised signal and does not change the property of the signals. The proposed method will be helpful to obtain the pure EEG signals for neuro physiological application development.

References

[1] Bhattacharya and H. Petsche, “Universality in the brain while listening to music”, Proc. R. Soc. London, Ser. B, vol. 268, **(2001)**, pp. 2423-2433.
[2] C. A. Joyce, I. F. Gorodnitsky and M. Kutas, “Automatic removal of eye movement and blink artifacts from EEG data using blind component separation”, Psychophysiology, vol. 41, no. 2, **(2004)**, pp. 313-325.
[3] S. Sanei and J. Chambers, “EEG Signal Processing”, Hoboken, NJ: John Wiley & Sons, **(2007)**.
[4] R. N. Vigario, “Extraction of ocular artifacts from electroencephalography using independent component analysis,” Electroencephalography and Clinical Neurophysiology, vol. 103, **(1997)**, pp. 395-404.
[5] T. Jung, “Removing EEG artifacts by blind source separation”, Psychophysiology, vol. 37, **(2000)**, pp. 163-178.
[6] A. Delorme, “Automatic artifact rejection from EEG data using higher-order statistics and independent component analysis”, Proc. of ICA, **(2001)**.
[7] K. H. Knuth, “Bayesian Source Separation and Localization”, SPIE Procedings: Bayesian Inference for Inverse Problems, vol. 3459, **(1998)** July, pp. 147-158.
[8] M. K. I. Molla, T. Tanaka, T. M. Rutkowski, D. P. Mandic and A. Cichocki, “Separation of EOG artifacts from EEG signals using bivariate EMD”, Proceedings of ICASSP, **(2010)**,pp. 562-565.
[9] C. Park, D. Looney, P. Kidmose, M. Ungstrup and D. P. Mandic, “Time-Frequency Analysis of EEG Asymmetry Using Bivariate Empirical Mode Decomposition”, IEEE transaction on Neural Systems and Rehabilitation Engineering, vol. 19, no. 4, **(2011)** August, pp. 366-373.
[10] Z. Wu and N. E. Huang, “A study of the characteristics of white noise using the empirical mode decomposition method”, proceedings of the Royel Society A, vol. 460, no. 2046, **(2004)**, pp. 1597-1611.
[11] G. Rilling, P. Flandrin, P. Goncalves and J. M. Lilly, “Bivariate empirical mode decomposition”, IEEE Signal Processing Letters, vol. 14, no. 12, **(2007)**, pp. 936-939.
[12] P. Flandrin, “Empirical mode decomposition as a filter bank”, IEEE signal processing letters, vol. 11, no. 2, **(2004)** February, pp. 112-114.
[13] P. Flandrin, “Empirical mode decomposition as a filter bank”, IEEE signal processing letters, vol. 11, no. 2, **(2004)** February, pp. 112-114.
[14] T. Tanaka and D. P. Mandic, “Complex empirical mode decomposition”, IEEE Signal Processing Letters, vol. 14, no. 2, **(2007)**, pp. 101-104.
[15] D. Looney and D. P. Mandic, “Multi-scale image fution using complex extensions of EMD”, IEEE Trans. Signal Processing, vol. 57, no. 4, **(2009)** April, pp. 1626-1630.
[16] M. B. Luca, S. Azou, G. Burel and A. Serbanescu, “On Exact Kalman Filtering of Polynomial Systems”, IEEE Trans. on circuits and systems, vol. 53, no. 6, **(2006)** June, pp. 1329-1340.
[17] S. Salahuddin, “Soft thresholding for DCT speech enhancement”, Electronics Letters, vol. 38, **(2002)**.

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