An effective frequency domain feature of atrial fibrillation based on time-frequency analysis

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Abstract

Background: Atrial fibrillation(AF) is a kind of persistent arrhythmia that can lead to serious complications. Therefore, accurate and quick detection of atrial fibrillation by surface electrocardiogram (ECG) has great importance on further treatment. The practical ECG signals contain various interferences in different frequencies, such as myoelectricity interference, power interference and so on. Detection speed and accuracy largely depend on the AF signal features extracted by algorithm. But some of the discovered AF features are not well distinguishable, resulting in poor classification effect.

Methods: This paper proposed a high distinguishable atrial fibrillation feature - the frequency corresponding to the maximum amplitude in the frequency spectrum (MAiFS). We used the R-R interval detection method optimized with mathematical morphology method and combined with the wavelet transform method for analysis. According to the two features - the MAiFS and R-R interval irregular, we can recognize AF in ECG signal by decision tree classification algorithm.

Results: The data used in the experiment comes from the MIT-BIH database[16], which is publicly accessible via the web and with ethics approval and consent. The dataset contains 23 annotated ECG records, each of which is approximately 10 hours with a sampling rate of 250Hz and a 12-bit resolution with a range of 10mv. Based on the input of time-domain and frequency-domain features, a supervised classifier is constructed by using decision tree algorithm, and the data obtained from the above experiments are brought in to carry out a 5-fold cross validation test, the accuracy of classification reaches 98.9%.

Conclusions: The frequency corresponding to the maximum amplitude in frequency spectrum in the normal signal is concentrated and the fluctuation is weak. But the frequency corresponding to the maximum amplitude in frequency spectrum in the atrial fibrillation signal is divergent and irregular.

The decision tree algorithm can detect the normal signal and AF signal with 98.9% accuracy.

Key words: atrial fibrillation; frequency domain feature; time-frequency analysis; ECG; decision tree algorithm

I. BACKGROUND

Atrial fibrillation (AF) is the most common arrhythmia, with a prevalence rate of 1.5% to 2% in developed countries[1]. When AF occurs, the regular order of atrial electrical activity disappears, replaced by a fast and disorderly tremor wave, and the atrial electrical activity is seriously disordered. Patients with AF are often accompanied by symptoms such as palpitations, arrhythmia, shortness of breath, and chest pain. The incidence of AF increases with age, and the most serious complication is stroke. Early diagnosis can effectively reduce the incidence of complications caused by AF.

An electrocardiogram (ECG) is a technique that uses a medical device to collect and record a pattern of changes in activity produced by a person's body surface every cycle of the heart. Compared with other bioelectrical signals, ECG signals are more easily monitored and have certain regularity. Typical ECG signals mainly include P wave, Q wave, R wave, S wave, and T wave, as shown in Figure 1. As the frequency of AF increases, the original normal P-waves disappear and are replaced by a series of irregular high-frequency oscillations called F-waves; the distance of R wave varies irregularly. The above two features have become the basis of the current automatic detection AF technology [2].

The current diagnosis of AF relies primarily on the presence of some typical symptoms of the patient and the characteristics of the ECG recording. However, early and accurately diagnosing AF remains a challenge. Symptoms of AF are less relevant than they occur, suggesting that there may be no symptoms of AF in some patients, and many paroxysmal AF episodes may be asymptomatic. It is required that clinicians have good professional knowledge and skills to accurately interpret ECG, and visual inspection of ECG signals is quite time consuming. Therefore, it is valuable to develop an automatic detection algorithm that can diagnose AF quickly, accurately and reliably[2]. It is also of great significance to explore effective and high distinguishable features of atrial fibrillation to realize automatic detection of atrial fibrillation.

The methods of extracting ECG features for AF are generally divided into time and frequency domain. The former is mainly about analysis of P-waves features [3-5] and detection of R-R intervals[6]; the latter is to detect AF by comparing the characters of all frequency bands that come from the fast Fourier transform (FFT) of P-waves or F-waves in ECG[7]. He Runnan et al[8] proposed a way of detecting AF based on Continue Wavelet Transform(CWT) and two dimensional convolutional neural network by analyzing ECG's overall time-frequency characteristics. S. Asgari et al[9] applied wavelet transform to extract peak-to-average power ratio and logarithmic energy entropy as feature vectors for AF detection. The method has no essential to detect the peak value of P-waves and R-waves while it has a narrow practical application owing to operated by hands. Rasmus S. Andersen et al[10] used deep learning techniques to combine convolutional neural network CNN with recurrent neural network RNN to establish an end-to-end model and extract R-R interval features for classification. Masci et al proposed a proof of AF based on hemodynamic information[11].

Based on time-frequency analysis, this paper proposes a new atrial fibrillation feature - the maximum amplitude in the frequency spectrum (MAiFS). And the feature has been carried out experimental verification. The processes of analysis are shown in Figure 2.

First of all, removing the high frequency noise and baseline drift of the ECG signal by filtering. Then, the ECG signal is segmented by 5s so that detecting the R wave peak of each period to extract the average and the variance of the R-R interval which can characterize the degree of regularity of the R-R interval and obtain the time domain characteristics of the signal. Next, the filtered signal is

segmented according to the R peak to obtain a single-period ECG waveform, and then the signal is reconstructed by means of wavelet decomposition to extract the R wave characteristic waveform. What's more, we can obtain the maximum amplitude in the frequency spectrum (MAiFS) by fast Fourier transform of the characteristic waveform. Thus we can obtain the frequency domain characteristic of the signal. The above two types of features are used as the finally extracted AF signal features. And using the decision tree classification algorithm to detect AF. Finally, we prove the validity and feasibility of the extracted features through the MIT-BIH AF dataset.

II. METHODS

A. Time domain features extraction method

1)Mathematical morphology filtering

Mathematical morphology[12] is a topology image structure analysis method based on geometric structure. It can be used to design morphological filters. The basic idea is to design probes to acquire the features of images. The basic operations include corrosion and expansion.

Let $f(n), (n = 0,1, \ldots, N-1)$ and $g(m), (m = 0,1, \ldots, M-1)$, among them$N \gg M$。

Defining corrosion operations

$$(f\Theta g)(n) = \min_{m=0,1,\ldots,M-1} \{f(n+m) - g(m)\}$$

Defining expansion operations

$$(f \oplus g)(n) = \max_{m=0,1,\ldots,M-1} \{f(n-m) + g(m)\}$$

As the different order of corrosion operation and expansion operation, mathematical morphology gives two different morphological operations and defines the first etching and then expansion as open operation and first expansion and then etching as closed operation.

Defining $f(n)$ on $g(n)$ open operation

$$f \circ g = (f\Theta g) \oplus g \tag{1}$$

Defining $f(n)$ on $g(n)$ closed operation

$$f \bullet g = (f \oplus g)\Theta g \tag{2}$$

Through mathematical analysis, it can be proved that the morphological opening operation can flatten the peak and the closed operation can fill the trough. For the ECG signal, the waveforms except the R wave can be flattened by the mathematical morphology operation.

2)Shannon Energy Envelope

Considering that the ECG signal fluctuates greatly near the R wave and according to the Shannon energy function[13], the response to the low amplitude is weak in the range of (0,1), and the response to the high amplitude is strong. We differentiate and normalize the filtered signal. And the resulting function values are smooth enveloped by a moving average method.

The Shannon energy operation is defined as:

$$y(n) = -|x(n)|^2 \times \ln(|d(n)|^2) \tag{3}$$

To prevent signal signature delays during smoothing, we use a sliding mean filter without phase shift:

$$y(n) = \frac{1}{N}(x(n - \frac{N-1}{2}) + x(n - \frac{N-1}{2} + 1) + \cdots + x(n + \frac{N-1}{2})) \tag{4}$$

If window overflow occurs in the head or tail segment of the signal, taking$\min(1, n - \frac{N-1}{2})$ and $\max(\text{length}(\text{signal}), n + \frac{N-1}{2})$ where L is the length of the signal, to do some appropriate changes and the N in denominator of the formula should be appropriately adjusted.

Through Shannon energy envelop, we can obtain the specific position of R peak. At the meantime, the refractory period is set after each R peak detection. In the refractory period, even if there is a peak in the signal, it is not considered to be an R peak. In this test model, the refractory period is set to 200ms.

B. Frequency domain feature extraction method

Wavelet transform (WT)[14] is a powerful technology for representing a signal in different translations and scales. In practical applications, since the ECG signal is a short-term non-stationary random process, the Fourier transform based on the stationary stochastic process cannot reflect the essential characteristics of AF. Wavelet transform analysis method provides the possibility of extracting non-stationary random signal features.

1) Wavelet transform theory

For any signal $f(t) \in L^2(T)$, the wavelet transform[14] is:

$$W_f(a, b) = < f, \psi_{a,b} > = |a|^{-\frac{1}{2}} \int_R f(t) \overline{\psi(\frac{t-b}{a})} dt \tag{5}$$

Where $\psi(t)$ is a mother wavelet, a is the dilation factor and b is the translation factor. Different frequency and time localizations can be achieved by adjusting a and b.

Since the ECG signal is stored in the form of discrete finite length signals, continuous wavelet changes must be discretized for ease of calculation. Usually, the discrete formula of the dilation factor and the translation factor in the continuous wavelet transform is taken as： $a = a_0^m$， $b = na_0^m b_0$， where $j \in z$， $a_0 \neq 1$. The corresponding discrete wavelet function can be expressed as:

$$\psi_{m,n}(t) = a_0^{-\frac{m}{2}} \psi(\frac{t - na_0^m b_0}{a_0^m}) = a_0^{-\frac{m}{2}} \psi(a_0^{-m} t - nb_0) \tag{6}$$

At this point, the discrete wavelet transform of $f(t)$ is:

$$WT_f(m, n) = \int_R f(t) \overline{\psi_{m,n}(t)} dt \tag{7}$$

Its reconstruction formula is:

$$f(t) = C \sum_{-\infty}^{\infty} \sum_{-\infty}^{\infty} WT_f(m, n) \psi_{m,n}(t) \tag{8}$$

2) Mallat algorithm

Multi-resolution analysis constructs a series of orthogonal function spaces to decompose the sequence into a low-frequency signal and a series of high-frequency signals (the number of high-frequency signals depends on the number of decomposition layers). As for discrete-time signals, the dyadic discrete wavelet transform (DWT) can be implemented by low-pass, h(n), and high-pass, g(n), filters[15]. The Mallat algorithm is a fast algorithm for constructing orthogonal wavelets. The recursive formula of the decomposition can be expressed as:

$$CA_{j+1} = HCA_j$$
$$CD_{j+1} = GCD_j$$

Where CA_j and CD_j are respectively column vector forms of wavelet coefficients, and H and G are respectively a matrix composed of low-pass filtering and high-pass filter coefficients of the corresponding filter.

The signal reconstruction process can be expressed as:

$$CA_j = H^* CA_{j+1} + G^* CD_{j+1} \tag{9}$$

It can be seen that the essence of wavelet transform is a filtering process. The obtained approximate coefficients represent the low-frequency characteristics of the signal, and the detail coefficients represent the high-frequency characteristics of the signal. Therefore, the wavelet transform can be used to analyze the ECG signal and extract the characteristics of AF.

III. RESULTS

A. Data source and preprocessing

The data used in the experiment comes from the MIT-BIH database[16], which is publicly accessible via the web and with ethics approval and consent. The dataset contains 23 annotated ECG records, each of which is approximately 10 hours with a sampling rate of 250Hz and a 12-bit resolution with a range of 10mv. The dataset covers 605 heart diseases: 12 borderline rhythms, 14 atrial flutter, 288 other thymus beats, and 291 AF. Each record contains ECG1 and ECG2 two Off Lead-linking. In the study, ECG1 recorded for each electrocardiogram is selected for the experiment.

The preprocessing is divided into two steps: splitting the signal and filtering. Splitting signal is to divide the input ECG signal into segments of 5 seconds for subsequent processing. Filtering is to design a FIR digital filter by using a window function method and filtering the ECG signal. Its cutoff frequency are set to 0.5Hz and 30Hz. The purpose of setting a cutoff frequency to 30Hz is to eliminate electromyography interference and 50Hz frequency interference. The purpose of setting a cutoff frequency to 0.5Hz is to eliminate human respiration, movement of the electrode and other low frequency interference. Results are shown in Figure 3.

B. Time domain feature extraction

As the mean and variance of R-R interval can represent the regularity of ECG signal in different conditions, the mean and variance of R-R interval in normal condition and AF condition are taken as time-domain features in this paper. The process can be divided into three steps: mathematical morphological filtering, determining the R-wave position by using the fragrance energy envelope, extracting R-wave waveform and analyzing time-domain features.

Firstly, the preprocessed ECG signal is filtered by mathematical morphology. The result is shown in Figure4.

Then using Shannon energy calculation for further activation and carry out zero phase shift envelope to extract the envelope curve peak and get R wave position, as shown in Figure5.

After the detection of R waves from normal and AF signal segments, carrying on statistical analysis of mean value, variance and number of R waves of R-R interval. The result shows in Figure 6.

It can be seen that normal signal and AF signal's R-R interval mean, variance, R-R interval and the number of waves have significant differences. Therefore, they can be considered as a time domain feature in ECG signal.

C. *Frequency domain feature extraction*

The processes of extracting frequency domain feature can be divided into three steps: performing four layer wavelet decomposition, reconstruction based on fourth layer, performing Fast Fourier Transform and marking the maximum amplitude in frequency spectrum (MAiFS).

The fourth layer discrete wavelet transform is performed on a single waveform, and the sub-band signal bandwidth obtained after decomposition is as shown in Table 1. The sampling frequency is 250Hz.

After using fast Fourier transform, the sub-band signals of this waveform is shown in Figure 7 and it can be seen that the frequency distribution of each sub-band signal is consistent with that shown in Table 1.

Then decomposing the AF signal and normal signal according to the frequency range of each sub-band, and the results are shown in Figure 8 and Figure 9.

Next, using the approximate decomposition coefficients of the fourth layer to reconstruct the normal signal and the AF signal, as shown in Figure 10.

Then performing fast Fourier transform to analyze the two kinds of reconstructed signals, which are shown in Figure 11.

We can obtain the frequency corresponding to the maximum amplitude in the spectrum, which can be used as the frequency domain characteristic of the ECG signal. Statistical results of frequency-domain characteristic of normal condition and AF condition as shown in Figure 12 (partial data).

It can be seen that the frequency corresponding to the maximum amplitude is intensively located in 1Hz in the spectrum of the reconstructed normal ECG signal. However, in the spectrum of the reconstructed AF ECG signal, the frequency corresponding to the maximum amplitude is discretely located from 2Hz to 8Hz. Therefore, the frequency corresponding to the maximum amplitude of the spectrum can be used as the frequency-domain feature in ECG signal in order to detect AF.

D. *Classification using decision tree algorithm*

Decision tree [17] is a tree structure composed of node and directed edge. There are two kinds of node in decision tree. One is internal node, another is leaf site. Each internal node represents a test on a feature attribute and each branch represents the output of the feature attribute in a value domain and each leaf node stores a category. The process of using decision tree to make decision is to start from the root node, test the corresponding characteristic attribute in the item to be classified, and select the output branch according to its value until reaching the leaf node, and take the category stored by the leaf node as the decision result.

Based on the input of time-domain and frequency-domain features, a supervised classifier is constructed by using decision tree algorithm, and the data obtained from the above experiments are brought in to carry out a 5-fold cross validation test, and the confusion matrix of the classification results is obtained as Figure 13.

From the confusion matrix, we can see that the accuracy of classification reaches 98.9%, which proves the effectiveness of the extracted features.

IV. CONCLUSION

There are significant differences in RR interval mean, variance and the number of R waves between normal ECG and AF ECG signals: RR interval mean of normal ECG signal is between 0.78s and 0.95s, RR interval variance is concentrated near 0, The number of R wave is between 4 and 6; RR interval

mean of AF ECG signal is between 0.35s and 0.6s, RR interval variance fluctuates greatly. The number of R wave is between 8 and 12.

The frequency corresponding to the maximum amplitude of frequency spectrum in the normal signal is concentrated and the fluctuation is weak. But the maximum amplitude in the frequency spectrum (MAiFS) in the atrial fibrillation signal is divergent and irregular.

The decision tree algorithm can detect the normal signal and AF signal with 98.9% accuracy.

The experimental results can prove the validity of the frequency corresponding to the maximum amplitude in frequency spectrum (MAiFS) proposed in this paper and the practicability and accuracy of the application of this feature in the detection of AF.

A. Abbreviations

MAiFS : the maximum amplitude in the frequency spectrum.

AF: Atrial fibrillation.

ECG: electrocardiogram

V. DECLARATIONS

A. Ethics approval and consent to participate

Not applicable.

B. Consent for Publication

Not applicable.

C. Availability of data and material

The MIT-BIH Atrial Fibrillation databases can be found here:HTTPS://WWW.PHYSIONET.ORG/CONTENT/AFDB/1.0.0/. Accessed 4th Nov 2000.

D. Competing interests

The authors declare that they have no competing interests.

E. Funding

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F. Authors' contributions

For this paper, YH. and YZ. have the equal contributions. Therefore, they are co-first author. As so. JL. supervises the whole project, she is the corresponding author. JP., CZ. and PL. also take part in the project. All authors read and approved the final manuscript.

G. Acknowledgements

Not applicable.

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VI. FIGURE LEGENDS

a)

b)

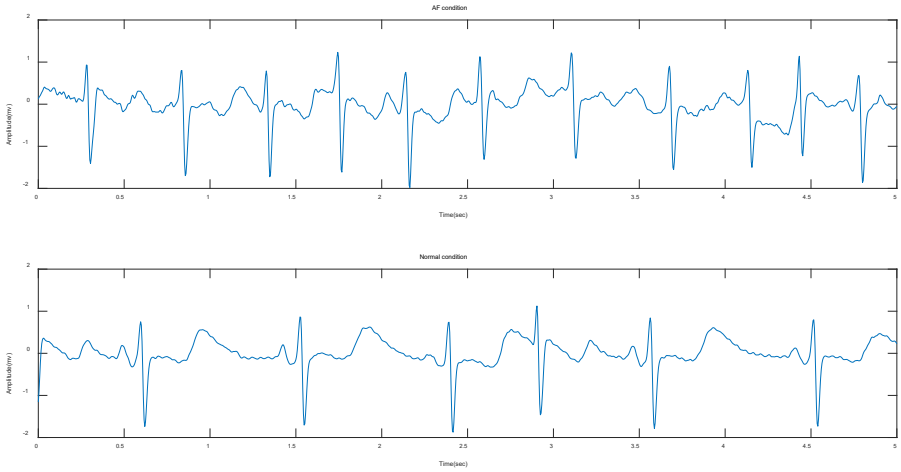

Figure 1 5s original ECG signal section in AF condition and normal condition.(a) normal condition,(b) AF condition. It can be seen that P waves are replaced by irregular F waves in AF condition. Other waves are not very different between AF condition and normal condition.

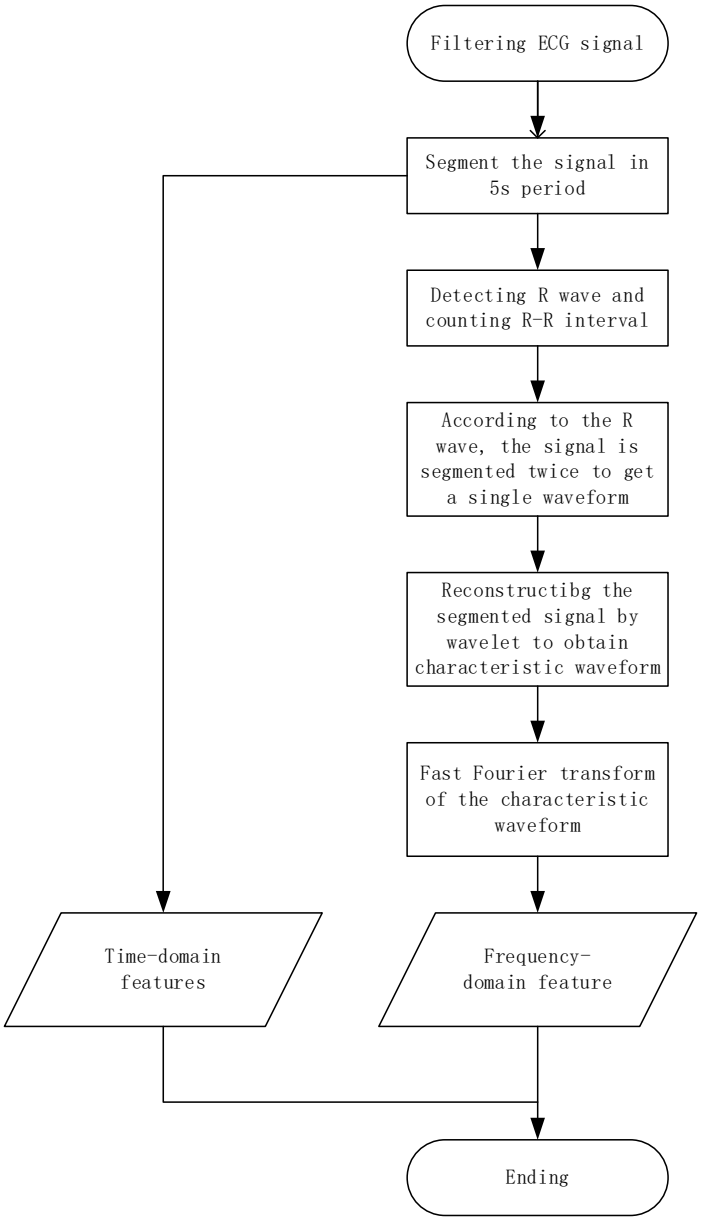

Figure 2 Procedures of extracting features

a)

b)

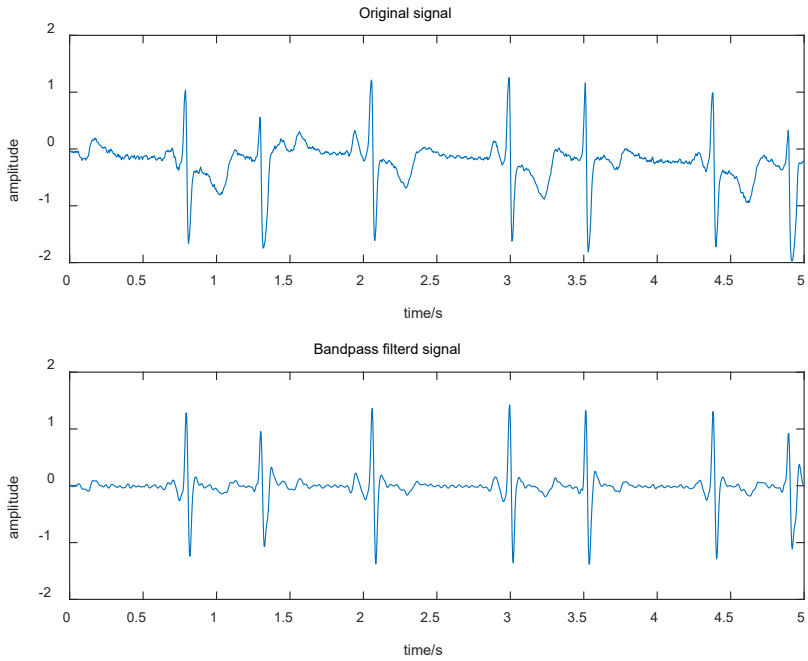

Figure 3 Comparation of original filtered signal and bandpass filtered signal. The images show that original signal have some kinds of frequency interference and the bandpass filtered signal is more regular than original signal.

a)

b)

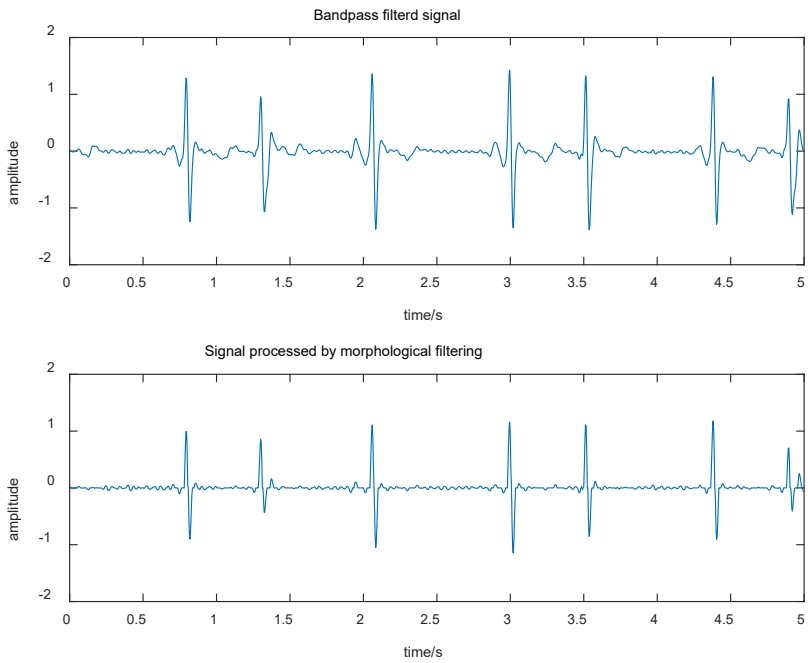

Figure 4 Comparation of band-pass filtered signal and morphological filtered signal. The image shows that morphological filter can further eliminate interferences than bandpass filter so that we can obtain the needful signal to do experiments.

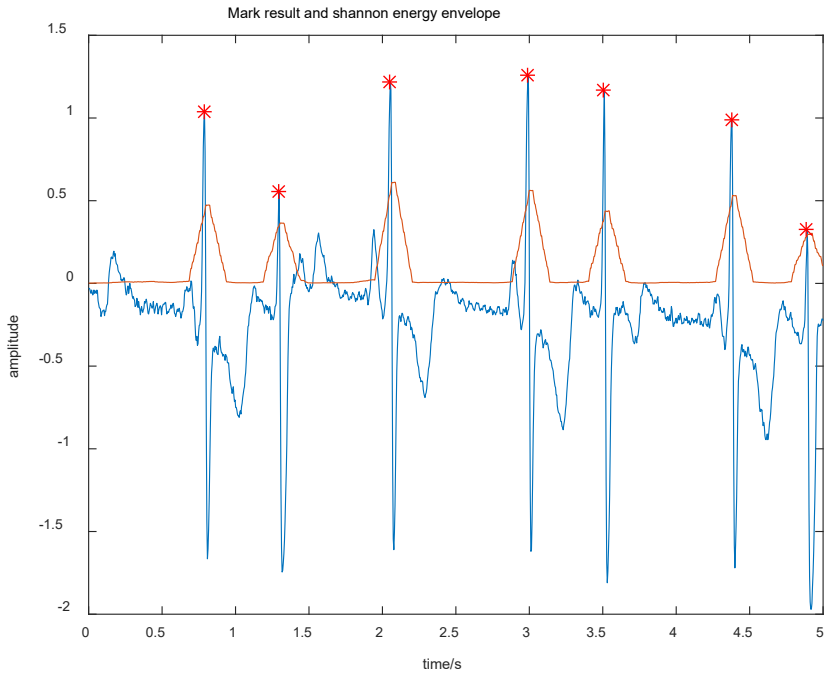

Figure 5 Detecting R wave. The image shows "*" is the result of detection - R peak and indicates the method to be of high accuracy. There is the Shannon energy envelope curve

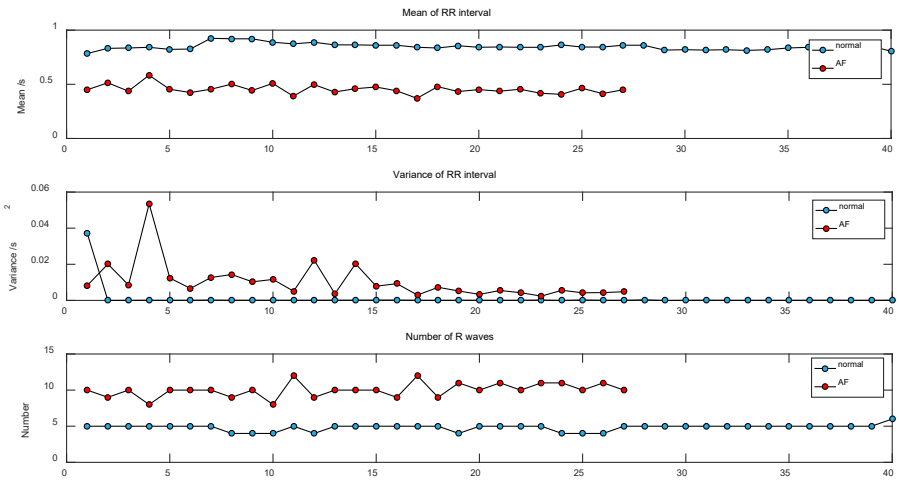

Figure 6 Time-domain features. There are three kinds of features in the image. For the mean of RR interval, normal ECG signal is larger than AF ECG signal. For the variance of RR interval, AF ECG signal is a little larger than normal ECG signal. For the number of RR interval, AF ECG signal is more than normal ECG signal.

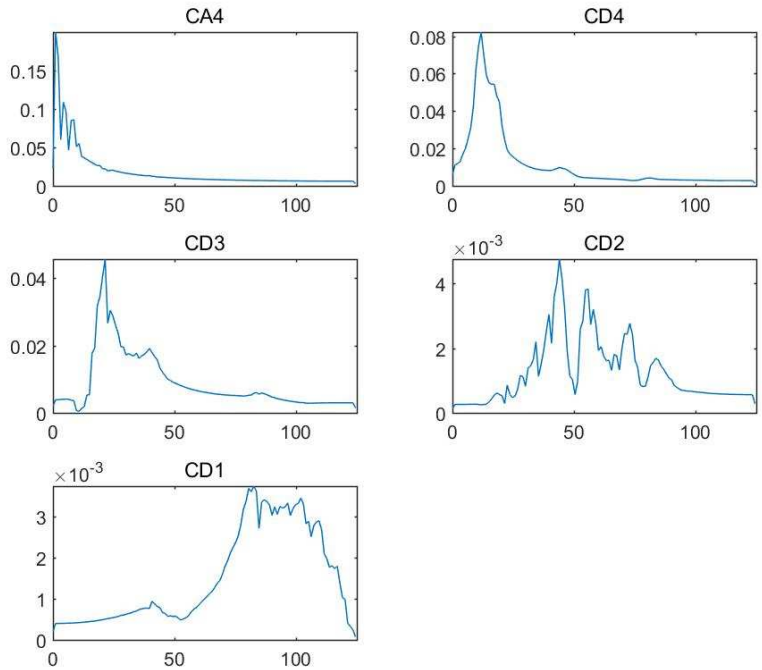

Figure 7 Frequency ranges of sub-band signal. It can be seen that different sub-band has different spectrum and contains different information in the single waveform.

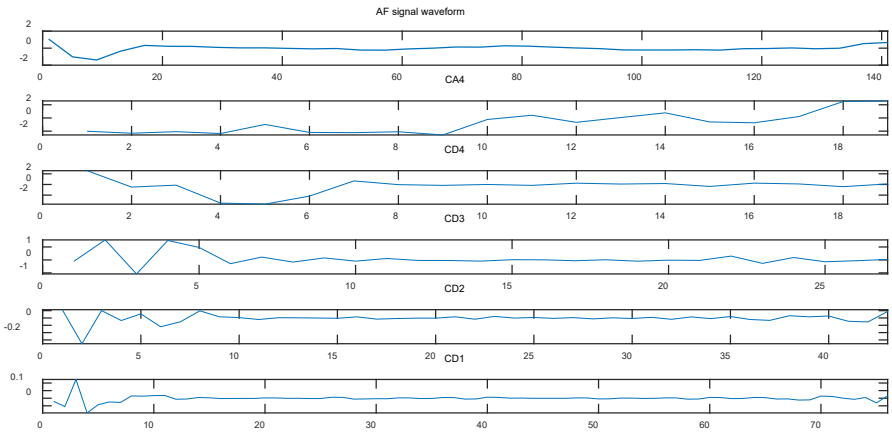

Figure 8 Decomposing single AF signal waveform.

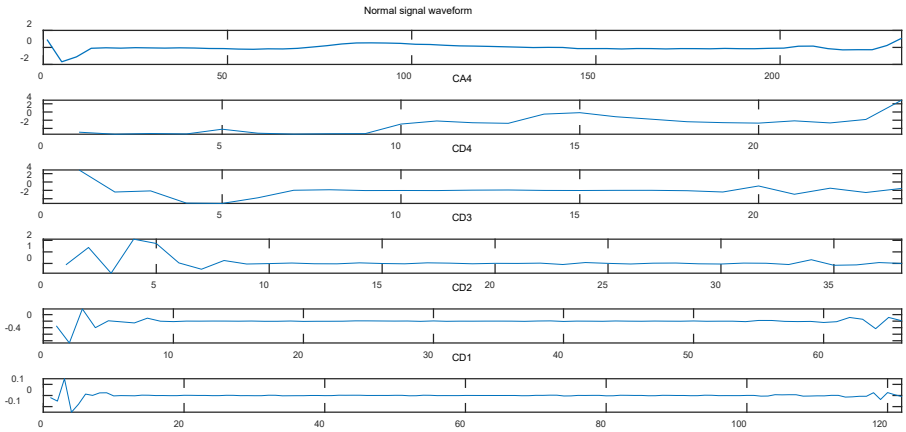

Figure 9 Decomposing single normal signal waveform.

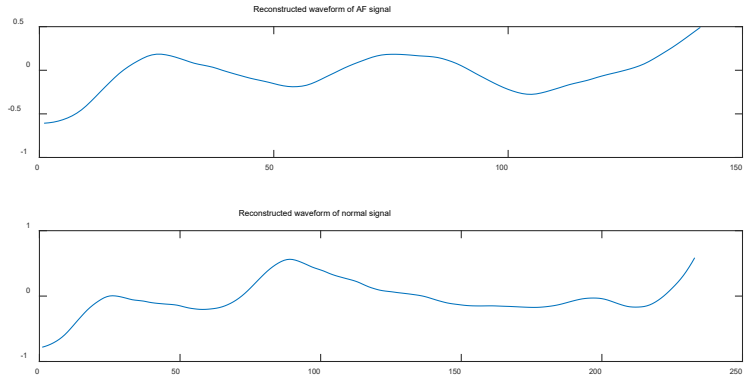

Figure 10 Reconstruction of single AF signal waveform and normal signal waveform. The two reconstructed waveforms are largely similar with the extracted single waveforms.

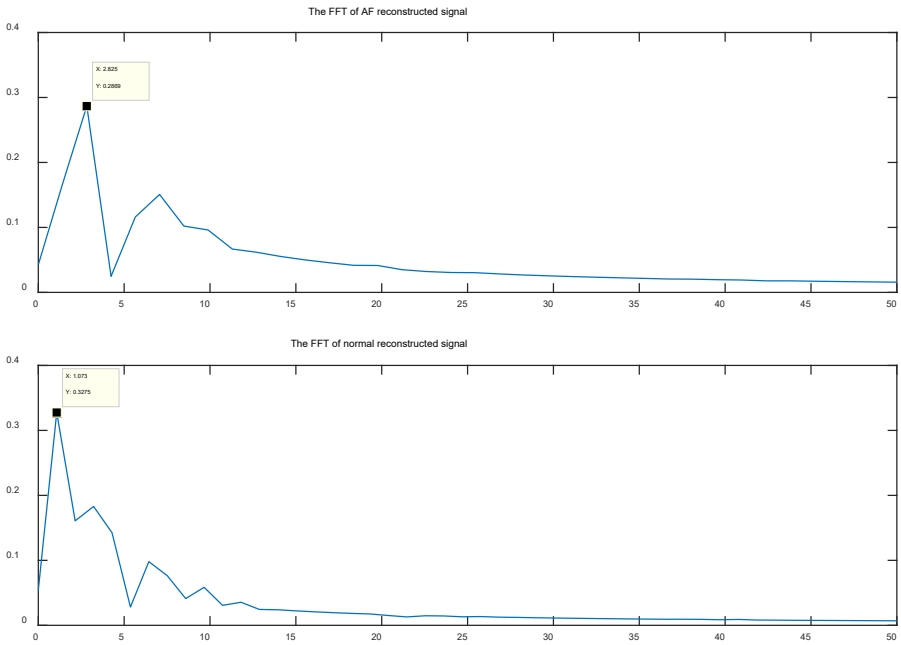

Figure 11 The FFT of AF reconstructed signal and normal reconstructed signal.

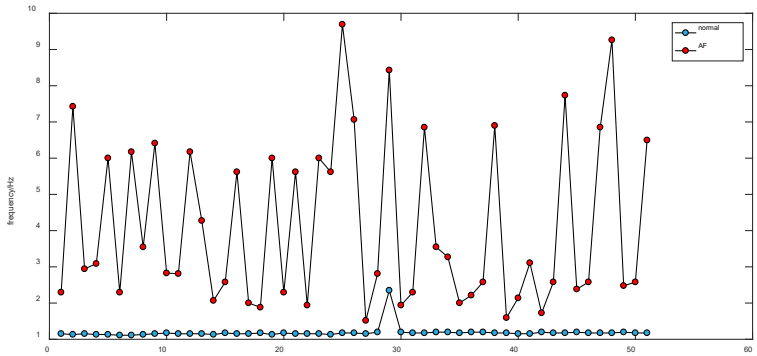

Figure 12 Frequency domain features of AF and normal. The frequency domain feature of AF ECG signal has volatility while normal ECG signal has stability.

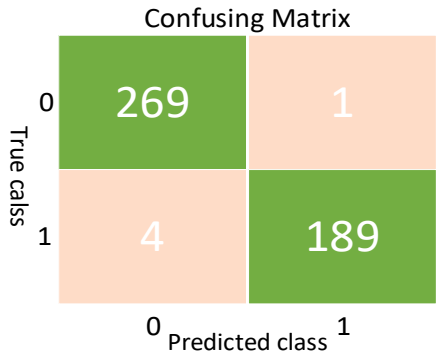

Figure 13 Result of classifing AF condition and normal condition. The number in the green rectangle means successful classification and the number in pink rectangle means failed classification.

Table 1 Frequency range of fourth layer discrete wavelet transform

Sub-band	Frequency range (Hz)
A4	0-7.813
D4	7.813-15.625
D3	15.625-31.25
D2	31.25-62.5
D1	62.5-125

Figures

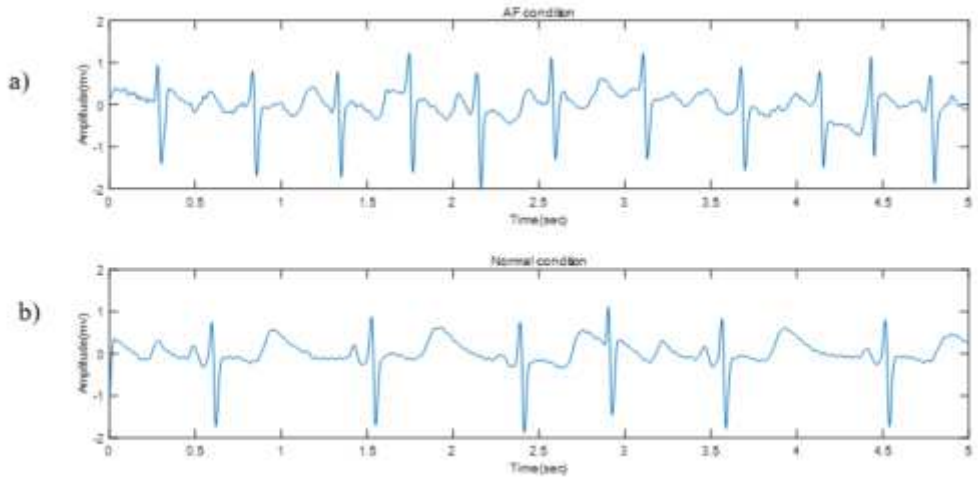

Figure 1

5s original ECG signal section in AF condition and normal condition.(a) normal condition,(b) AF condition. It can be seen that P waves are replaced by irregular F waves in AF condition. Other waves are not very different between AF condition and normal condition.

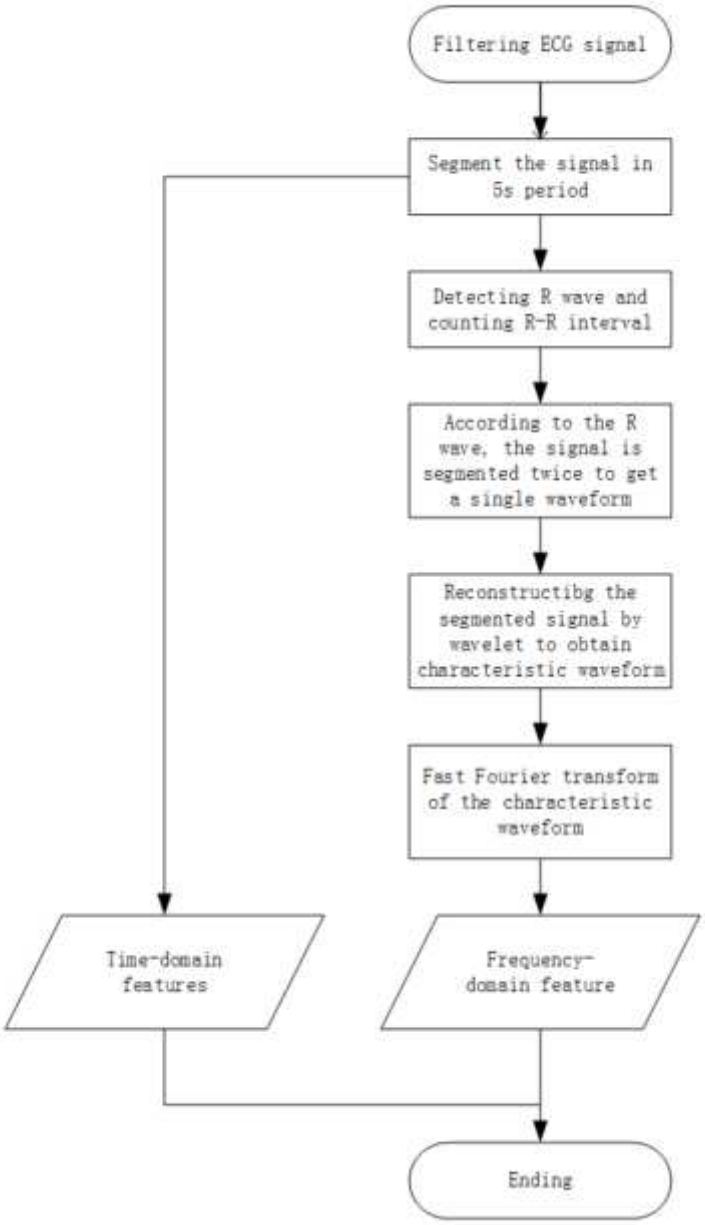

Figure 2

Procedures of extracting features

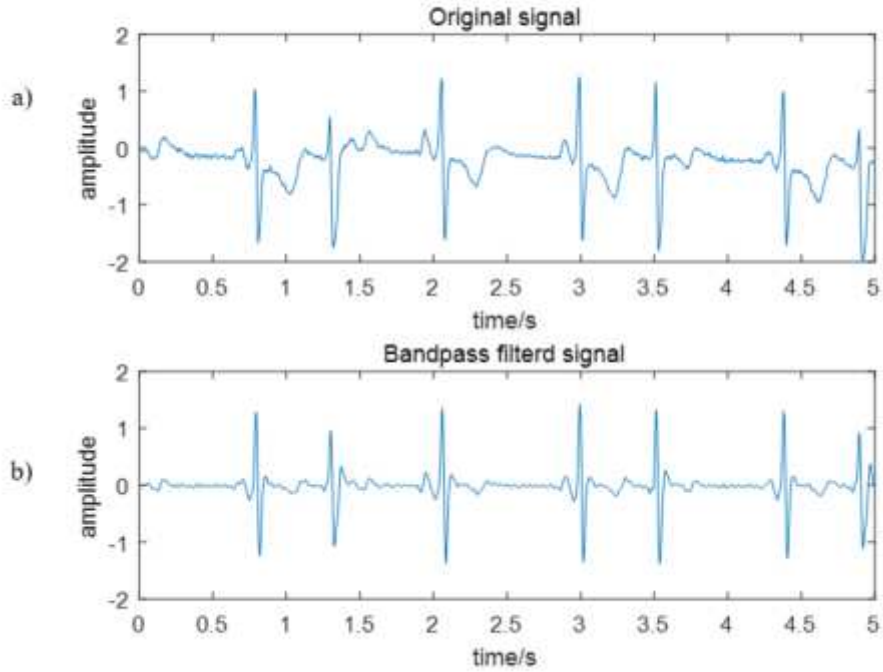

Figure 3

Comparation of original filtered signal and bandpass filtered signal. The images show that original signal have some kinds of frequency interference and the bandpass filtered signal is more regular than original signal.

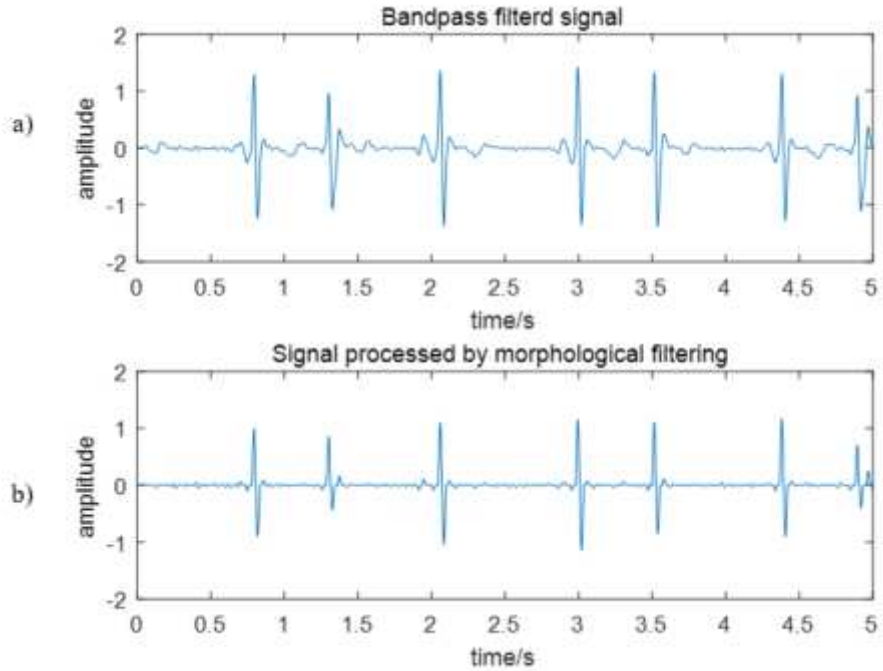

Figure 4

Comparation of band-pass filtered signal and morphological filtered signal. The image shows that morphological filter can further eliminate interferences than bandpass filter so that we can obtain the needful signal to do experiments.

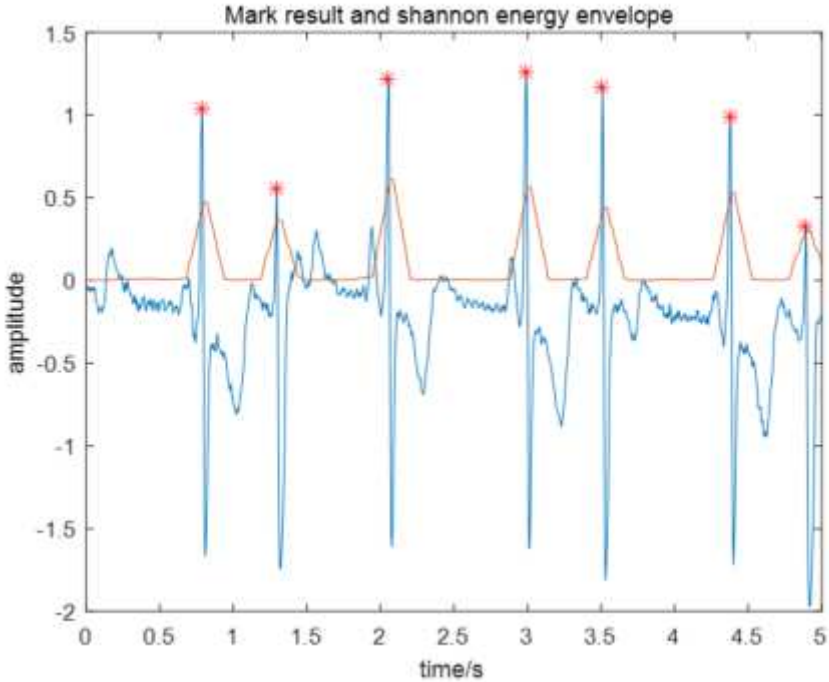

Figure 5

Detecting R wave. The image shows “*” is the result of detection - R peak and indicates the method to be of high accuracy. There is the Shannon energy envelope curve

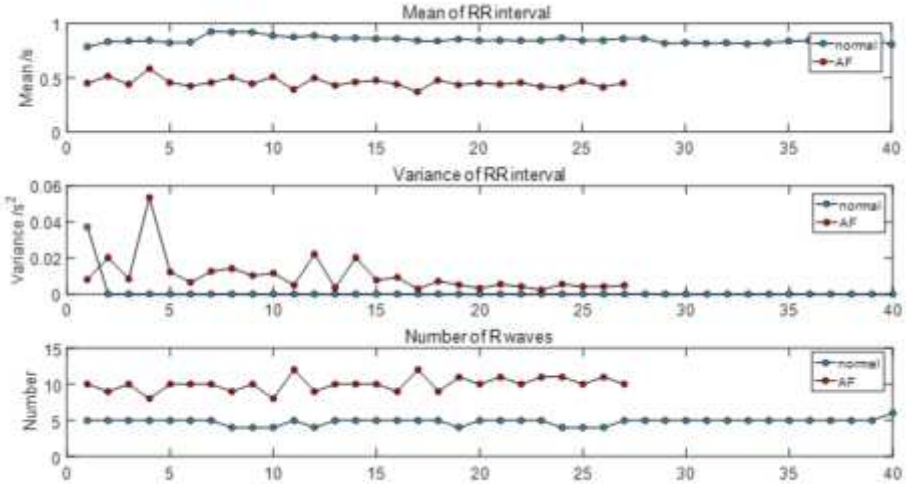

Figure 6

Time-domain features. There are three kinds of features in the image. For the mean of RR interval, normal ECG signal is larger than AF ECG signal. For the variance of RR interval, AF ECG signal is a little larger than normal ECG signal. For the number of RR interval, AF ECG signal is more than normal ECG signal.

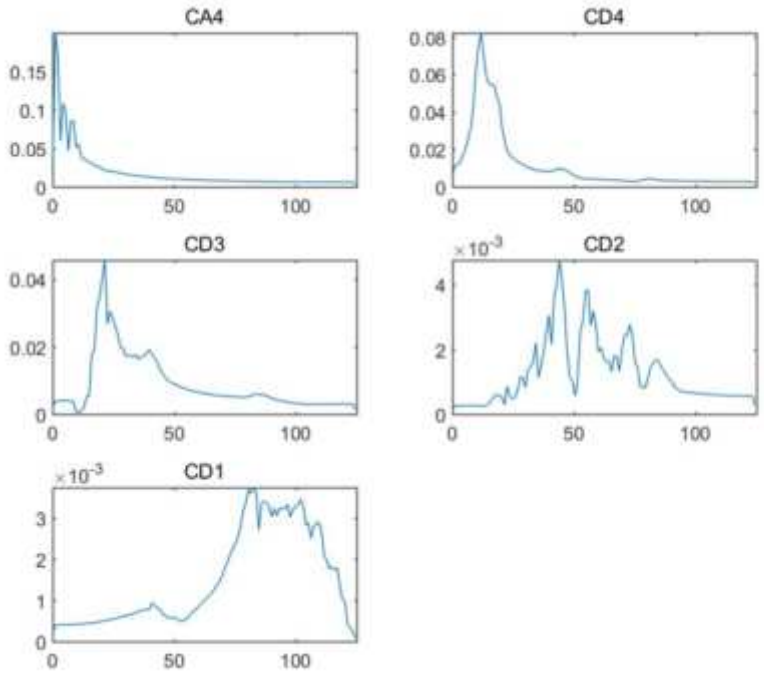

Figure 7

Frequency ranges of sub-band signal. It can be seen that different sub-band has different spectrum and contains different information in the single waveform.

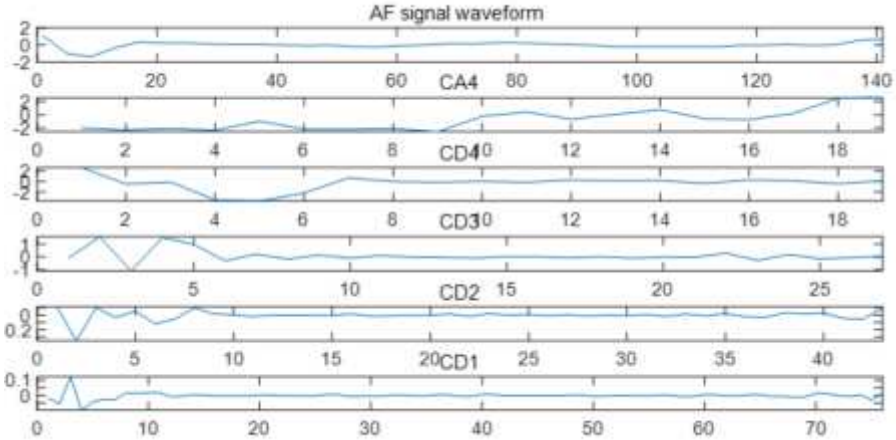

Figure 8

Decomposing single AF signal waveform.

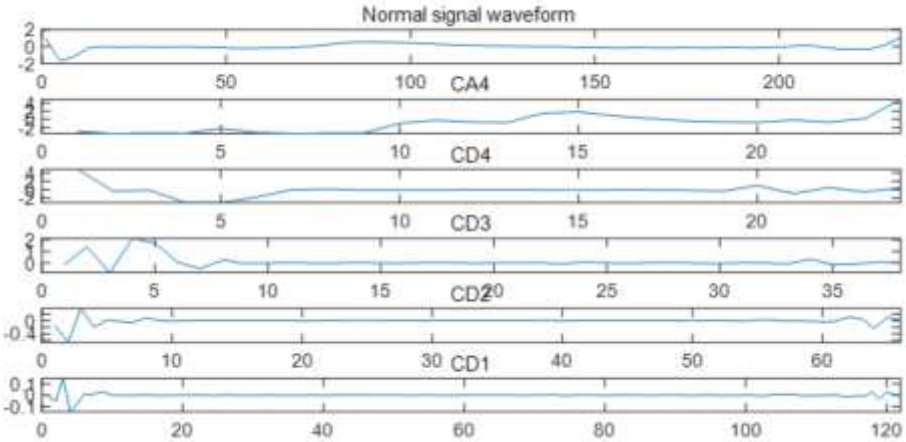

Figure 9

Decomposing single normal signal waveform.

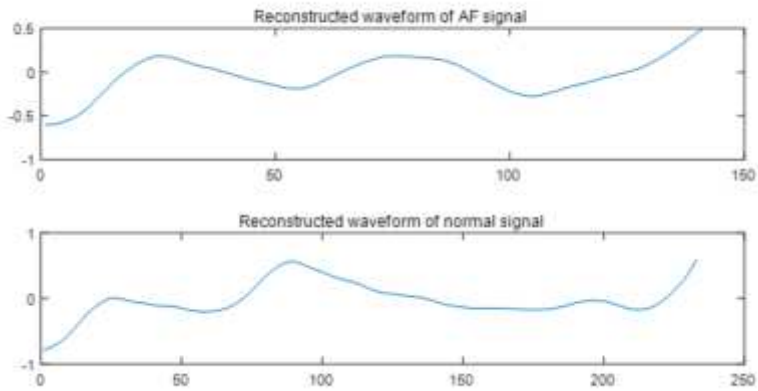

Figure 10

Reconstruction of single AF signal waveform and normal signal waveform. The two reconstructed waveforms are largely similar with the extracted single waveforms.

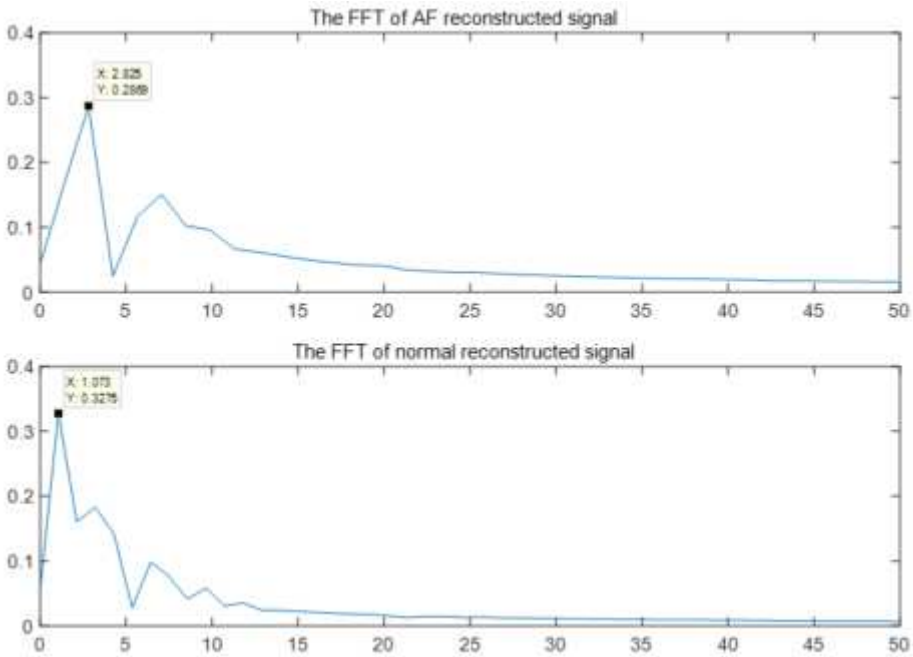

Figure 11

The FFT of AF reconstructed signal and normal reconstructed signal.

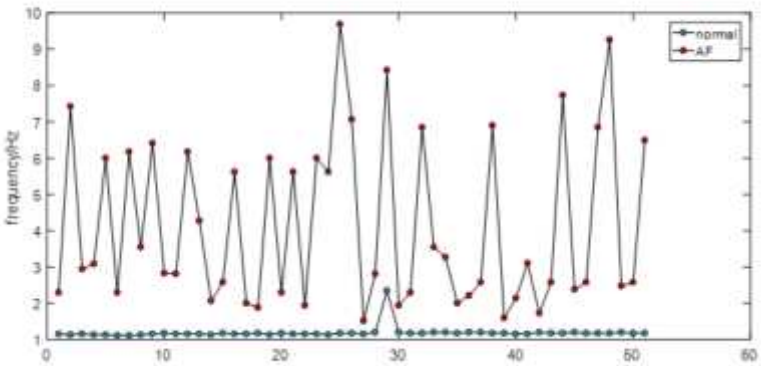

Figure 12

Frequency domain features of AF and normal. The frequency domain feature of AF ECG signal has volatility while normal ECG signal has stability.

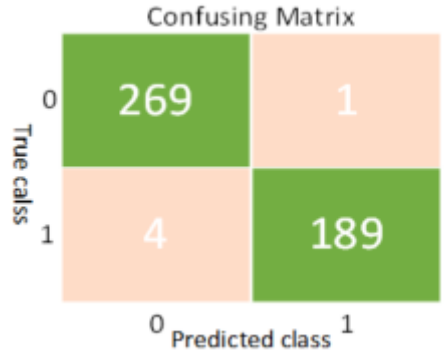

Figure 13

Result of classifing AF condition and normal condition. The number in the green rectangle means successful classification and the number in pink rectangle means failed classification.