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RESEARCH ARTICLE

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ECG Baseline Wander Correction Based on Ensemble Empirical Mode Decomposition with Complementary Adaptive Noise

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The baseline wander in electrocardiogram (ECG) may greatly affect the normal medical diagnosis. Since the empirical mode decomposition (EMD) has a good time-frequency characteristics, this paper proposes an improved EMD algorithm to solve the ECG baseline wander problem. First, in order to obtain better intrinsic mode functions, the ensemble empirical mode decomposition with adaptive noise (EEMDAN) is improved by adding pairs of positive and negative noises. Then, the zero-crossing rate (ZCR) is used to adaptively extract the baseline wander after the decomposition. The experimental results indicate that the proposed method can remove the baseline wander signal existing in the ECG signal effectively.

Keywords: Baseline Wander, EMD, Zero-Crossing Rate, ECG.

1. INTRODUCTION

The ECG is the data recording the cardiac activity and plays a very important role in the clinical diagnosis of heart health. However, there are many interferences in the process of human ECG acquisition, such as baseline wander (BW), the electromyographic (EMG) noise and power line interference.[1] Among them, the baseline wander is one of the most important issues, which is a low-frequency signal. It is mainly caused by the respiratory motion or the slide between the collecting electrode and the patient body. This kind of the interference will raise the ST segment and cause a serious distortion of the ECG trace. Furthermore, it may affect the normal medical diagnosis.[2] Therefore, eliminating the baseline wander is very important for ECG recording preprocessing.

There are many methods to correct the ECG baseline wander, such as median filtering, wavelet transform[3,4] and empirical mode decomposition developed in recent years.[5,6] Although the median filtering method has a low computational burden, it suffers from the 'ladder' wave distortion problem, which results to a low reconstruction accuracy. In the wavelet transform method, the highest order approximation component is used to estimate the baseline wander signal. However, the method usually determines the wavelet function and decomposition levels according to different ECG signals empirically. Since the empirical mode decomposition (EMD) has a good time-frequency characteristics, some researchers employ the traditional EMD to eliminate the ECG baseline wander.[5,6] However, it is well-known that the traditional EMD method suffers from mode mixing problems that can make the decomposition results lose physical significance.[7] Torres, et al.[8] proposed the ensemble empirical mode decomposition with adaptive noise (EEMDAN) to fairly solve the mode mixing problem and achieved better reconstruction performance compared to the ensemble empirical mode decomposition (EEMD).[7] However, there still exist many residual noises in each IMF during the decomposition especially when the ensemble size is not big enough. Moreover, for the ECG baseline wander problem, how to adaptively select the intrinsic mode functions (IMFs) corresponding to the baseline signal after decomposition is another unsolved problem in the existing methods.

Inspired by the complementary ensemble empirical mode decomposition (CEEMD),[9] we propose a new EMD method called the complementary ensemble empirical mode decomposition with complementary adaptive noise (EEMDCAN) in this paper. The so-called complementary adaptive noise means that pairs of positive and negative adaptive noises are added in the signal before the each decomposition. Then, we combine the proposed EEMDCAN with the zero-crossing rate (ZCR) to correct the ECG baseline wander.

2. ENSEMBLE EMPIRICAL MODE DECOMPOSITION WITH COMPLEMENTARY ADAPTIVE NOISE

Compared to the EEMD, there are two improvements in the EEMDAN.[8] First, the EEMDAN adds the IMFs of the standard

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white noise decomposed by the EMD instead of adding the standard white noise directly in the decomposition process. The bandwidth of the IMFs of the noise is split adaptively by the EMD. Second, EEMD calculates the ensemble mean of each IMF after achieving all the IMFs. However, EEMDAN calculates the ensemble mean immediately when the first IMF is shifted. Then, it extracts the first IMF and treats the residual signal as a new signal. Finally, the above steps are repeated until extracting all the IMFs.

Torres, et al. informed that the reconstruction error of EEMDAN was smaller than the EEMD with the same ensemble size.[8] However, this does not imply that the residual noise in each IMF is very small after the decomposition especially when the ensemble size is small, which influences the reconstruction performance. In order to reduce the residual noise existing in each IMF, it must increase the ensemble size. However, this will inevitably result to heavy computational burden. To solve this problem, this paper improves the EEMDAN via adding pairs of positive and negative noises, which is termed as EEMDCAN. For simplicity, we define an operation $E_k()$ to produce the kth IMF of the signal by the EMD. Define a_k as the standard deviation of the kth residual signal which will be decomposed at the next stage. The implementation process of the EEMDCAN is described as follows:

Step 1: Add the pairs of positive and negative white noises $(-1)^q a_0 n^i(t)$ to the original signal $s(t)$ and achieve the mixed-signals $s(t)+(-1)^q a_0 n^i(t)$ before decomposing, where $i = 1, 2, \ldots, M/2$, $q = 1, 2$, and $n^i(t)$ is the ith white Gaussian noise. M is the ensemble size and an even number. Then, decompose the mixed-signals by EMD until obtaining all of their first IMFs. Next, calculate the ensemble mean of all the first IMFs as:

$$\overline{\text{imf}}_1(t) = \frac{1}{M}\sum_{i=1}^{M} \text{imf}_1^i(t) \tag{1}$$

Step 2: Consider the ensemble mean $\overline{\text{imf}}_1(t)$ as a new first IMF for the original signal. Then, extract $\overline{\text{imf}}_1(t)$ from the original signal $s(t)$ and achieve the residual signal $r_1(t)$ as:

$$r_1(t) = s(t) - \overline{\text{imf}}_1(t) \tag{2}$$

Step 3: Add the pairs of the positive and negative adaptive noises $(-1)^q a_1 E_1(n^i(t))$ to the residual signal $r_1(t)$ and achieve the new mixed-signals $r_1(t)+(-1)^q a_1 E_1(n^i(t))$. Next, decompose the new mixed-signals again by EMD. Then, achieve the second ensemble mean $\overline{\text{imf}}_2(t)$:

$$\overline{\text{imf}}_2(t) = \frac{1}{M}\sum_{i=1}^{M} \text{imf}_2^i(t) \tag{3}$$

Step 4: For any new residual signal $r_k(t)$, where $k = 1, 2, \ldots$, add the pairs of positive and negative adaptive noises $(-1)^q a_k E_k(n^i(t))$ to the residual signal and achieve the new mixed-signals $r_k(t)+(-1)^q a_k E_k(n^i(t))$, a_k is usually chosen as 0.1–0.2 times of the standard deviation of the new residual signal $r_k(t)$. Decompose the new mixed-signals by EMD. Then, achieve the $(k+1)$th ensemble mean $\overline{\text{imf}}_{k+1}(t)$:

$$\overline{\text{imf}}_{k+1}(t) = \frac{1}{M}\sum_{i=1}^{M} \text{imf}_{k+1}^i(t) \tag{4}$$

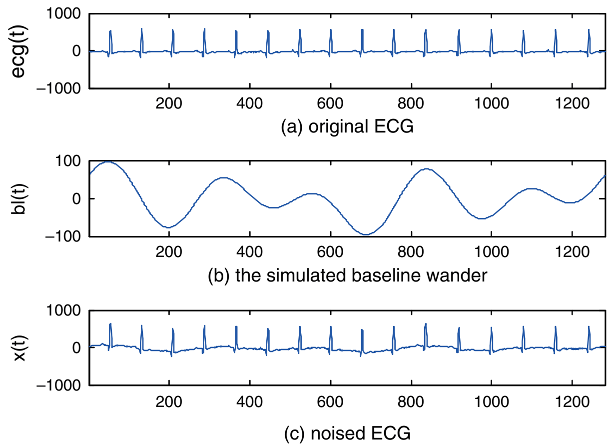

Fig. 1. The No. 16272 ECG signal, the simulated baseline wander signal and the simulated noised ECG signal.

Step 5: After extracting all of the ensemble mean $\overline{\text{imf}}_k(t)$, achieve the final residual component $R(t)$, where N is the total number of ensemble mean IMFs:

$$R(t) = s(t) - \sum_{k=1}^{N} \overline{\text{imf}}_k(t) \tag{5}$$

3. NEW ECG BASELINE WANDER CORRECTION METHOD BASED ON EEMDCAN

A series of the ensemble mean IMFs are obtained by the EEMDCAN. In this method, high-frequency IMFs that have small scales are separated first. Then, low-frequency IMFs that have large scales are separated. In others word, the frequencies of the IMFs decrease gradually. Usually, the ECG baseline wander signal is a slow-changing signal, whose frequency is less than 1.5 Hz.[10, 11] Thus, the baseline wander signal is decomposed into the last few IMFs by the EEMDCAN. So, the baseline wander can be corrected if the IMFs from the Qth to the last IMF are removed

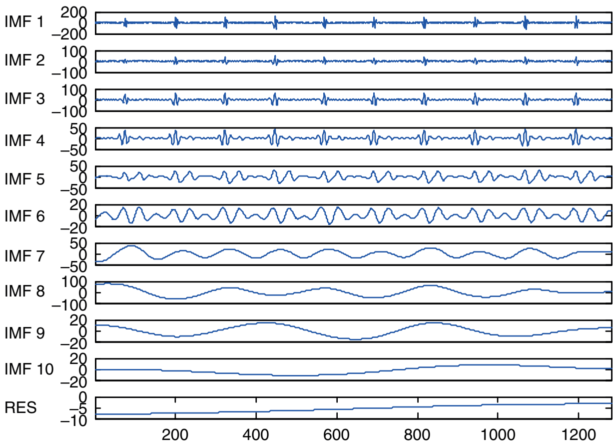

Fig. 2. The decomposition results for the noised ECG signal by the EEMDCAN.

Table I. ZCRs of all the IMFs and the residual component.

IMF	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6
ZCR	79.4	53.0	32.9	17.5	7.9	5.9
IMF	IMF7	IMF8	IMF9	IMF10	Residual	
ZCR	1.9	1.0	0.6	0.1	0	

from the noised ECG signal $s(n)$. Then, we can obtain the clean ECG signal $ecg(n)$.

$$ecg(n) = s(n) - \sum_{i=Q}^{N} \overline{\mathrm{imf}}_i(n) \tag{6}$$

Now, the only issue is how to determine the parameter Q. Here we employ the ZCR to determine Q. In the whole dataset, the number of extrema of an IMF and the number of zero-crossings must either equal or differ at most by one. That is to say, there is no 'riding wave' in an IMF. The ZCR is often used to extract the signal feature and has some relationship with frequency.[12,13] Thus, average ZCR can be used to roughly estimate the frequency of an IMF. Then, we directly remove the IMFs whose ZCRs are less than 1.5 from the original ECG signal. That is because those IMFs whose frequencies are less than 1.5 Hz are considered as the baseline wander signals. The ECG baseline wander correction method can be summarized as follows:

- Decompose the noised ECG signal by the EEMDCAN.
- Count the ZCRs of all the IMFs and the final residual component. Then, remove the IMFs whose ZCRs are less than 1.5 from the noised ECG signal. That is to say, reconstruct the clean ECG signal through formula (6).

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

4.1. The Simulation Experiment

Here we select the No. 16272 ECG signal from Normal Sinus Rhythm Database[14] for reconstruction. The sampling frequency of this signal is 128 Hz. The sampling duration is 10 seconds. As shown in Figure 1(a), there is no baseline wander phenomenon in this ECG signal. The baseline wander signal shown in Figure 1(b) is simulated as follows:

$$bl(t) = 50\sin(\pi t) + 40\cos(0.6\pi t) + 20\cos(0.2\pi t) \tag{7}$$

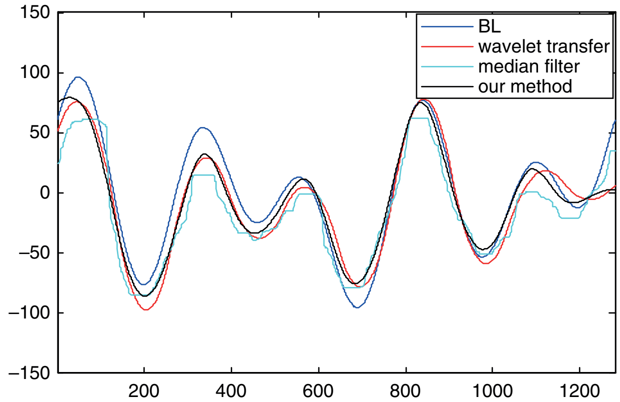

Fig. 3. The extracted wander signals obtained by three methods.

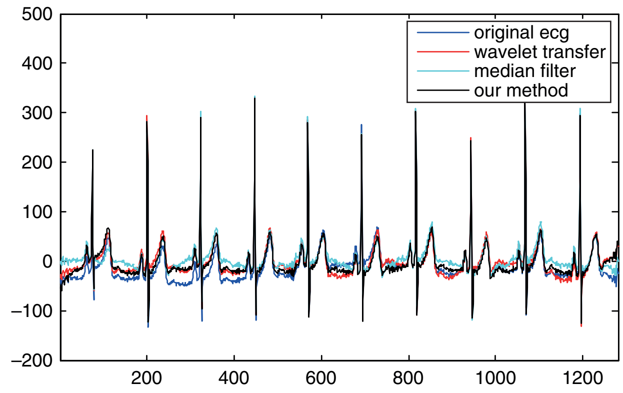

Fig. 4. Corrected ECG signals obtained by three methods.

Then, it is added into the original ECG signal to construct the simulated noised ECG signal $x(t) = ecg(t) + bl(t)$ shown in Figure 1(c).

First, we decompose the noised ECG signal by the EEMDCAN. At the decomposition stage, the amplitudes of the added white noises are 0.2 times of the standard deviation of the original signal, and 500 pairs of positive and negative noise are employed. As shown in Figure 2, the noised ECG signal is decomposed into 10 IMFs and one residual component. Then, we compute the ZCRs of all the IMFs and the residual component shown in Table I. Since the baseline wander is a low-frequency signal whose frequency is less than 1.5 Hz, the IMFs 8–10 and the final residual component should be removed. Then, we reconstruct the ECG signal through the rest of the IMFs according to formula (6). To validate our proposed method, we compare our proposed correction method to two existing methods, i.e., wavelet decomposition and median filtering, in reconstruction performance (shown in Figs. 3 and 4).

Figure 3 shows the extracted wander signals obtained by three methods. Figure 4 shows the corrected ECG signals. We use three metrics, i.e., S/N ratio, Pearson's correlation coefficient (PCC) and root mean square error (RMSE), to evaluate the reconstruction performances (shown in Table II). For the median filtering method, the window length is set 105. For the wavelet method, the wavelet function is bior 3.7 selected from biorthogonal wavelets and the decomposition level is set 7. As shown in Table II, our method outperforms the wavelet decomposition method and the median filtering method.

4.2. Real Signal Test

As discussed in Section 4.1, our method has the potential ability to correct the ECG baseline wander. In this subsection, the No. 18177 ECG signal in MIT-BIH Normal Sinus Rhythm Database[14] is chosen for further verification. As shown in Figure 5(a), the ECG signal obviously contains the baseline wander. We use the EEMDCAN to decompose the ECG signal. Also, the amplitudes

Table II. S/N ratio, PCC and RMSE obtained by three methods.

Methods	Median filtering	Wavelet decomposition	Our method
S/N ratio	6.0237	8.4775	9.2982
PCC	0.9299	0.9453	0.9503
RMSE	21.7114	16.3681	14.8924

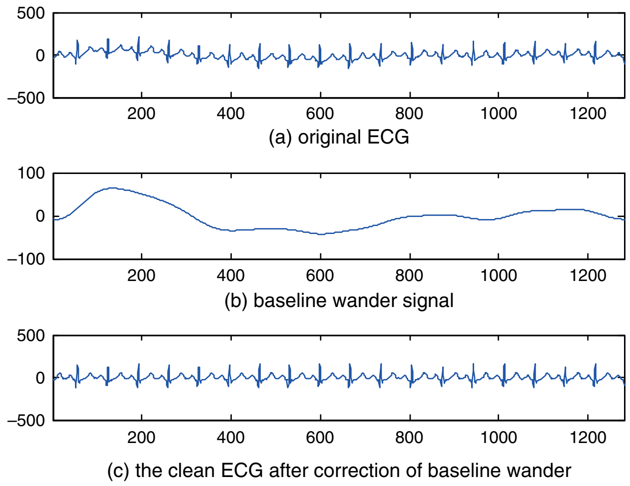

Fig. 5. Reconstruction results of the No. 18177 ECG signal by the EEMD-CAN. (a) Original ECG signal; (b) extracted baseline wander signal; (c) reconstructed clean ECG signal.

of the white noises are set 0.2 times of the standard deviation of the original signal. 500 pairs of positive and negative noise are employed. Then, we extract the baseline wander signal from the last few IMFs and the final residual component according to their ZCRs. Finally, we reconstruct a clean ECG signal through the rest of the IMFs according to formula (6). Figures 5(b) and (c) illustrate the extracted baseline wander signal and the reconstructed clean ECG signal, respectively. The experimental results indicate that our proposed method can correct the baseline wander existing in the ECG signal effectively.

5. CONCLUSION

We propose a new method based on the EEMDAN and the ZCR to remove the baseline wanders existing in the ECG signals. First, we improve the EEMDAN by adding pairs of positive and negative adaptive noises into the signal, which is termed as EEMD-CAN. Then, the baseline wander signal is adaptively extracted from the IMFs by means of the ZCR after the decomposition. The experimental results indicate that the proposed method can remove the baseline wander in the ECG signal effectively compared to the existing methods.

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