Baseline wander removal of electrocardiogram signals using multivariate empirical mode decomposition

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A new method for removing the baseline wander (BW) noise based on multivariate empirical mode decomposition is presented. The proposed method is compared with recently introduced technique for BW removal using Hilbert vibration decomposition in terms of correlation coefficient criterion and signal-to-noise ratio. To evaluate the performance of the proposed method, real BW signals are added to synthetic and clinical electrocardiogram (ECG) signals. It is shown that presented methodology has significant scope of removing BW noise in real world ECG signals.

1. Introduction: Baseline wander (BW) is a low-frequency artefact in electrocardiogram (ECG) signal recordings of a subject [1]. BW removal is an important step in processing of ECG signals because BW makes interpretation of ECG recordings difficult. The main cause of the BW in the ECG signal is movement and respiration of the patient [2].

One of the approaches to remove BW artefacts is the high-pass filtering of ECG signals [2]. However, high-pass filtering for BW removal is not recommended as it can distort the ECG waveform because of variations in the frequency spectrum of the ECG signal [2].

The other technique for BW removal based on empirical mode decomposition (EMD) and mathematical morphology (MM) is proposed in [2]. In this scheme two basic morphological operators (opening and closing) are utilised to realise a low-pass filter. The EMD technique is a tool for time-frequency analysis and is being used in a number of applications [3]. EMD decomposes a time varying signal into series of intrinsic mode functions (IMFs) [3].

Recently a technique called Hilbert vibration decomposition (HVD) has been proposed [4]. The HVD extracts the mono-components of a signal by using its analytic form where the first component corresponds to the highest instantaneous amplitude [4]. Based on HVD a technique is proposed to remove the BW of the ECG signal [5]. This HVD based method is compared with EMD and MM based method [2] and shown to have superior performance [5].

In this Letter, a novel method of BW removal of ECG signals based on multivariate empirical mode decomposition (MEMD) is presented. MEMD technique is the multivariate extension of EMD and recently attracted the attention of the researchers in many applications [6, 7]. Motivation behind the proposed method is to remove higher indexed IMFs to obtain baseline corrected ECG signals. The unique ability of MEMD technique facilitates equal number of IMFs across the channels.

2. Proposed method: EMD is a fully data-driven method for non-linear and non-stationary real word signals [3]. It decomposes the signal in to a finite set of IMFs which represent its inherent oscillatory modes. A special ‘sifting’ process is employed to extract all of IMFs. This sifting process is described in [3]. The real signal under consideration is $x(t)$, then using EMD this signal is decomposed into IMFs: $c_1(t)$, $c_2(t)$, $c_3(t)$, ..., $c_n(t)$ and $r_n(t)$. Here $r_n(t)$ is a small residue. Using EMD signal $x(t)$

can be represented as

$$x(t) = \sum_{i=1}^n c_i(t) + r_n(t) \quad (1)$$

However, multivariate extension of EMD facilitates real valued projections along multiple directions on hyperspheres (n-spheres) in order to calculate envelopes and the local mean of multivariate signal [6, 7]. The MEMD is described fully in [6, 7].

In general equal length signals from M channels are simultaneously processed through MEMD and each channel is decomposed in N equal number of IMFs. The lower indexed IMF is corresponding to highest frequency components in the signal while the higher indexed IMFs are corresponding to low frequency components in the signal. In present study, we have applied MEMD technique using four channels. First channel consists of simulated ECG signal (ECG signal+BW), while other channels are replica of first channel with added small amount of white Gaussian noise.

As a fact that BW is a low frequency signal, we propose estimate of baseline wander $BW(t)$: a sum of IMFs numbered N and $N-1$. The Baseline corrected signal $y'(t)$ can be obtained through original ECG signal $y(t)$ by subtracting $BW(t)$ from the original ECG signal. Therefore $y'(t) = y(t) - BW(t)$.

3. Simulation results: We performed simulation studies on synthetic ECG signals as well as on real life clinical ECG signals. For BW we used only real life clinical data. The synthetic ECG signals were obtained using ECGSYN. The algorithms used by ECGSYN are described in [8]. Real life clinical ECG signals were used from MIT-BH arrhythmia database [9] while real life clinical BW signals were obtained from MIT-BIH noise stress test database (nstdb/bw) [10]. All such datasets are available at [11].

We used record number 100, 105 and 119 for the real life clinical ECG signals, similar to that used in the HVD based method [5]. The real life clinical ECG signals were digitised at 360 Hz with 11 bit resolution over ± 5 mv range. The motivation to add real BW signals into ECG signals was to test the method in real situations.

To analyse the performance of the proposed method quantitatively, two criterions are used. First criterion is based on correlation coefficient (CR) while the second one is based on signal-to-noise-ratios (ϵ) of the signals of interest. These criterions are defined as:

Table 1 Performance of proposed method with HVD method [5] based on correlation and SNR criterions, case 1

Test ECG [8]	Test BW [9]	Correlation (CR)		Error in SNR (ϵ)	
		Proposed method (MEMD)	HVD [5]	Proposed method (MEMD)	HVD [5]
ecgsyn1	bw1	0.844	0.407	1.44	8.78
ecgsyn2	bw2	0.885	0.616	0.4	10.43
ecgsyn3	bw3	0.833	0.542	3.1	10.33
ecgsyn4	bw4	0.892	0.461	3.39	9.81
ecgsyn5	bw5	0.958	0.631	4.37	9.67

(i) $CR = (P \cdot Q) / (\|P\| \|Q\|)$ where P and Q are the signals under consideration. CR reflects similarity between the signals. (ii) $\epsilon = |SNR1 - SNR2|$ where SNR1 is the signal-to-noise ratio of the test ECG to BW signals and SNR2 is the signal to noise ratios of the estimated ECG to BW signals. In general signal-to-noise ratio SNR of a signal S with noise N (in our case BW) can be calculated as: $SNR = 10 \log_{10} S_{\sigma} / N_{\sigma}$. For a given signal S , S_{σ} is defined as $S_{\sigma} = \sum_{T=0}^{T-1} (S(T) - \mu_S)^2$ where T is the length and μ_S is the mean value of the signal S , respectively.

For simulation purposes we considered three different cases, which are described below:

Table 2 Performance of proposed method with HVD method [5] based on correlation and SNR criterions, case 2

Test ECG [8]	Test BW [9]	Correlation (CR)		Error in SNR (ϵ)	
		Proposed method (MEMD)	HVD [5]	Proposed method (MEMD)	HVD [5]
ecgsyn1	bw1	0.85	0.407	0.39	18.6
ecgsyn2	bw2	0.885	0.616	2.17	10.43
ecgsyn3	bw3	0.868	0.542	4.08	10.33
ecgsyn4	bw4	0.754	0.461	0.552	9.81
ecgsyn5	bw5	0.93	0.631	4.83	9.67

Table 3 Performance of proposed method with HVD method [5] based on correlation and SNR criterions, case 3

Test ECG [10]	Test BW [9]	Correlation (CR)		Error in SNR (ϵ)	
		Proposed method (MEMD)	HVD [5]	Proposed method (MEMD)	HVD [5]
100	bw1	0.888	0.305	3.33	46.32
	bw2	0.876	0.2892	2.13	25.38
	bw3	0.919	0.334	0.2	21.7
	bw4	0.934	0.441	1.17	15.58
	bw5	0.957	0.565	0.22	5.28
105	bw1	0.841	0.332	1.13	11.6
	bw2	0.865	0.279	1.82	14.93
	bw3	0.927	0.453	2.2	7.7
	bw4	0.919	0.425	1.58	11.89
	bw5	0.989	0.757	0.18	13.78
119	bw1	0.779	0.468	4.01	11
	bw2	0.896	0.509	2.07	10
	bw3	0.89	0.403	5.14	11.25
	bw4	0.872	0.181	3.98	8.61
	bw5	0.968	0.448	1.24	20.18

Fig. 1 Baseline corrected signal using proposed technique (Case 3)

Case 1: In this case, we used five different instances of synthetic ECG signals [8], however for BW signals we used five different instances taken from real BW signals [10]. Real BW signals are added to synthetic ECG signals. For BW estimation purpose, we used sum of IMFs numbered N and $N-1$. Simulation results of this case are presented in Table 1.

Case 2: This case is quite similar to the case 1, however for BW estimation purpose we used sum of IMFs numbered N , $N-1$ and $N-2$. Simulation results of this case are tabulated in Table 2.

Case 3: In this case, we used five different instances of real ECG signals [9] and five different instances from real BW signals [10]. We used sum of IMFs numbered N and $N-1$ for estimation of BW. Simulation results of this case are presented in Table 3. Outcome of one of the instance of this study is shown in Fig. 1. From Fig. 1, it is evident that proposed method works well for real clinical signals.

4. Discussion: Simulation results of Tables 1 and 3 clearly indicate that the proposed method for BW removal significantly improves the performance as compared with the method based on HVD [5]. Results of case 2 (Table 2) indicate decrease in CR for signal ecgsyn4 and increase in error for signals ecgsyn2, ecgsyn3 and ecgsyn5 as compared with corresponding signals in case 1. This is the reason, we have utilised IMFs numbered N and $N-1$ for BW estimation in the proposed methodology. The ability of MEMD technique for denoising of multivariate EEG signals is already illustrated in [6]. Proposed methodology is presented in the paradigm of removing BW from real life multichannel cardiac signals. However, in the present study a single channel ECG signal is utilised only to compare proposed method with the HVD method and three more signals are generated to apply MEMD algorithm. It is pertinent to mention that mode alignment and decomposition of signal into similar number of IMFs across the channels are the unique features of the MEMD algorithm [6, 7] which otherwise, is not available in EMD algorithm. Computational cost of the proposed method is higher on account of complex decomposition procedure as compared with the HVD method.

5. Conclusion: A novel method for removal of BW from real ECG signals based on MEMD technique is proposed. Only two higher indexed IMFs correspond to lowest frequency contents are used to estimate the BW in real life clinical ECG signals. Simulation results pertaining to synthetic and real life ECG signals with real life BW demonstrated the ability of the method to remove BW of the ECG signals while preserving the morphology of the ECG signals.

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