Removal Of Blink From EEG By Empirical Mode Decomposition (EMD)

Mohammad Shahbakhti
Department of biomedical engineering
Islamic Azad University
Dezfoul, Iran
mohammad_shahbakhti@yahoo.com

Vahidreza Khalili
Department of biomedical engineering
Islamic Azad University
Dezfoul, Iran
khalili001@gmail.com

Golnoosh Kamaee
Department of biomedical engineering
Islamic Azad University
Dezfoul, Iran
golnooshkamaee@yahoo.com

***Abstract*— The electroencephalographic signals (EEG) are rather weak and contaminated with different artifacts that have biological and external sources. Among these artifacts, blinks and eye movements are the most common of them. In this paper, we introduce a new method, Empirical Mode Decomposition (EMD), for removal of blink contamination from EEG signal. The proposed method is compared to a fourth order Butterworth high-pass filtering with cutoff frequency at 2 Hz. The performance index of our experiment is mean square error (MSE) between bands of pure EEG and corrected EEG. Results obtained from the analysis of contaminated EEG signal show that EMD method outperforms the high pass filtering for elimination of blink contamination from EEG. However, EMD could not be applied on-line.**

***Index Terms*— EEG, Blink, Empirical Mode Decomposition (EMD), High pass filter, mean square error (MSE)**

I. Introduction

EEG is a medical technique for evaluating and recording physiological properties of brain, which is useful for clinical diagnosis and in biomedical research. EEG signals are often contaminated with different artifacts that have biological sources similar to EOG (blinks and eye movements), ECG (cardiac potentials) and EMG (muscular potentials) or external sources like line interference and/ or leads. In comparison with EEG, blink artifact, due to its amplitude, might be considered as one of the main problem in EEG analysis. The human eye generates an electrical dipole caused by a positive cornea and negative retina. Eye movements and blinks change the dipole causing an electrical signal known as an EOG. The shape of the EOG waveform depends on factors such as the direction of eye movements. A fraction of the EOG spreads across the scalp and it is superimposed on the EEG [1]. Two kinds of ocular artifacts can be observed in EEG records, eye blinks and eye movements. Eye blinks are represented by a low frequency signal (< 4 Hz) with high amplitude. It is a symmetrical activity mainly located on the front electrodes (FP1, FP2) with low propagation. Eye movements are also represented by a low frequency signal (< 4 Hz) but with higher propagation [2]. To reduce EOG in EEG, many techniques have been proposed, such as ICA [3], PCA [4], regression-based methods, high-pass filtering [5] and adaptive filtering [6]. ICA can not be applied online and it requires storing the data and off-line processing [7]. In addition, its success largely depends on correct identification of the noise components [6]. PCA cannot completely separate eye-movement artifacts from the EEG signal, especially when they have comparable amplitudes [8]. All regression methods, whether in time or frequency domain depend on having one or more regressing (EOG) channels [9]. High-pass filter will remove most of the EOG's artifacts, however, this method will loss lots of EEG components, particularly in theta and delta band [10], [11]. Adaptive filtering is useful for on-line removal of EOG [6], however, owing to using an extra channel, it is not affordable. In this paper, we compare EMD and high pass filtering techniques to remove eye blink in EEG. The EMD was introduced by Huang [12] and has become an established tool in analysing real world data such as nonlinear and non-stationary signals with a number of important applications in signal processing. The basis of this technique consists of decomposing any signal into a finite number of intrinsic mode functions, which is called IMF [13]. The remainder of the letter is organized as follows. In Section 2, we describe EMD technique, proposed algorithm for removing of eye blink from EEG by EMD method and data acquisition. In Section 3, we compare the effectiveness of EMD method and a forth order Butterworth high-pass filtering with cutoff frequency at 2 Hz. In Section 4, we make a few concluding remarks.

II. METHODS

A. The Empirical Mode Decomposition

The EMD step builds on the assumption that any data set consists of different, simple, intrinsic modes of oscillation that need not be sinusoidal, with the non-sinusoidal character of each mode of oscillation derived from the data. At any given time, the recorded data may have many different coexisting modes of oscillation, which may or may not relate to different seismological phases. Each of these oscillatory modes, called an intrinsic mode function (IMF), is defined by the following conditions:

1-In the whole dataset, the number of extrema and the number of zero crossings should be equal or differ at most by one. 2-At any point of IMF the mean value of the envelope defined

978-1-4673-4892-8/12/$31.00 ©2012 IEEE

by the local maxima and the envelope defined by the local minima should be zero.

The process of IMF extraction from a signal x(t) (sifting process) is based on the following steps:

1. Determine the local maxima and minima of the analyzed signal x(t)

2. Generate the upper and lower signal envelopes by connecting those local maxima and minima, respectively, by the chosen cubic spline method

3. Determine the local mean, m(t), by averaging the upper and lower signal envelopes

4. Subtract the local mean from the data:

$$h_1(t) = x(t) - m_1(t) \quad (1)$$

Ideally, $h_1(t)$ is an IMF candidate. However, in practice, $h_1(t)$ may still contain local asymmetric fluctuations, e.g., undershoots and overshoots; therefore, if h_1 had 2 condition of a IMF, it will be consider as first extracted component from the data, otherwise h_1 Will be a signal and the process (steps 1-4) will be done again.

$$h_1(t) - m_{11}(t) = h_{11}(t) \quad (2)$$

This flow will be continued k times until h_{1k} is chosen as the first component of signal (IMF).

$$h_{1(k-1)}(t) - m_{1k}(t) = h_{1k}(t) \quad (3)$$

$$c_1(t) = h_{1k}(t) \quad (4)$$

In next step, $c_1(t)$ will be subtracted from the data, $r_1(t)$, and the process would be done again for the extraction of second IMF.

$$r_1(t) = x(t) - c_1(t) \quad (5)$$

The residue r_1, which contains longer-period components, is treated as the new data and subjected to the same sifting process as described above. This procedure can be repeated to obtain all the subsequent r_j functions as follows:

$$r_1(t) - c_2(t) = r_2(t) \quad (6)$$

The original data are thus the sum of the IMF components plus the final residue r_n

$$x(t) = \sum_{j=1}^{n} c_j(t) + r_n(t) \quad (7)$$

Therefore, the data are decomposed into n IMF components and a residue r_n that can be either the mean trend or a constant [14].

B. The algorithm for elimination of eye blink contamination based on the EMD

Since, the contaminating blinks increase the power of the frequencies in the lower end of EEG spectrum, the artifact components lie in the last several IMFs. Hence, while sifting process does not reach the artifact components the entropy between two consecutive IMFs decreases toward the decomposition levels. That is, when suddenly the entropy starts to go up, the decomposition of artifact contamination starts. Therefore, we propose the following procedure for EEG signal filtering:

1. Decompose the signal into IMFs.
2. Calculate entropy between two consecutive IMFs.
3. Find the decomposition level, M, at which the entropy starts to go up.
4. Reconstruct the filtered signal by summing up the first M IMFs.

C. *Data Acquisition for the known contaminated EEG*

In this experiment, EEG data were recorded from F_z electrode and eye blink data were recorded from a pair of electrodes were placed above (negative terminal) and below (positive terminal) the eye. The data had been used for 15^{th} ICMBE conference [15]. Both signals were bandpass filtered at 0.1–40 Hz and sampled at 200 Hz. Using a linear combination of the blink-contaminated EEG signal and the blink signal, is the most common technique for removing ocular artifacts from EEG signals [16]. Thus, to generate blink contaminated EEG, 600 samples from pure EEG and blink artifact, under assumption linear combination, have been summed.

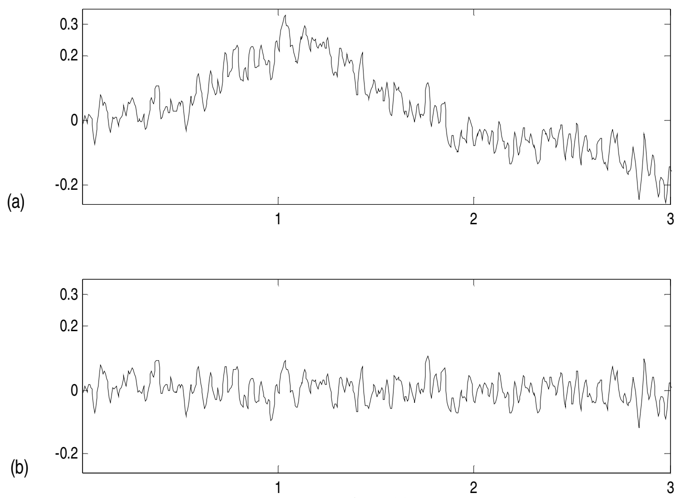

Fig. 1. (a): Uncontaminated and (b): Blink contaminated EEG signals, respectively.

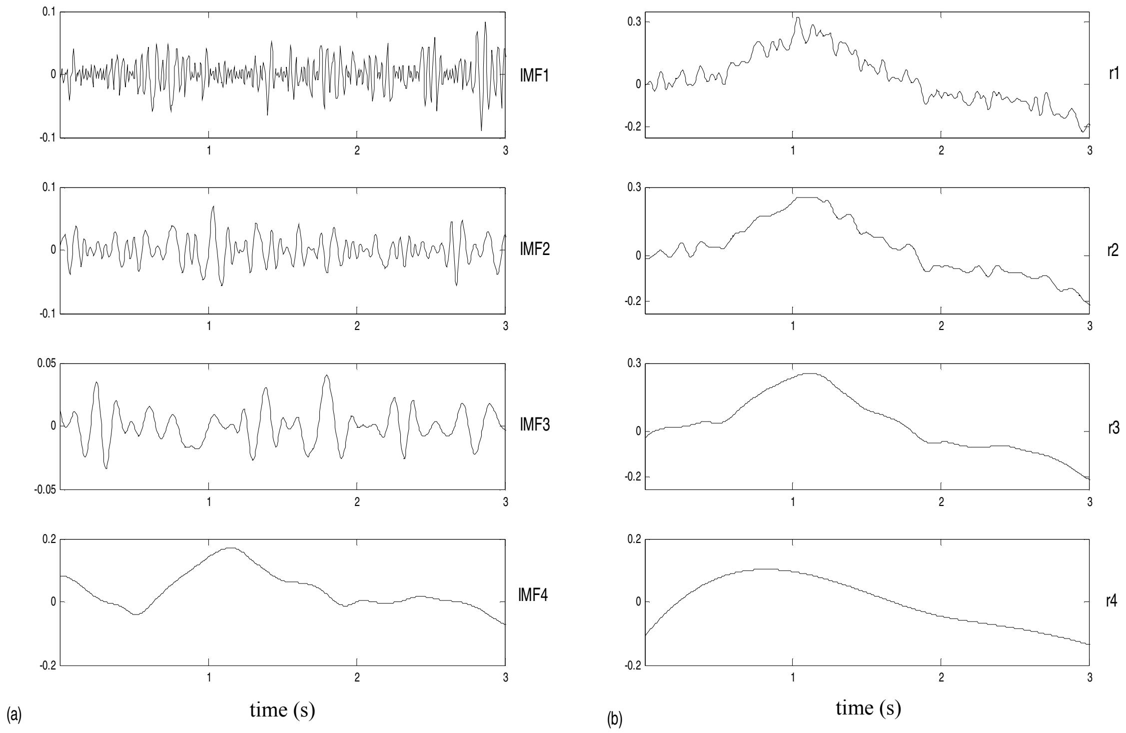

Fig. 2. (a): The IMFs and (b) the residues for known contaminated signal (Fig. 1(b)).

III. RESULTS

3 seconds EEG from Fz electrode with sampling rate of 200 Hz, recorded for 15th ICBME conference, has been used in this study. In our study, after third IMF, entropy between 3rd and 4th IMF is started to go up .Hence, third IMF, is proposed as the end level of the decomposition. The filtered signal is formed by summing up first three IMFs. Figure 3 illustrates the corrected EEG by EMD technique and pure EEG.

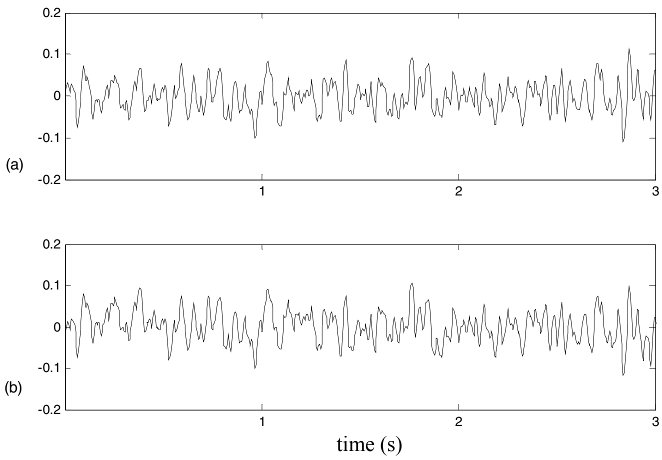

Fig. 3. (a): Corrected EEG with EMD (summing up first three IMFs) (b): Pure EEG, respectively.

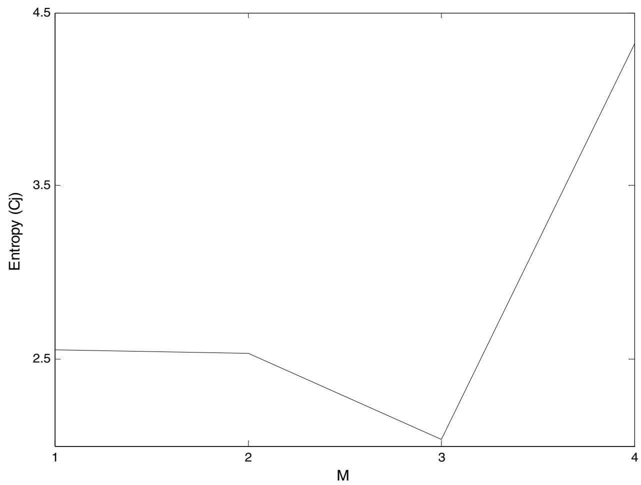

Fig. 4. The Entropy plot shows that the reconstructed signal is obtained by summing up the first three IMFs. (after third IMF, entropy starts to go up, therefore, third IMF should be considered as end level of decomposition)

The proposed method has been compared with the fourth order Butterworth high pass filtering with cutoff frequency at 2 Hz. Figure 4 shows pure and filtered EEGs with both methods.

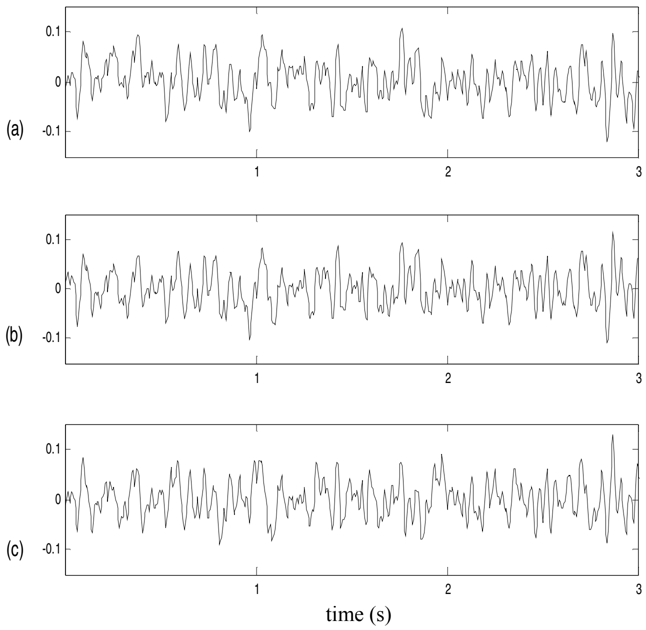

Fig. 5. (a): Pure EEG (b): Corrected EEG with EMD method (c): Corrected EEG with Butterworth high-pass filtering with cut-off frequency at 2 Hz, respectively

The performance index of our experiment is the **mean square error (MSE)** between bands of the pure EEG and the corrected EEG, which is known as:

$$\mathrm{MSE} = 1/N \sum_{i=1}^{N} (f_i - g_i)^2 \times 100 \qquad (8)$$

Where

f_i is the filtered signal, g_i is the pure signal and N is number of samples. Table 1 shows the MSE between bands of pure EEG and filtered EEG by EMD and high pass filtering techniques.

TABLE (I) COMPARISON OF THE DENOISING TECHNIQUES FOR A KNOW CONTAMINATED SIGNAL

Band	Beta	Alpha	Theta	Delta
EMD	0.0004	0.0006	0.0066	0.1141
BW2	0.0387	0.0764	0.1815	0.2833

Results obtained from the table 1 show that EMD based denoising compared with Butterworth high pass filtering gives better results on blink-contaminated EEG signal.

IV. CONCLUSIONS

In this paper, EMD approach compared to a high pass filtering for elimination of blink artifact. The results indicated EMD is a more efficient method for removal of blink in EEG. In comparison with ICA, EMD process is not requiring of processing of data collected from a sufficiently large number of channels. In addition, determination of transformation function between EEG and EOG channel, as regression-based methods, is not necessary. Preservation of data with EMD is satisfied rather than high-pass filtering and no extra channel recording is needed like adaptive filtering. However, this method could not be applied on-line.

REFERENCES

[1] L. Vigon, M.R Saatchi, J.E.W Mayhew, R. Fernandes, “Quantitative evaluation of techniques for ocular artifact filtering of EEG waveforms,” IEE Processing Science Meas. Technology, Vol. 147, No. 5, pp. 219-228, 2000

[2] A. Crespel, P. Gélisse, M. Bureau, and P. Genton, “Atlas of Electroencephalography (1st ed),” Paris : J. Libbey Eurotext, 2005.

[3] T. Jung, S. Makeig, M. Westerfield, J. Townsend, E. Courchesne, and T. Sejnowski, “Removal of eyeactivity artifacts from visual event-related potential in normal and clinical subjects,” Clin. Neurophysiol., vol. 111, pp. 1745–1758, 2000.

[4] P. Berg, M. Scherg, “Dipole models of eye activity and its application to the removal of eye artifacts from the EEG and MEG,” Clinical Physics and PhysiologicalMeasurements, Vol. 12, pp. 49–54, 1991

[5] M. A. Correa , E. Laciar , H. D. Patiño, and M. E. Valentinuzzi “Artifact removal from EEG signals using adaptive filters in cascade”, IOP publishing Ltd., vol. 90, pp. 1-10.5., 2007.

[6] P. He, G. Wilson, and C. Russell, “Removal Of Ocular Artifacts From Electro-Encephalogram By Adaptive Filtering,” Med. Biol. Eng. Comput., vol. 42, pp. 407–412, 2004.

[7] P. Shooshtari, G. Mohamadi, B. Ardekani, and M. Shamsollahi, “Removing Ocular Artifacts from EEG Signals using Adaptive Filtering and ARMAX Modeling,” Proceeding of World Academy of Science, Engineering and Technology, vol.11, pp. 277-280, 2006

[8] G. Getha, S.N Gethalakshi, “Scrutinizing different techniques for artifact removal from EEG signals,”International Journal of Engineering Science and Technology (IJEST), vol.3, 2011

[9] V. Krishnaveni, S. Jayaraman, S. Aravind, V. Hariharasudhan, and K. Ramadoss, “Automatic Identification and Removal of Ocular Artifacts from EEG using Wavelet Transform,” MEASUREMENT SCIENCE REVIEW, vol.6, pp. 45-57, 2006.

[10] N. A. De Beer, M. van de Velde, “Clinical evaluation of a method for automatic detection and removal of artifacts in auditory evoked potential monitoring, ” J Clin Monit., vol.11, pp.381-391, 1995.

[11] J. Gao, H. Sultan, J. Hu, and W. Tung, “Denoising Nonlinear Time Series by Adaptive filtering and Wavelet Shrinkage: A Comparison,” IEEE SIGNAL PROCESSING LETTERS., vol.17, pp. 237-240, 2010.

[12] N. E. Huang, Z. Shen, S. R. Long, M. C. Wu, H. H. Shih, Q. Zheng,N. Yen, C. C. Tung, and H. H. Liu, “The empirical modedecomposition and the Hilbert spectrum for nonlinear and nonstationary time series analysis, ” *Proc. R. Soc. Lond.,* 454 : 903-995, 1998.

[13] M. Naji, M. Firoozabadi, and S. Kahrizi, “The Application of Empirical Mode Decomposition in Elimination of ECG contamination from EMG signals, ” Proc. IEEE Int. Conf. Iranian Conference on BioMedical Engineering., vol.18, pp. 143-146, 2011.

[14] Ch. Hemanth, A. Sivasa ram, N. Rama krishna, and P. S. Barahmandam, “Non linear and non-Stationary data analysis using Hilbert-huang transform,” Journal of Theoretical and Applied Information Technology., vol.29, pp.74-84, 2011.

[15] N. Hafezimotlagh, M. Khalilzadeh, A. Moghimi, "Removal of blinks from EEG by PCA and Adaptive filtering," Proc. IEEE Int. Conf. Iranian Conference on BioMedical Engineering, vol.15, pp.308-315, 2008.
[16] R. Croft, R. Barry, "Issues relating to the subtraction phase in EOG artefact correction of the EEG," International Journal of Psychophysiology., vol.44, pp.187-195, 2002.