COMBINING FORWARD-BACKWARD RR INTERVAL DETECTOR WITH ARRHYTHMIC BEAT CLASSIFICATION IN ECG SIGNALS

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ABSTRACT

An Electrocardiogram (ECG) provides valuable information about the functional aspects of the heart and cardiovascular system. This research develops a Forward-Backward (FB) algorithm to extract the QRS complex and combines with the arrhythmic beat classification rules on medical knowledge. The purpose of this study is to increase the R-wave detection accuracy and to monitor a patient's arrhythmia condition in real time. The FB algorithm augments forward and backward searching rules from QRS onset and eliminates lower amplitude signal near the baseline using statistical process control (SPC) concept to improve the R-wave detection performance. The MIT-BIH arrhythmia database (MITDB) is used as training data to determine the parameters on proposed approach and classified into four arrhythmia beat types, i.e., normal (N), premature ventricular contraction (PVC), ventricular flutter/fibrillation (VF) and second-degree heart block (BII) beat. According to QRS complex extraction and beat classification rules, the proposed method provides 99.52% accuracy in the detection of R-wave location; 99.14% for N classified beats; 93.37% for PVC classified beats; 93.00% for VF classified beats and 89.852% for BII classified beats in the MITDB. To conclude, the proposed procedure could be useful because it only uses RR interval for arrhythmic beat classification and is affected slightly by noisy and complicated signal.

KEYWORDS

QRS complex, Forward-Backward (FB) algorithm, statistical process control (SPC), MIT-BIH database, cardiac arrhythmia classification

1. INTRODUCTION

The QRS complex is the most prominent feature of the ECG signal and corresponds to the ventricular excitation. The peak point of QRS complex is denoted by R and time distance between two consecutive QRS complexes is known as RR interval. Any disturbance in the regular rhythmic activity of the heart (amplitude, duration, and the shape of rhythm) is termed arrhythmia. Arrhythmias are disorders of the regular rhythmic beating of the heart, which indicate the electrical stability of the heart. Automatic arrhythmia detection and classification of ECG beat is important in clinical cardiology. An experienced clinician would be able to utilize these features to directly recognize ectopic beats. Hence, realistic analysis of RR intervals may offer valuable insights into mechanisms of arrhythmia genesis, clinical management of heart disease and develop signal processing tools for ECG analysis.

Various approaches have been performed for the detection and classification of ECG beats (Hamilton and Tompkins, 1986; So and Chan, 1997; Osowski and Nghia, 2002; Soltani, 2002; Sternickel, 2002; Paoletti and Carlo, 2006; Jiang et al., 2007; Madeiro et al., 2007). However, any gain obtained is generally offset by the greater complexity of the algorithms, involving higher computational costs. The main problem is due to various types of noise presence (slow baseline drift, high frequency noise, and impulsive noise) and the great variability of patterns, which depend on the patient and change over time. The most popular method for QRS complex detection is the Pan-Tompkins (PT) algorithm (1985).

Several researchers have discussed the problem of automatic detection and classification of cardiac rhythms (Osowski and Nghia, 2002; Soltani, 2002; Sternickel, 2002; Nurettin, 2005; Ravier et al., 2007). Some techniques have included artificial neural network (Carrault et al., 2003; Ravier et al., 2007), support vector machine (SVM) (Nurettin, 2005; Übeyli, 2007), Fourier and wavelet analysis (Soltani, 2002; Sternickel, 2002; Ravier et al., 2007), time-frequency analysis (Christov et al., 2006), statistical classifier model (Chazal et al., 2004), decision support system (Nilsson et al., 2006) and pattern recognition (Sternickel, 2002). Most of abnormal beat classifications are achieved by extracting characteristics from the signal (duration, slope, amplitude of waves) and frequency domain (energy in bands).

An automatic and quick procedure to identify individuals with characteristics of arrhythmia patients is clinically important as it would indicate the convenience of more specific and complex diagnostic tests for certain populations classified as arrhythmia patients. Different authors (Carrault et al., 2003; Kadambe and Srinivasan, 2006; Ravier et al., 2007; Sternickel, 2002) studied methods for arrhythmia classification based on various parameters of ECG feature, however, none of them obtained definitive results, and thus the problem has remained open.

2. COMPUTATIONAL METHODS AND ALGORITHMS

In this research, the proposed procedure is divided into two phases. Phase I is beat detection and feature extraction from raw ECG signals and phase II is the feature selection and arrhythmic beat classification. The functional modules flowchart is shown in Figure1.

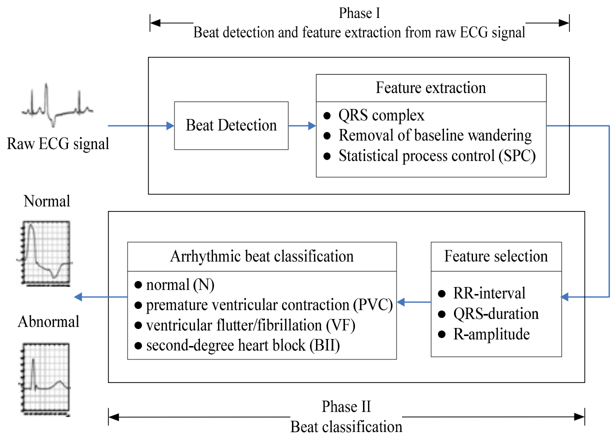


Figure 1 Functional modules flowchart in ECG feature extraction and arrhythmic beat classification

In Phase I, the main work is to utilize the Forward-Backward (FB) algorithm for ECG signal features extraction and the features on a QRS complex could be used for arrhythmic beat classification. Following the Phase II, the QRS complex is transferred to RR-interval, QRS duration, and R amplitude that could be used in pathological discrimination. Based on clinical medicine criteria of arrhythmia, beats measured could be divided into four types: normal (N), premature ventricular contraction (PVC), ventricular flutter/fibrillation (VF) and second-degree heart block (BII). Detail statement of methods is following.

2.1. Forward-backward (FB) algorithm

There were nine traditional mathematic algorithms to detect QRS complex (Gary et al., 1999). The advantages of these methods were to analyze ECG records without pre-processing and simpler than previously used in the literature. Friesen (1999) summarized test results and found that FD1 (First Derivative Only 1, FD1) had the better detection performance. So and Chan (1997) improved FD1 and $x_{(n)}$ represents the amplitude of the ECG signal at discrete time n. The slope of each $x_{(n)}$ is obtained by equation (1).

$$\text{slope}_{(m)} = -2x_{(m-2)} - x_{(m-1)} + x_{(m+1)} + 2x_{(m+2)} \quad (1)$$

The $\text{ST}_{(m)}$ is defined as slope threshold value and given by equation (2).

$$\text{ST}_{(m)} = \text{slope threshold value} = \frac{\text{tp}}{16} \times \text{maxi} \quad (2)$$

where m is from 3 to (n-2) and maxi (maximum slope) in equation (2) is initial maxi representing the maximum slope from first 200 points of each batch ECG signal and the threshold parameter (tp) indicates the ratio relation between $ST_{(m)}$ and maxi. The QRS onset is detected when two successive values (sv) satisfy the condition of $slope_{(m)} > ST_{(m)}$. The second point where the $slope_{(m)}$ is larger than the $ST_{(m)}$ is taken as the onset of a QRS complex. The Q wave is detected by first concave turning point forward and R wave is determined by first convex turning point backward. After the detection of the onset of a QRS complex from first 200 points in each ECG signal, maxi is updated by equation (3).

$$\text{maxi} = \frac{\text{first maxi} - \text{maxi}}{\text{fp}} + \text{maxi} \tag{3}$$

where fp is filter parameter and indicates the ratio relation on (first maxi-maxi) and first maxi is the amplitude difference between R point and QRS onset from first 200 points in one ECG record. Following detecting QRS onset, looking for the first convex turning point backward and regard it as a R wave in So and Chan method. The So and Chan method based on slope concept has presented good performance for regular and less noise ECG pattern. However, there are significant and composite noises on ECG signals, the several turned points are produced between Q and R wave, and that couldn't properly detect actual R wave location. As Figure 2 illustrates, (a) point designates QRS onset and (b) point is detective result by So and Chan approach but actual R wave is located on (c) point

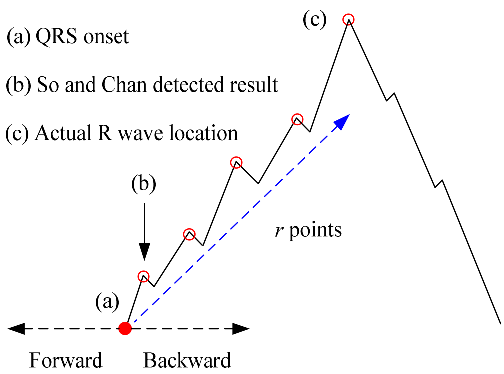


Figure 2 Actual R wave location is presented at several turning points after QRS onset

To avoid regarding other turning points as actual R waves, this study proposed the Forward-Backward (FB) algorithm to improve the So and Chan approach.

Figure 3 shows the Forward-Backward (FB) algorithm procedure and parameters set at each stage, such as initial max, tp, fp, sv, r, and k.

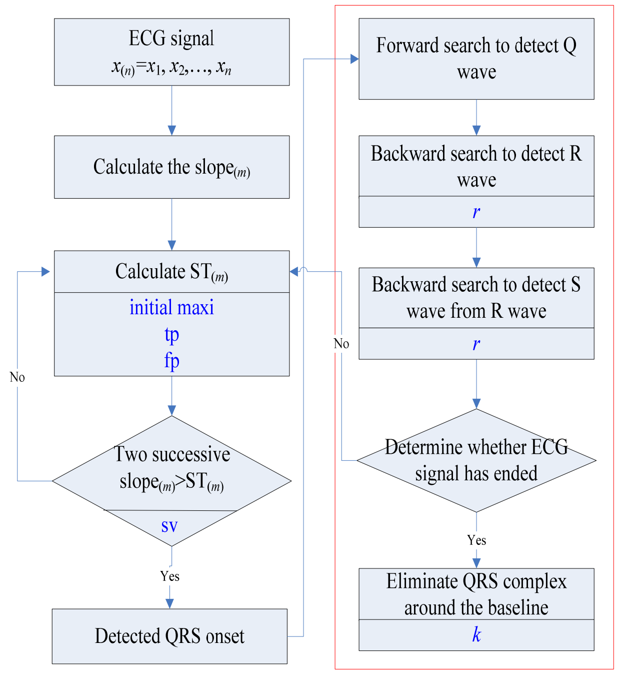


Figure 3 Phase I—the procedure of Forward-Backward (FB) algorithm

The left half of operation of the FB algorithm was similar to the So and Chan approach, whereas, there were two particular characteristics in the right half of FB algorithm. Firstly, we proposed to look for backward r turning points between QRS onset and actual R wave (see Figure 2). The function of parameter r is to increase detective accuracy of R wave and to reduce misjudgments for Q and S wave. After detecting the R wave, S wave is a first concave turning point by searching backward. However, the similar condition to R wave would occur while looking for S wave in the actual sample test. In our work, parameter r is also added for detecting real S wave. This study recommends using sampling frequency and an exponential smoothing method to adjust a proper r value for each QRS complex, such modification could improve shortcomings in the So and Chan approach. Adaptive r value is given by equation (4).

$$r_k = \alpha \cdot R_{k-1} + (1-\alpha) \cdot r_{k-1} \tag{4}$$

where α is smoothing coefficient, $R_{k\text{-}1}$ is the amplitude of (k-1)th R wave, and r_k and $r_{k\text{-}1}$ are k^{th} and (k-1)th r value respectively. After all Q, R and S features are detected, the difference of amplitude between R wave and QRS onset could be calculated, and then maxi is updated by equation (3). Continuous updating operations in the above procedures, the QRS complex of the whole ECG signal could be obtained.

Secondly, we eliminated the similar QRS complex around baseline in order to increase feature detective accuracy of the QRS complex. To improve such weaknesses, compute all R wave amplitudes and calculate their mean and standard deviations using a statistical process control (SPC) concept to eliminate the R waves around the baseline. In other words, to eliminate amplitude of R wave below the lower control limit (LCL), as shown in equation (5).

$$R_{amp} < \mu_{amp} - k * \sigma_{amp} \quad (5)$$

where R_{amp} is amplitude of R wave, k is a constant, μ_{amp} is the mean of amplitude of the entire ECG signal and σ_{amp} is the standard deviation of amplitude of the entire ECG signal.

2.2. Arrhythmic beat classification

According to detection results of Phase I, the results of QRS complex could be converted to features for pathological diagnosis, such as RR interval, QRS duration, and R amplitude. The RR interval signal is constructed by measuring the time interval between successive R waves. Tsipouras (2005) proposed to utilize RR intervals for arrhythmia classification. The algorithm starts with window i consisting of $RR1_i$, $RR2_i$ and $RR3_i$ intervals. The classification concerns the second beat of the middle RR interval ($RR2_i$) and is considered as a priori normal initially. Figure 4 shows classifications and sliding windows in RR interval series.

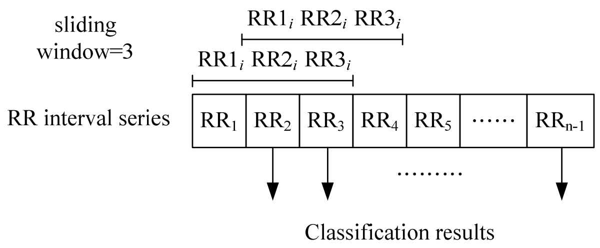
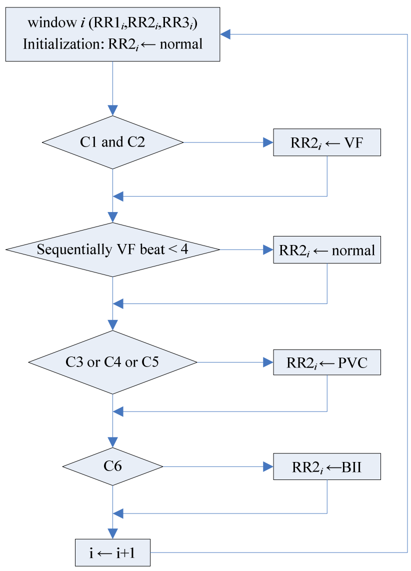


Figure 4 Classifications and sliding windows in RR interval series

The six rules (C1~C6) are provided by medical experts and are based on clinical procedures for detecting arrhythmic events from the RR intervals. The rules are used for the classification of the middle RR interval of a 3-RR interval sliding window (see Figure 4). These conditions are applied sequentially, when a beat is classified to a category by one rule, this classification cannot be changed by a following rule. The beat classification procedure is summarized in Figure 5. The method is limited to detecting types of arrhythmic episodes that are related to the information carried by the RR interval signal. Thus, arrhythmias such as atrial flutter and atrial fibrillation could not be detected.



C1	$RR2_i < 0.6$ and $1.8^* RR2_i < RR1_i$
C2	$RR1_k < 0.7$ and $RR2_k < 0.7$ and $RR3_k < 0.7$ or $RR1_k + RR2_k + RR3_k < 1.7$, k=i+1, i+1,…, i+n
C3	$1.15^* RR2_i < RR1_i$ and $1.15^* RR2_i < RR3_i$
C4	$\mid RR1_i - RR2_i \mid < 0.3$ and $RR1_i < 0.8$ and $RR2_i < 0.8$ and $RR3_i > 1.2^*\text{mean}(RR1_i, RR2_i)$
C5	$\mid RR2_i - RR3_i \mid < 0.3$ and $RR2_i < 0.8$ and $RR3_i < 0.8$ and $RR1_i > 1.2^*\text{mean}(RR2_i, RR3_i)$
C6	$2.2 < RR2_i < 3.0$ and $\mid RR1_i - RR2_i \mid < 0.2$ or $\mid RR2_i - RR3_i \mid < 0.2$

Note: if the number of sequential RR intervals classified in category 3 is less than 4, the algorithm returns to i and continues with the next rule. This is because a threshold of four consecutive classified RR intervals has been used to define a VF episode.

Figure 5 Phase II—Procedure of the arrhythmia classification algorithm (Tsipouras, 2005)

The beats are classified into four categories: (1) normal sinus beats (N), (2) premature ventricular contractions (PVC), (3) ventricular flutter/fibrillation (VF) and (4) second-degree heart block (BII). It is assumed that a beat not belonging to one of the above arrhythmic categories is classified as normal. The beat classification categories and their corresponding annotations from the MIT-BIH arrhythmia database for each category are given in Table 1.

Table 1 Beat annotations in the MITDB and classification in this study

Beat symbol	Type of arrhythmia	classification
N	normal	category 1
V	premature ventricular contractions	category 2
[	start of ventricular flutter/fibrillation	category 3
!	ventricular flutter wave	
]	end of ventricular flutter/fibrillation	
(BII	second-degree heart block	category 4

2.3. Assessment indicators

The digital ECG signal was processed by a series of computer programs written in MATLAB. Based on R wave detection results, assessment indicators can be classified as TP, FN, FP and TN. A true-positive (TP) value indicates the number of correct positive predictions, false-positive (FP) value indicates the number of incorrect positive predictions, false-negative (FN) value indicates the number of incorrect negative predictions and true-negative (TN) value indicates the number of correct negative predictions. The TP is favored by doctors and medical professionals, thus, R accuracy is the most important assessment indicator, as shown by equation (6).

$$\text{R accuracy}(\%) = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}} \tag{6}$$

In addition to R accuracy, as mentioned above, indicators often used in statistics to assess algorithm include Type I error (α) and Type II error (β), as shown by equation (7) and (8).

$$\alpha = \text{Type I error}(\%) = \frac{\text{FP}}{\text{FP} + \text{TN}} \tag{7}$$

$$\beta = \text{Type II error}(\%) = \frac{\text{FN}}{\text{TP} + \text{FN}} \tag{8}$$

This study uses three assessment indicators R accuracy, Type I error (α) and Type II error (β) to compare detection results with other literatures.

3. PERFORMANCE EVALUATION AND DISCUSSION

In this section, the parameters of the Forward-backward (FB) algorithm are trained for 27 records in the MITDB and then tested the arrhythmic beat classification rules, which are proposed by Tsipouras (2005). The MITDB is the first commonly available set of standard test materials for the evaluation of arrhythmia detectors, and it has been used for basic research in cardiac dynamics (Moody and Mark, 2001). After parameter training of the Forward-backward (FB) algorithm, actual Holter ECG signals are used as test samples, fortunately, this algorithm still achieves good detection and identification results in case the actual ECG signal might be affected by noise.

3.1. parameter setting

The improvement of Jiang (2007) for So and Chan approach could be used in actual ECG signal analysis and the optimal parameters were shown in Table 2.

Table 2 Optimal parameters setting on initial max, sv, tp and fp (Jiang, 2007)

parameter	optimal value or range
initial maxi	150
sv	2
tp	$8 \leqq \text{tp} \leqq 16$
fp	$1 \leqq \text{tp} \leqq 16$

Apart from the above parameters, the Forward-Backward (FB) algorithm has two parameters to determine, r and k value. The parameter r hopes to include the number of data points that are from QRS onset to the actual R wave. Our work suggests to setting a wider r value based on sampling frequency and then used amplitude of R wave to integrate the concept of statistical process control (SPC) limit, thereby determines initial r value. The purpose is to acquire reasonable and appropriate initial r value, then apply an exponential smoothing method to obtain efficient and accurate detection results.

Arrhythmia criteria proposed by clinicians regard that RR interval is abnormal when it is less than 0.4 second and greater than 1.5 second (beat rate less than 40/min or greater than 150/min). The sampling frequency is 360Hz that indicates the reasonable number of data points between two beats is 140~540 in the MITDB. The *r* value is average of reasonable data points to multiply a ratio and ratios are considered as 1/2, 1/4 and 1/8. Using 1/2 would result in greater *r* value, exceeding the width of QRS interval in literatures and 1/8 fails to include entire QRS waveform. Therefore, the ratio is set as 1/4 and the parameter *r* is calculated by equation (9)

$$\frac{1}{4}\cdot\left(\frac{144+540}{2}\right)=85.5\approx 86 \qquad (9)$$

Combining optimal parameters setting in Table 2 with *r* = 86, a common 27 record was used for the testing and training of the presented approach in the MITDB. This study found that, the mean was 15.955 data points and standard deviation was 3.878 data points from QRS onset to R wave. Based on SPC concept, the initial *r* value is considered as the average amplitude of R wave of each record and plus thrice standard deviation, is calculated as in equation (10).

$$13.955+3*3.87825.589 ≒ 26 \qquad (10)$$

In an actual case, beat amplitude is different from every patient, however, this research adopts an exponential smoothing method to set adaptive *r*, and uses mean absolute deviation (MAD) to determine optimal α setting. Figure 6 shows trends of α (0.1~0.9) and MAD.

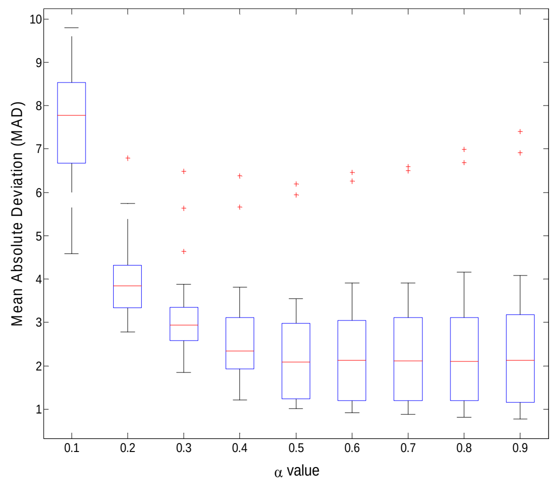


Figure 6 Box plot of test results of various α values and MAD in an exponential smoothing method

The MAD and its variation are the greatest when α is 0.1. In contrast, minimal MAD can be acquired when α is 0.5 and the variation of MAD is smaller than α is from 0.6 to 0.9. Therefore, the optimal setting of the smoothing coefficient α is 0.5 would have the minimal variation. This indicates that the current beat would be subjected to previous beat.

The test results showed that R accuracy was affected by noise around the baseline and gives rise to misjudgment in 10 ECG records. To correct this defect, a statistical process control (SPC) concept could be utilized to eliminate data of R waves below lower control limits (LCL). As shown in equation (5), different *k* values would affect determination in R wave, Figure 7 shows FP and FN test results of various *k* values (*k*=1 , 1.5 , 2 , 2.5) and wrongly identified R waves.

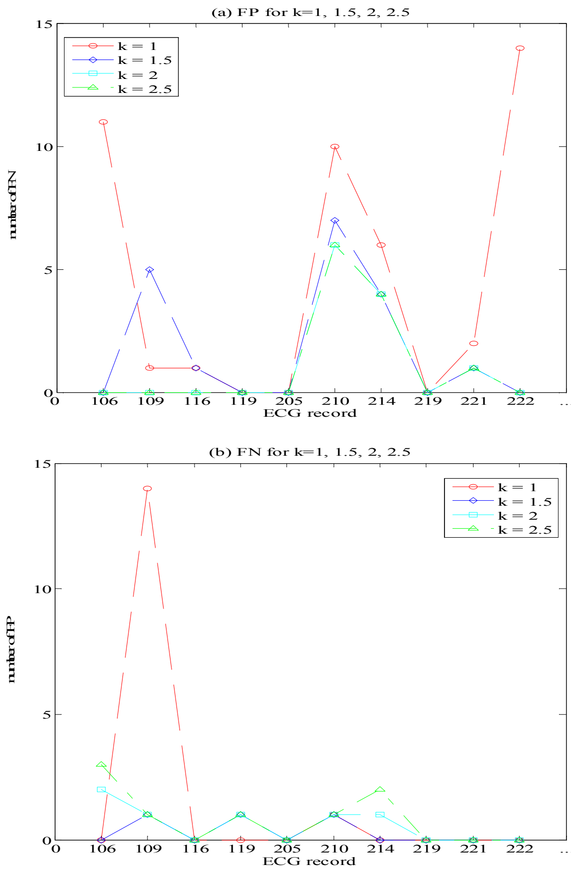


Figure 7 Various *k* values (*k*=1, 1.5, 2, 2.5) and wrongly identified R wave in FP and FN test results.

As shown in Figure 7(a) and (b), fewer FN and FP misjudgment could be obtained when *k* is 2, thus the optimal setting of *k* value is 2. This study added *r* and *k* to improve the So and Chan approach, based on test results, initial r was set as 26, k was set as 2 and there would be better QRS complex detection results and optimal parameter settings are summarized in Table 3.

Table 3 Optimal parameter settings on Forward-Backward (FB) algorithm

parameter	optimal value
initial max	150
sv	2
tp	8
fp	8
initial r	26
k	2

3.2. Performance evaluation

The optimal results obtained after applying the proposed method to the standard database are shown in Table 4 and the parameters were set as Table 3 respectively. The proposed method achieved good performances when applied to the tested database. The QRS detection algorithm achieves 99.52% accuracy, 1.87% Type I Error and 0.001% Type II Error in the detection of QRS complex in the ECG data. The performances of our approach are compared to the achieved detection results overviewed in the literature. A good algorithm for detecting is evaluated by higher accuracy and lower Type I and Type II error; it is evident that the performance of our approach is better than those of the others. In the MITBD, six approaches including our approach yield accuracy values of over 97%, suggesting that these approaches are useful and effective.

Some of the most popular QRS detection algorithms are described below. Commonly, a point in the QRS complex is detected (QRS point), using the algorithm proposed by Hamilton and Tompkins (Pan and Tompkins, 1985; Hamilton and Tompkins, 1986). Then, the main wave of the QRS complex (R wave) is identified in the window [QRS − 280 ms, QRS + 120 ms] by locating the point where the signal has its maximum absolute value. Mexican hat wavelets employed an adaptive threshold by using a digital band-pass filter for QRS segmentation (Madeiro et al., 2007). The advantage of using the adaptive threshold is that the T and P-waves are no longer necessary and the artifacts are eliminated, but it induces a large number of FP and FN beats. ECG patterns were recognized by the K-harmonic means clustering approach and a principal component analysis; nevertheless, the algorithm was suitable for long-term recordings (Paoletti and Carlo, 2006).

Table 4 Comparison of QRS detection performances obtained from various literatures on MITBD

	R accuracy (%)	Type I Error (%)	Type II Error (%)
FB algorithm	99.52	1.87	0.001
Madeiro et al. (2007)	97.94	3.59	0.048
Paoletti and Carlo (2006)	98.67	3.14	0.025
So and Chan (1997)	98.46	2.23	0.032
Hamilton and Tompkins (1986)	99.21	1.96	0.016
Pan and Tompkins (1985)	99.03	2.15	0.010

Most of ECG feature extraction algorithms included So and Chan approach have improved for Hamilton and Tompkins method by various concept. As mentioned above, the QRS detection methods are important in clinical cardiology and our study proposed an efficient approach to improve the QRS detection accuracy. Some ECG records in MITDB, including record 106, 109, 119, 210, 214 and 221, produce R wave detection errors. The main reason is that many noises around the baseline made Forward-Backward (FB) algorithm mistake a P wave for an R wave, resulting in small Type I and II errors. The red circles are R points detected by Forward-Backward (FB) algorithm and detailed graphs are shown in Figure 8.

After the QRS complex is determined, the next step is beat classification. Two datasets are applied for arrhythmic beat classification. The first dataset was created using all beats from 27 records of the MITDB. The efficiency measures also used accuracy (%), Type I error (%) and Type II error (%). The obtained results are given in Table 5. As we known from MITDB, most beats belong to normal beats and fewer belong to PVC and some VF and BII.

Table 5 Results for beat classification in MITDB

Dataset		Conditions (beat classification)				Accuracy (%)	Type I error (%)	Type II error (%)
		N	PVC	VF	BII			
MITDB	N	47314	403	3	5	99.14	7.10	0.80
	PVC	311	4465	5	1	93.37	0.65	8.52
	VF	23	13	478	0	93.00	0.07	1.65
	BII	47	0	0	416	89.85	0.09	1.42

The respective results for MITDB for accuracy (%), Type I error (%) and Type II error (%) are 99.14, 7.10 and 0.80% for N classified beats; 93.37, 0.65 and 8.52% for PVC classified beats; 93.00, 0.07 and 1.65% for VF classified beats and 89.85, 0.09 and 1.42% for BII classified beats. Only 311 normal beats are misclassified as PVC (0.65%) and 403 PVC beats are misclassified as normal beats (9.03%), while there are few normal or PVC beats classified to other two categories. The respective results for the second case for accuracy (%), Type I error (%) and Type II error (%) are 98.68, 9.98 and 1.14% for N classified beats; 91.17, 1.05 and 10.61% for PVC classified beats; 87.20, 0.12 and 8.04% for VF classified beats. There is no BII records existed in our real ECG signal so that accuracy (%), Type I error (%) and Type II error (%) are not meaningful.

3.3. Discussion

The FB algorithm detected QRS complex and easily extracted feature form ECG records. The obtained results indicated that the proposed method performs well (99.52% accuracy for MITDB). At feature extracted stage, some parameters on Forward-Backward algorithm were optimized through parametric analysis and improve the So and Chan approach. After the QRS complex is determined, the next stage is beat classification using RR intervals and beats which are categorized into four common arrhythmic types. The proposed procedure is advantageous to what has been presented in the literature because (1) the QRS complex could be easily detected by Forward-Backward algorithm even for complicated and actual ECG records and more robust than other literature (So and Chan, 1997; Pan and Tompkins, 1985; Hamilton and Tompkins, 1986; Paoletti and Carlo, 2006; Madeiro et al., 2007); (2) beat classification rules are based on medical knowledge and expert cardiologist who have proposed the range of the 3-RR interval sliding window (Tsipouras et al., 2005); (3) integrating QRS detector and beat classification and processing time is reduced since only one feature (RR interval) was used the classified scheme.

4. CONCLUSION

This study proposed a Forward-Backward algorithm and succeeded in integrating a concept of statistical process control (SPC) to parameter optimization, effectively improving the defects of the So and Chan approach in QRS complex detection. In addition, by improving R wave detection accuracy, the whole research procedure made proper application of arrhythmia classification rules as proposed by Tsipouras (2005) and to build a model that could determine four categories of varied cardiac arrhythmia.

This research used MITDB to be training samples to train optimal parameter setting and to detect the QRS complex, and used RR intervals to classify beats among overall ECG signals. In regard to ECG feature extraction, the approach proposed in this study yields 99.52% accuracy for MITDB and good performance in beat classification (overall classification accuracy is above 85%). However, there is no atrioventricular block classification in the rules because the RR interval is difficult for use in distinguishing supraventricular from ventricular arrhythmia; RR intervals monitor the ventricular activity. Since the proposed procedure includes the ECG feature extractor and arrhythmic beat classification, and is affected only slightly by noise and complicated signal, it is useful in clinical medicine and evaluations for heart diseases.

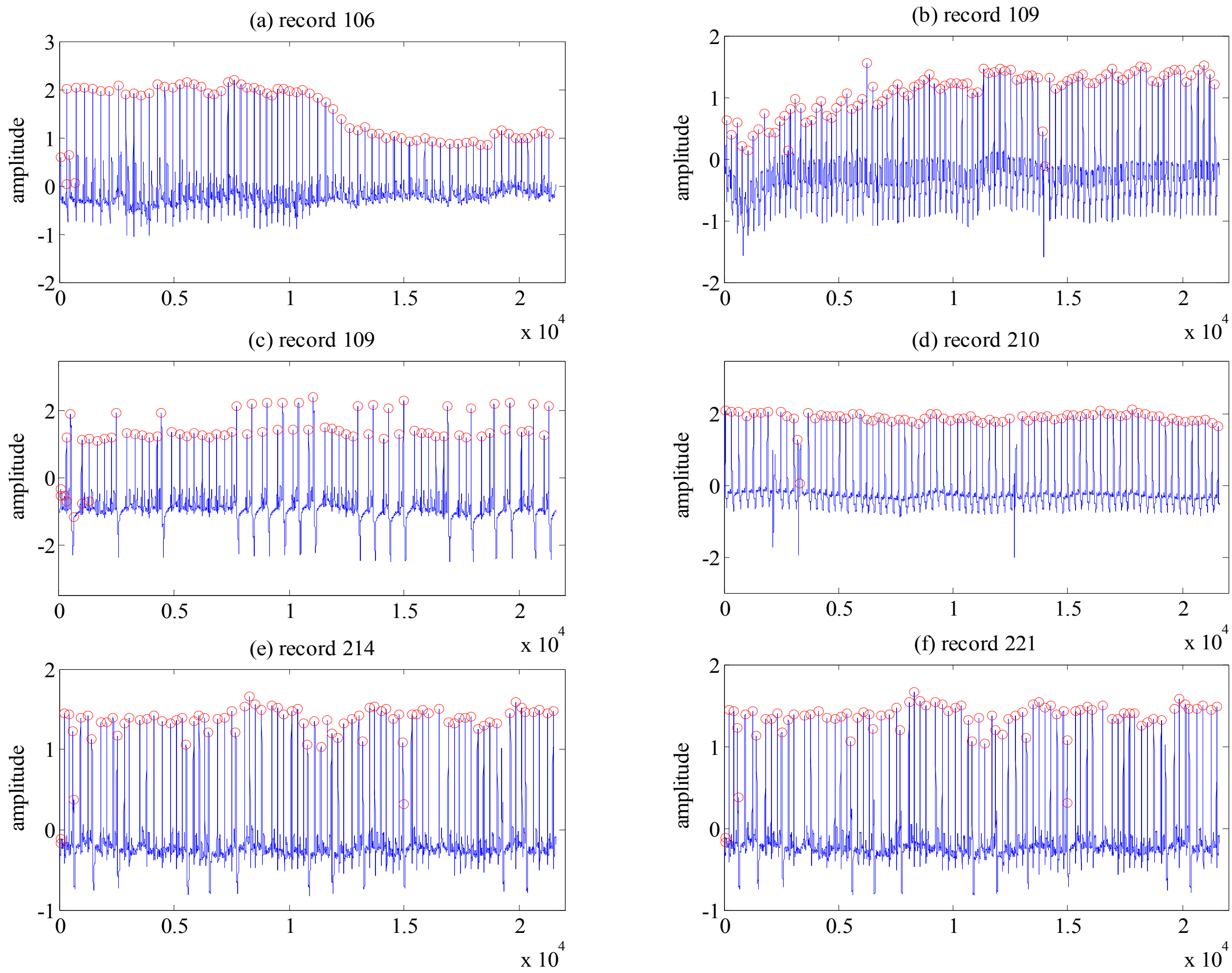


Figure 8 Special ECG record graph in MITDB

ACKNOWLEDGMENTS

We gratefully acknowledge the support from the National Science of Taiwan (NSC 95-221-E-155-024).

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