



## High accuracy in automatic detection of atrial fibrillation for Holter monitoring

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**Abstract:** Atrial fibrillation (AF) has been considered as a growing epidemiological problem in the world, with a substantial impact on morbidity and mortality. Ambulatory electrocardiography (e.g., Holter) monitoring is commonly used for AF diagnosis and therapy and the automated detection of AF is of great significance due to the vast amount of information provided. This study presents a combined method to achieve high accuracy in AF detection. Firstly, we detected the suspected transitions between AF and sinus rhythm using the delta RR interval distribution difference curve, which were then classified by a combination analysis of P wave and RR interval. The MIT-BIH AF database was used for algorithm validation and a high sensitivity and a high specificity (98.2% and 97.5%, respectively) were achieved. Further, we developed a dataset of 24-h paroxysmal AF Holter recordings ( $n=45$ ) to evaluate the performance in clinical practice, which yielded satisfactory accuracy (sensitivity=96.3%, specificity=96.8%).

**Key words:** Atrial fibrillation, Delta RR interval distribution difference curve, Holter monitoring

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### 1 Introduction

Atrial fibrillation (AF) is a growing epidemiological problem in the world, with a substantial impact on morbidity and mortality (Wolf *et al.*, 1978; Chugh *et al.*, 2001). However, a significant portion of patients with AF has no obvious clinical symptoms, which makes them at risk of other diseases (e.g., cryptogenic stroke) (Humphries *et al.*, 2001; Page *et al.*, 2003; Kaufman and Waldo, 2004). Thus, AF diagnosis, especially asymptomatic AF detection, is necessary in clinical practice.

Ambulatory electrocardiography (ECG) (e.g., Holter) monitoring is usually used to diagnose AF or evaluate AF therapy (Roche *et al.*, 2002; Schaer *et al.*, 2004). Since this technology provides a vast amount of valuable information, automated detection of AF is of great significance. Several algorithms have been

developed to detect AF based on two ECG traces: (1) absence of P waves, and/or (2) irregularly irregular RR intervals. The absence of P waves is the most significant marker of AF; however, since locating the P wave fiducial point is often difficult when extensive noise is present, the results relied on this hallmark are moderate to high (73.0% to 91.0%, 71.0% to 80.0%, respectively) (Fukunami *et al.*, 1991; Opolski *et al.*, 1997; Budeus *et al.*, 2003). The methods based on RR intervals are, therefore, preferable, with a higher sensitivity and specificity compared to the former method (93.7% vs. 80.7%, 93.0% vs. 75.7% on average, respectively) (Moody and Mark, 1983; Tateno and Glass, 2001; Duverney *et al.*, 2002; Dash *et al.*, 2009). However, it is important to note that regular RR intervals occur in the presence of an atrioventricular (AV) block or ventricular or AV junctional tachycardia when AF is present (Levy *et al.*, 1998). In addition, irregular RR intervals also can be seen in the other arrhythmias (e.g., atrial impure flutter, multifocal atrial tachycardia, sinus arrhythmia), and

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therefore this method cannot completely distinguish AF from other arrhythmias. A combined approach of these two ECG characteristics, therefore, may be the most optimal approach to appropriate AF diagnosis (Couceiro *et al.*, 2008; Babaeizadeh *et al.*, 2009). Previous studies have shown that the analysis of P waves leads to improved performance (Babaeizadeh *et al.*, 2009), though the improvement is limited. This study presents our findings on achieving high accuracy for AF detection. The proposed method is based on the combination analysis of P wave and RR interval according to our previously published methods (Huang *et al.*, 2011).

## 2 Materials and methods

### 2.1 Databases

#### 2.1.1 Dataset of 24-h paroxysmal AF Holter recordings

For algorithm development, we gathered 45 24-h Holter recordings with paroxysmal AF from the ECG Department of the Sir Run Run Shaw Hospital and the First Affiliated Hospital, School of Medicine, Zhejiang University, China. All the recordings, recorded using V1, V5 and aVF leads and sampled at 200 Hz, were first analyzed by the Holter system and AF episodes were independently annotated by two cardiologists. All the atrial flutter (AFL) episodes were treated as non-AF. Thus, a list of beat annotations and their labels (AF or non-AF) was obtained for further processing. Of the total 45 recordings, most were in association with other arrhythmias, e.g., AFL, AV block, and atrial tachycardia. The detailed statistics are shown in Table 1.

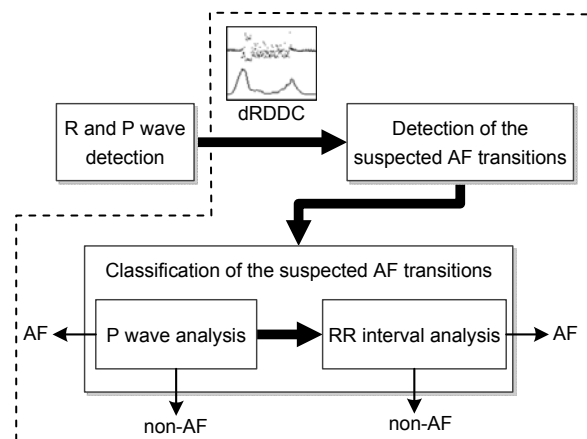
#### 2.1.2 MIT-BIH AF database (Goldberger *et al.*, 2000)

This database is commonly used for validation of AF detection algorithms. It includes 23 10-h

multi-lead ECG recordings with AF (21 paroxysmal and 2 persistent) and each record is digitized at a sample rate of 250 Hz. The summary of AF episodes and beats is also listed in Table 1.

### 2.2 Methods

The proposed method starts with the detection of R and P waves (Fig. 1), and then goes on to detect AF in two steps: (1) detection of the suspected AF transitions using the delta RR interval distribution difference curve (dRDDC); (2) classification of the suspected AF transitions by a combination analysis of P wave and RR interval. Here, the AF transition represents the transition between AF and sinus rhythm, the delta RR interval is defined as the difference between two successive RR intervals and the dRDDC is defined as the difference between the distribution of the delta beRRs and delta afRRs (beRRs: RR intervals before the current RR interval; afRRs: RR intervals after the current RR interval). In this study, since the annotations of the R wave have already been prepared according to the databases, we solely focused on the detection of P waves and AF.



**Fig. 1** Flowchart of the proposed method

The steps surrounded by dotted line box are the procedure for AF detection. The dRDDC is the abbreviation of the delta RR interval distribution difference curve

**Table 1** Statistics of the used databases

Database name	Record	AF		AF (>30 s)*		Non-AF Beat
		Beat	Episode	Beat	Episode	
24-h paroxysmal AF Holter recordings	45	1322402	893	1310598	541	3380906
MIT-BIH AF database	23	508419	291	506872	226	620123

The 24-h paroxysmal AF Holter recordings are used for algorithm development. All records have paroxysmal AF and some of them contain more than one other type of arrhythmia. The MIT-BIH AF database is used for algorithm validation. Of the total 23 records, 21 have paroxysmal AF and the other 2 have persistent AF. All the atrial flutter episodes were treated as non-AF. \* AF (>30 s) indicates AF episodes larger than 30 s

### 2.2.1 P wave detection

The morphological transform method as proposed by Sun *et al.* (2005) was used to detect P waves. The procedures were performed as: (1) signal pre-processing, (2) multi-scale morphological derivative transform, and (3) detection of P waves of each beat in morphological derivative transformed signals according to the annotations of the R wave. Since P waves are absent in atrial arrhythmia, especially in AF, the P waves would not always be detected. These undetected P waves were marked as invalid for further processing.

### 2.2.2 AF detection

We first detected the suspected AF transitions using the dRDDC. The dRDDC reflects the variability of RR interval and its peaks (local maximum points) represent the major changes including the transitions between two rhythms, especially between AF and sinus rhythm. Thus, the suspected AF transitions could be located by detecting the peaks in the dRDDC. In this study, we used the density histogram of the 50 delta beRRs and the 50 delta afRRs to calculate the dRDDC by the following equation (Huang *et al.*, 2011):

$$D_i = \sum_{j=1}^N (b_j - a_j)^2,$$

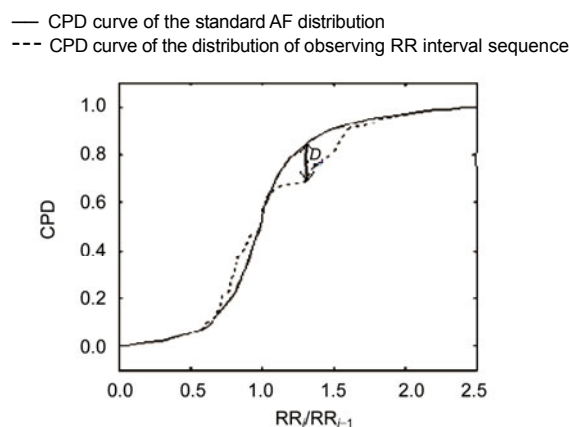
where  $D_i$  is the value of dRDDC of each beat;  $j$  is the bin index of histogram and  $N$  is the bin number of histogram;  $b_j$  and  $a_j$  are the bin counts in the density histogram of the 50 delta beRRs and the 50 delta afRRs, respectively. All the delta RR intervals were limited to the range of  $-1200$  to  $1200$  ms and the histogram parameters were fixed as: range= $-1200$  to  $1200$  ms, bin number= $21$ , bin width= $114.3$  ms.

When a suspected AF transition was detected, a classifier was used to determine if it was the transition between AF and sinus rhythm or not. In this study, the classifier was based on a combination analysis of P wave and RR interval surrounding the 50 afRRs.

In the P wave analysis, we used the P-R intervals to distinguish AF and non-AF rhythms. Here, the P-R interval is defined as the time between the peak of the P wave and the peak of the R wave. Since some of the peaks would be invalid due to the absence of P waves

during AF, the P-R intervals included two types: valid ( $>0$ ) and invalid ( $=0$ ). Of the valid P-R intervals, we calculated the minimum standard deviation (MinSD) of 16 consecutive P-R intervals to quantify the variation of the P-R interval. In sinus rhythm, the variation is relatively small but during AF or strong noise affected signals, it is very large due to the easy detection of pseudo-P waves (P-wave-like artifact). Therefore, we used the MinSD smaller than a fixed threshold (SDThresh= $10$ ) to determine non-AF rhythms. Of the invalid P-R intervals, we counted their numbers to quantify the absence of P waves and if the number was sufficiently larger than a fixed threshold (PRThresh= $24$ ), it was considered to be an AF rhythm. These two strategies ensure that some of the apparent AF and non-AF rhythms be detected, with the remaining to be classified by RR interval analysis.

The RR interval analysis involved four steps as proposed in the previously published algorithm (Huang *et al.*, 2011): (1) histogram analysis, (2) standard deviation analysis, (3) numbering aberrant rhythms recognition, and (4) Kolmogorov-Smirnov (K-S) test. The first three steps were used to filter some apparent non-AF rhythms (especially the numbering aberrant rhythms) and the final step is the core of classification. The assessment of the K-S test reflects the difference between two distributions. Thus, we developed a standard AF distribution to identify AF rhythm and evaluated the difference between the distribution of observed RR interval sequence and the standard AF distribution by the K-S test (Fig. 2).



**Fig. 2 Example of evaluation of difference between the distribution of observing RR interval sequence and the standard AF distribution using the K-S test**

*D*: the greatest distance between the two curves. The cumulative probability distribution (CPD) is derived from ratio of two successive RR intervals ( $RR_i/RR_{i-1}$ )

The significance level (*prob*) is given as follows (Press et al., 1992):

$$prob = Q_{KS}(\lambda) = 2 \sum_{j=1}^{\infty} (-1)^{j-1} e^{-2j^2\lambda^2},$$

where,

$$\lambda = (\sqrt{N_e} + 0.12 + 0.11/\sqrt{N_e})D,$$

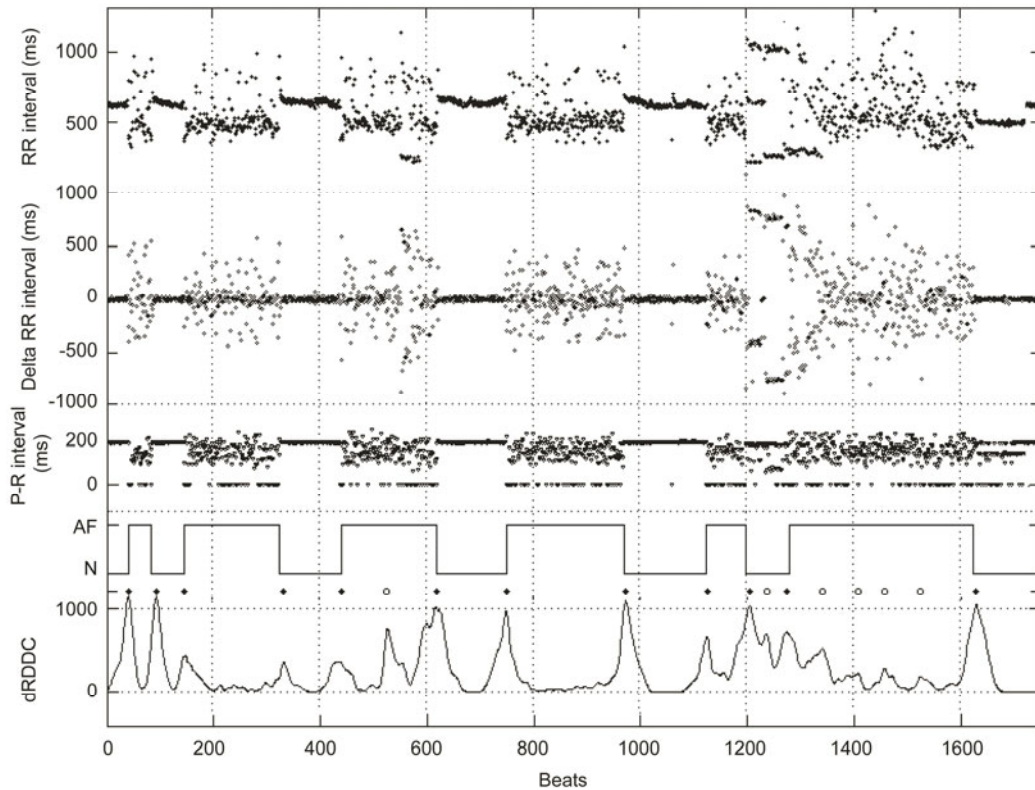
$$N_e = N_1 N_2 (N_1 + N_2).$$

*D* is the greatest distance between two distributions; *N<sub>e</sub>* is the effective number of data points; *N<sub>1</sub>* and *N<sub>2</sub>* are the numbers of data points of two distributions, respectively.

A small *prob* signifies the significant difference between two distributions. Therefore, we used a fixed threshold (ProbThresh=0.1) to distinguish the AF and non-AF rhythms according to the previous study.

### 3 Results

We used the single-lead annotations of R and P waves to detect AF. Fig. 3 shows an example of the intermediate results of the proposed method. The delta RR interval filters out the baseline drift of RR interval, which makes the histogram of delta RR interval vary symmetrically and thus the calculated dRDDC performs more stable. Also, since the variation of the delta RR interval is larger than that of the RR interval, the transitions between two rhythms can be shown more prominently in the dRDDC. From the dRDDC, we detected several peaks as shown in Fig. 3 and many of the peaks were true AF transitions. Note that the P-R intervals are always invalid (=0) during AF, while they only vary slightly during the sinus rhythm. We could classify some of the transitions by analyzing the P waves, with the remaining transitions to be confirmed using RR interval analysis procedures.



**Fig. 3 Intermediate results of the proposed method**

The RR/delta RR intervals were calculated from subject 04043 of the MIT-BIH AF database. The P-R intervals were derived from the proposed P wave detection method and the value of zero indicates the invalidation of P-R interval. The solid line in the fourth row shows the assessment of AF as published in the MIT-BIH AF database. ♦: the detected peaks represented the AF transitions in the dRDDC; ○: the detected peaks represented the false AF transitions in the dRDDC. The bottom line shows the dRDDC calculated by the density histograms of the 50 delta beRRs and the 50 delta afRRs

The performance results are listed in Table 2. We applied the algorithm to all single-lead annotations of the MIT-BIH AF database to evaluate the performance and the results are reported in two parts: AF and AF (>30 s). The AF part reports the statistics of all AF episodes and the AF (>30 s) part ignores episodes shorter than 30 s. Looking at the results of the MIT-BIH AF database, we achieved a high sensitivity and specificity in all leads (98.2% and 97.5% on average in AF part, respectively). Note that in the part of AF (>30 s), the sensitivity is larger than that of AF.

Moreover, of the total 291 AF episodes, 260 were correctly detected in the AF part, and of the total 226 episodes in the AF (>30 s) part, the number of correctly detected episodes was 224. This shows that accuracy increases with the duration of AF episodes.

Furthermore, we tested the proposed method on the dataset of 24-h paroxysmal AF Holter recordings (Table 2). The average sensitivity and specificity were 96.3% and 96.8%, respectively. Since the single-lead P wave annotation of the same record is not the same, the accuracy slightly varies with different leads.

**Table 2 Performance results of the proposed method**

Database name		AF			AF (>30 s)		
		Beat		Episode	Beat		Episode
		SE (%)	SP (%)		SE (%)	SP (%)	
MIT-BIH AF database	Lead 1	98.0	97.6	260	98.1	97.4	224
	Lead 2	98.3	97.4	260	98.4	97.2	224
	Average	98.2	97.5	260	98.3	97.3	224
24-h paroxysmal AF Holter recordings	Lead 1	96.2	96.8	757	96.4	96.4	499
	Lead 2	96.3	96.9	732	96.6	96.5	487
	Lead 3	96.5	96.8	738	96.7	96.5	494
	Average	96.3	96.8	742	96.6	96.5	493

SE: sensitivity; SP: specificity; TP: true positive

#### 4 Discussion

This study presents a combined method to AF detection. The method first detects the suspected AF transitions and then classifies these transitions using a combination analysis of P wave and RR interval. A comparison with previously published algorithms on the MIT-BIH AF database is listed in Table 3. The proposed method achieved the highest performance, with 98.2% sensitivity and 97.5% specificity. In comparison with our previously published results (Huang et al., 2011), the sensitivity significantly increased (2.1%), while the specificity has a moderate decrease of -0.6%.

The irregularity of RR intervals is the most accessible ECG characteristic for AF detection (Babaeizadeh et al., 2009). However, since irregular RR intervals can be seen in other arrhythmias and regular RR intervals are possible in AF, some of the AF and non-AF rhythms may be misclassified if only analyzing the RR intervals. Analyzing the P wave location and/or morphology can improve the performance

**Table 3 Comparison of algorithm performance on the MIT-BIH AF database**

Methods	SE (%)	SP (%)
The proposed method	98.2	97.5
Huang et al., 2011*	96.1	98.1
Tateno and Glass, 2001*	94.4	97.2
Dash et al., 2009*	94.4	95.1
Couceiro et al., 2008	93.8	96.1
Babaeizadeh et al., 2009	92.0	98.0

\* These methods are based on RR intervals and the remains are based on analyses of P wave and RR interval. SE: sensitivity; SP: specificity

of algorithm. However, since the detection of P wave is easily affected by noise, the P wave analysis would be unreliable under certain circumstances. In this study, we proposed a simple and conservative P wave strategy to classify AF and non-AF rhythms. The strategy is based on two P-R interval characteristics: (1) small variation in sinus rhythm, and (2) large number of invalid P-R intervals during AF. These characteristics could distinguish some of the apparent AF and non-AF rhythms in good signal conditions but would fail in the presence of noise. Thus, the P wave strategy ensures the accuracy even in the strong noise

situations. The purpose of P wave analysis is to filter some apparent AF and non-AF rhythms; therefore, the thresholds should be applied strictly and kept constant in order to prevent misclassifying the AF and non-AF rhythms.

## 5 Conclusions

In this study, we proposed an automatic AF detection method based on the combination analysis of P wave and RR interval and achieved high accuracy on both validation and development databases. The proposed algorithm has been applied for Holter monitoring in clinical practice.

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