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# ECG Baseline Wander Correction by Mean-Median Filter and Discrete Wavelet Transform

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***Abstract*—Electrocardiographic (ECG) analysis plays an important role in diagnosis of heart diseases. High quality ECG pushes forward new drug development and improves clinical diagnosis. This paper introduces a novel method to correct baseline wander (BW) components of ECG signals based on Mean-Median (MEM) filter and discrete wavelet transform (DWT). We obtain the BW estimation via MEM, and decompose the estimation into different scales by DWT. Then, an iterative sifting process based on *t*-test is adopted to select the scales to reconstruct the refined BW components. The proposed method is applied to MIT-BIH Arrhythmia Database. The experimental results verify that the proposed method can effectively remove BW components and preserve useful waveform information.**

## I. Introduction

Baseline wander (BW) is a low-frequency artifact that occurs in ECG signals, and is usually caused by respiration of patients or the motion of instruments. Removing this type of artifact serves as a primary step in ECG signal analysis, for subsequent processing or visual interpretation. A myriad of different methods have been utilized to normalize BW in ECG signals.

Some previous developments in this area include approaches based on linear filters, nonlinear filters, Polynomial interpolation, and wavelet filters [3]. As for linear filters [5], finite impulse response (FIR) and infinite impulse response (IIR) filters are the usual techniques to correct BW. However, fixed cut-off frequencies of these linear filters may lose useful information of waveform or cannot correct BW completely. In addition, adaptive filters are presented in [6,7], but these filters need a suitable reference signal difficult to be estimated and identified. Polynomial interpolation depends on an accurate determination on knots, and may be unreliable when it comes to separated knots [8]. As a nonlinear filtering technique, Mathematical morphology can obtain local shape features of signals based on structuring element sequences [9]. However, its application may result in 'step-like' waveform distortion. This paper introduces Mean-Medain (MEM) filter as a nonlinear filter that can not only effectively preserve the outline of BW but also avoid waveform distortion caused by median filter and morphology filter [11]. Then we combine discrete wavelet transform (DWT), a time-frequency analysis tool well suited for nonstaionary signals, with a selection process through *t*-test to obtain an enhanced quality ECG.

This paper is organized as follows: Section II introduces the theories about MEM [2] and DWT [1].The proposed algorithm of BW correction of ECG signal is described in Section III. In Section IV, we test the proposed algorithm on MIT-BIH Arrhythmia database [4], and experimental results used to validate the proposed algorithm are presented. Finally, we draw conclusions in Section V.

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## II. Methodology

### A. Mean-Median Filter

The MEM output of a sample vector $X$ can be seen as a convex combination of the sample median $\tilde{x}$ and sample mean $\bar{x}$ of $X$ respectively, and is described as follows:

$$y = (1-\alpha)\bar{x} + \alpha\tilde{x} \tag{1}$$

Where $\alpha \in [0, 1]$ is the known fraction of 'contamination'. In this paper, we define operator $Mean\_Median$ to get the M-estimation of $X$ which is the numerical solution of the following equation:

$$\sum_{i=1}^{n} \psi(X_i - \theta) = 0 \tag{2}$$

Where

$$\psi(x) = \begin{cases} x & |x| \le k \\ k \cdot \operatorname{sgn}(x) & |x| > k \end{cases} \tag{3}$$

Usually the proper range of $k$ is [1.14, 1.945] [2] based on experiments. To obtain the estimation $\theta_n$ of BW, a window of length, $W$, is slid along the samples of ECG signal. The value of

$W$ is usually assigned between one third and two thirds of the sample rate. It can be proved in [2] that estimating deviations follow an asymptotic normal distribution:

$$\sqrt{n}(\theta_n - \theta) \to N(0, V(\psi, F)) \quad (4)$$

Where

$$V(\psi, F) = \frac{\int \psi(x)^2 \, dF(x)}{\left(\int \psi'(x)^2 \, dF(x)\right)^2} \quad (5)$$

*B. Discrete Wavelet Transform*

In general, the wavelet transform is a power time-frequency analysis tool. Usually, discrete wavelet function can be obtained by discretizing the scale parameter and the space parameter [1], and is described as follows:

$$\phi_{j,k}(t) = a_0^{\frac{-j}{2}} \phi(a_0^{-j} - kb_0) \quad (6)$$

Thus the coefficients of discrete wavelet functions can be obtained:

$$C_{j,k} = \int_{-\infty}^{\infty} f(t)\phi^*_{j,k}(t)dt = \langle f, \phi_{j,k} \rangle \quad (7)$$

The reconstruction formula is as follows:

$$f(t) = C\sum_{-\infty}^{\infty}\sum_{-\infty}^{\infty} C_{j,k}\phi_{j,k}(t) \quad (8)$$

Where $C$ is a constant dependent of the wavelet.

For the uncertain information of BW in wavelet domain, it is difficult to confirm wavelet coefficients of which scales to reconstruct BW especially in clinical application. Thus, in the following section, we first estimated the supremum of BW information by MEM, and then further elaborated BW information with the estimated deviations removed by DWT.

## III. THE PROPOSED ALGORITHM

*A. BW estimation*

To use MEM filter on a given ECG signal $X(n)$ with length of $L$, we need to firstly extend the head and tail of $X(n)$ with $X(0)$ and $X(L-1)$, respectively. Then a window with length of W is slid sample to sample on the extended signal to obtain the low frequency components of the ECG signal. The MEM filtering processing is rewritten as follows:

Extend the ECG signal $X_1$ to get $X_2$:

$$X_2(i) = \begin{cases} X_1(0) & 0 \le i \le \frac{W-1}{2} \\ X_1(i - \frac{W-1}{2}) & \frac{W-1}{2} < i < \frac{W+1}{2} \\ X_1(L-1) & L - \frac{W-1}{2} < i < L + W - 2 \end{cases} \quad (9)$$

Then we obtain low frequency parts:

$$X_{low}(i) = Mean\_Median[X_2(i) : X_2(i+W)] \quad (10)$$

Where $i \in [0, L-1]$.

*B. Amending BW estimation*

Even though MEM estimates BW well and avoids serious waveform distortion, (4) indicates that the output of MEM still introduces some undesired information which follows an asymptotic normal distribution with a mean of zero. In the frequency domain, these deviations mainly distribute in P and T wave band, a higher than BW frequency band. Then we decompose $X_{low}$ into different scales by DWT and reconstruct BW from the lowest scale. A *t*-test will be performed to determine on which scale the reconstruction progress stops. The whole step is written as follows:

i. Decompose $X_{low}$ by DWT and obtain M scales of wavelet coefficients.
ii. Reconstruct the current scale approximate wavelet coefficients and obtain $BW_M$
iii. Perform a *t*-test to determine whether the difference between $X_{low}$ and $BW_M$ has a zero mean. Two hypothesis are:

$$H_0 : mean(X_{low} - BW_M) = 0 \quad (11)$$

$$H_1 : mean(X_{low} - BW_M) \ne 0 \quad (12)$$

iv. In step iii, if $H_0$ is accepted, the amending procedure terminates. Otherwise, repeat step ii and step iii on the $M-1_{th}$, $M-2_{th}$, $\cdots$,wavelet coefficients until $H_0$ is accepted.

We can obtain the accurate BW estimation $BW_Q$ when the amending process stops at the $Q_{th}$ scale wavelet coefficients. In fact, we have studied direct BW reconstruction from the highest scale wavelet coefficient. However, for the DWT decomposition characteristics experimental results reflect the proposed idea works better.

## IV. EXPERIMENTS

In this part, all ECG signals come from MIT/BIH Arrhythmia Database [4]. The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range. Sample values ranged from 0 to 2047, with a value of 1024 corresponding to 0 mV. Generally we truncate 3000 sample points of each ECG signal, and accordingly, the range of MEM window length $W$ is from 120 to 200 points. In addition, for the sample frequency and the BW frequency band, the DWT decomposition level should be no less than 10.

We compare the original ECG signal (record 103) with the corrected signal by the proposed method based on different wavelet functions. BW components by MEM filter and the corrected BW components are also compared. These results are shown in the following figures.

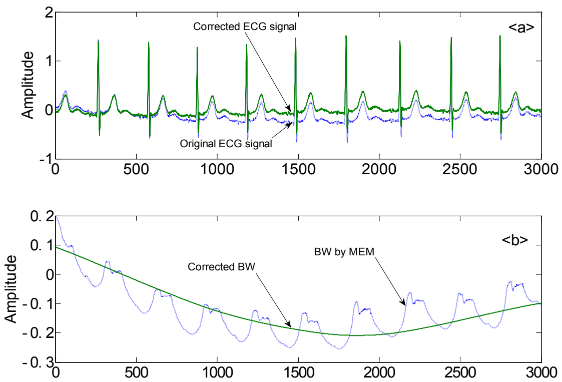


Fig.1 Experimental results based on db6 wavelet
<a> Comparision of original signal (record 103) and corrected ECG signal
<b> Comparision of BW by MEM and corrected BW

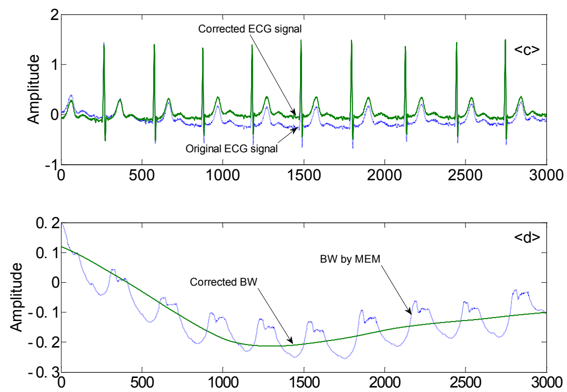


Fig.2 Experimental results based on sym6 wavelet
<c> Comparision of original signal (record 103) and corrected ECG signal
<d> Comparision of BW by MEM and corrected BW

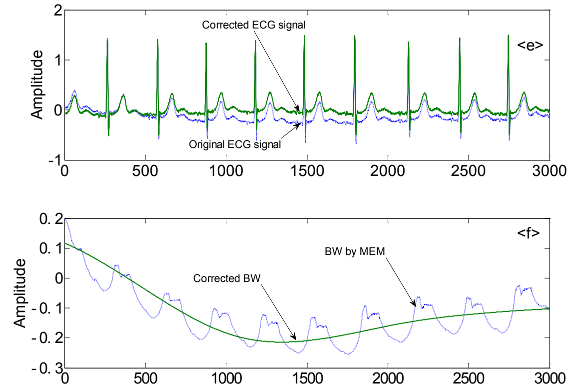


Fig.3 Experimental results based on coif5 wavelet
<e> Comparision of original signal (record 103) and corrected ECG signal
<f> Comparision of BW by MEM and corrected BW

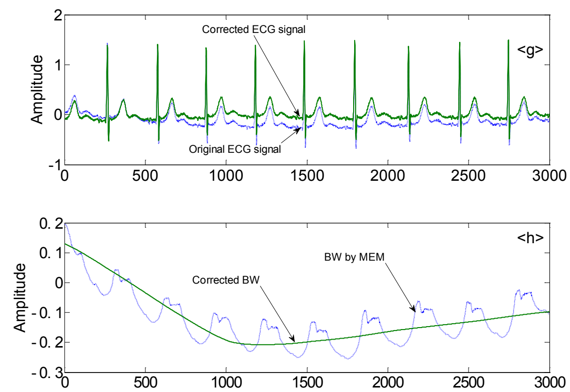


Fig.4 Experimental results based on bior4.4 wavelet
<g> Comparision of original signal (record 103) and corrected ECG signal
<h> Comparision of BW by MEM and corrected BW

To further investigate the proposed method, a series of artificial BW (ABW) are generated by lowpassing a random signal. The random amplitude α is uniformly distributed in an interval of [0, c] [10]. The average enhancement of signal-to-noise ratio (SNR) of the MIT/BIH Arrhythmia Database under different c values is listed in Table.1. SNR value is defined as $SNR = 20\log_{10}(S_\sigma / N_\sigma)$ where $S_\sigma$ and $N_\sigma$ denotes the standard deviation of signal and noise, respectively. In Table.1, we compare the performance of SNR enhancement of the proposed method based on different wavelets with that of method in [12]. The first and the second row of data corresponding to db6 denote the average and the maximal enhancement of SNR under different c values when using db6 wavelet, respectively. Data groups corresponding to other wavelets and method are understood as db6.

TABLE.1

Comparison of different wavelets on the whole MIT/BIH Arrhythmia Database under SNR criterion

| **Amplitude of ABW** | **c=100** | **c=300** | **c=500** | **c=700** | **c=900** |
|---|---|---|---|---|---|
| **db6** | 9.731 | 8.092 | 9.589 | 11.84 | 13.40 |
| | 20.56 | 16.62 | 16.68 | 17.21 | 18.37 |
| **sym6** | 9.737 | 8.106 | 9.609 | 11.86 | 13.44 |
| | 20.60 | 16.75 | 16.78 | 17.27 | 18.47 |
| **coif5** | 9.722 | 8.068 | 9.555 | 11.79 | 13.37 |
| | 20.56 | 16.66 | 16.67 | 17.16 | 18.27 |
| **bior4.4** | 9.757 | 8.128 | 9.634 | 11.89 | 13.47 |
| | 20.62 | 16.74 | 16.77 | 17.27 | 18.51 |
| **The method of** | 4.456 | 3.769 | 6.047 | 9.531 | 11.29 |
| **Blanco-Velasco** | 17.23 | 16.25 | 17.77 | 20.78 | 22.17 |

From Table.1 we can see that the proposed method based on different wavelet functions can remove the BW well. Under the ABW of different amplitude, the average enhancement of SNR values of the whole database is better than that of the method of Blanco-Velasco [12]. However, when dealing with sever ABW, the maximal enhancement of SNR is inferior to that of the method of Blanco-Velasco, which may be relevant to the innate BW of the ECG signal.

## V. CONCLUSION AND FUTURE WORK

A new BW correction method based on MEM and DWT is proposed in this paper. The MEM filter removes the low frequency parts of the original ECG signal in a nonlinear way. The DWT decomposes the MEM filter output into different levels of wavelet coefficients based on which the *t*-test selects the levels to reconstruct the accurate BW parts. Experimental results show that the proposed method can remove baseline wander effectively while preserve the useful information of the waveform of ECG signals.

Even though the proposed method performs well, future work includes researching the detailed influence of different wavelet functions as well as corresponding decomposition level on the performance of the proposed method. On the other hand, we will also study some other transform ways such as the Hilbert-Huang transform to correct the innate defects of MEM for a better BW correction result.

## REFERENCES


[1] I. Daubechies, *Ten Lectures on Wavelets.* Philadelphia, PA: SIAM, 1992, notes from the 1990 CBMS-NSF Conference on Wavelets and Applications at Lowell, MA

[2] P. Huber, *Robust estimation of location parameter.* Ann. Math. Statist. vol.4,no.1,1964,pp.73-101

[3] R. F. von Borries, J. H. Pierluissi and H. Nazeran, "Wavelet Transform-Based ECG Baseline Drift Removal for Body Surface Potential Mapping."in *Proc.27th International Conference of the IEEE Engineering in Medicine and Biology Society*, Shanghai, China, September 1-4, 2005

[4] http://www.physionet.org/physiobank/database/mitdb/

[5] L. Shen, P. Johnston , " A review of electrocardiogram filtering", *J -ornal of Electrocardiol,*vol.43,no.6, pp.486-496,2010

[6] R.Vullings,B.de Vries, J.W.M.Bergmans "An Adaptive Kalman Filter for ECG Signal Enhancement," *IEEE Transaction on Biomedical Engineering , v*ol. 58, no. 4, pp. 1094–1103, April 2011

[7] L.Chmelka, J. kozumplik, "Wavelet-based Wiener filter for electrocardiogram signal denoising," *Computers in Cardiology*, vol.32, pp.771-774,2005.

[8] L.F.Brown,S.P.Arunachalam, "Real-time T-p knot algorithm for baseline wander noise removal from the electrocardiogram," *Biomed Sci Instrum,*vol. 45, pp. 65–75, 2009

[9] Y. Sun, K.L. Chan, S.M. Krishnan, "ECG signal conditioning by morphological filtering" *Computers in Biology and Medicine*, vol.32, no.6, pp.465-479,Nov 2002

[10] T.Y. Ji, Z. Lu, Q.H. Wu and Z. Ji, "Baseline normalization of ECG signals usingempirical mode decomposition and mathematical morphology," *Electronic Letter*, vol.43, no.6, pp.486-496, 2010.

[11] Nie,X.,Unbehauen,R., "Edge preserving filtering by combining nonlinear mean and median filters", *IEEE Transactions on Signal Processing,* vol. 39, no. 11, pp. 2252–2254, Nov 1991.

[12] Blanco-Velasco M, Weng B.W, Barner K.E, "ECG signal denoising and baseline wander correction based on the empirical mode decomposition" *Computers in Biology and Medicine*, vol.38, no.1, pp.1-13,2008