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Arrhythmia Recognition and Classification using Modified ECG Morphology and Signal Feature Extraction Analysis

S.Venkatesh Babu[1], P.K.Santhosh[2], P.Annamalai[3], Sujitha.G [4], Ganesh.S [5],

[1]Professor, Department of BioMedical Engineering, Jaya Sakthi Engineering College Chennai 602024, INDIA.
[2,3]Assistant Professor, Department of BioMedical Engineering, Jaya Sakthi Engineering College Chennai,602024, INDIA
[4,5]Professor, Department of Electrical & Electronics Engineering, Jaya Engineering College Chennai 602024,INDIA.

Abstract
Arrhythmia appearing with the presence of abnormal heart electrical activity is efficiently recognized and classified. ECG data set used isderived from the MIT-BIH in which ECG signals are divided into the three classes: normal beat (N), Tachycardia (fast heartbeat), Bradycardia (slow heartbeat). Our proposed method can distinguish these with an accuracy of 97.80%.The morphological features are extracted along with basic signal features. The features are supplied to Generalized Regression Neural Network (GRNN) for classification. The sensitivities for the classes are 99.27%, 87.47%, 94.71% and the positive predictivities are 98.48%, 95.25%, 95.22% respectively. The detection sensitivity of the has a better performance by combining proposed features than by using the ECG morphology. The proposed method is compared with four selected peer algorithms and delivers solid results.

Introduction

The total number of cardiovascular diseases (CVD) increases tremendously, according to 2014 China Cardiovascular Report, and the number of CVD in the next decade is supposed to continue growing rapidly. Currently, CVD is the main cause of the total death of Chinese residents: 44.8% in rural areas, 41.9% of the city[1]. The common causes of CVD include smoking, high blood pressure, dyslipidemia, overweight, lack of physical activity and irrational dietary structure. The growing number of CVD has become a major public health problem. In all of CVD, arrhythmias are most fatal cardiac disease. Hence, diagnosis of arrhythmia patients timely and accurately is of great significance for the prevention of heart disease and sudden cardiac death. The electrocardiogram(ECG) is used for recording electrical activity and states the main direction of electrical impulses throughout the heart. Arrhythmia will appear with the presence of abnormal heart electrical activity on ECG. ECG mainly contains depolarization and repolarization of atrial and ventricular. So, two main types are identified as atrial arrhythmias and ventricular arrhythmias. However, arrhythmias recognition and diagnosis by human are timeconsuming and always inaccurate. Therefore, automatic computer assisted algorithm is a high-efficient way for diagnosis. Long-term monitor is necessary for reporting acute arrhythmia and controlling chronic disease progression, such as ventricular premature, atrial premature and myocardial infarction. Appearance of some ectopic beats might provide indictors for detection of chronic arrhythmia. Therefore, automatic computer assisted algorithm is a high-efficient way for diagnosis.

A. Related work

Heartbeat segmentation detector is critical for arrhythmia classification since some errors may have a certain impact on the final classification results during ECG heartbeat detection. Heartbeat segmentation mainly contains detection of P-QRS-T waves. Detection of QRS complex has been studied for years, differential threshold method[1], template matching method[3] and wavelet transform[2][3] are frequently used. Some algorithms are also put forward to detect other waves in the ECG signal such as the P and T wave, and detection methods are also mentioned in the literature[2][3]. Some informationextracted from ECG signal is useful for arrhythmia classification, and the information is considered as features. Regarding the ECG features commonly employed for classification, features surrounding RR intervals are most widely used [3]. In a previous literature[2], normalized RR interval and morphological features are employed to identify ectopic beats and the results demonstrate that positive predictive accuracy has been greatly improved. In this work, other heartbeat interval features including PP interval, ST interval, PR interval and RP interval are also considered. In addition, ECG morphology features in P-QRS-T waves have been used, such as wave amplitude, duration and positive and negative area. These features have been clinically studied and related diagnostic standards have been stipulated [2]. YükselÖzbay[3] has shown that utilizing the points of the segmented ECG curve as features is considered as the simplest feature extraction method. Signal processing methods include Dual Tree Complex wavelet transforms. Even though these features are correlated with mathematical interpretations, they do not have physiological meaning that permits doctors to understand intuitively. Furthermore, high computational cost also could be a disadvantage for using sophisticated methods.

B. ECG data description

The ECG data used in this paper is derived from the MIT-BIH arrhythmia database[1]. The database is set up by collecting data from 47 experimental subjects, and 48 ECG recordings are obtained. Twenty-three of the recordings (100~124) were obtained from subject's daily routine. The rest of 25 recordings (200~234) were selected to include un-frequent but clinically significant arrhythmias and these arrhythmias is not well- represented in the 100~124 recordings. And the four recordings with paced beats, namely, 102,104,107 and 217 are discarded in the study. For each recording, there are two channels of data,the channel was a modified limb lead II (MLII), the other channel was generally V1(or V2, V4, V5, up to subjects). We choose the first channel since the quality of signal performed better than the second one. In our work, AAMI recommendation is complied, and all ECG heartbeat labels are mapped to AAMI labels with the mapping rules listed in TABLE I. It is worth mentioning that we mainly focus on the study of the 200~234 recording, since main ectopic beats, namely supraventricular and ventricular ectopic, are well represented in the 200~234 recording (excluding 217 pacedbeat). In addition, the 200~234 recording also contains a certain number of normal beats incorporated in ectopic beats. Hence, the dataset in this study involved 4,0730 beats, and ectopic beats contain normal beats(N),Bradycardia, Tachycardia, normal(F).

Table.1. The Mapping Rules Of Ecg Heartbeat Labels Mapped To Aami

MIT-BIH heartbeat classes	AAMI classes
Normal (N)	N
Left and Right bundle branch block (LBBB, RBBB)	
Nodal premature and escape (J, j)	
Atrial premature and escape beat (A, e)	SVEBs
Aberrated atrial premature(a)	
Supraventricular premature(S)	
Ventricular escape(E)	VEBs
Premature ventricular contraction(V)	
Fusion of ventricular and normal(F)	F

II. METHODS

There are four main parts in an ECG arrhythmia recognition and classification system, containing pre-processing, heartbeat segmentation detector, feature extraction and classifier construction. Fig.1 shows the proposed method for classification of four types of ECG beats.

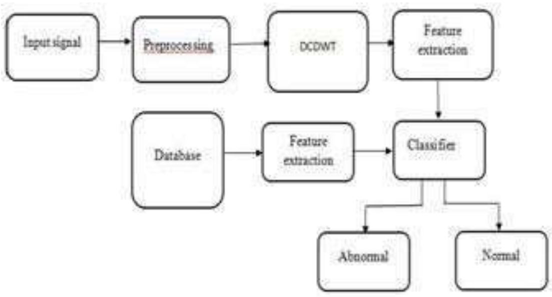
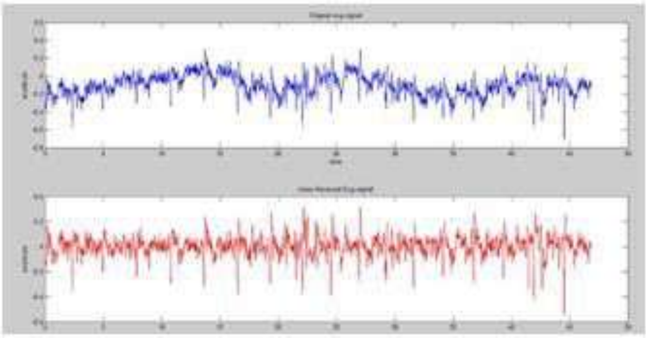


Figure.1. Proposed arrhythmia recognition and classification system

A. Pre-processing

Because of the signals in the MIT-BIH database collected by Holter devices, the ECG signals were contaminated by different natures of noise, such as baseline wandering. Notch filter is used in this step ECG signal is affected with periodic noise. Itis observed as discrete spikes. ECG signal preprocessing isshown in Fig. 2. After being processed, the ECG signals are fedinto the next stage for further processing.

Figure.2. Pre processing



B. Dual tree complex wavelet transform

The two real wavelet transforms use two different sets of filters, with each satisfying the PR conditions. The two sets of filters are jointly designed so that the overall transform is approximately analytic. Let h0(n), h1(n) denote the low- pass/high-pass filter pair for the upper FB, and let g0(n), g1(n) denote the low-pass/high-pass filter pair for the lower FB. We will denote the two real wavelets associated with each of the two real wavelet transforms as ψh(t) and ψg(t). In addition to satisfying the PR conditions, the filters are designed so that the complex wavelet ψ(t) :=ψh(t)+jψg(t) is approximately analytic. Equivalently, they are designed so that ψg(t) is approximately the Hilbert transform of ψh(t) [denoted ψg(t)≈H{ψh(t)}].

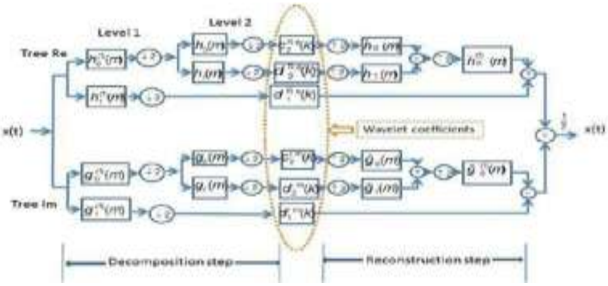
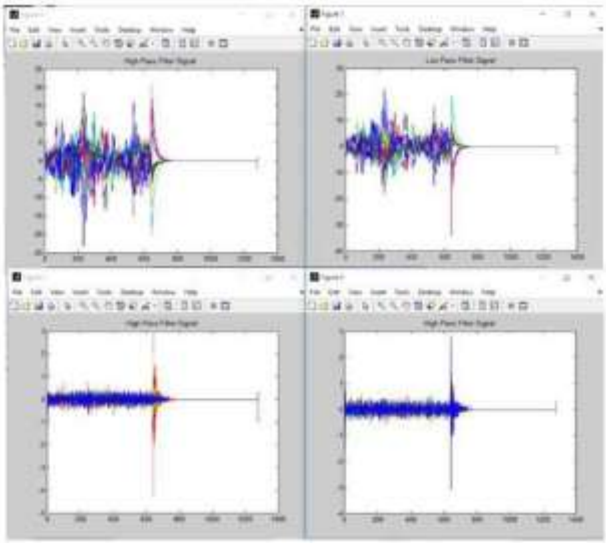


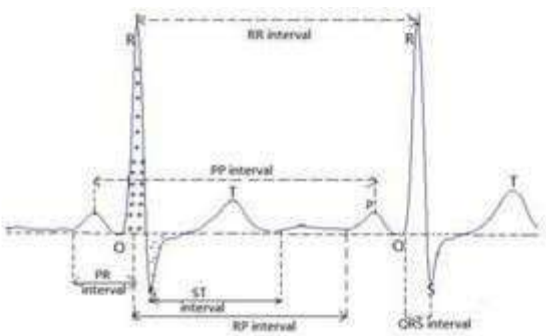
Figure.3. Illustration of interval-based feature in ECG: regions filled with + and – sign to represent positive and negative areas.

Note that the filters are themselves real; no complex arithmetic is required for the implementation of the dual-tree CWT. Also note that the dual-tree CWT is not a critically sampled transform; it is two times expansive in 1-D because the total output data rate is exactly twice the input data rate. The inverse of the dual-tree CWT is as simple as the forward transform. To invert the transform, the real part and the imaginary part are each inverted— the inverse of each of the two real DWTs are used—to obtain two real signals. These two real signals are then averaged to obtain the final output. Note that the original signal x(n) can be recovered from either the real part or the imaginary part alone; however, such inverse dual-tree CWTs do not capture all the advantages an analytic wavelet transform offers. The dual-tree CWT is also easy to implement. Because there is no data flow between the two real DWTs, they can each be implemented using existing DWT software and hardware. Moreover, the transform is naturally parallelized for efficient hardware implementation. In addition, because the dual-tree CWT is implemented using two real wavelet transforms, the use of the dual-tree CWT can be informed by the existing theory and practice of real wavelet transforms. For example, criteria for wavelet design (such as vanishing moments) and wavelet-based signal processing algorithms (such as thresholding of wavelet coefficients) that have been developed for real wavelet transforms can also be applied to the dual-tree CWT. It should be noted, however, that the dual-tree CWT requires the design of new filters. Primarily, it requires a pairof filter sets chosen so that the corresponding wavelets form an approximate Hilbert transform pair. Existing filters for wavelet transforms should not be used to implement both trees of the dual-tree CWT. For example, pairs of Daubechies' wavelet filters do not satisfy the requirement that ψg(t)≈H{ψh(t)}.



1) ECG morphology

Based on the detection of P-QRS-T waves, a total of 13 ECG morphology features are analyzed in the study, which are illustrated in Fig. 3. There are five features that aren't marked inthe Fig.3, which are amplitude of R, P and T waves, P and T wave duration.



a) Feature related to the QRS complex morphology

The QRS complex is the main wave in ECG signal, which shows the process of the ventricles depolarize. RR interval and R wave morphology amplitude are selected in this work. Besides, the QRS duration also is listed since the QRS duration can represent how fast the ventricles depolarize. It was stated in some literature [19][20] that the normal QRS is shorter than0.10 seconds. In addition, RP interval which starts at a given heartbeat's R wave and ends at the beginning of the following heartbeat's P wave, is adopted. And we introduce wave-area- based features to improve the classification performance in this study, which represents the combined characteristics of wave interval and sample amplitude. Specially, as illustrated in Fig. 2, it is obvious that QRS complex regions are enclosed by the wave and baseline. The sum of the area above baseline is defined as positive area, and conversely, the area below the baseline is regarded as a negative area. Thus, the positive and negative areas of the QRS complex are obtained.

b) Feature related to the P wave morphology

There was a predictive relationship between P wave morphology and right or left atrial hypertrophy or atrial arrhythmia. Features related to the P wave morphology contain P wave amplitude, P duration between P onset and P offset, PP interval and PR interval. Since PR interval refers to the process of starting from P wave to the beginning of the QRS complex in the ECG, and this process is from atrial contraction to the onset of ventricular contraction. Besides, PR interval represents how fast the electric potential is transmitted through the AV node (atrioventricular) from the atria to the ventricles. The normal PR interval ranges from 0.12 to 0.20 seconds, when a prolonged PR interval occurs, there is a sign of a degradation ofthe conduction system.

c) Feature related to the T wave morphology

The T wave is usually followed by the QRS complex. From a medical point of view, the T wave represents ventricular repolarization and the cardiomyocytes elongate, preparing for the next heartbeat during repolarization. Features related to the T wave morphology comprise T wave amplitude, T duration between T onset and T offset and ST interval. ST interval starts at the offset of QRS complex and ends at the offset of T wave.

IV. CONCLUSION

As per the above table we have found that extraction of the features and classifications of them by the proposed methods yields the best result.

V. REFERENCE

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