International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878, Volume-8 Issue-4, November 2019

Removal of Baseline Wander from Electrocardiogram using Ensemble Empirical Mode Decomposition and Low Pass Filter

Roshan M. Bodile, T.V.K. Hanumantha Rao

Abstract*: *Electrocardiogram (ECG) is a graphical visualization of the electrical activity of human heart. The biomedical signal, such as ECG, has a major issue of separating the pure signal from artifacts due to baseline wander (BW), electrode artifacts, muscle artifacts, and power-line interference. Reduction of these artifacts is vital for clinical purposes for diagnosis and interpretation of the human heart condition. This paper presents removal of BW from ECG using ensemble empirical mode decomposition (EMD) with multiband filtering approach. A comparative performance analysis of EMD and ensemble EMD for synthetic as well as real BW on normal sinus rhythm and arrhythmia ECG signal are presented. This method can remove the BW in different inherent signal to noise ratio (SNR) including negative and positive as well. This method shows that quantitative and qualitative results with miniscule signal distortion via experiments on several ECG records.

Keywords*: *ECG; EMD; ensemble EMD; low pass filter.

I. INTRODUCTION

The ECG is a noninvasive technique used for identification and diagnosis of different heart diseases. The ECG is a key tool which is allowing to monitor patients at a remote area and home, by using telemedicine application. For assistant and monitoring the ECG signal, various telecommunication systems are used. In this scenario, due to the poor condition of the channel though ECG is being transmitted introduces noise in the signal. Moreover, inherent noises in ECG while recording are baseline wander (due to respiration) and electromyographic noise (due to muscle activity). It is also seen that the effects of leads and motion of patients add artifacts in the ECG. The contamination of noises/artifacts leads to difficulty in the feature extraction from ECG, misjudgment, and reduce the diagnostic accuracy. The purpose of removing artifacts is to separate out clean ECG from the noise and makes a signal for better visual interpretation. Therefore, ECG denoising is a crucial stage for clinical purposes. Many researchers contributed to enhancing the quality of ECG by reducing artifacts. The conventional noise minimization approach is constructed with standard filtering; it may be either high pass filter or low pass filter. A low pass filter eliminates the high-frequency artifacts, and high pass filter eliminates the low-frequency components. However, while removing artifacts from the signal, these filters reduce the desired components within that band. The Wiener filter [1] is the Optimal linear filtering approach for stationary signals, either it applied in a "noncausal sense" in the frequency domain or "causal sense" in the time domain. The nature of the cardiac signal is non stationary hence outcomes for a noisy ECG using Wiener filter does not meet to expectation, that is, it does not give the good denoising result. Other researcher has been proposed the removal of artifacts from ECG using a non-linear filter bank [2]. Due to less complexity of adaptive filters, they are extensively used in many applications including detection of arrhythmia and denoising of ECG signal [3,4].

R. Sameni et al. proposed Bayesian filtering [5] which removes the noise components from ECG efficiently. In this approach, the dynamical model used to generate the synthetic ECG. The non-linear Bayesian filtering methods like Unscented Kalman Filter, Extended Kalman Smoother, and Extended Kalman filter were applied in conjunction with dynamical model results in reduction of artifacts from noisy ECG. The statistical method such as independent component analysis [6] used to reduce in-band artifacts by rejecting the dimension related to noise. Though this is commanding in-band artifacts filtering method, the statistical model of noise and signal is arbitrary and, unless its basis functions trained on various set of beats, it can be very sensitive to small alteration of either noise or signal.

The advances in the signal processing helps to reduce the artifacts from ECG. The signal possesses multiresolution characteristics like ECG, wavelet denoising [7,8] is common approach for reduction of noisy signals. It is also observed that the wavelet approach used for many applications, including denoising high-resolution ECG and automatic arrhythmia classification [9]. In [10], M. Blanco-Velasco et al. proposed EMD-based approach can enhance the ECG in both BW and high-frequency noise. The EMD can be alternate to wavelet, and it also behaves as a 'wavelet-like' dyadic filter bank.

The EMD [11] approach divides the signal into the fast and slow oscillations, which may have same scales in a different mode or dissimilar scales in one mode called as scale separation or mode mixing problem. To overcome this difficulty, a new approach was proposed known as ensemble EMD [12] that alleviates the problem associated with EMD.

Manuscript published on November 30, 2019.
* Correspondence Author
Roshan M. Bodile*, Department of ECE, National Institute of Technology, Warangal, India
. Email: roshanmbodile110@gmail.com
T.V.K. Hanumantha Rao, Department of ECE, National Institute of Technology, Warangal, India

In [10], M. Blanco-Velasco et al. proposed EMD with a multiband filter approach to remove the BW and the denoising approach shows that method significantly removes the BW from ECG signal.

The advances in EMD and later version which good tool for removal BW from ECG. Therefore, in this work ensemble EMD with multiband filter approach is proposed for removal of baseline wander and also comparative performance analysis of EMD and ensemble EMD for different range of input SNR is studied.

The remaining paper is organized as follows: A brief description of ensemble EMD is given in Section 2. Section 3. Provides method for removal of BW Section 4. Discussion on simulated results and final part provides the concluding remark.

II. ENSEMBLE EMD

The ensemble EMD considers the average of the IMFs obtained from an ensemble of the original signal and finite variance white noise to define corresponding true modes. The steps for the algorithm is as follows:

(1) Consider x as the signal of interest. Generate $x^{(i)} = x + \phi v^{(i)}$, where $v^{(i)} (i = 1,...,I)$ is a realization zero mean unit variance white noise, and $\phi > 0$.

(2) Using EMD, decompose each $x^{(i)} (i = 1,...,I)$ to obtain the modes $d_k^{(i)}$, where each mode is indicated by $k = 1,...,K$.

(3) The kth mode of x i.e. $\bar{d}_k$ is obtained by considering it as the average of corresponding modes:

$$\bar{d}_k = \frac{1}{I}\sum_{i=1}^{I} d_k^{(i)}. \tag{1}$$

Every mode is extracted using different number of sifting iterations. In ensemble EMD, each $x^{(i)}$ is independently decomposed for every realizations, a residue $r_k^{(i)} = r_{k-1}^{(i)} - d_k^{(i)}$ is obtained at each stage, irrespective of other realizations.

III. BW IN ECG REMOVAL USING ENSEMBLE EMD

The BW is the low-frequency component located in the higher order IMFs. The spread of BW can be seen over some last IMFs and removing these IMFs may introduce distortion. Therefore, removal of BW from these may result in loss of desired components. To eliminate the BW, the contribution of BW to IMFs must be known that can be achieved using BW order [10]. The estimation of BW is calculated using multiband filtering method. The reconstructed signal is obtained by subtracting this estimated BW. In multiband filtering method, a bank of "lowpass" filter is applied to IMFs resulting in the collection of estimated BW as an output of filter bank.

Consider $s_2(\mathrm{t})$ is the signal with BW, the all IMFs obtained by using ensemble EMD is:

$$s_2(\mathrm{t}) = \sum_{k=1}^{M+1} c_k(\mathrm{t}), \tag{2}$$

where $c_{M+1}(\mathrm{t})$ is the residue which added to IMFs as the last IMF. The design lowpass filter bank $l_j(\mathrm{t}), j = 1,2,...P,$ where P is the BW orderis applied toIMFs, and it is starting from last IMF $c_{M+1}(\mathrm{t})$ for this filter bank. Therefore, the outcomes of these applied filters are

$$\begin{aligned} a_1(\mathrm{t}) &= \mathrm{l}_1(\mathrm{t}) * \mathrm{c}_{M+1}(\mathrm{t}), \\ a_2(\mathrm{t}) &= \mathrm{l}_2(\mathrm{t}) * \mathrm{c}_M(\mathrm{t}), ... \\ a_P(\mathrm{t}) &= \mathrm{l}_P(\mathrm{t}) * \mathrm{c}_{M-P+2}(\mathrm{t}), \end{aligned} \tag{3}$$

where the operator * denotes convolution operation. The selection of cutoff frequency is another aspect for filter bank, and it is set for $l_1(\mathrm{t})$ lowpass filter as ω_0. Therefore, cutoff frequency for its jth lowpass filter is set by

$$\omega_j = \omega_0 / N^{j-1}, \tag{4}$$

where the frequency folding number is denoted by N>1. The order of BW P can be calculated from the output $a_j(\mathrm{t})$ of extracted BW in every IMF, such that P value is chosen as $\mathrm{var}\{\mathrm{a}_{P+1}(\mathrm{t})\} < \tau$ and $\mathrm{var}\{\mathrm{a}_P(\mathrm{t})\} \geq \tau$, where τ is the threshold value. After estimation of the order of BW P, the outcomes of all filters are formed as

$$aa(\mathrm{t}) = \sum_{j=1}^{P} a_j(\mathrm{t}). \tag{5}$$

therefore, the reconstructed signal after removing the BW is given as

$$s_{22}(\mathrm{t}) = \mathrm{s}_2(\mathrm{t}) - \mathrm{aa}(\mathrm{t}). \tag{6}$$

As mention, the above BW covers few higher order IMFs, in this scenario, the denoising process for high-frequency artifacts can be achieved by filtering lower-order IMFs. Hence, this process does not create any interference for high-frequency noise filtering.

IV. RESULTS AND DISCUSSION

A. Database and quantitative evaluation

The ECG data was taken from MIT-BIH arrhythmia, normal sinus rhythm and noise stress database [13] for both denoising and analyzing purpose. The database consists of different attributes like binary file (. Dat format), text header (. hea format) and binary annotation (. atr format). The header file is providing the information about patient history, clinical information, a number of samples, sampling frequency, leads used in ECG and format of the ECG.

In this simulation, the several ECG signals were taken with arrhythmia (100, 103, 105, 201, and 210) and normal sinus rhythm (16420, 16539, 17052, 18184 and 19140) which has BW in it. The ECG with BW signal $s_{22}(\mathrm{t}) = \mathrm{s}_{11}(\mathrm{t}) + \mathrm{n}_1(\mathrm{t})$ is enhanced and obtain a reconstructed signal is $\hat{s}_{22}(\mathrm{t})$. The signal $\mathrm{s}_{11}(\mathrm{t})$ is pure signal and $\mathrm{n}_1(\mathrm{t})$ is BW, the combination of both is corrupted signal $s_{22}(\mathrm{t})$. The quantitative estimation is measured by using the signal to error ratio (SER) [10]:

$$SER = \frac{\sum_{t=1}^{J} s_{11}^2(t)}{\sum_{t=1}^{J} \{s_{11}(t) - \hat{s}_{22}(t)\}^2}, \quad (7)$$

the quantity signal to noise ratio evaluate the noise present at the signal $s_{22}(t)$, and it is given as:

$$SNR = \frac{\sum_{t=1}^{J} s_{11}^2(t)}{\sum_{t=1}^{J} n_1^2(t)}. \quad (8)$$

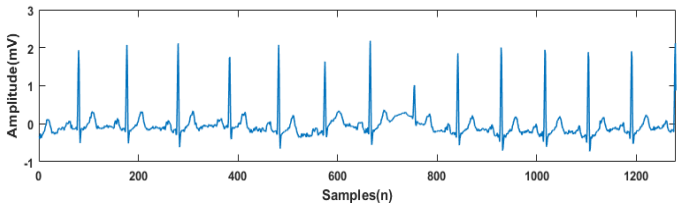
B. Results on EMD and ensemble EMD

In this subsection, the efficiency of presented methods is evaluated by studying two types of BW i.e., synthetic and real, that appears in the ECG signal. The synthetic BW is generated by using sinusoids. For different ECG signals with different sampling frequency i.e., arrhythmia records and normal sinus rhythm with frequencies 360Hz and 128 Hz, the synthetic BW are generated according to the pure signal. The sinusoids (combination of different frequency) are chosen to account for synthetic BW caused by respiration.

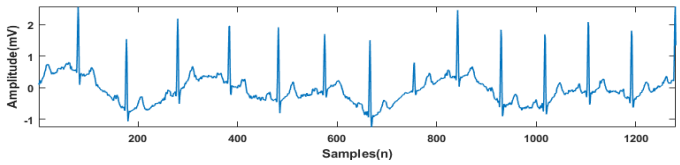
After generation of synthetic BW, this BW added to pure ECG to obtain corrupted version of ECG. The pure ECG record "18184" and corrupted version of it with synthetic BW are shown in Figure 1. The corrupted version of ECG signal now decomposed into IMFs using EMD and ensemble EMD as shown in Figure 2. The BW is estimated using Equation (5) which is subtracted from noisy ECG to obtain reconstructed ECG and after removal of BW, denoised signal shown in Figure 3. It can be observed from Figure 3 that the ensemble EMD illustrates less noticeable residual BW when compared to EMD. The original and estimated BW, in Figure 4, are observed to be similar with small bias owing to DC offset which is removed by using EMD and ensemble EMD. Quantitatively, for record "18184" the ensemble EMD based method yields an SER of 7.88 dB, which is better than 6.96 dB obtained using EMD, respectively, as demonstrated in Table 1.

Table 1: SER for different ECG records.

ECG Records	Input SNR(dB)	SER (dB)	
		EMD	Ensemble EMD
16420	-5.86	6.68	7.29
16539	-7.03	5.27	6.77
17052	-8.86	4.11	5.01
18184	-4.29	6.96	7.88
19140	-2.75	9.34	10.66
100	5.05	12.93	13.88
103	5.56	14.55	15.36
105	5.83	15.33	16.17
201	2.62	10.44	10.92
210	2.82	10.11	10.84
210#	-7.35	0.03	0.50

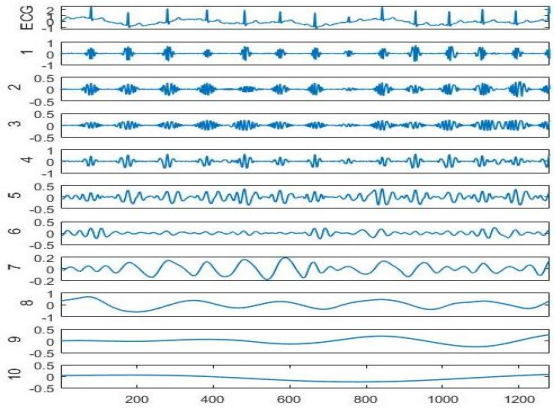


(a)

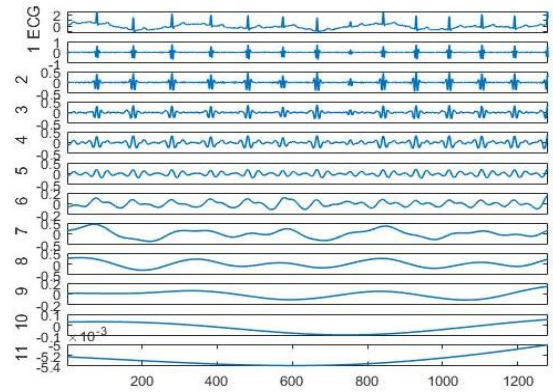


(b)

Figure 1: Record "18184" with BW and without BW, (a) Pure ECG and (b) ECG with BW.

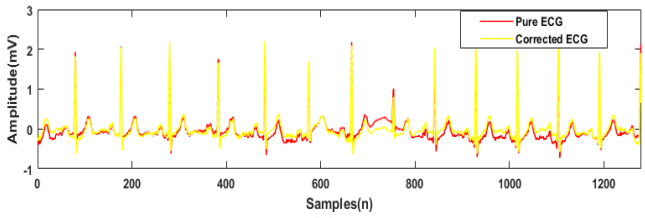


(a)

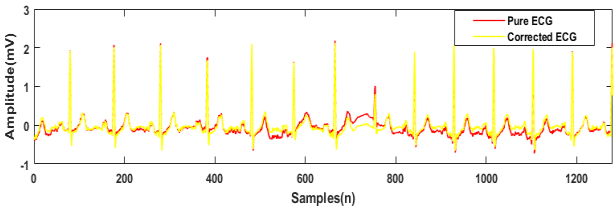


(b)

Figure 2: Decomposition of "record 18184" using (a) EMD and (b) Ensemble EMD.

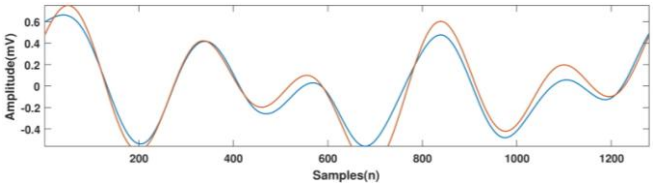


(a)

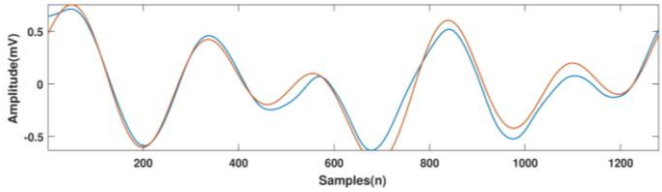


(b)

Figure 3:Filtering results of "record 18184" using (a) EMD and (b) Ensemble EMD.



(a)



(b)

Figure 4:BW estimation for "record 18184" using (a) EMD and (b) Ensemble EMD.

The presented methods are also validated using the pure ECG from record "210". Here, the record "210#" is used as benchmark for real BW to evaluate EMD and ensemble EMD using the similar process. Quantitatively, for record "210#," the ensemble EMD based method yields an SER of 0.5 dB, which is better than 0.03 dB obtained using EMD. Therefore, presented method is efficient to remove both synthetic and real BW from corrupted ECG signal.

To further validate the performance of EMD and ensemble EMD, they are tested on different records, i.e.,16420, 16539, 17052, 19140, 100, 103, 105, 201 and 210. The quantitative results by testing the afore mentioned algorithms, on these records, are presented in Table 1. Table 1 shows that for all the records, ensemble EMD results in better SER when compared to EMD. It is vivid that for all the records considered, ensemble EMD demonstrates better result for the removal of BW due to respiration.

V. CONCLUSION

In this paper, an effective method for the removal of BW from the ECG signal using noise reduction algorithm and their comparison is presented. The EMD and ensemble EMD were successfully employed to remove the BW for signals with both positive and negative SNR values. Several ECG records are considered as benchmark for the validation of the presented method. The simulation results reveal that the ensemble EMD demonstrates better performance with highest SER values for all the tested records. Moreover, ensemble EMD achieves good retention of the morphology of the ECG signal with minimum signal distortion.

REFERENCES

1. K. Chang and S. Liu, "Gaussian Noise Filtering from ECG by Wiener Filter and Ensemble Empirical Mode Decomposition," J. Signal Process Sys., vol. 64, pp. 249–264, 2011.
2. J.M. Leski and N. Henzel, "ECG baseline wander and power line interference reduction using nonlinear filter bank," Signal Process., vol. 35, pp. 781–793, 2004.
3. N.V. Thakor and Y.-S. Zhu, "Applications of adaptive filtering to ECG analysis: noise cancellation and arrhythmia detection," IEEE T. Biomed. Eng., vol. 38, pp. 785–794, 1991.
4. Kevin Kærgaard, Søren Hjøllund Jensen and Sadasivan Puthusserypady, "A comprehensive performance analysis of EEMD-BLMS and DWT-NN hybrid algorithms for ECG denoising," Biomed. Signal Proces., vol.25, pp. 178-187, 2016.
5. R. Sameni, M.B. Shamsollahi, C. Jutten and G.D. Clifford, "A nonlinear Bayesian filtering framework for ECG denoising," IEEE T. Biomed. Eng., vol. 54, pp. 2172–2185, 2007.
6. T. He, G. Clifford and L. Tarassenko, "Application of ICA in removing artefacts from the ECG," Neural Process. Lett., pp. 105–116, 2006.
7. Md. Ashfanoor Kabir and Celia Shahnaz, "Denoising of ECG signals based on noise reduction algorithms in EMD and wavelet domains,' Biomed. Signal Proces., vol.7, pp. 481– 489, 2012.
8. N. Li and P. Li, "An improved algorithm based on EMD-wavelet for ECG signal denoising," In: 2009 International Joint Conference on Computational Sciences and Optimization, pp 825–827, 2009.
9. Manu Thomas, Manab Kr Das andSamit Ari, "Automatic ECG arrhythmia classification using dual tree complex wavelet based features," AEU - International Journal of Electronics and Communications, vol. 69, pp. 715-721, 2015.
10. M. Blanco-Velasco, B. Weng and K. E Barner, "ECG signal denoising and baseline wander correction based on the empirical mode decomposition," Comput. Biol. Med., vol. 38, pp. 1–13, 2008.
11. Huang N.E., Z. Shen, S.R. Long, M.L. Wu, H.H. Shih, Q. Zheng, N.C. Yen, C.C. Tung and H.H. Liu, "The empirical mode decomposition and Hilbert spectrum for nonlinear and nonstationary time series analysis," In: Proceedings of the Royal Society of London Series A., pp 903–995, 1998.
12. Z. Wu and N. Huang, "Ensemble empirical mode decomposition: A noise-assisted data analysis method," Adv. in Adaptive Data Analy.vol. 1, pp. 1–41, 2009.
13. Goldberger AL, Amaral LAN, Glass L, Hausdorff JM, Ivanov PCh, Mark RG, Mietus JE, Moody GB, Peng C-K and Stanley HE, "PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals," Circulation, 101(23), pp. 215-220, 2000.

Retrieval Number: D6883118419/2019©BEIESP
DOI:10.35940/ijrte.D6883.118419
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)