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An SPC-Based Forward-Backward Algorithm for Arrhythmic Beat Detection and Classification

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ABSTRACT

Large variation in electrocardiogram (ECG) waveforms continues to present challenges in defining R-wave locations in ECG signals. This research presents a procedure to extract the R-wave locations by forward-backward (FB) algorithm and classify the arrhythmic beat conditions by using RR intervals. The FB algorithm shows forward and backward searching rules from QRS onset and eliminates lower-amplitude signals near the baseline using a statistical process control concept. The proposed algorithm was trained the optimal parameters by using MIT-BIH arrhythmia database (MITDB), and it was verified by actual Holter ECG signals from a local hospital. The signals are classified into normal (N) and three arrhythmia beat types including premature ventricular contraction (PVC), ventricular flutter/fibrillation (VF), and second-degree heart block (BII) beat. This work produces 98.54% accuracy in the detection of R-wave location; 98.68% for N beats; 91.17% for PVC beats; and 87.2% for VF beats in the collected Holter ECG signals, and the results are better than what are reported in literature.

Keywords: RR Intervals, Forward-Backward Algorithm, Statistical Process Control, MIT-BIH Database, Arrhythmia Classification

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1. INTRODUCTION

The QRS complex is the most important feature of the electrocardiogram (ECG) signal. The R-wave location is the peak point of the QRS complex and the time-distance between two consecutive R-wave locations is known as the RR interval (Figure 1). Any disturbance in the regular rhythmic activity of the heart (e.g., amplitude, duration, the shape of rhythm) is termed arrhythmia. Various approaches have been taken in the detection and classification of ECG beats (Friesen *et al*., 1990; Kadambe and Srinivasan, 2006; Meyer *et al*., 2006; Osowski and Nghia, 2002). The basic method is the Pan-Tompkins algorithm (Hamilton and Tompkins, 1986; Pan and Tompkins, 1985). The accuracy of detection of each cardiac cycle is important since it contributes significantly to the overall classification result.

Arrhythmias are disorders affecting the regular rhythmic beating of the heart and indicate the electrical stability of the heart. Numerous approaches have been adopted for detecting and classifying cardiac rhythms (Madeiro *et al*., 2007; Paoletti and Marchesi, 2006; Ravier *et al*., 2007; Ubeyli, 2007). Some techniques have applied artificial neural networks (Osowski and Nghia, 2002; Ravier *et al*., 2007; Tsipouras *et al*., 2005), support vector machines (Acir, 2005; Ubeyli, 2007), Fou-

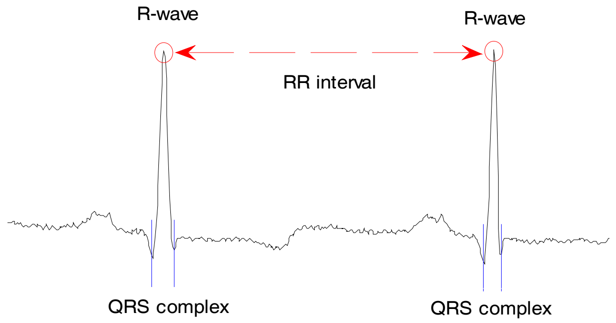

Figure 1. Representative cycles of a human electrocardiogram showing the R peak, QSR complex boundaries and the corresponding RR interval.

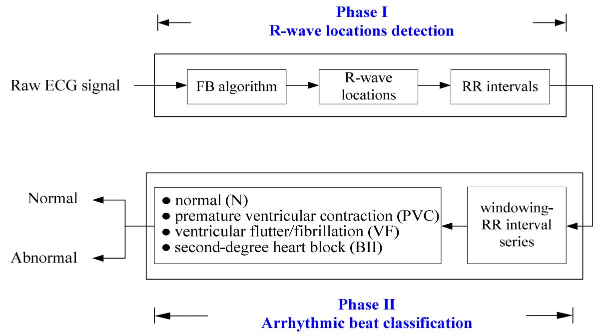

Figure 2. Flowchart of electrocardiogram (ECG) feature extraction and arrhythmic beat classification. FB: forward-backward.

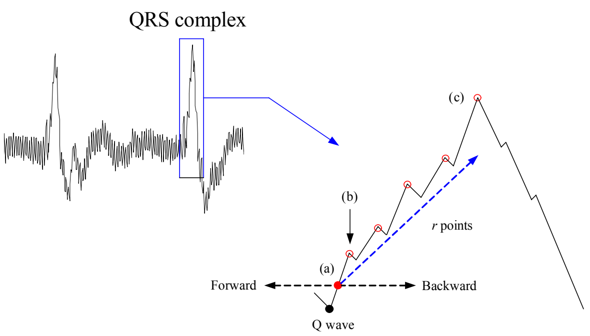

Figure 3. Actual R-wave location is presented at several turning-points after QRS onset. (a) QRS onset, (b) false peak, and (c) actual R-wave location.

rier and wavelet analysis (Chan *et al*., 2008; Chen *et al*., 2006; Medeiro *et al*., 2007; Osowski and Nghia, 2002), time-frequency analysis (Christov *et al*., 2006), the statistical classifier model (Dubois *et al*., 2007; De Chazal *et al*., 2004; Paoletti and Marchesi, 2006), and pattern recognition (Ros *et al*., 2004; Sternickel, 2002). However, large variations in ECG waveforms as noise continue to present challenges for these algorithms, and thus the problem persists. Key problems include the various types of noise present (e.g., slow baseline drift, high frequency noise, and impulsive noise) and the great variability of patterns, the latter of which are patient-dependent and change over time.

The objective of this study is to develop an algorithm which can reduce the influence of noise derived from original ECG morphology and integrate an arrhythmic beat classification method to categorize four common arrhythmia symptoms. Some arrhythmias appear infrequently and result in weak ECG signals that may need to be recorded using a Holter ECG monitor. Therefore, our work is not only trained by a standard database but also tested by using actual Holter ECG signals.

2. METHOD

In this research, the proposed procedure is divided into two phases. In phase I, the main work is to use the forward-backward (FB) algorithm for extracting R-wave locations and then to transfer it to an RR interval for arrhythmic beat classification. In phase II, beats can be classified into normal (N), premature ventricular contraction (PVC), ventricular flutter/fibrillation (VF), and second-degree heart block (BII). The functional module flowchart is shown in Figure 2.

2.1 Forward-Backward Algorithm

There are nine traditional mathematic algorithms used to detect R-wave, and first derivative only 1 (FD1) had the better detection performance (Friesen *et al*., 1990). So and Chan (1997) improved FD1 and extracted R-wave locations without pre-processing or filtering the raw ECG signals. However, there are significant and composite noises on ECG signals, as well as several turning-points between the Q- and R-waves, so this method cannot properly detect actual R-wave locations. The turning-points are resulted from muscle contraction, respiration, electrode contact noise and instrumentation noise generated by electronic devices. As Figure 3 illustrates, point (a) designates QRS onset and point (b) is detected via So and Chan's method, but the actual R-wave is located at point (c).

To identify R-waves, this study proposes an FB algorithm to improve upon So and Chan's method. Figure 4 shows the procedure and the parameters set at each stage.

The left half of operation in Figure 4 is the original So and Chan approach, and the right half is the proposed FB algorithm to improve detected results on QRS complexes. First, $x_{(n)}$ is the amplitude of the ECG signal at discrete time n, and the slope of each $x_{(n)}$ is obtained by Eq. (1).

$$slope_{(m)} = -2x_{(m-2)} - x_{(m-1)} + x_{(m+1)} + 2x_{(m+2)} \tag{1}$$

The $ST_{(m)}$ is defined as the slope threshold value and

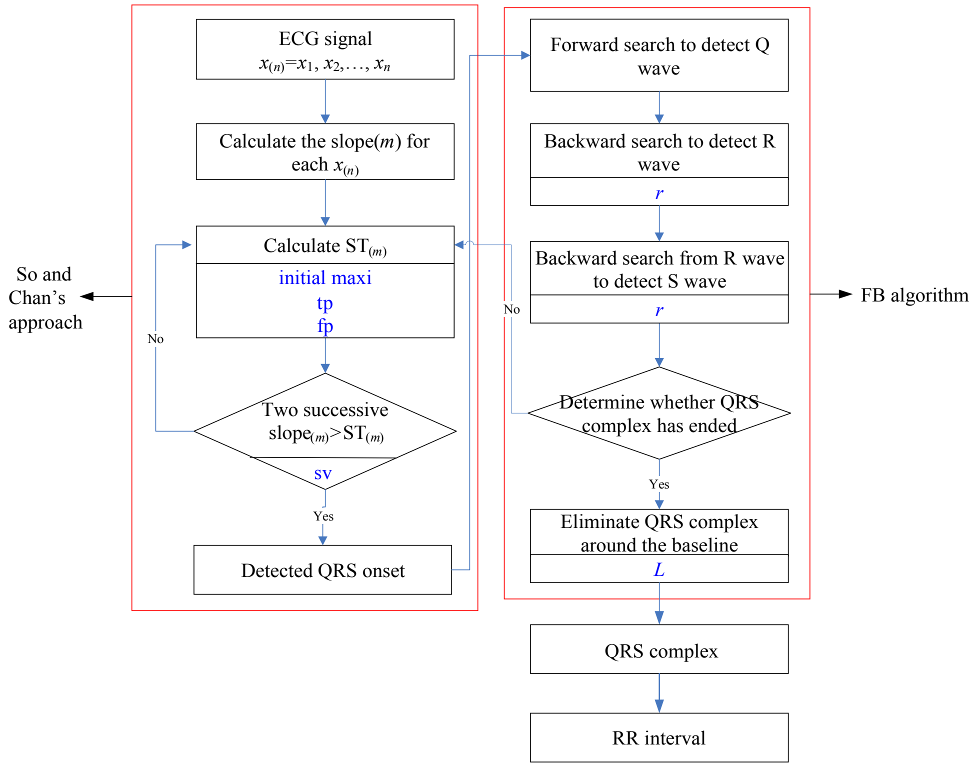

Figure 4. Procedure of extracting QRS complex and RR interval. ECG: electrocardiogram, ST$_{(m)}$: slope threshold value, FB: forward-backward.

it is derived via Eq. (2).

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

where m is from 3 to (n–2), maxi (maximum slope) is the first maxi representing the maximum slope from the first 200 points of each batch ECG signal (So and Chan, 1997), and the threshold parameter (tp) is 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. Then the maxi value is updated via Eq. (3).

$$\text{maxi} = \frac{\text{first maxi-maxi}}{\mathrm{fp}} + \text{maxi} \qquad (3)$$

where fp is the filter parameter that indicates the ratio relation on (first maxi–maxi); the first maxi is defined previously.

In the FB procedure, after QRS onset detection, the Q-wave is detected by the first concave turning-point forward from QRS onset and looks for backward r turning-points between the QRS onset and an actual R-wave. The function of parameter r is to overcome the noise effects during the QRS complex and thus increase accuracy in detecting R-waves. Therefore, an initial r is calculated by the statistical process control (SPC) concept (Montgomery, 2005), and then an exponential smoothing method is adopted to adjust it to a proper r value for each QRS complex. This SPC concept has been widely used in industry to detect abnormal process or products; and such a modification could improve the shortcomings of So and Chan's method. An initial r and adaptive r value are derived as Eqs. (4) and (5), respectively.

$$initial\ r = m_R + 3 \cdot \sigma_R \qquad (4)$$

$$r_k = \lambda \cdot R_{k-1} + (1-\lambda) \cdot r_{k-1} \qquad k = 2, 3, \cdots \qquad (5)$$

where m_R is the mean of data points from the QRS onset to the detected R-wave and σ_R is the standard deviation, λ is a smoothing coefficient, k is the beat number for each ECG record, R_{k-1} is the amplitude of the $(k-1)^{\text{th}}$ R-wave, and r_k and r_{k-1} are the k^{th} and $(k-1)^{\text{th}}$ r values, respectively.

The difference in amplitude between the R-wave and the QRS onset for each QRS complex can be calculated. In our research, the mean and standard deviation of all R-wave amplitudes in each ECG record are calculated to eliminate the small fluctuations around the baseline using a SPC technique (Montgomery, 2005). The SPC technique helps to distinguish the significant variables of normally distributed variables caused by abnormal conditions from the variables occurring naturally in a time series data set. If an observation falls outside of the limits, the process is out of control. By using the control limit to monitor ECG, the amplitude of the R-wave below a lower control limit (LCL) can be removed, as shown in Eq. (6).

$$R_{amp} < \mu_{amp} - L \times \sigma_{amp} \tag{6}$$

where R_{amp} is the amplitude of the R-wave, L is a constant, and μ_{amp} and σ_{amp} are the mean and standard deviation of the amplitude of the a ECG signal, respectively.

Four parameters in So and Chan's approach, namely, initial maxi, tp, sv, and fp, have been optimized in previous work (Jiang *et al*., 2007; Yen, 2007). Aside from four parameters, the r and k values need to be determined in the FB algorithm. Clinically, an RR interval of less than 0.4 seconds and greater than 1.5 seconds is considered as arrhythmia (i.e., beat rate less than 40/min or greater than 150/min). The sampling frequency is 360 Hz in the MITDB (Moody and Mark, 2001; MIT/BIH Arrhythmia Database, 2007), which indicates that the reasonable number of data points between two beats is 140–540, and that the approximate number of data points during the QRS complex is about 86 data points. Combining the optimal parameter-setting (Jiang *et al*., 2007) with approximate data points during the QRS complex, ECG records in the MITDB were used to train the presented method. According to the results of So and Chan's method, the mean and standard deviations of data points from the QRS onset to the detected R-wave were 13.9 and 3.8 points in the MITDB, respectively. To improve the detection performance, based on the Shewhart control technique, the initial r value is considered to be about 26, or 13.9 data points (m_R) plus three times 3.8 data points (σ_R) for each record (refer to Eq. (4)).

In fact, the beat amplitude is different in every patient. Therefore, an exponential smoothing method is applied to set adaptive r, and it uses a mean absolute deviation (MAD) to determine the optimal λ setting (refer to Eq. (5)). Figure 5 shows the trained results of λ (0.1–0.9) and MAD in the standard set. The circle symbols illustrate the mean value of MAD for all ECG records in the MITDB and error bars illustrate the standard deviation of MAD.

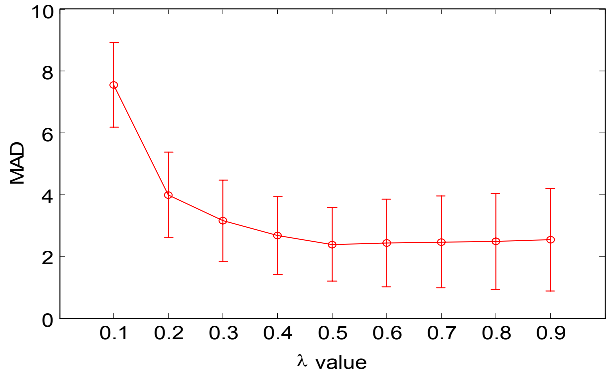

Figure 5. Trained results of various λ values and mean absolute deviation (MAD) in MIT-BIH arrhythmia database (MITDB).

The MAD is greatest when λ is 0.1; in contrast, the smallest MAD and its variation are acquired when λ is 0.5. In this case, the optimal setting of the smoothing coefficient λ is 0.5, and it would have the smallest variation. This indicates that the current beat would be subject to the previous beat.

The trained results showed that the R-wave accuracy was affected by noise around the baseline. For this reason, poor detection performances arose in 10 ECG records in MITDB. To improve this weakness, signals around the baseline can be eliminated below a LCL. As shown in Eq. (6), different L values affect the determination of the R-wave. These 10 ECG records were used to adjust the L values to enhance R-wave detection accuracy. Table 1 presents the number of false positive and false negative between various L values and 10 ECG records.

As shown in Table 1, the fewest FN and FP are obtained when L is set at 2; thus the optimal setting for the L value is 2. This study added r and L to improve the So and Chan's method; based on the trained results in the MITDB, the initial r was set as 26, L was set as 2, and there are better QRS complex detection results. The optimal parameter settings, following a previous study, are summarized in Table 2.

Table 1. FP and FN trained results for various L values (L = 1, 1.5, 2, and 2.5) in MITDB

Record	FN				FP			
	$L=1$	$L=1.5$	$L=2$	$L=2.5$	$L=1$	$L=1.5$	$L=2$	$L=2.5$
106	11	0	0	0	0	0	2	3
109	1	5	0	0	14	1	1	1
116	1	1	0	0	0	0	0	0
119	0	0	0	0	0	1	1	1
205	0	0	0	0	0	0	0	0
210	10	7	6	6	0	1	1	1
214	6	4	4	4	0	0	1	2
219	0	0	0	0	0	0	0	0
221	2	1	1	1	0	0	0	0
222	14	0	0	0	0	0	0	0

FP: false positive, FN: false negative, MITDB: MIT-BIH arrhythmia database.

Table 2. Optimal parameter settings on forward-backward algorithm in MIT-BIH arrhythmia database (MITDB)

Parameter	Optimal value	Explanation
initial max	150	It affects initial slope threshold and updates by maxi (Eq. (3)).
sv	2	The lower sv value causes higher sensitivity for detecting R-wave.
tp	8	Threshold parameter (tp) is positive relation to $ST_{(m)}$. The tp value is higher, the $ST_{(m)}$ is higher, but the sensitivity of detecting R-wave is lower.
fp	8	This is a one-pole filter which could smooth out the effect of abrupt change.
initial *r*	26	To avoid recognizing turning and noisy points as actual R-waves in So and Chan's approach and improve accuracy of detecting R-wave.
L	2	The appropriate parameter *L* could eliminate noise around baseline and improve accuracy of detecting R-wave.

2.2 Arrhythmic Beat Classification

According to the detection results of phase I, the results of the QRS complex can be converted to features for pathological diagnosis, such as RR interval series. Tsipouras *et al*. (2005) proposed utilizing RR intervals for arrhythmia classification. The algorithm starts with windowing-RR interval series consisting of $RR1_i$, $RR2_i$, and $RR3_i$ intervals, where *i* is the number of windows from 1 to the end of the beats in the ECG signal. The classification concerns the second beat of the middle RR interval ($RR2_i$) and is initially considered a priori normal. Figure 6 shows sliding windows in the RR interval series.

The six conditions (C1–C6) have been provided by medical experts, and they are based on clinical procedures for detecting arrhythmic events from the length and timing on windowing-RR interval series (Tsipouras *et al*., 2005). The conditions are used for classifying the middle RR interval of a three-RR interval sliding window (Figure 6). These conditions are applied sequentially; when a beat is classified into a category according to one rule, the classification involved cannot be changed by a subsequent rule. The beat classification procedure of the arrhythmia classification algorithm (Tsipouras *et al*., 2005) is used here. This method is limited to detecting three types of arrhythmic episodes: ventricular flutter/fibrillation, premature ventricular contraction, and second-degree heart block. The arrhythmias such as an atrial flutter would not be detected. The beats are classified into four categories as shown in Figure 2.

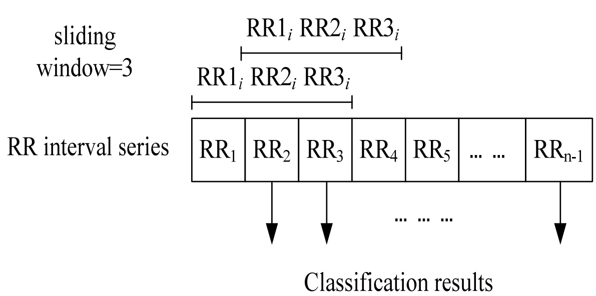

Figure 6. Sliding windows procedure in an RR interval series.

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; a false-positive (FP) value indicates the number of incorrect positive predictions; a false-negative (FN) value indicates the number of incorrect negative predictions; and a true-negative (TN) value indicates the number of correct negative predictions. TP values are favored by doctors and medical professionals, so R accuracy is the most important assessment indicator, as shown in Eq. (7).

$$\text{R accuracy (\%)} = \frac{TP + TN}{TP + FP + FN + TN} \tag{7}$$

In addition to R accuracy, indicators often used in statistics to assess algorithms include type I error (α) and type II error (β), as shown in Eqs. (8) and (9).

$$\alpha = \text{Type I error (\%)} = \frac{FP}{FP + TN} \tag{8}$$

$$\beta = \text{Type II error (\%)} = \frac{FN}{TP + FN} \tag{9}$$

This study uses three assessment indicators—R accuracy, type I error (α), and type II error (β)—to compare detection results with those in the literature.

3. PERFORMANCE EVALUATION AND DISCUSSION

The MITDB is a publicly available set of standard test materials for the evaluation of arrhythmia detectors, and it intends to represent real world signals that contain the broadcast possible range waveforms including ambiguous cases which maybe the most interesting challenges for automated analysis (Moody and Mark, 2001; MIT/BIH Arrhythmia Database, 2007). In this section, the FB algorithm is trained by MITDB and applied to actual Holter ECG signals for verification.

The optimal results obtained after applying the proposed procedure to the MITDB are shown in Table 3. The proposed method performed well when applied to the MITDB and the optimal parameters are shown in Table 1. The QRS detection algorithm achieved 99.52% accuracy, 1.87% type I error, and 0.001% type II error in the detection of the QRS complex in the ECG data. Table 3 presents a comparison of the performance of our approach to the achieved detection results in the literature.

Some ECG records in MITDB, including records 106, 109, 119, 210, 214, and 221, produce R-wave detection errors, mainly because many noises around the baseline prompted the FB algorithm to mistake a P-wave for an R-wave, resulting in small type I and II errors. Figure 7 provides detailed graphs, and the circles

Table 3. Comparison of QRS detection performances obtained from various studies in MIT-BIH arrhythmia database (MITDB)

	R accuracy (%)	Type I error (%)	Type II error (%)
Forward-backward algorithm	99.52	1.87	0.001
Madeiro *et al.* (2007)	97.94	3.59	0.048
Paoletti and Marchesi (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

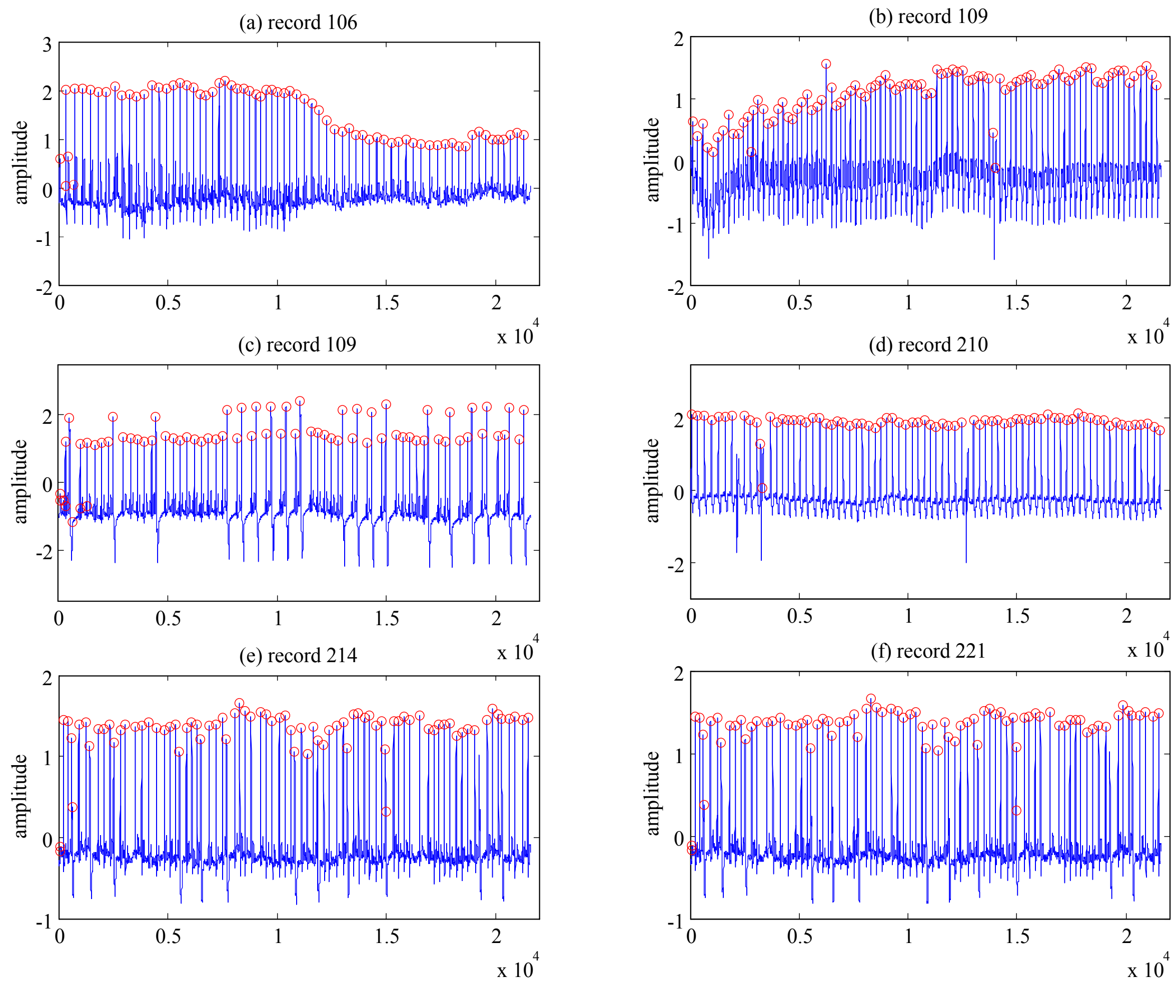

Figure 7. Special electrocardiogram record graph in MIT-BIH arrhythmia database (MITDB).

therein are R points detected by the FB algorithm.

To further test the proposed algorithm, 52 actual Holter ECG signals were used as test samples. The ECG signals in MITDB are measured when patients are in a stationary state; however, the Holter ECG signals are more complex than a standard database. Table 4 summarizes the detected results. The proposed method achieved 98.54% accuracy, 3.17% type I Error, and 0.0172% type II Error. The FB algorithm obtained higher accuracy and lower type I and type II errors, clearly indicating that the detection effects of the algorithm proposed in this study are better than those in other studies, and that it is capable of improving the shortcomings of the So and Chan's approach.

After the R-wave is determined, the next step is beat classification. Two datasets are applied for arrhythmic beat classification. The first dataset was created using all the beats from ECG records in the MITDB. The second dataset was all beats from 52 records of Holter ECG signal. The performance indexes also used accuracy (%), type I error (%), and type II error (%) (Table 5). As we have known from MITDB, most beats are normal, fewer belong to PVC, and only a few to VF and BII.

There were no BII records in our Holter ECG signal, so the accuracy (%), type I error (%), and type II error (%) were not meaningful.

A similar decrease in the performance of the proposed approach is observed between the MITDB and actual Holter signal (Table 5). This is due to the higher complexity of the recordings of the 200 series (presence of noise, types of arrhythmias which cannot be detected by RR interval). The accuracies for MITDB and real ECG signals for N classified beats are similar, but they are different in VF classified beats: the 93.00% accuracy is obtained in the MITDB records, while in the actual Holter ECG records are much smaller (87.20% accuracy). Accuracy of the four types of arrhythmic beats is also high. It is noted that the percentage of normal beats in the datasets is high because this is close to reality, as ECG recordings have high percentages of normal beats. In the actual Holter ECG signal, the misclassification rates are higher, especially for PVC: 396 PVC beats are misclassified as normal (11.5%) and 11 as ventricular flutter/fibrillation beats (0.32%).

4. CONCLUSION

This study proposed an FB algorithm and succeeded in integrating the concept of SPC to eliminate the artifact around the baseline, effectively overcoming the weaknesses of the So and Chan's method in QRS complex detection. In addition, by improving R-wave detection accuracy, the whole research procedure properly

Table 4. Comparison of QRS detection performances on actual Holter electrocardiogram signal

	R accuracy (%)	Type I error (%)	Type II error (%)
Forward-backward algorithm	98.54	3.17	0.0172
Madeiro *et al*. (2007)	95.46	5.51	0.0916
Paoletti and Marchesi (2006)	97.91	6.61	0.1252
So and Chan (1997)	93.06	11.63	0.4830
Hamilton and Tompkins (1986)	97.32	4.48	0.0425
Pan and Tompkins (1985)	97.56	4.17	0.0432

Table 5. Results for beat classification in MITDB and actual Holter signal

Dataset	Condition (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
Holter signal							
N	30980	396	18	0	98.68	9.98	1.14
PVC	325	3430	7	0	91.17	1.05	10.61
VF	31	11	286	0	87.20	0.12	8.04
BII	0	0	0	0		0.00%	

MITDB: MIT-BIH arrhythmia database, N: normal, PVC: pre-mature ventricular contraction, VF: ventricular flutter/fibrillation, BII: second-degree heart block.

applies the arrhythmia classification rules proposed by Tsipouras *et al*. (2005) and builds a process that can determine four categories of various cardiac arrhythmias. This study used MITDB as training samples, to train optimal parameter settings and detect the QRS complex, and used RR intervals to classify beats among overall ECG signals; then actual Holter signals were used for test analysis. The FB algorithm detected the QRS complex and easily extracted features from the ECG records. The obtained results indicate that the proposed method performs well (i.e., 99.52% accuracy for MITDB and 98.54% accuracy for actual Holter ECG signal). The proposed procedure is advantageous compared to the procedures presented in the literature, for 1) the QRS complex can be easily detected by the FB algorithm, even in complicated and actual ECG records, and it is more robust than those in the literature (Hamilton and Tompkins, 1986; Madeiro *et al*., 2007; Paoletti and Marchesi, 2006; So and Chan, 1997); 2) beat classification rules are based on medical knowledge and the expertise of cardiologists, who have proposed the range of the three-RR interval sliding window (Tsipouras *et al*., 2005); and 3) integration of the QRS detector and beat classification and processing time is reduced, since only one feature (i.e., RR interval) was used in the classification scheme. Although the proposed SPC-based FB algorithm performed well in this study, future studies are needed to continue to apply this algorithm to real world ECG data, and spot out other possible noise sources for improving the detection R-wave algorithm.

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