Electrocardiography Signal Decomposition Using a Novel Modulated Ensemble Empirical Mode Decomposition Method

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***Abstract*—Electrocardiography (ECG) is an important test in the diagnosis of heart disease. The analysis of T waves in the ECG is an essential clinical tool, however, it is often difficult to extract the T waves from the ECG. Empirical Mode Decomposition (EMD) can decompose nonlinear and nonstationary signals, but this method suffers from the problem of mode mixing. Ensemble Empirical Mode Decomposition (EEMD) can solve the mode mixing problem but generates a new problem, namely, that of the reconstruction error. Moreover, noise may remain in the decomposed signals and pollute the waveforms. Therefore, we propose a new method based on EEMD to solve these problems and to decompose the T wave from ECG. The results show that the T waves' waveforms can be successfully decomposed in the fourth Intrinsic Mode Functions (IMFs) in all 3 cases studied, namely, no noise, power line noise, and Gaussian white noise.**

Keywords- Electrocardiography; Empirical Mode Decomposition; Ensemble Empirical Mode Decomposition; Reconstruction error.

I. INTRODUCTION

Electrocardiography (ECG) is an important biomedical signal which can help to diagnose heart diseases [1]. ECG usually consists of several waveforms. These waveforms are labeled as P wave, QRS-complex, and T wave. Figure 1 shows the ECG and the waveforms. The P wave represents the depolarization of the atria. The QRS-complex is caused by the depolarization of the right and left ventricles. Because the ventricle muscles are bigger than the atria, the QRS-complex's amplitude is usually larger than the P wave. The T wave is generated by the ventricular repolarization, so the T wave is after the QRS-complex. The times or segments between these waveforms are also important features of ECG. The PR-interval is the time cost of the impulse from the sinus node to the atrioventricular node. The PR-interval can help to evaluate the function of the atrioventricular node. The ST-segment represents the period of ventricles depolarization and usually isoelectric. The depression or elevation of ST-segment may represent a cardiac abnormality. The QT-interval is from the beginning of the QRS complex to the end of the T wave and varies with the heart rate. The corrected QT-interval is the QT-interval divided by the square root of the RR-interval. Prolonged Corrected QT-interval is a risk factor for ventricular tachyarrhythmia and sudden death. Therefore, feature extraction and detection of ECG are critical.

For ECG feature extraction and detection, the R wave is important for its timing. Most common feature extraction methods mark QRS-complex firstly and then search the P wave forwardly and the T wave backwardly [2][3]. Unlike the R wave, T wave's amplitude and shape are also as important as its timing. But, the noise like power line noise and Gaussian white noise will affect ECG [4]. The T wave will be influenced, too. Getting ECG features without noise is very important [5]. Many diseases are diagnosed by T wave's feature. For example, T-wave inversion, biphasic T-wave, T-wave alternans, etc. However, most judgments need a long time signal analysis and, moreover, these judgments always depend on doctors and professionals. Therefore, extracting the T wave is necessary and helpful for judging the performance of the heart system [6].

Mahmoodabadi et al. use a multiresolution wavelet to decompose ECG and extract features of ECG [7]. However, the wavelet is not adaptively [8]. The selection of the mother wavelet will limit the performance of the wavelet analysis. Pal and Mitra use Empirical Mode Decomposition (EMD) [9] to detect the QRS-complex of ECG [10]. EMD is a decomposition method that can decompose nonlinear and nonstationary signals into Intrinsic Mode Functions (IMFs) adaptively. However, it has several problems like boundary effect and mode mixing problem. The boundary effect is caused by that extrema value is hard to define at boundary, and will cause IMFs are distorted at the boundary. The mode mixing problem usually occurs when patterns appear intermittently and will cause two issues. The first issue is the

IMFs of EMD will have different scale patterns mixed in. The second issue is the same scale pattern may be separated in different IMFs. So, the ECG, which is one of the signals with intermittent pattern, will hardly to decompose well by EMD. Ensemble Empirical Mode Decomposition (EEMD) is a method which solves the aforementioned problem of the EMD [11]. Unfortunately, EEMD adds noise into signal and will remain noise in it [12]. Because the noise remains in, EEMD is not a good choice to decompose ECG.

In this study, we propose a new method based on EMD and EEMD. The new method will not add noise to the original signal. The Gaussian white noise will only assist to get the reference points which are treated as the extrema points. The modified part will solve the mode mixing problem and avoid adding external noise into the ECG signal. Furthermore, we use this new method to decompose the T wave from ECG. This new method is temporarily named as modulated ensemble empirical mode decomposition.

In Section 2, we will introduce the proposed method and the testing data. In Section 3, we will decompose ECG and simulated ECG by the proposed method. Otherwise, we will add some external noise to test whether the new method is influenced by noises. In Section 4, we will discuss the result and the main IMF of the T wave. In Section 5, the conclusion and further work will be proposed.

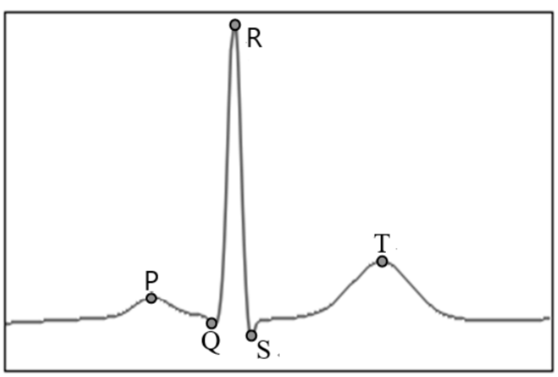

Figure 1. ECG

II. MATERIAL AND METHODS

A. Data

In this study, we verify our method by simulated data and PhysioNet QT database ECG. Simulated data is generated by LabVIEW “Simulate ECG”. The database ECG will take one-minute data and test (A) original signal, (B) signal with 60 Hz power line and (C) signal with Gaussian white noise. The sampling rate is 250 Hz for all signals.

B. Methods

Our method is modified from EMD and EEMD. The detailed processes of EMD and EEMD are shown in Figure 2 and Figure 3.

$SD(.)$ means standard deviation. SD_{input} is the setting of stop criteria. $M(t)$ is the mean envelope. $r_i(t)$ is IMF or residue. Compared to EMD, EEMD adds white noise and averages each IMF to reduce the influence of noise adding.

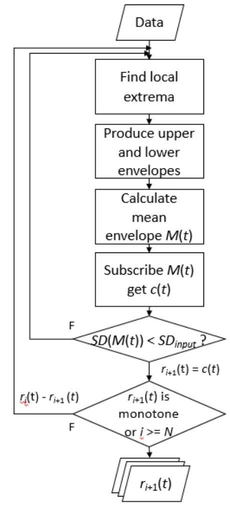

Figure 2. EMD algorithm procedure

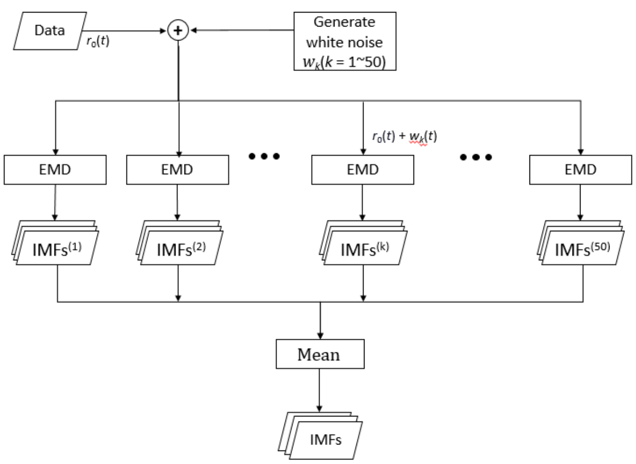

Figure 3. EEMD algorithm procedure

Adding local extrema by adding controlled noise is the main idea of the noise-assisted variations of EMD [13]. Adding noise is a method to solve the mode mixing problem. However, the main idea is gaining local extrema to assist in getting local means. Therefore, we find other points and treat these points as local extrema. Using these upper and lower envelopes’ reference points can also find the local mean of different time scales. To find the upper and lower envelopes’ reference points, we use Gaussian white noise to assist. Different from other methods, our method only picks up the timing of the extrema after adding Gaussian white noise. Then, we use these timings to get the reference points of upper and lower envelopes. Figure 4 illustrates the proposed method.

III. RESULT

A. Simulated ECG

Figure 5(a) is the simulated ECG which is generated by LabVIEW “Simulate ECG”. Figure 5(b) shows IMF_1 to

IMF_4 which are decomposed by the proposed method. The QRS-complex timing can be found easily in IMF_1. The T wave might be decomposed in IMF_4.

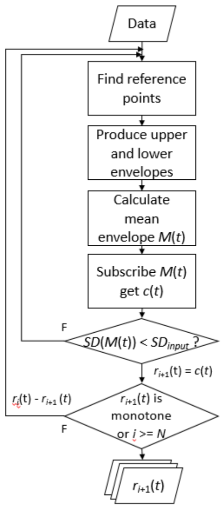

Figure 4. Modulated EMD algorithm procedure

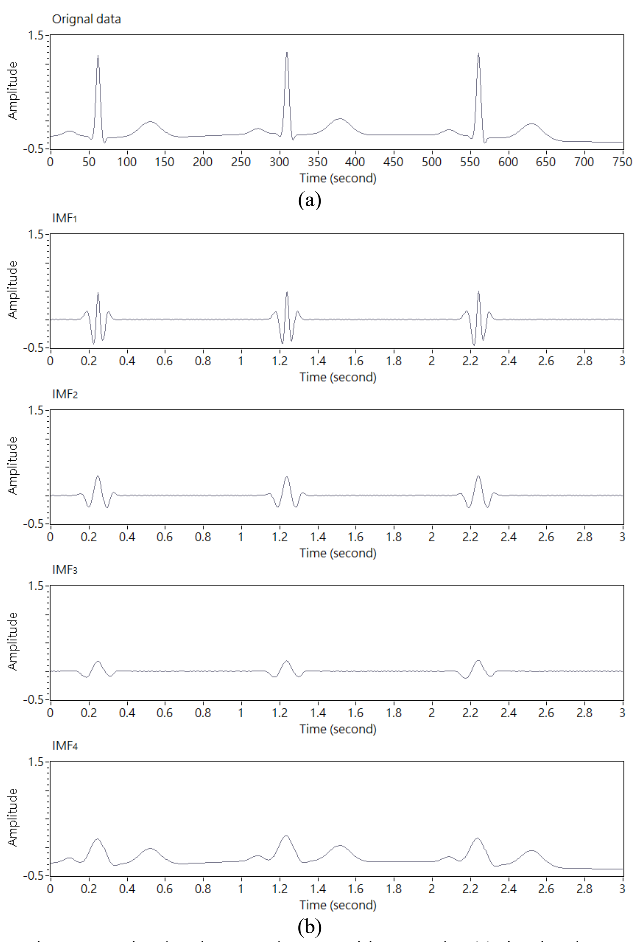

Figure 5. Simulated ECG decomposition result: (a)Simulated ECG which is generated by LabVIEW "Simulate ECG" and (b) decomposition results.

B. QT Database ECG

Because the main purpose is extracting T waves, comparing T wave and IMFs is necessary. T wave timing is obtained by PhysioNet QT database annotation. Figure 6(a) shows the ECG signal sel30 and the T wave is marked by a thick line.

Figure 6(b) shows the results of decomposition and the same periods of T wave are marked by a thick line. IMF_1 might make QRS-Timing obviously. IMF_4 can clearly show the T wave.

C. QT Database ECG with Power Line Noise

The power line is a common noise of the ECG signal and might influence the T wave's waveform. To test whether decomposition can remove the power line noise, the power line is added into signals. The adding power line's amplitude is 1/10 of the ECG signal and the frequency is 60 Hz.

The ECG signal sel30 with power line noise is shown in Figure 7(a) and the T wave period is also marked. Figure 7(b) shows that power line noise is almost dissembled in IMF_1. Therefore, IMF_4 can still find clear T waves. The QRS-complex timing can be checked in IMF_2.

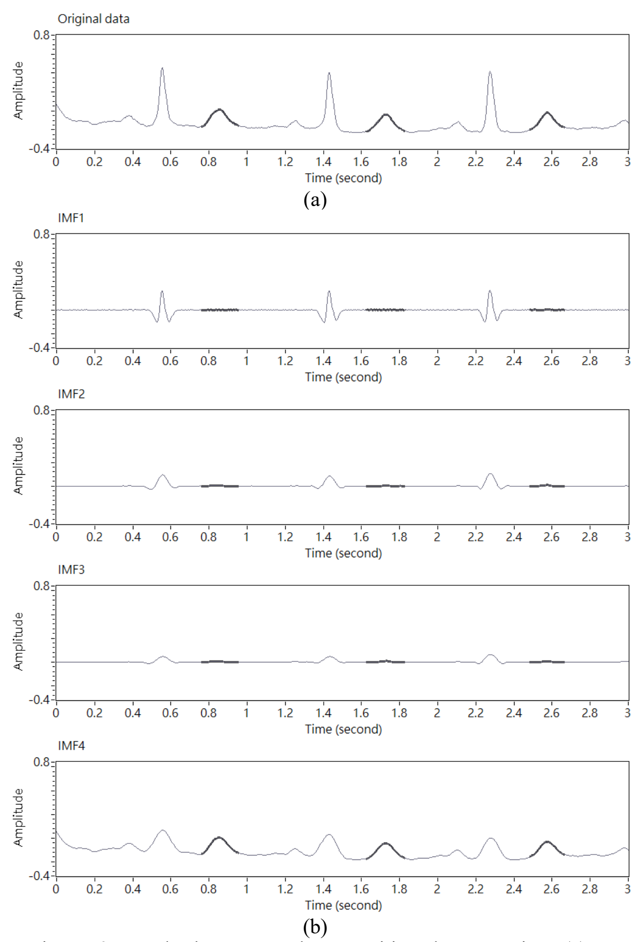

Figure 6. QT database ECG decomposition demonstration: (a) ECG signal sel30 and (b) decomposition results. The thick line marks the T wave period.

D. QT Database ECG with Gaussian White Noise

Gaussian white noise is also a common noise in the ECG signal. To test the decomposition method, Gaussian white noise is added to the ECG signal. The added Gaussian white noise's standard deviation is 1/10 of ECG's standard deviation. Figure 8(a) shows the ECG signal sel30 with Gaussian white noise. Figure 8(b) shows the decomposition results. The T wave can still be seen in IMF_4 clearly. The R-wave timing can be easily marked from IMF_2.

IV. DISCUSSION

Comparing Figure 6, Figure 7, and Figure 8, adding white noise will increase the difficulty of the QRS-complex timing extracting. Moreover, if adding noise in ECG, the IMF number of judgment QRS-complex timing will be changed. Otherwise, the T wave seems to be decomposed in IMF_4. No matter if adding power line noise, Gaussian white noise, or none, the T wave's waveform remains good. Noise seems to be decomposed to other IMFs except for IMF_4. The T wave is always decomposed in IMF_4. It has an advantage of automatically finding IMF with T wave. However, it still needs some judgment indicator to confirm the result.

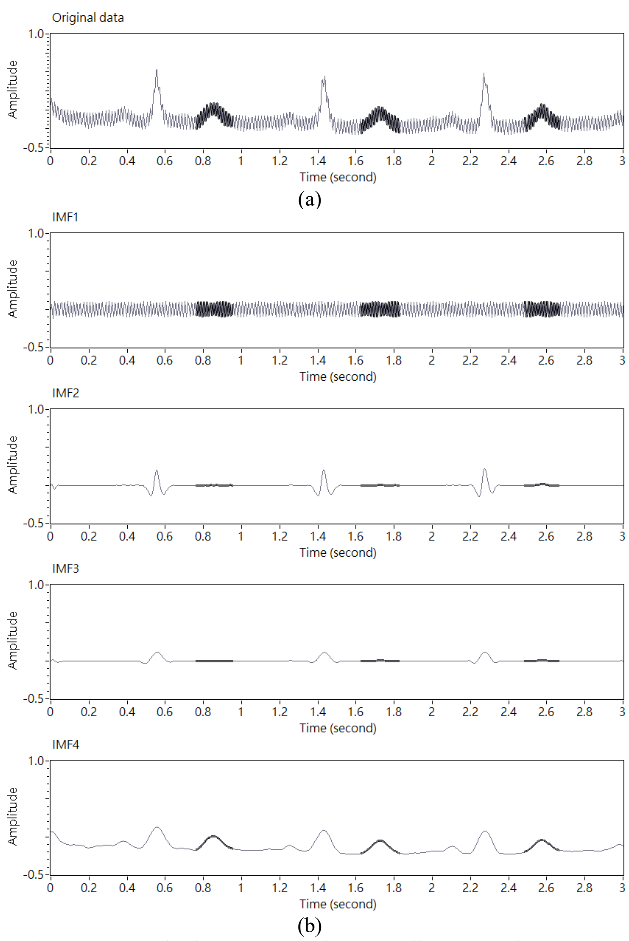

Figure 7. QT database ECG with power line noise decomposition demonstration : (a) ECG signal sel30 with power line noise and (b) decomposition results. The thick line marks the T wave period.

To judge whether decomposition results can extract the T wave, calculating the Correlation Coefficient (r) and the Root Mean Square Error (RMSE) between decomposition results in the T wave period is helpful. These two judgment indicators can check whether the T wave's phase and amplitude are retained.

Figure 9 shows the result of 105 records in the QT database. T waves are decomposed in IMF_4. Most of IMF_4's correlation coefficients are more than 0.9 and most of RMSE are less than 0.1. The result shows that T waves remain good in IMF_4.

Figure 10 and Figure 11 show the results of 105 records with power line noise and 105 records with Gaussian white noise. The results are as good as the results of the clear ECG signals.

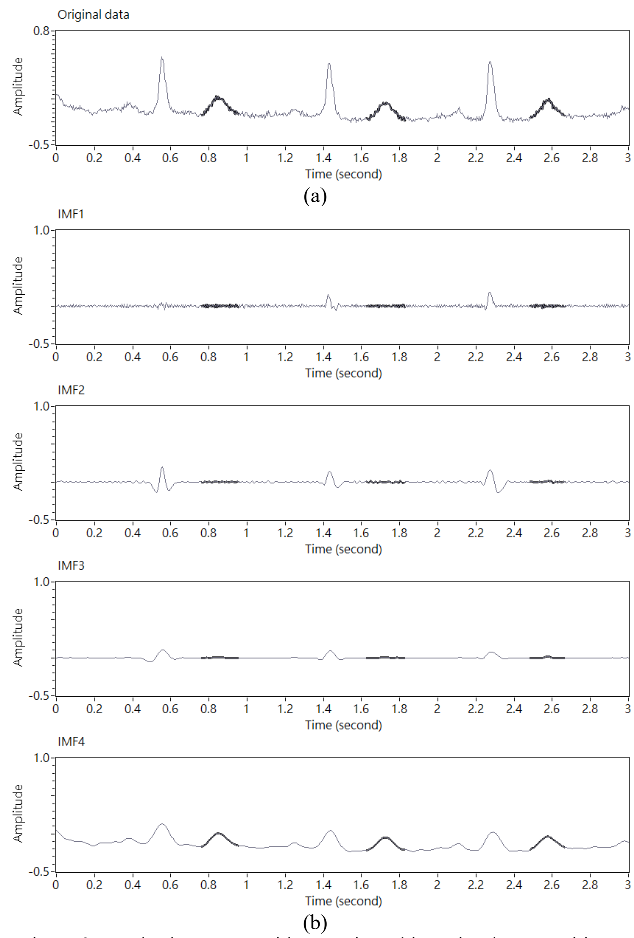

Figure 8. QT database ECG with Gaussian white noise decomposition demonstration : (a) ECG signal sel30 with Gaussian white noise and (b) decomposition results. The thick line marks the T wave period.

Table 1 shows the result of all records with treatments. The IMF_4's correlation coefficients are all over 0.95 and RMSE are all less than 0.04. The proposed method seems to extract the T wave in the IMF_4 and retains the waveform and phase well. Moreover, with the method we proposed, adding slight noise will not influence the T wave extracting. The results show that our method is useful for decomposing T waves. This might be helpful for several heart diseases diagnosing like T-wave inversion, biphasic T-wave, T-wave alternans, etc.

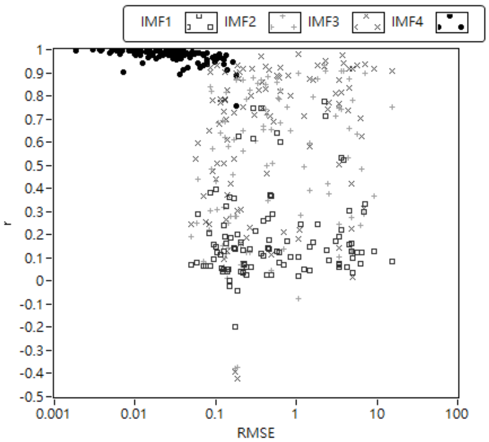

Figure 9. Correlation coefficient and RMSE between ECG signal decomposition results in T wave periods

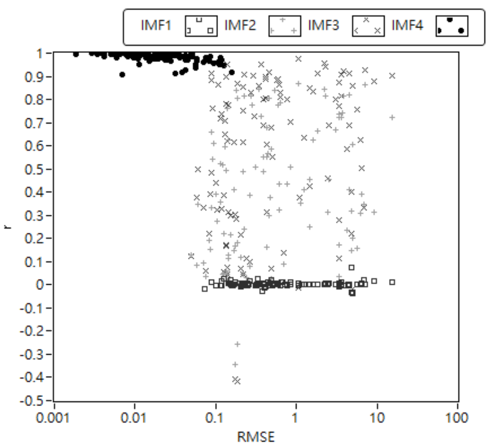

Figure 10. Correlation coefficient and RMSE between decomposition results of ECG signal with power line noise in T wave periods.

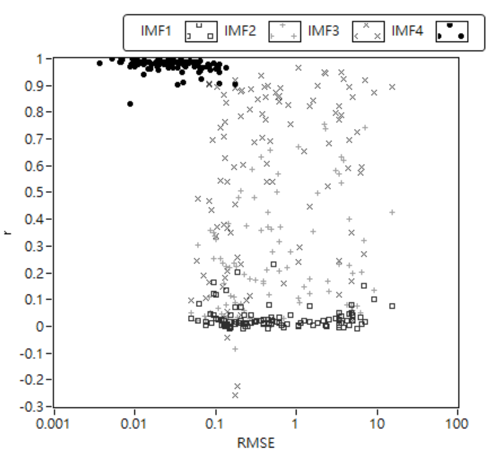

Figure 11. Correlation coefficient and RMSE between decomposition results of ECG signal with Gaussian white noise in T wave periods.

V. CONCLUSION

The results of ECG signal decomposition show that the proposed method extracts T wave well and is helpful for detecting QRS-complex timing. Furthermore, the new decomposition method has less influence on power line noise and Gaussian white noise. The proposed method might help ECG feature extraction and detection.

Although the new method can help to decompose ECG signals, how to automatically mark ECG's features is the next important research.

TABLE I. CORRELATION COEFFICIENT AND RMSE

Judgment indicator	Signal treatments		
	Original signal	***Add power line noise***	***Add Gaussian white noise***
r	0.97±0.03	0.98±0.02	0.98±0.02
RMSE	0.04±0.04	0.03±0.03	0.04±0.03

correlation coefficient and RMSE between IMF_4 and T wave in T wave period

VI. ACKNOWLEDGMENT

This work was fully supported by Taiwan Ministry of Science and Technology under grant numbers MOST 108-2221-E-009-087.

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