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New Strategy for Stopping Sifting Process during Bio-signals De-nosing By EMD: In Case of Low Frequency Artifact Reduction from ECG and EMG

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Abstract

Removal of artifacts from bio-signals is a necessary step before automatic processing and obtaining clinical information. Recently, many applications of Empirical Mode Decomposition (EMD) on biomedical researches have been presented that artifact reduction from bio-signals is one of them. EMD separates a time series into finite numbers of its individual oscillations, which are called intrinsic mode function (IMF). The process of the IMF extraction from a signal is known as the sifting process. The main issue during sifting process is to select an appropriate criterion for stopping IMF extraction when the process reaches the artifact components. In this paper, we try to investigate mean power frequency (MPF) for stopping sifting process, in case of low frequency artifact reduction from ECG and EMG signals. In order to evaluate effectiveness of the proposed index during sifting process, reduction of baseline noise from electrocardiogram signals (ECG) and ECG artifact from electromyogram signals (EMG) have been investigated. The obtained results indicate MPF can be considered as an acceptable criterion to stop sifting process during low frequency artifact elimination.

Keywords: *Artifact reduction, EMD, Sifting process, ECG, EMG, MPF*

1. Introduction

Bio-medical signals are often affected by artifacts which have external and biological sources [1-3]. Removal of artifacts from bio-signals is the primary step before classification or even visual diagnosis. In the last two decades, to correct or remove artifacts from bio-signals, various methods have been proposed, including wavelet, ICA, PCA, adaptive filtering and etc [4-8]. In this paper, the application of empirical mode decomposition (EMD) is investigated for elimination of baseline wander from ECG and heart muscle electrical activity from EMG. EMD is a new non-linear technique that has been introduced by Haung [9] for adaptively representation of signals as sum of zero-mean AM and FM components. The basis of this technique consists of decomposing any signal into finite number of intrinsic mode functions (IMF). IMFs are extracted from a signal during a process called "sifting process". The main issue during sifting process is to determine an index for stopping IMF extraction when the process reaches the artifact components. For this aim, we apply mean power frequency (MPF) as the desired index.

Baseline wander (BW) is a low frequency artifact that might be caused by breathing, body movements and lose sensor contact during ECG recording. It overlaps whole cycle of ECG, however, it mainly affects low-frequency part, specially T-waves [10, 11].

EMG signals collected from the trunk musculature are often contaminated with the heart muscle electrical activity (ECG) [12]. Comparing to EMG, frequency spectrum of ECG is significantly lower. Therefore, ECG could be considered as a low-frequency artifact in EMG.
Recently, various methods based on EMD for removal of artifacts from bio-signals, have been presented [13-18].
The reminder of this paper is organized as follow: in section 2, EMD technique and the desired criterion will be described. Section 3 presents useful information about the bio-signals that have been used in this study. Computationally effective implementation of the proposed filter is presented in Section 4. Section 5 presents experimental investigation of the introduced method and a discussion of obtained results. In last section a few concluding remarks will be made.

2. Methods and Materials

2.1 Empirical Mode Decomposition (EMD)

The empirical mode decomposition (EMD) was designed by Haung for analyzing non-stationary and nonlinear data. In contrast to conventional decomposition methods such as wavelets, which perform the analysis by projecting the signal under consideration into a number of predefined basis vectors, EMD expresses the signal as an expansion of basis functions which are signal-dependent, and are estimated via an iterative procedure called sifting [19]. Recently, many application of EMD for biomedical purposes have been developed, including artifact reduction, diagnosis and prediction of the diseases and etc, [13-21]. The purpose of EMD is to decompose a signal into series of intrinsic mode functions (IMFs) and one residue. An IMF represents a simple oscillatory mode as a counterpart to the simple harmonic function used in Fourier analysis. Each IMF should have 2 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 by the local maxima and the envelope defined by the local minima should be zero.

Since the second condition of an IMF is ideal and will not be achieved in practice, it is controlled by a threshold. In this project, the accepted range of the mean signal of the minima–maxima envelopes is an absolute value below 0.2.

The process of IMF extraction, "sifting process", is arranged as follow:

1. Identity of exterma (minima and maxima) of the signal y(t).
2. Generate the upper and lower envelopes of y(t) by connecting maxima and minima, respectively, using cubic spline.

3. Compute the average envelope, m(t), as the arithmetic mean between the upper and lower envelope.
4. Estimate the first IMF as the difference between y(t) and m(t).

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

5. If $h_1(t)$ does not fulfill the criteria defining an IMF, it will be considered as a signal and the steps 1-4 are repeated k times until the first IMF is achieved.

$$h1(k\text{-}1)(t) - m1k(t) = h1k(t) \quad (2)$$

6. When the conditions of the IMF is reached by $h_{1k}(t)$, it is saved as the first IMF.

$$c1(t) = h1k(t) \quad (3)$$

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

$$r1(t) = x(t) - c1(t) \quad (4)$$

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:

$$r1(t)\text{-}\ c2(t) = r2(t), \ldots\ldots\ rn\text{-}1(t)\text{-}cn(t) = rn(t) \quad (5)$$

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

$$y(t) = \sum_{j=1}^{n} cj(t) + rn(t) \quad (6)$$

2.2 MPF Strategy for stopping sifting process

Because the artifacts consist of low-frequency components, it is expected to reach them in the lower end of the contaminated signal's spectrum, therefore, artifact components are mainly involved in the last several IMFs.
Our new research shows that sifting process could be controlled by a threshold based on mean power frequency (MPF) when it reaches to artifact components. The threshold depends on frequency range of the artifact, for example, if the aim is to eliminate baseline wander from ECG, the decomposition process should be continued till MPF of an IMF is a value below 1 Hz.

MPF is defined as follow:

$$MPF = \frac{\sum_{i=1}^{fs/2} fi * Pxx(fi)}{\sum_{i=1}^{fs/2} Pxx(fi)} \quad (7)$$

Where fs, fi and Pxx(fi) are sampling rate, frequencies and power density per each frequency, respectively. Hence, we propose the following produce for removal of low-frequency artifacts from ECG and EMG:

1. Decompose the signal into n IMFs.
2. Compute the MPF of each IMF.
3. Find the decomposition level, M, at which the MPF of the IMF is a value below the determined threshold.
4. Reconstruct the filtered signal by summing up the first M-1 IMFs.

3. Dataset

3.1 General description

In this paper, simulated and real data have been applied. Since the information about pure signal is vital for evaluating the proposed method, first we investigate simulated artifact contaminated signals. Afterwards, two real signals have been studied.
A noisy signal z(t)=x(t)+n(t) is processed to obtain an enhanced reconstructed version $x_1(t)$. The contaminated signal z(t) consists of a pure signal x(t) and an artifact n(t), that can be synthetic or real . Then, the artifact and the pure signal, under assumption of linear combination, have been summed [1, 22].

3.2 Baseline contaminated ECG

Baseline wander is a low-frequency phenomenon (less than 1 Hz) which disturbs whole cycle of ECG, however, it mainly affects T waves [13, 22, 23]. The ECG signals come from MIT-BIH Normal Sinus Rhythm Database (record 16265) which is free of artifacts and noises [24]. To generate simulated BW contaminated ECG, an artificial BW is produced using combination of sin and cosine waves with the frequency of 0.2 Hz and 0.44 Hz while their corresponding amplitudes are 150 mV and 100 mV, respectively. For more experiments, four other ECG signals with different baseline wanders have been investigated. Each signal is 10 seconds and sampled at 128 Hz.

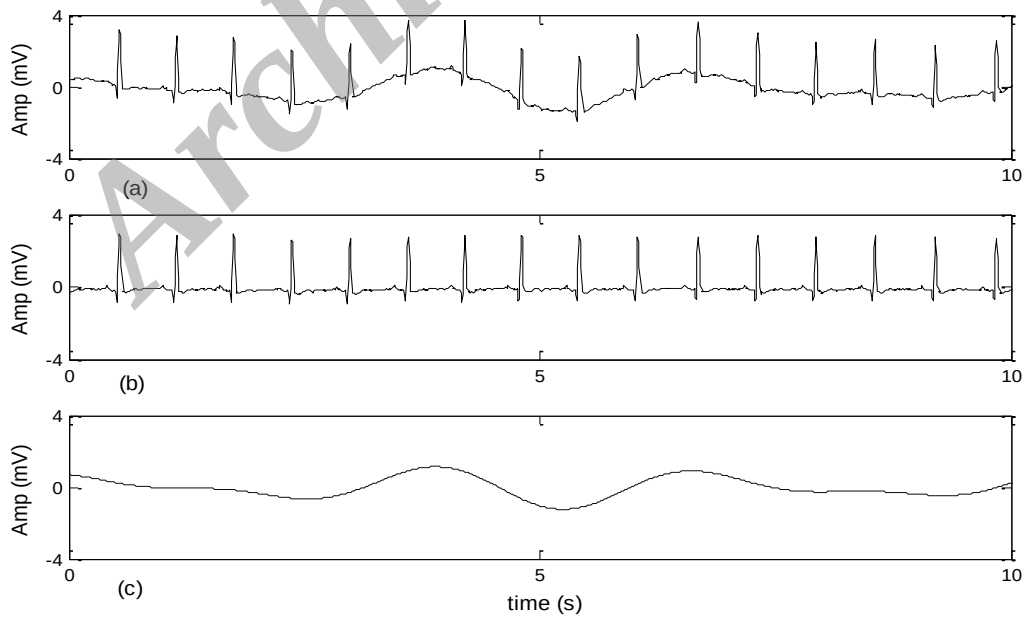

Figure 1. (a). baseline contaminated ECG 1, (b). Pure ECG 1, (C). synthetic bw 1

3.3 ECG contaminated EMG

Recorded EMG from the trunk musculature is often contaminated with the heart muscle electrical activity (ECG). Compared to EMG spectrum, ECG is a low frequency phenomenon which overlaps in the whole cycle of EMG with the frequency range of 1 to 30 Hz [25].

EMG signals were recorded from a twenty-five years male with Ag-AgCl surface electrode. The right biceps brachii EMG was used as the gold standard with which to compare the efficacy of the removal techniques. The minimum contraction EMG which contains the most ECG contamination was also collected from External Oblique (EO) during standing position of the subject. Each record was 5 seconds and sampled at 800 Hz. A low-pass filter with cut-off frequency at 350 Hz was used for avoiding aliasing. Furthermore, four additional EMG and ECG signals were recorded.

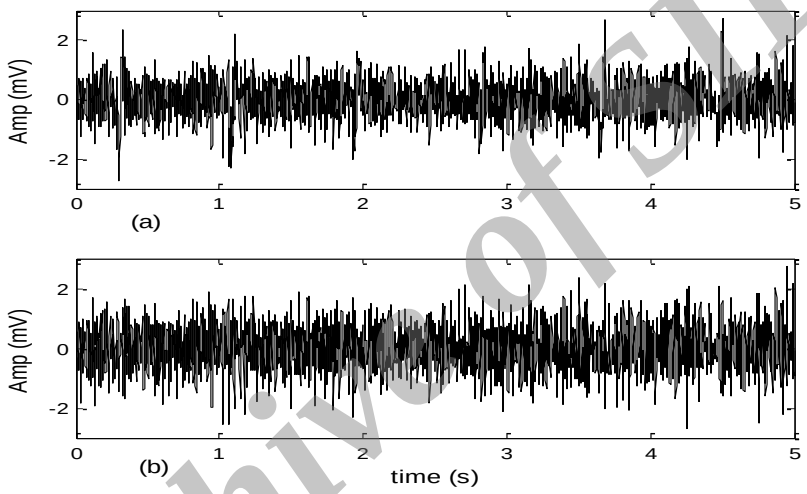

Figure 2. (a). ECG contaminated EMG 1, (b). Pure EMG 1

4. Results

The purpose of this research is to introduce an index for stopping sifting process, when it reaches the artifact components, in case of low-frequency artifact reduction from ECG and EMG. To implement the algorithm, MATLAB 2009 software has been used. Elimination quality is assessed by calculating correlation coefficient and mean square error between uncontaminated and de-noised signal.

Correlation coefficient is expressed by

$$\rho xy = Cxy / \sigma x \sigma y \quad (8)$$

Where the Cxy is the covariance between corrected and pure signals and σx, σy are the standard deviation of the filtered and pure signals.

Mean Square Error (MSE) is the average of the squares of the difference between measured and true values. Indeed, it represents the difference between actual observations and the observation value predicted by a model.

If Z is a vector of n prediction, and Y is the vector of true values, then the MSE of the predictor is defined as follow:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Z_i - Y_i)^2 \qquad (9)$$

4.1. BW contaminated ECG

The figure 4 shows that the IMFs and residuals of simulated BW contaminated ECG. The corrupted signal decomposed into 7 IMFs and a residue.

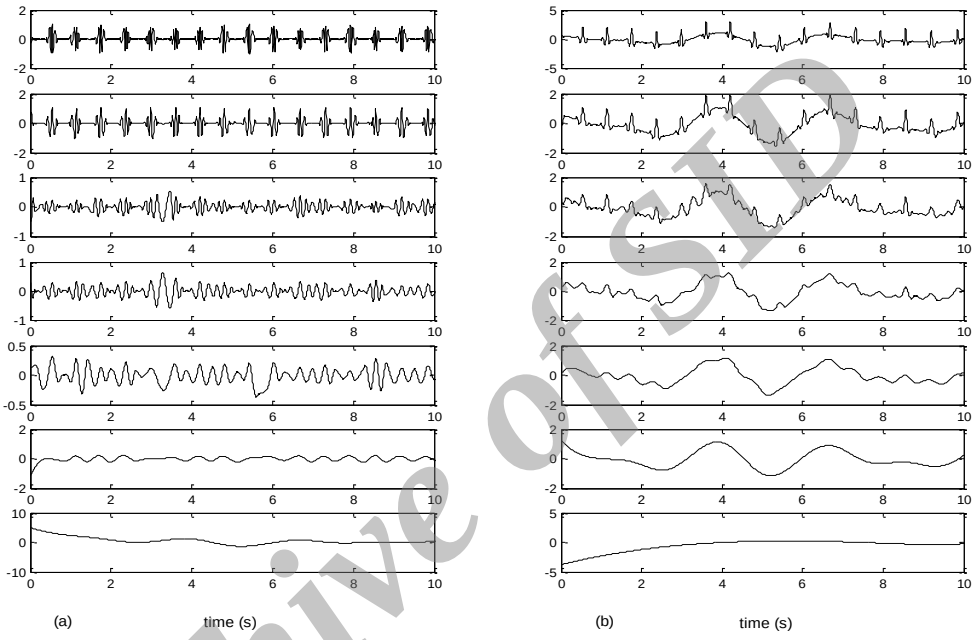

Figure 3. (a) The IMFs and (b): The residues for known baseline contaminated ECG (Fig. 1. (a)). The horizontal axis is time in seconds, the vertical axis is signal amplitude (mV).

The frequency range of baseline wander is generally less than 1 Hz, therefore, the MPF threshold is assumed 1 Hz. After 6th IMF, MPF of the IMFs is started to go down than 1 Hz, therefore, the process was stopped and the filtered signal was formed by summing up first 6 IMFs. Figure 4 illustrates the filtered ECG and pure ECG.

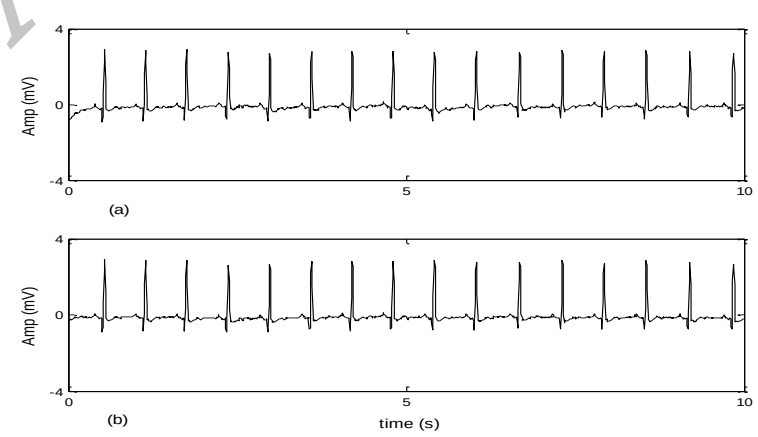

Figure 4. (a): corrected ECG 1 by EMD (b):uncontaminated ECG 1.

Table 1. Performance of proposed method subject to MSE and correlation coefficient criteria for simulated ECG signals.

ECG signal	BW amplitude	BW frequency	MSE	Correlation coefficient
ECG 1	150 mV +100 mV	0.2 and 0.44 Hz	0.0030	0.9980
ECG 2	100 mV	0.1 Hz	0.0058	0.9985
ECG 3	150 mV	0.15 Hz	0.0035	0.9977
ECG 4	200 mV	0.12 Hz	0.0052	0.9942
ECG 5	250 mV	0.2 Hz	0.0017	0.9987

To evaluate the performance of proposed method for real noisy signals, two ECGs corrupted by real BW artifact are considered. The signals come from MIT-BIH Noise Stress Test Database [26] (Record 118e00 and 118e06) with sampling rate of 360 Hz and duration of 10 seconds.

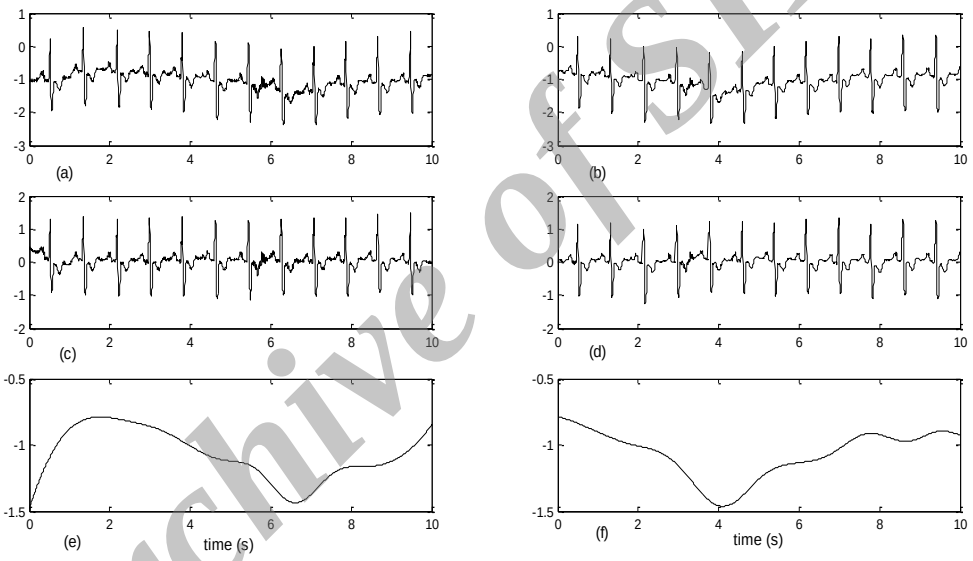

Figure 5. (a), (b): two real BW contaminated ECG signals (record 118e00 and 118e06) (c), (d): The filtered ECG signals by EMD, (e), (f): the last residuals, r6, of the real contaminated ECG signals which are considered as the BW noise respectively. The horizontal axis is time in seconds, the vertical axis is signal amplitude (mV).

4.2. ECG contaminated EMG

The IMFs and residuals of ECG contaminated EMG are shown in figure 6. The contaminated EMG has been decomposed into 8 IMFs and one residue.

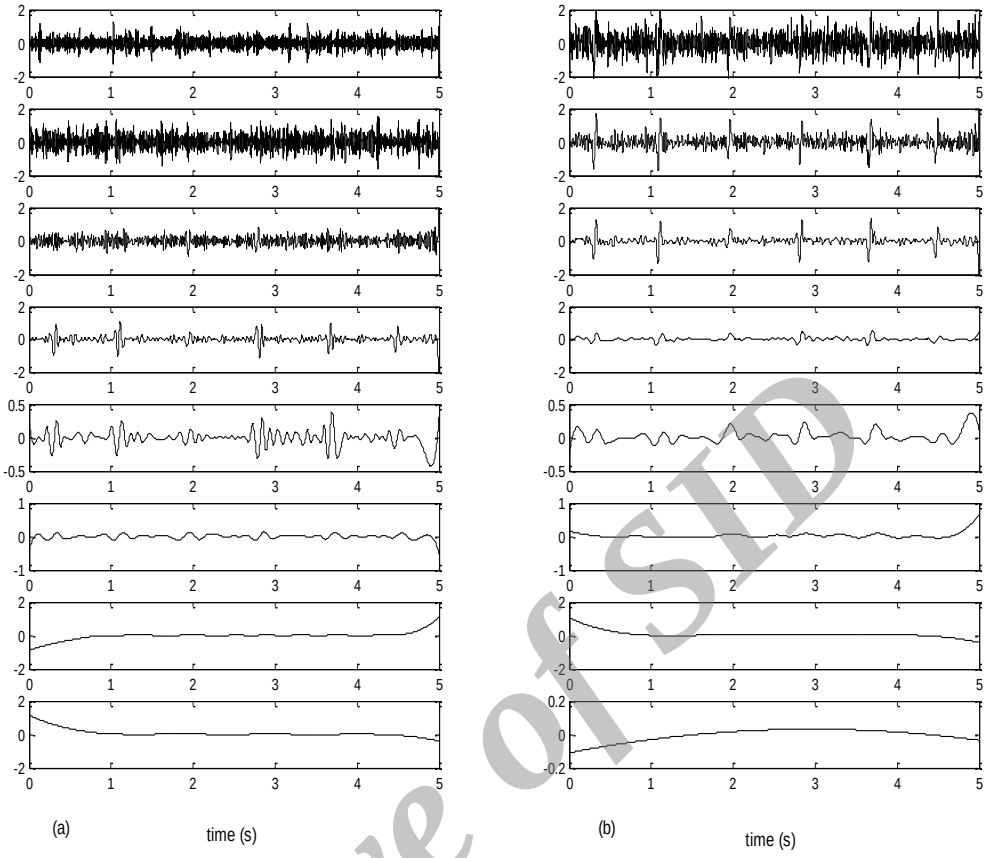

Figure 6. (a) The IMFs and (b): The residues for known ECG contaminated EMG (Fig. 2. (a)). The horizontal axis is time in seconds, the vertical axis is signal amplitude (mV).

Drake et al. [25] concluded that fourth-order Butterworth filter with a 30 Hz cutoff outperformed the other techniques for maximal ECG removal with minimal EMG distortion. Therefore, MPF threshold is considered 30 Hz. After the 3rd IMF, MPF of the IMFs started to go below 30 Hz, thus, the filtered signal was reconstructed by summing up by first three IMFs.

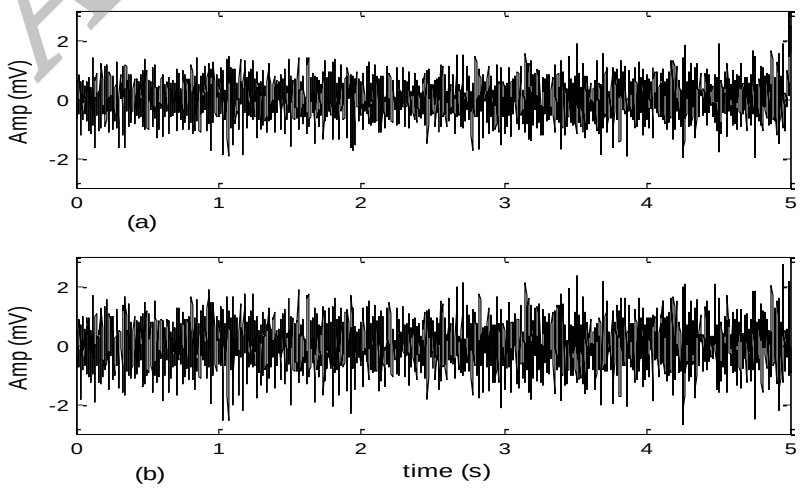

Figure 7. The filtered EMG 1 signal obtained by EMD and (b) Pure EMG 1

Table 2. Correlation coefficient and MSE between filtered and pure EMG for five simulated signals.

EMG signal	MSE	Correlation coefficient
EMG 1	0.0693	0.9361
EMG 2	0.0753	0.9111
EMG 3	0.0697	0.9254
EMG 4	0.0811	0.9101
EMG 5	0.0687	0.9204

Two real surface EMG signals were obtained by using the same instruments described at section 3. The electrodes were placed over the EO muscle. A reference electrode was placed on the Iliac crest. The subjects were asked to maintain their trunk flexion angle at 15 degree.

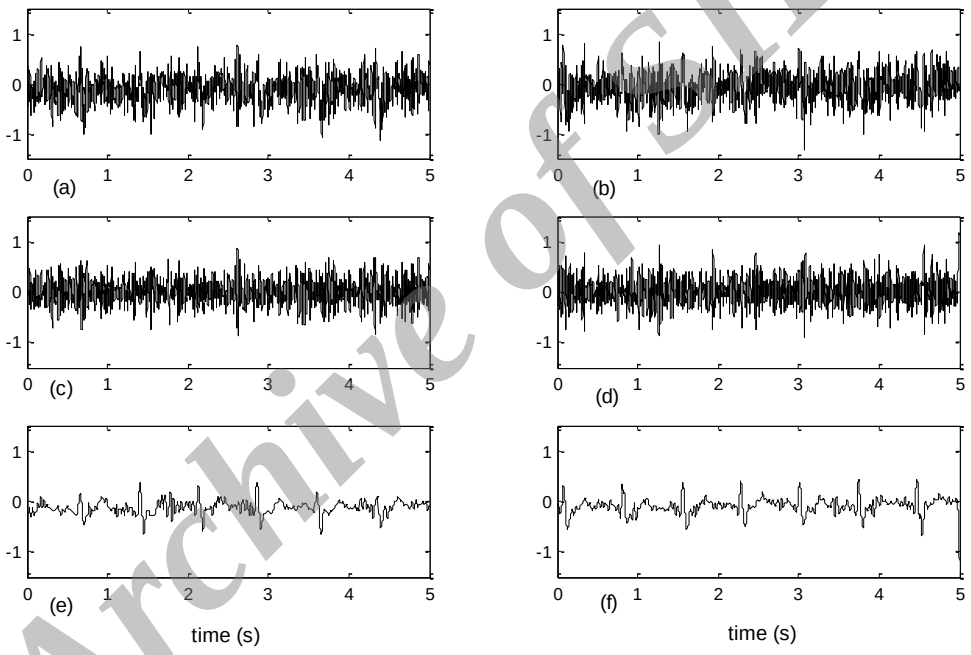

Figure 8. (a), (b): two real ECG contaminated EMG signals, (c), (d): The filtered EMG signals by EMD, (e), (f): the last residuals, r3, of the real contaminated EMG signals which are considered as the ECG noise, respectively. The horizontal axis is time in seconds, the vertical axis is signal amplitude (mV).

5. Discussion

The bio-medical signals generally suffer from artifacts and noises that have external and biological sources. Reduction of these artifacts is the primary step before automatic processing and extracting clinical information. Recently, many techniques based on EMD have been presented for elimination of artifacts from bio-signals. The main issue during sifting process is to determine an index for stopping sifting process when it reaches the artifact components. The purpose of this paper was to examine the criterion "mean power frequency" during EMD decomposition levels, for removal of low frequency artifacts from ECG and EMG, when the sifting process reaches the artifact

components. To this aim, reduction of baseline from ECG and ECG from EMG had been evaluated.

The program was tested with a 2.20 GHz Core i2 processor. Averagely, it takes 5 seconds to extract an IMF from the signals, therefore, the proposed method can not be considered as an on-line filtering. The obtained results express MPF of IMFs could be considered as the proper index for stopping sifting process during artifact reduction. MPF threshold should be defined based on frequency range of the artifact. In this research, it was tried to eliminate low-frequency artifact from bio-signals, therefore, it was expected that the artifact components lie in last several IMFs.

The frequency range of baseline wander is generally less than 1 Hz [13, 22, 23], thus, the sifting process will be continued till the mean power frequency of an IMF is a value below 1 Hz.

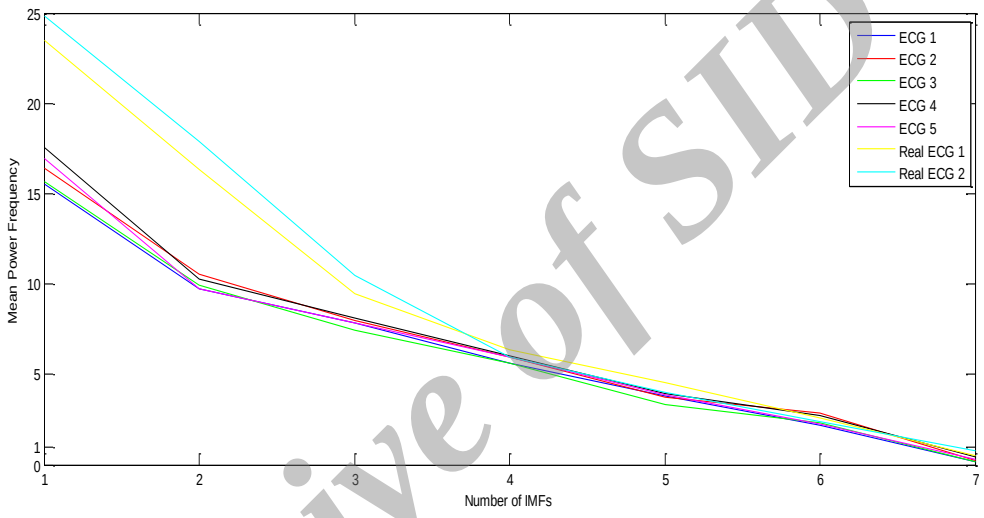

Figure. 9. The Mean Power Frequency plot shows that the reconstructed ECG signals are obtained by summing up the first six IMFs.

According to the EMG spectrum, cardiac activity is a low-frequency phenomenon with frequency range of 1 to 30 Hz. Drake et al [25] concluded a Butterworth filter with cut-off frequency at 30 Hz is the best technique for elimination of ECG components from EMG. Consequently, MPF threshold for ECG removal from EMG was assumed 30 Hz.

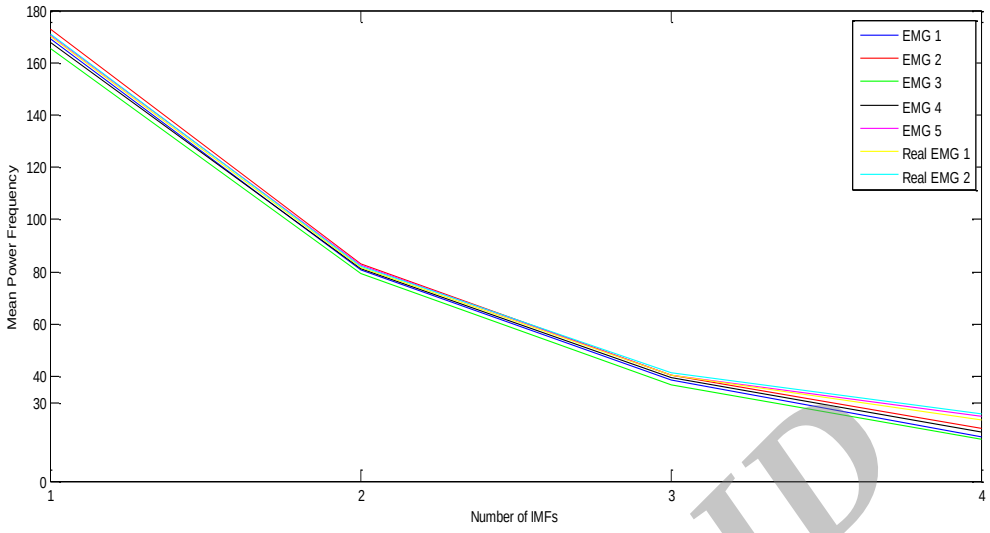

Figure. 10. The Mean Power Frequency plot shows that the reconstructed EMG signals are obtained by summing up the first three IMFs.

5.1 Comparison with the previous research

In our last research [18], MSE had been applied to stop the sifting process for removal of eye blinks from EEG. While sifting process does not reach the artifact components, MSE between two consecutive IMFs decreases toward the decomposition levels. That is, when suddenly the MSE starts to go up, the decomposition of artifact contamination starts.

The analysis of this research indicated that MSE fails for ECG and EMG de-noising. In some cases, when the sifting process had not been reached the artifact components, MSE started to go up and the process stopped while more decomposition levels were required. Therefore, it was concluded that MSE could not be considered as the acceptable index for stopping sifting process during ECG and EMG de-noising. Consequently, a new index based on frequency, MPF, was chosen. Table 3 contains the results of filtered signals based on previous research.

Table 3. MSE and correlation coefficient of the filtered signals based on MSE index

Signals	Number of decomposed levels with MSE	MSE	Correlation coefficient
ECG signals			
ECG 1	6	0.0030	0.9980
ECG 2	4	0.0261	0.8972
ECG 3	5	0.0112	0.9285
ECG 4	5	0.0144	0.9134
ECG 5	6	0.0017	0.9987
EMG signals			
EMG 1	2	0.1254	0.8432
EMG 2	2	0.1534	0.7711
EMG 3	3	0.0697	0.9254
EMG 4	2	0.1423	0.7983
EMG 5	3	0.0687	0.9204

6. Conclusion

In this paper, mean power frequency was presented as the index for stopping sifting process during low-frequency artifact reduction from bio-signals. To evaluate the performance of proposed criterion, removal of baseline wander from ECG and ECG artifact from EMG, had been studied. Artifact reduction quality was assessed by computing correlation coefficient and mean square error between the filtered and pure signal. The analysis of the obtained results from table 1 and 2 indicated MPF performed excellent for stopping IMF extraction process when it reached the artifact components.

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7. References

[1] G. Geetha and S.N. Geethalakshmi, "Scrutinizing different techniques for artifact removal from EEG signals" Int. J. Eng. Sci. Tech. 3 1167-1172, 2011.

[2] E.A. Clancy, E.L. Morin and R. Merletti "Sampling, noise-reduction and amplitude estimation issues in surface electromyography" *J. Electromyogr Kinsiol*. 12 1-16, 2002.

[3] M. ZiaUrRahman, R.A. Shaik and R. KotiReddy "Efficient sign based normalized adaptive filtering techniques for cancelation of artifacts in ECG application to wireless biotelemetry" *Elsevier signal processing*. 91 225-239, 2011.

[4] Z. Donghui "Wavelet approach for ECG baseline wander correction and noise reduction" *Proceeding of 27th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC05)*, Shanghai, 1212– 1215, 2005.

[5] T.P. Jung, S. Makeig, M. Westerfield, J. Townsend, E. Courchesne and T.J. Sejnowski "Removal of eye activity artifacts from visual event related potential in normal and clinical subjects" *Clin. Neurophysiol*. 111 1745–1758, 2000.

[6] Lins O G, Piction T W, Berg P and Scherg M 1993 Ocular artifacts in recording EEG and event related potentials II: source dipole and source components *Brain Topography*. 6 65-77.

[7] P. Zhou and T. A. Kuiken "Eliminating cardiac contamination from myoelectric control signals developed by targeted muscle reinnervation" *Physiol Meas.* 27, 1311-1327, 2006.

[8] Y. Deng, Wolf W and Schnell R "New aspects to event-synchronous cancellation of ECG interference: an application of the method in diaphragmatic EMG signals" *IEEE Trans Biomed Eng*. 47 1177-1184, 2000.

[9] 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 mode decomposition and the Hilbert spectrum for nonlinear and nonstationary time series analysis" *Proc. R. Soc. Lond*, 454 903-995, 1998.

[10] A. Rashid, Zahooruddin, A.M. Qureshi and A. Sallem "Electrocardiogram signal processing for baseline removal using blind source separation techniques: a comparative analysis" *Proceedings of the 2011 International Conference on Machine Learning and Cybernetics*. 1756-1761, 2011.

[11] N. Pan, I. Mang, M.P. Un and P.S. Hang "Accurate removal ob baseline wander in ECG using empirical mode decomposition" *Proceedings of Noninvasive Functional Source Imaging of the Brain and Heart and the International Conference on Functional Biomedical Imaging*. 177-180, 2007.

[12] L.U. Guohua, J.S. Brittain, P. Holland, J. Yianni, A.L. Green, J.F. Steina, T.Z. Aziza, S. Wang "Removing ECG noise from surface EMG signals using adaptive filtering" *Neuroscience Letters*. 462 14–19.

[13] M.B. Velasco, B. Weng and K.E. Barner "ECG signal denoising and baseline wander correction based on the empirical mode decomposition" *Computers on Biology and Medicine*. 38 1–13, 2008.

[14] B.N. Krupa, M.A. Mohd and E. Zahedi "The application of empirical mode decomposition for the enhancement of cardiotocograph signals" *PhysiologicalMeasurment*. 30 729–743, 2009.

[15] A.O. Andrade, S. Nasuto, P. Kyberd, C.M. Sweeney-Reed and F.V. Kanijn "EMG signal filtering based on empirical mode decomposition" *Biomedical Signal Processing and Control.* 1, 44–55, 2008.

[16] Y. Zhang, Y. Gao, L. Wang, J. Chen and X. Shi "The removal of wall components in Doppler ultrasound signals by using the empirical mode decomposition algorithm" *IEEE Transaction on Biomedical Engineering*. 54 1631–1642, 2007.

[17] M. Shahbakhti, V.R. Khalili and G. Kamaee "Removal of blink from EEG by empirical Mode decomposition (EMD)" *Processing of 5th International Conference on Biomedical engineering*. Ubon, 1-4, 2012.

[18] M. Shahbakhti, M.R. Bavi and M. Eslamizadeh "Elimination of blink from EEG by adaptive filtering without using an extra channel" *Processing of 4th International Conference on Intelligent Systems, Modeling and Simulation*. Bangkok, 2013.

[19] Y. Kopsinis and S. McLaughlin "Development of EMD-based denoising methods inspired by Wavelet thresholding" *IEEE Transaction on Signal Processing*. 57 1351-1362, 2009.

[20] A.J. Nimunkar and W.J. Tompkins "R-peak detection and signal averaging for simulated stress ECG using EMD" *Proceedings of the 29th Annual International Conference of the IEEE EMBS Cité Internationale*, Lyon, 1261–1264, 2007.

[21] S.C. Villalobos, R.G. Camarena, G. Lem and T. Corrales "Crackle sounds analysis by empirical mode decomposition" *IEEE Engineering in Medicine and Bilogy magazine.* 26 40-47, 2007.

[22] M. Blanco-Velascoa, B. Weng and K.E. Barner "ECG signal denoising and baselinewander correction based on the empirical mode decomposition" *Computers in Biology and Medicine*. 38 1–13 , 2008.

[23] N. Pan, I, Mang , M.P. Un and P.S. Hang "Accurate removal ob baseline wander in ECG using empirical mode decomposition" *Proceedings of Noninvasive Functional Source Imaging of the Brain and Heart and the International Conference on Functional Biomedical Imaging*. 177-180, 2007.

[24] http://www.physionet.org/physiobank/database/nsrdb/

[25] J.D.M. Drake and J.P. Callaghan "Elimination of electrocardiogram contamination from electromyogram signals: an evaluation of currently used removal techniques" *J Electromyogr Kinsiol*. 16 175-187, 2006.

[26] http://www.physionet.org/cgi-bin/atm/ATM?database=pbi&tool=plot_waveforms