f-Wave Suppression Method for Improvement of Locating T-Wave Ends in Electrocardiograms during Atrial Fibrillation

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This article is to propose an algorithm for improving T-wave ends location during atrial fibrillation (AF). The traditional algorithms do not take the irregular baseline fibrillation of AF into consideration, so their location accuracy is relatively low. Based on simple assumptions that AF is a random signal while T waves and QRS complexes are deterministic signals, we suggest a novel method to suppress f wave for improving location of T-wave ends during AF. We firstly define a new cardiac cycle and then match R peaks and T peaks in the three adjacent cardiac cycles. Finally, we suppress the interference of the f wave by averaging. When evaluating with the PhysioNet QT database and simulated AF signals in terms of the mean and the standard deviation of the T-wave ends location errors, the proposed algorithm improves the performance of existing popular methods. Besides, the clinical significance of the proposed method is illustrated.

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atrial fibrillation; f wave; electrocardiogram; T-wave ends; location

INTRODUCTION

Atrial fibrillation (AF) is the most common arrhythmia encountered in clinical practice, affecting about 0.5–1% of the general population,¹ and 10% of those over 75.² Hypertension is a common association with AF patients. In addition, several cardiac disorders are associated with AF, including rheumatic heart disease, pericarditis, congenital heart disease and coronary artery disease.³ Electrocardiogram (ECG) is a noninvasive way to study cardiac electrophysiology. Doctors can get the ventricular rate, QRS complex, QT interval, and ST changes of patients from the ECG, and use these features to diagnose arrhythmia, ventricular hypertrophy, coronary artery disease, myocardial infarction, etc.^{4,5} In the ECG, AF is characterized by a fluctuating baseline which occurs in place

of the P waves. The patterns of f wave vary from person to person; they could be jagged or similar to sine wave.² The f wave could change the location and shape of Q wave, S wave and T wave dramatically, thus disturbing the measurement of these characteristic waves. Especially for the patients with persistent AF, it is a challenge to diagnose the accompanying heart diseases using the ECG; as for paroxysmal AF patients, if the accompanying diseases (such as coronary artery disease) and the AF occur simultaneously, precise detection of characteristic waves in the ECG is also a hard task.

Among the numerous characteristic parameters of the ECG, the QT interval represents electrical depolarization and repolarization of the left and right ventricles. Various methods have been proposed to study QT intervals, and the core issue

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is the location of T wave ends. There are some popular algorithms for detecting the end of T wave: the methods based on thresholds⁶; the methods based on principal component analysis (PCA)⁷; the methods based on slope⁸; and the methods based on wavelet transforms.⁹ For the methods based on thresholds, the thresholds are usually set by the T-peak values or the areas under T wave. Zhang et al. introduced a T wave location method by computing the indicators under T wave. This method firstly established a sliding window, and then computed the ratio of maximal area and minimum area within the sliding window, finally compared the ratio with the thresholds to detect T-wave ends.⁶ Jukk et al. proposed a robust method for estimating ventricular repolarization characteristics, which is based on principal component regression. In their article, they assumed QT intervals were the principal components of signals matrix that was formed based on the R peaks. After obtaining QT intervals without the interference of noise, they located T-wave ends.⁷ Diamant et al. compared the obtained QT intervals from three algorithms of QT extraction with that of manual annotation and then proved that the Mida1000/CoroNet system can accurately and quickly detect the LQTS.¹⁰ Vazquez-Seisdedos et al. developed a location algorithm of T-wave ends based on the computation of Trapezium's areas. This method did not rely on any empirical threshold, and had a good performance in strong noisy environment.¹¹ Among all of these methods, Zhang et al.'s method has a controlled amount of computation and good accuracy. Therefore, it is a common way to locate T-wave ends in recent years. The methods above can locate T-wave ends accurately when the f waves do not appear in the ECG, whereas their location accuracy greatly decreases during AF. The main reason is that the fluctuation of the f wave probably overlaps on T-wave ends, which causes the deformation of T wave. Thus, the additional location errors for T-wave ends will be generated when the above methods are used to locate T-wave ends in the ECG with AF. According to our knowledge, there is no customized method for improvement of location of T-wave ends during AF so far.

In this paper, we propose to suppress the f wave before the popular detection methods of T-wave ends are applied. For this reason, we develop an f wave suppression algorithm. The algorithm feasibility and effectiveness are then evaluated

with the data from PhysioNet QT database.¹² Finally, the practical values of the proposed method are illustrated through analyzing clinical meaning of QT interval measurement.

The article is organized as follows: the f-wave suppression algorithm is introduced in the Method section. The method performance is then evaluated and analyzed in Results, followed by the Discussion.

METHOD

The R peak in QRS complex and T peak have higher amplitudes compared with other characteristic waves in the ECG, so they are hardly disturbed by the f wave during AF and noises. Thus, this article proposed to locate the two wave peaks in the preprocessed ECG first and then suppress the f wave for decreasing its influence on location of T waves.

Preprocessing

We first used a band pass filter with the bandwidth 0.5–40Hz to eliminate the baseline wander, artifacts and high-frequency noise in the ECG signals. After the band pass filtering, the baseline wander at high frequency still remained and impacted the location of characteristic waves. A moving average filter and the root mean square (RMS) method are subsequently applied to further eliminate the rest interference.¹³ For convenience of presentation, the preprocessed ECG signal is represented as $s(n)$, where n is discrete time variable.

Location of R Peak and T Peak

The QRS complex is the predominant characteristic in the ECG signal. Plenty of detection methods for QRS complex have been presented.^{6,11,14–17} This method directly adopted the modified derivative method¹⁷ to detect the R peak in each cardiac cycle of $s(n)$. The T peak in each cardiac cycle is detected by the method proposed by Elgendi et al.¹⁸ The method locates T peak in a block which begins from $40 \cdot (RR/f_s)$ after the previous R peak to $(RR/f_s)/135$ before the next R peak in each cardiac cycle of $s(n)$, where RR is the distance between two adjacent R peaks and f_s is the sampling rate.

The Suppression of f wave

As we all know, AF is uncoupled to ventricular activity² and the morphology, and the position of f wave is irregular.¹⁹ Therefore, the QRS complex and the T wave could be regarded as the deterministic signals, while AF signal could be seen as a random signal. Assuming that the f wave randomly appears and there are no significant changes of the T wave and the QRS complex in three continuous cardiac cycles in the ECG, we proposed to suppress the f wave by averaging the three ECG segments within three adjacent cardiac cycles. The suppression algorithm is detailed as follows.

(1) Defining a new cardiac cycle

Generally speaking, a cardiac cycle in the ECG is from P wave to the end of T wave/U wave, and is traditionally calculated by setting the starting point at 0.3 times of the RR interval before the R peak, and setting the end point at 0.7 times of the RR interval after the R peak.¹⁹ We defined a new cardiac cycle based on the R peak and the T peak to avoid distortion of the T wave morphologies during suppression of the f wave. The starting point of a new cardiac cycle is set at 0.15 times of the RR interval before the R peak, while its ending point is set at 0.2 times of the RR interval after the T peak. It can be seen that the new cardiac cycle defined here is different from the traditional one. Our later analysis will be based on the new cardiac cycle, but it is still called the cardiac cycle for simplicity.

(2) Matching the R peaks and the T peaks in the three adjacent cardiac cycles

Assuming that there are N cardiac cycles in $s(n)$ and the ECG segment extracted from the i th cardiac cycle is represented as a_i . Thus, N ECG segments can be obtained from the $s(n)$. The distance between the R peak and the T peak in the i th cardiac cycle is denoted by $RTI(i)$, $i = 1, 2, \dots, N$. Assuming the number of the ECG samples within the $RTI(i)$ is $Sn(i)$, since the RTI s in the three adjacent cardiac cycles are usually unequal for AF patients, the corresponding $Sn(i-1)$, $Sn(i)$ and $Sn(i+1)$ are unequal. The T peaks in three cardiac cycles cannot be aligned if the R peaks in three cardiac cycles are matched, vice versa. When performing the averaging operation of a_{i-1} , a_i and a_{i+1} ,

the morphologies of the T waves or the R waves in the averaged ECG will change. For example, the T wave in the averaged ECG would become wider than real one. To overcome this, we proposed to synchronously match the R peaks and the T peaks in the three adjacent cardiac cycles through keeping $Sn(i-1)$, $Sn(i)$ and $Sn(i+1)$ equal.

$Sn(i)$ of a_i is first considered as a template and then we, respectively, resample a_{i-1} and a_{i+1} for letting $Sn(i-1)$ and $Sn(i+1)$ are equal to $Sn(i)$. The resampling frequency f_{rs} is defined as follows:

$$f_{rs} = f_s * (Sn(i) / Sn(x))$$

where f_s is the sampling frequency; x is equal to $i-1$ or $i+1$. The resampled a_{i-1} and a_{i+1} are represented as a'_{i-1} and a'_{i+1} . Thus, the R peaks and the T peaks in a'_{i-1} , a_i and a'_{i+1} can be matched since $Sn(i-1)$, $Sn(i)$ and $Sn(i+1)$ are equal after resampling.

(3) Averaging for the suppression of f wave

We need to cut or pad a'_{i-1} and a'_{i+1} for averaging a'_{i-1} , a_i and a'_{i+1} due to unequal lengths of a'_{i-1} , a_i and a'_{i+1} when their R peaks and T peaks are matched. If the head or the end of a'_{i-1} or a'_{i+1} exceed the length of a_i , the extra parts will be cut, whereas the zero padding is used to make the amount of sampling points of a_i , a'_{i-1} and a'_{i+1} the same.

The f wave in a_i is suppressed through averaging a_i , a'_{i-1} and a'_{i+1} . The ECG segment in the i th cardiac cycle after averaging is represented as b_i . Afterwards, the original a_{i+1} will be used as the next reference beat. And b_{i+1} will be obtained when the steps above are repeated. Thus, N ECG segments with the f-wave suppression can be obtained in $s(n)$. The block diagram of the f-wave suppression algorithm is shown in Figure 1.

RESULTS

Data

Since it is hard to collect the benchmark data with annotated T-wave ends from AF patients, we generated the simulated ECGs to evaluate our method by adding simulated AF signals into the standard ECG signals with annotated T-wave ends from PhysioNet QT database.¹²

PhysioNet QT database contains 105 ECG records, and each record consists of two leads of

Figure 1. Block diagram showing the suppression process of f waves.

15-min ECG signals sampled at 250 Hz. However, only T-wave ends in 3542 beats have been annotated by a cardiologist in 105 records. These annotated data are used as the standard ECG signals in our experiment.

Stridh et al. presented a sinusoid and M -1 harmonics to generate the sawtooth-similar shape of AF.² The nonstationary behavior is produced by a time-varying amplitude and cycle length of the sawtooth signal. The method could mimic the vibration of the f wave whose frequency ranges from 3 to 10 Hz. The main parameters in the method include the sawtooth amplitude— a , the modulation peak amplitude— Δa , and the amplitude modulation frequency— f_a , etc. The fibrillation waveform is assumed to vary around the frequency f_0 with a maximum frequency

deviation of Δf and the modulation frequency given by f_f . The fibrillation waveform varies with the selection of parameters. In order to assess the universality of the proposed method, two kinds of AF f-wave models which are very different from each other are selected.

- (1) Rather long cycle lengths, large amplitude and several harmonics. This stands for a large amplitude vibration (here called as pattern A).
- (2) Less sharp waveforms with shorter cycle length and low amplitude. The pattern is assumed to be a small amplitude fibrillation (here called as pattern B).

The setup of parameter values that define each of these two types of fibrillation is presented in

Table 1. Parameter Values Defining the Simulated Fibrillation for Patterns A and B

Parameter	Pattern A	Pattern B
f_0	6	8
Δf	0.5	0.3
f_f	0.23	0.23
M	2	3
a	0.0625	0.0313
Δa	0.0083	0.0075
f_a	0.5	0.5

Figure 2. The AF signals of pattern A (a) and pattern B (b).

Table 1. Figure 2 depicts AF signals of pattern A and pattern B.

The simulated AF signals in pattern A and pattern B are, respectively, superimposed with 3542 beats of standard ECG signals. We obtained two groups of simulated AF ECG signals, which are denoted by group A and group B, as shown in Figure 3.

Location of T-Wave Ends

Zhang’s algorithm,⁶ Pablo’s algorithm²⁰ and Juan’s algorithm²¹ are very popular methods for location of T-wave ends. In this article, three algorithms are applied, respectively, to test the effectiveness of the f-wave suppression method. After that, the clinical significance of the proposed method is illustrated.

In this work, the mean and the standard deviation (SD) of the detection errors, which is defined as the difference between the detected T-wave ends and the annotated T-wave ends, are applied to evaluate the performance of our method. The mean value reveals the average accuracy of T-wave ends location for an algorithm. The SD of

Figure 3. The simulated AF ECGs. (a) The normal ECG; (b) The ECG signals with AF in pattern A; (c) The ECG signals with AF in pattern B. The normal ECG is extracted from the sample point 150419–151919 in the record sel100.

Table 2. The Measurements of T-Wave Ends before Adding AF Signal for Three Algorithms

	Zhang’s Algorithm		Pablo’s Algorithm		Juan’s Algorithm	
	Mean	SD	Mean	SD	Mean	SD
Before adding AF signal	0.25	17.57	4.40	30.79	1.6887	32.50

the detection errors is to reflect the robustness of the algorithm to process different kinds of data.

We measure T-wave ends of all the testing data before adding AF signal using above three algorithms for an intuitive comparison. The results are shown in Table 2. We find that three algorithms have quite different location accuracies.

After adding AF signal, the mean values of the detection errors for the above three algorithms with the f-wave suppression and without it are shown in Figure 4, respectively. The SD values are shown in Table 3. In Figure 4, the mean values of all the methods with the f-wave suppression are obviously lower than that without f-wave suppression. It is shown in Table 3 that the SD increases modestly in some situations after f-wave suppression.

For Zhang’s algorithm, its mean is 0.25 before adding AF signal. This indicates that its average accuracy is very high in this case. After adding AF signal, the mean values decrease from 13.29 without f-wave suppression to 10.6 with f-wave suppression for group A and from 4.95 to 2.49 for group B (Figure 4 (a)). The results showed that

Figure 4. The comparisons of the mean values (a) Zhang's algorithm. (b) Pablo's algorithm. (c) Juan's algorithm.

the influence of the f wave on the performance of Zhang's algorithm is very large and the influence of pattern A is larger than that of pattern B. The main reason is that Zhang's algorithm determines T-wave ends based on the areas under T wave. However, the area is largely affected by the amplitude of the f wave, so the performance of this algorithm is easier to be affected by the AF signals, especially by the pattern A. The SD values without and with f-wave suppression after adding AF signal are lightly larger than that before adding AF signal.

The SD decreases a little in both groups after f-wave suppression compared with that before f-wave suppression (Table 3). Using our method, the improvement on Zhang's algorithm keeps almost the same under two f-wave patterns. Although our method can improve the location performance of Zhang's algorithm during AF, the improved effectiveness is still limited by the weakness of this method.

For Pablo's algorithm, its mean is 4.40 before adding AF signal. After adding AF signal, the mean values decrease from 5.57 without f-wave suppression to 3.15 with f-wave suppression for group A and from 5.47 to 1.07 for group B (Figure 4(b)). Two similar mean values before the f-wave suppression illustrate that the derivative-based method has a stable property when it deals with the f waves of different patterns. After the f-wave suppression, both mean values in group A and B are lower than that before f-wave suppression. This phenomenon can be explained as follows: our method can suppress not only the f wave but also the residual noise in the ECG. The SD of Pablo's algorithm increases in both groups after the f-wave suppression. Taken the decrease in the mean values into consideration, it illustrates that in some records, the accuracy is higher than others.

Juan's algorithm is based on wavelet transform technique. The wavelet transform allows the representation of the temporal features of a signal at different resolutions. For this algorithm, its mean is 1.6887 before adding AF signal. After adding AF signal, the mean values decrease from 7.37 without f-wave suppression to 2.39 with f-wave suppression for group A and from 5.63 to 0.59 for group B (Figure 4(c)). It is shown that using our method, the improvement is obvious under f wave with pattern A and the average accuracy is higher under f wave with pattern B compared with that before adding AF signal. From the SD's perspective, in group A, after the f-wave suppression, the SD increases considerably. Since the mean in this case is close to the mean before adding AF signal and has been decreased by over 60% compared with the one without f-wave suppression, this phenomenon implies the proposed method improves the accuracy of Juan's algorithm modestly in some records, but in others the increase in accuracy is larger. In group B, the SD keeps stable after f-wave suppression. So the accuracy under these two f-wave patterns are very different.

Table 3. The Comparisons of the SD after Adding AF Signal for Three Algorithms

		Zhang's Algorithm	Pablo's Algorithm	Juan's Algorithm
Group A	Without suppression	31.13	41.63	49.84
	suppression	30.35	50.66	74.3
Group B	Without suppression	21.98	37.97	43.98
	suppression	21.86	47.38	44.38

Table 4. The Values and Status of QTc Annotated and Computed by the Improved Version and Zhang's Algorithm for Data sel310

The Occurrence Time (Sampling Point)	Annotation		Zhang's		Improved Version	
	QTc	Status	QTc	status	QTc	status
150150-150228	0.4296	Normal	0.4411	Abnormal	0.4353	Normal
150272-150354	0.4296	Normal	0.4411	Abnormal	0.4296	Normal
150398-150473	0.4296	Normal	0.4468	Abnormal	0.4296	Normal
150522-150597	0.4296	Normal	0.4411	Abnormal	0.4354	Normal
150644-150719	0.4354	Normal	0.4411	Abnormal	0.4354	Normal
150765-150840	0.4354	Normal	0.4411	Abnormal	0.4296	Normal
150885-150962	0.4354	Normal	0.4411	Abnormal	0.4354	Normal
151007-151084	0.4296	Normal	0.4411	Abnormal	0.4296	Normal

Among three locating methods, before adding AF signal, Zhang's algorithm has the best location accuracy. The accuracy of Juan's algorithm is better than that of Pablo's algorithm. After adding AF signal, without the f-wave suppression, Pablo's algorithm performs best among all since derivative-based method can restrain disturbance of fibrillation; with the f-wave suppression, Juan's algorithm has the best mean values, but the SD is increased largely. Zhang's algorithm is based on the area under T wave, so it is sensitive to the fibrillation and performs worse than other algorithms in terms of mean values. However, Zhang's algorithm has stable SD in both groups.

The Clinical Significant Analysis

Our method can improve the location accuracies of T-wave ends of popular methods during AF. By considering the mean and SD comprehensively, we adopted Zhang's algorithm to further illustrate the practical values of the proposed method.

The QT interval is defined as the time duration between the onset of the QRS complex and the end of the T wave. Thus, the location accuracy of T-wave ends is one of the important factors that impact the correct measure of QT intervals.

Clinically, the QTc is one of the important diagnose indexes for heart diseases. The QTc is defined by Equation (1).

$$QTc = QT / \sqrt{RR} \quad (1)$$

The normal range of QTc is between 350 and 440 ms.²² If the QTc value of a patient is beyond the normal range, the patient is probably diagnosed as long QT syndrome or short QT syndrome. The abnormalities of QTc may also lead to the diagnosis of Rheumatic heart disease or drug-induced arrhythmia.²³

We demonstrated the practical values of our method by analyzing a special case: "borderline" long QTc, whose values are labeled between 440 and 470 ms and which often cause uncertain diagnosis. In our experiment, the starting point of Q wave is set at the annotated position according to the QT database and the T-wave ends are located by Zhang's algorithm and its improved method which is processed by our f-wave suppression method.

For Zhang' algorithm, 40 QTc values annotated as normal status are wrongly measured as the "borderline" long QTc since of its great location errors of T-wave ends during AF, while 72 QTc values that are annotated to be beyond the normal range cannot be located. However, the measuring results using the improved method based on

Zhang's algorithm for 112 QTc above are consistent with that annotated by the experts. As an example, the QTc values in record sel310 annotated and measured by the improved version and Zhang's algorithm were shown in Table 4 for comparison.

The results in Table 4 show that the improved method can effectively correct the QTc values computed by Zhang's algorithm from the abnormal status to the normal status and reduce possible misdiagnosis. Hence, the improved method has a great clinical application value.

DISCUSSION

In this article, a novel method that improves the location of T-wave ends during AF has been proposed. The novel method takes advantage of non-stationary and random characteristics of f wave and cancels the fluctuation of the f wave using the simple averaging technique. A great amount of simulated data has been used to confirm the feasibility and effectiveness of our method. Compared with locating T-wave ends directly, the proposed method is considered to improve the accuracy when locating the T-wave ends during AF. The proposed method can improve the diagnosis results based on the QTc measures in some cases. For example, the normal QTc are measured as the "borderline" long QTc by popular algorithms. Similarly, our method can also be applied to improve the location accuracies of other characteristic waves (such as Q and S waves) during AF. Thus, our method has great practical prospects in clinical diagnosis.

So far, many researches have focused on extraction of AF signal from ECG, such as average beat subtraction (ABS) algorithm, QRST Cancellation, PCA algorithm and so on. We tried to extract AF signal first and then subtracted it from the original ECG signals for suppressing the f wave. However, due to the accuracy limitation of AF signal extraction methods, the morphology of residual ECG is seriously distorted, which produces new interference and brings new challenges to locate T-wave ends using popular algorithms.

The T-peak location during AF is a key step in our method. If T peaks in the three adjacent cardiac cycles are wrongly located, but their relative positions in the adjacent cardiac cycles keep same, the effectiveness of f-wave suppression of our method is not affected. It shows that our method is robust to inaccurate location of T peaks. However,

our method is dependent on the consistence of relative positions of T peaks in three adjacent beats. If the T peak of reference beat is dislocated and the T peaks in adjacent beats are recognized correctly, the f wave can still be suppressed, but T-wave end will be blurred. Under this special situation, the suppression of f wave would lose its meaning. Therefore, we need assume that there are no significant changes of the T wave and the QRS complex in three continuous cardiac cycles in the ECG when our method is applied. In most situations, the morphologies and the SNR condition of adjacent T peaks abruptly varying from beat to beat are not very common phenomenon in term of all signals.

In our future studies, we shall develop novel algorithms of characteristic wave detection in the ECG which are robust to the influence of the f waves with different patterns.

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