A Novel Method for Detection of the Transition Between Atrial Fibrillation and Sinus Rhythm

Chao Huang, Shuming Ye*, Hang Chen, Dingli Li, Fangtian He, and Yuewen Tu

***Abstract*—Automatic detection of atrial fibrillation (AF) for AF diagnosis, especially for AF monitoring, is necessarily desirable for clinical therapy. In this study, we proposed a novel method for detection of the transition between AF and sinus rhythm based on RR intervals. First, we obtained the delta RR interval distribution difference curve from the density histogram of delta RR intervals, and then detected its peaks, which represented the AF events. Once an AF event was detected, four successive steps were used to classify its type, and thus, determine the boundary of AF: 1) histogram analysis; 2) standard deviation analysis; 3) numbering aberrant rhythms recognition; and 4) Kolmogorov–Smirnov (K–S) test. A dataset of 24-h Holter ECG recordings ($n = 433$) and two MIT-BIH databases (MIT-BIH AF database and MIT-BIH normal sinus rhythm (NSR) database) were used for development and evaluation. Using the receiver operating characteristic curves for determining the threshold of the K–S test, we have achieved the highest performance of sensitivity and specificity (SP) (96.1% and 98.1%, respectively) for the MIT-BIH AF database, compared with other previously published algorithms. The SP was 97.9% for the MIT-BIH NSR database.**

***Index Terms*—Atrial fibrillation (AF), delta RR interval distribution difference curve (dRDDC), RR interval.**

I. Introduction

ATRIAL fibrillation (AF) is the most common arrhythmia in clinical practice. In China, approximately 10 million of people suffer from AF [1], and the estimated prevalence of AF is probably 1% in the general population, increasing with age, more so in men than in women [2]–[5]. Since the aging of population and the improving survival from conditions predisposing to AF, the AF prevalence is increasing significantly [6], [7]. AF is not a benign entity; rather, it is associated with an increased risk of cardiovascular and metabolic comorbidities (coronary artery disease, hypertension, etc.), and also stroke [8]. Moreover, the increased mortality associated with AF is independent of the underlying cardiovascular condition. Therefore, AF diagnosis, especially AF monitoring, is necessarily desirable for clinical therapy, such as stroke prevention [9], [10] and postoperative observation [11].

AF is typically diagnosed by analyzing the two ECG traces: 1) absence of P-wave, replaced by rapid oscillations or fibrillatory waves, and 2) irregularly irregular RR intervals. Previous studies have developed several algorithms to identify AF based on either characteristics or both. Fukunami *et al*. [12], Opolski *et al*. [13], Budeus *et al*. [14], and Michalkiewicz *et al*. [15] used signal-averaged P-wave analysis method for AF detection, and the sensitivity (SE) and specificity (SP) are both moderate to high (73% to 91%, 71% to 83.5%, respectively) due to the difficulty of locating the P-wave fiducial point. The methods based on RR intervals have been proved to be a preferable way [16]–[25], and also the methods combined with these two characteristics [26], [27], mostly derived a result of over 90% SE and SP for the MIT-BIH AF database. However, the previous studies, which are based on RR intervals do not propose an effective method for detecting the exact time of transitions between AF and sinus rhythm, and most of them use beat segments, which may cause short AF duration failing to detect.

In this study, we first detect the transitions between two different cardiac rhythms, and then, use a four-step process to determine the transitions between AF and sinus rhythm. Here, we use the AF event to represent the transition between two different cardiac rhythms, especially between AF and sinus rhythm. The AF event includes three types: *onset*, *cessat*, and *none*. The *onset* and *cessat* event represents the onset and cessation of AF, respectively, and the *none* event indicates the transition between two non-AF rhythms.

II. Materials and Methods

A. ECG Records

A dataset of 24-h Holter ECG recordings ($n = 433$) and two MIT-BIH standard databases (MIT-BIH AF database and MIT-BIH normal sinus rhythm (NSR) database) from Physiobank [28] were used in this study.

The 24-h Holter ECG recordings were gathered from the ECG department of Sir Sun Sun Shaw Hospital. All the recordings, recorded using V1, V5, and aVF leads, and digitized at a sample rate of 100 Hz, were first analyzed by the Holter system and the AF episodes were annotated by two cardiologists independently. The atrial flutter (AFL) episodes were treated as non-AF. Thus, for each recording, a list of labeled RR intervals (AF or non-AF) was obtained for further processing. Moreover, the ECG recordings were separated into four groups: paroxysmal AF (paAF) set ($n = 20$), persistent AF (peAF) set ($n = 54$), abnormal non-AF (abnAF) set ($n = 54$), and normal non-AF (nnAF) set ($n = 305$).

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C. Huang, H. Chen, D. Li, and Y. Tu are with the Key Laboratory of Biomedical Engineering of Education Ministry, Zhejiang University, Hangzhou 310027, China.

*S. Ye is with the Key Laboratory of Biomedical Engineering of Education Ministry, Zhejiang University, Hangzhou 310027, China (e-mail: ysmln@vip.sina.com).

F. He is with the Department of Electrocardiographic, Sir Sun Sun Shaw Hospital, Hangzhou 310016, China.

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TABLE I
STATISTICS OF THE TEST DATABASES

Database Name	Records	Beats		
		AF	AFL	Non-AF
* paAF set	20	524820	-	1486501
* peAF set	54	5554963	-	-
* abnAF set	54	-	-	5237741
* nnAF set	305	-	-	28080251
MIT-BIH AF database	25	519816	11711	690036
MIT-BIH NSR database	18	-	-	1729629

The 24-hour Holter recordings were separated into four groups (*): paroxysmal AF (paAF) set, persistent AF (peAF) set, abnormal non-AF (abnAF) set and normal non-AF (nnAF) set. All the recordings were annotated for AF and non-AF, and the AFL episodes were treated as non-AF.

The abnAF and nnAF sets had no AF episodes but contained at least one other type of arrhythmia. Specifically, the abnAF set contained irregular rhythms, including atrioventricular (AV) block, persistent AFL, atrial or ventricular tachycardia, sinus arrhythmia, etc. The total number of beats of the four groups is listed in Table I.

The MIT-BIH AF database is in common use for validation of AF detection algorithms. It includes 25 long-term (10 h) ECG recordings with AF (23 paroxysmal and 2 persistent) and contains 299 AF episodes (about 93.4 h). The detailed statistics is shown in Table I.

The MIT-BIH NSR database consists of 18 long-term (24 h) ECG recordings. These recordings originate from subjects, who do not have significant arrhythmias, and thus, this database is useful for evaluation of the SP of AF detection algorithms. This database is also summarized in Table I.

B. Methods

The proposed method for AF detection involves two steps: 1) AF event detection using the delta RR interval distribution difference curve (dRDDC) and 2) AF event classification. Here, 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 and afRRs: RR intervals after the current RR interval).

Step 1: AF event detection using the dRDDC: The variation of RR interval reveals the alteration of cardiac rhythm. Especially, the RR interval varies irregularly during AF, which is the most important characteristic to distinguish it from the other rhythms. In this study, we used the dRDDC to quantify the variability of RR interval, and detected its peaks (local maximum points), which represent the major changes of the delta RR interval distribution, including the transition point of two cardiac rhythms, defined as AF event.

Step 1–1: Calculating the dRDDC: To obtain the dRDDC, the density histograms of the 50 delta beRRs and the 50 delta afRRs of each beat were calculated. Here, all delta RR intervals were limited to the range of –1200 to 1200 ms and the parameters of histogram were fixed as: range = –1200–1200 ms, bin number = 21, and bin width = 114.3 ms.

The difference *Diff* was calculated as follows:

$$Diff = \sum_{j=1}^{21} (b_j - a_j)^2 \tag{1}$$

where b_j and a_j are the bin counts in the density histogram of the 50 delta beRRs and the 50 delta afRRs, respectively.

Step 1–2: Detecting a peak in the dRDDC: In the dRDDC, we detected a peak by observing when the dRDDC changes direction within a segment. The segment is defined by noting points, where the dRDDC ascends, and then, descends below a threshold, which is a half of the local maximum value. Once a peak is detected, a new peak cannot be detected for at least 20 delta RR intervals.

Step 1–3: Filtering noise peak: Not all peaks were used to determine event type, but many are established to be noise peaks and others to be event peaks. The event peak is a peak that represents an AF event, and the noise peak is any peak that is not related to the AF event.

To be an event peak, the peak must exceed a threshold, which is set between the mean of the noise peak and event peak buffers, according to

$$\text{Threshold} = \overline{\text{NPK}} + \text{TH} * (\overline{\text{EPK}} - \overline{\text{NPK}}) \tag{2}$$

where $\overline{\text{EPK}}$ is the average event peak, $\overline{\text{NPK}}$ is the average noise peak, and TH is the threshold coefficient, from 0 to 1. Here, the noise peak and event peak buffers use the previous eight values, and the TH is typically set to 0.375. The threshold was initialized to 0 and the detected peaks were first classified as event peaks until the threshold was adjusted upon a noise peak.

If the peak was established to be an event peak, the event type (*onset*, *cessat*, or *none*) was determined in the next step. Fig. 1 illustrates an example of the event peaks in the dRDDC and their represented AF event types.

Step 2: AF event classification: When an AF event was detected, we first classified it as *onset* or *none* type, and then, determined if an *onset* event has just occurred or not, if yes, the *none* type was changed to *cessat* type and the *onset* type was ignored.

The event classification process involves four successive steps: 1) histogram analysis (HA); 2) standard deviation analysis (SDA); 3) numbering aberrant rhythms (NARs) recognition (NARsR); and 4) Kolmogorov–Smirnov (K–S) test [29]. The first three are optional steps for algorithm improvement and the final is an indispensable step for classification. All the steps are based on the 50 afRRs surrouding the event.

Step 2–1: Histogram analysis: The density histogram reflects the irregularity of RR (and delta RR) intervals. Fig. 2 shows an example of delta RR intervals during paroxysmal AF, together with two sample histograms at the time of NSR and AF. Note that number of nonempty bins (NEB) of the density histogram of NSR is more concentrated than that of AF. Thus, we counted the NEB of the density histogram of the 50 delta afRRs, and classified the event by the rule.

1) The AF event is classified as *none*, if NEB < 3 or histogram height > 40; else.

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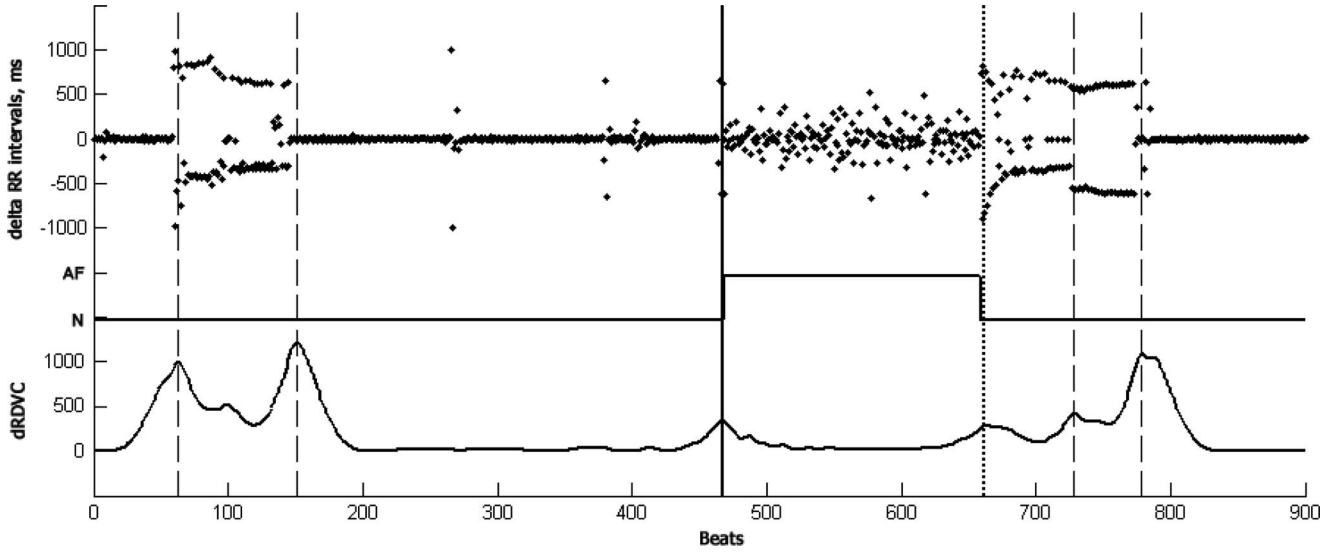

Fig. 1. Event peaks in the dRDDC and their represented AF event types (*none* event: dash vertical line, *onset* event: solid vertical line, and *cesat* event: dot vertical line). The delta RR intervals were calculated from subject 04043 of the MIT-BIH AF database. The middle solid line shows the assessment of AF as published in this database. The bottom line is the dRDDC calculated by the standard density histograms of the 50 delta beRRs and the 50 delta afRRs.

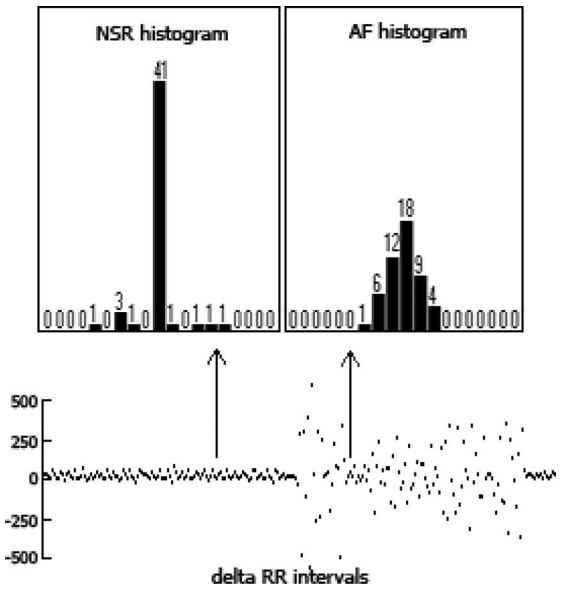

Fig. 2. Delta RR intervals were calculated from subject 04043 of the MIT-BIH AF database, together with two sample histograms at the time of NSR and AF.

2) The AF event is classified as *onset,* if NEB $>$ 14 and histogram height $<$ 25; else.
3) Go to next step.

Step 2–2: Standard deviation analysis: The previous step may fail to detect the *none* event when premature beats appears during regular sinus rhythm. In this step, we used a seven-point median filter to eliminate premature beats of the 50 afRRs, and then, calculated the minimum standard deviation (MinSD) of 20 consecutive RR intervals. The AF event was classified as *none* if MinSD $<$ 16, else the algorithm proceeded to the next step.

Step 2–3: Numbering aberrant rhythms recognition: Although Step 2–2 has already considered the effect of premature beats, it is not enough because the seven-point median filter did not eliminate all premature beats, such as NARs. The NARs is a descriptor for a heart arrhythmia in which abnormal heartbeats occur every other concurrent beats, such as bigeminy, trigeminy, quadrigeminy, etc. The heartbeat to be processed here contains three types: normal beat (N), ventricular premature beat (V), and atrial premature beat (A). The NARs have known patterns, e.g., the NV bigeminy can be recognized by the signature of short–long–short–long RR sequence. In order to characterize the short–long pattern, we computed the RRr of each beat, and thus, the pattern of NARs can be described by the RRr sequence $\{r_0, r_1, \ldots, r_k\}$ where r_i is the value of RRr and k is the number of beats involved in the NARs. Here, the RRr is defined as the ratio of RR[i]/RR[$i-1$] in the time series.

In this study, we established a standard template database ($n = 23$) to cover the most common patterns of NARs. All the standard templates were divided into three groups according to their length (4, 5, or 6). Using these templates, we matched the NARs occurs in the 50 afRRs, and then, eliminated them.

Assume that the RRr sequence of the 50 afRRs would be $\{s_0, s_1, \ldots, s_{49}\}$, where s_i is the value of RRr, we computed the correlation coefficient of the standard template and the equilong RRr sequence $\{s_j, s_{j+1}, \ldots, s_{j+k}\}$, where $j = 0, 1, \ldots, 49-k$, and if the correlation coefficient is extremely high ($>$0.995), it means the equilong RRr sequence is the NARs, and we increased the match count (MC) of the corresponding template and set the equilong RRr sequence to 1.0. After traversing the RRr sequence of the 50 afRRs (increasing j from 0 to $49-k$), we checked the MC of each template and classified the AF event as *none* if one of the MCs and its corresponding template length (CTL) met the following conditions.

1) MC $>$ 1 and CTL $=$ 6; else.
2) MC $>$ 2 and CTL $=$ 5; else.
3) MC $>$ 4 and CTL $=$ 4.

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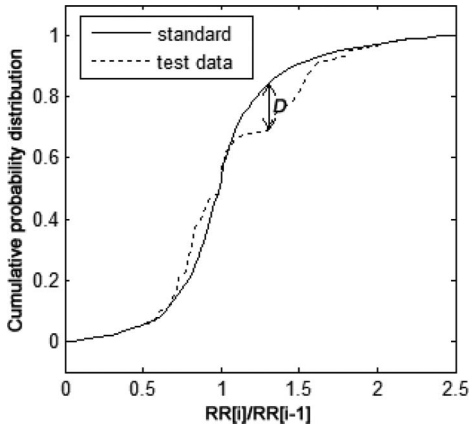

Fig. 3. Example of cumulative probability distributions of the standard AF distribution compares with a distribution of test data. Cumulative probability distribution is derived from RR[i]/RR[i – 1] and D is the greatest distance between two distributions.

If the AF event has not yet been classified as a *none* event, the algorithm proceeded to the final test.

Step 2–4: Kolmogorov–Smirnov test: In the final step, we evaluated the difference between the distribution of the RRr sequence after the NARsR processing and a standard AF distribution by using the K–S test.

The K–S test accesses whether two distributions are different from each other by measuring the maximum value of the absolute difference (D) between two cumulative probability distributions. Fig. 3 shows an example of cumulative probability distributions of the standard AF distribution compares with a distribution of test data.

The significance level of an observed value of D (*prob*) is given approximately by the formula

$$prob = Q_{\mathrm{KS}}(\lambda) = 2\sum_{j=1}^{\infty}(-1)^{j-1}e^{-2j^2\lambda^2} \tag{3}$$

where

$$\lambda = [\sqrt{N_e} + 0.12 + 0.11/\sqrt{N_e}] * D. \tag{4}$$

The N_e is the effective number of data points

$$N_e = \frac{N_1 N_2}{N_1 + N_2} \tag{5}$$

where N_1 and N_2 are the number of data points of two distributions, respectively.

A small *prob* signifies that the two distributions are significantly different from each other. Therefore, a value of *prob* $> P_c$ of a test RRr distribution and the standard AF distribution is associated with a positive identification of AF [17], and if *prob* $> P_c$, we classified the AF event as *onset*, else it is a *none* event.

Previous studies have applied the K–S test to discriminate AF from non-AF [16], [17]. Here, we also used the K–S test to classify the type of the AF event. However, note that using the K–S test, the threshold of the difference between AF and non-AF was statistically, but not exactly, determined. Thus, we added three optional steps to filter some apparent *none* events to reduce the misclassification in the final test.

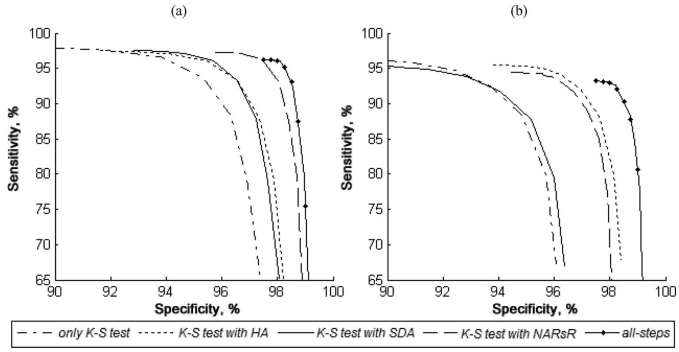

Fig. 4. ROC curves corresponding to five methods: *only K–S test*, *K–S test with HA*, *K–S test with SDA*, *K–S test with NARsR*, and *all-steps*, applied to the MIT-BIH AF database (left panel) and the paAF set (right panel).

TABLE II
PERFORMANCE OF ALGORITHM USING DIFFERENT METHODS

Database Name		only K-S test	K-S test with HA	K-S test with SDA	K-S test with NARsR	all-steps
		$P_c = 0.3$	$P_c = 0.3$	$P_c = 0.3$	$P_c = 0.1$	$P_c = 0.1$
paAF set	SE (%)	94.8	94.1	93.9	93.7	92.6
	SP (%)	92.4	96.2	92.9	96.0	98.2
peAF set	SE (%)	99	98.8	98.9	99.3	98.9
	SP (%)	-	-	-	-	-
abnAF set	SE (%)	-	-	-	-	-
	SP (%)	76.3	83.7	77.5	84.0	88.6
nnAF set	SE (%)	-	-	-	-	-
	SP (%)	98.6	99.2	98.7	99.1	99.4
MIT-BIH AF database	SE (%)	96.6	96.1	96.1	97.0	96.1
	SP (%)	93.8	95.5	95.7	97.2	98.1
MIT-BIH NSR database	SE (%)	-	-	-	-	-
	SP (%)	98.2	98.2	98.2	97.9	97.9

III. EVALUATIONS AND RESULTS

In order to evaluate the improvement performance of each optional step and *all-steps*, we varied the value of P_c to calculate the SE and SP of the MIT-BIH AF database and the paAF set, and then, plotted the receiver operating characteristic (ROC) curves for five methods applied to these two databases (see Fig. 4): *only K–S test*, *K–S test with HA*, *K–S test with SDA*, *K–S test with NARsR*, and *all-steps*. Fig. 4 shows the results that using any of the optional steps before the K–S test was almost always better than that of using *only K–S test*, except the *K–S test with SDA* method applied to the paAF set, which is similar to the *only K–S test* result.

From the ROC curves, we obtained the optimal values of P_c for each method, respectively, by a reasonable tradeoff between SE and SP on the MIT-BIH AF database and the paAF set: *only K–S test* $= 0.3$, *K–S test with HA* $= 0.3$, *K–S test with SDA* $= 0.3$, *K–S test with NARsR* $= 0.1$, and *all-steps* $= 0.1$. Using these values of P_c, we achieved the optimized results of each method applied to these two databases (see Table II). At the P_c of 0.1, the *all-steps* result is SE $= 96.1\%$ and SP $= 98.1\%$ for the MIT-BIH AF database and SE $= 92.6\%$ and SP $= 98.2\%$ for the paAF set. Accordingly, the result in the *only K–S test* method is SE $= 96.6\%$ and SP $= 93.8\%$, and SE $= 94.8\%$ and SP $= 92.4\%$ when $P_c = 0.3$. The SP of *all-steps* method is 4.3% and 5.8% higher than that of *only K–S test* method, respectively, while the SE has a decrease of –0.5% and –2.4%.

Further, we applied these optimal values of P_c to the other databases to evaluate the algorithm performance. The results

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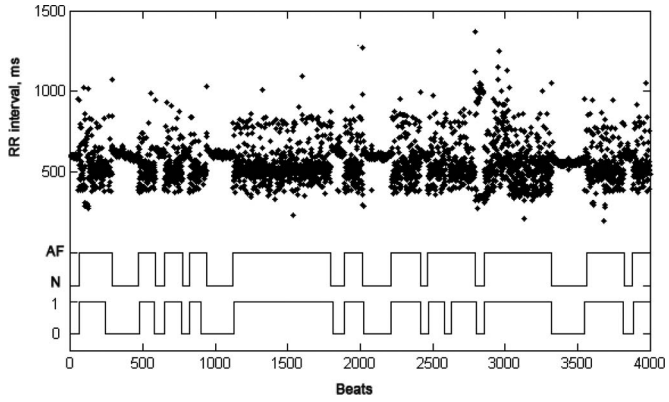

Fig. 5. Our AF assessment compared with the assessment published in the MIT-BIH AF database. The RR intervals were calculated from subject 04043 and the middle solid line shows the assessment of AF as published in the database. The bottom solid line shows our AF assessment indicated by 1, and non-AF indicated by 0.

of each method applied to these databases are also listed in Table II. Note that the peAF set only has SE, and the abnAF set, the nnAF set and MIT-BIH NSR database only have SP, due to these databases containing only AF rhythm or non-AF rhythm. All the SE are greater than 92.6%, and mostly, the SE of optional steps with K–S test are lower than that of the *only K–S test* method, the largest decrease is the result of the *all-steps* method applied to the paAF set (–2.4%). The SP is greater than 92.4%, except for the results of the abnAF set, which the SP ranges from 76.3% to 88.6%. However, compared with the SP of the *only K–S test* method, almost all the methods of optional steps with K–S test lead to improved performance, particularly in the result of the *all-steps* method applied to the abnAF set, which has the largest increase of 12.3%. Only the SP of the MIT-BIH NSR database has a slight decrease (–0.3%) in the *K–S test with NARsR* and *all-steps* method.

IV. Discussion

We proposed a novel method for detection of the transition between AF and sinus rhythm based on RR intervals. The method first detects AF events from the dRDDC, and then, classifies their event type using four successive steps.

The dRDDC reflects the variability of RR interval, and its peaks represent the major changes including the transitions between AF and sinus rhythm. Since the dRDDC is calculated beat by beat, the transitions can be accurately located, and thus, the exact AF boundary can be determined. Fig. 5 shows an example of our assessment compared with the assessment published in the MIT-BIH AF database, and it shows that when the AF episode is correctly detected, the boundary detected by our algorithm is similar to the published assessment.

A comparison with other previously published algorithms on the MIT-BIH AF database is listed in Table III. The proposed algorithm outperformed all the other published results, with the highest SE and SP (96.1% and 98.1%, respectively).

TABLE III
Comparison of Algorithm Performance on the MIT-BIH AF Database

Methods	SE (%)	SP (%)
Proposed algorithm	96.1	98.1
Tateno and Glass [16, 17]	94.4	97.2
Logan and Healey [19]	96	89
Kikillus et al [20]	94.1	93.4
Ghodrati et al [22]	86	90*
Dash et al [23]	94.4	95.1
Couceiro et al [26]	93.8	96.1
Babaeizadeh et al [27]	92	97*

* These values correspond to positive predictive value (PPV).

Moreover, compared with the result reported by Kikillus *et al*. [21] in the MIT-BIH NSR database, our algorithm has higher SP (97.9% versus 96.9%).

Although using the *only K–S test* method, we achieved a well-performed result for the MIT-BIH AF database (SE = 96.6% and SP = 93.8%), adding the optional steps lead to improved performance. Using the *all-steps* method, we had a significant improvement with all databases. Considering the optimization of algorithm and the effect of each step, we set the optional steps into successive order mainly according to their computational complexity.

The low SP in the abnAF set points out the limitation of AF detection method based on RR intervals. Although the irregularity of RR intervals is one of the most important characteristics of AF, it is not the gold standard for AF detection. Regular RR intervals are possible in the presence of AV block or ventricular or AV junctional tachycardia when AF is present [30]. Also, irregular RR intervals can be seen in other arrhythmias, for example, atrial impure flutter, multifocal atrial tachycardia, or sinus arrhythmia. The abnAF set contains many irregular RR intervals and some of the non-AF rhythms cannot be distinguished from AF rhythm by observing the RR intervals. Hence, a great number of AF events are erroneously classified in this database.

In (2) of Step 1–3, the value of TH was typically set to 0.375 by considering the tradeoff between accuracy and time for computation. Note that a smaller value of TH will filter fewer noise peaks, and thus, more AF events will need to be classified. Since the classification time is about 80 times the AF event detection time, a lower TH will increase the computation time. What is more, the probability of false detection of AF will increase when the number of lost noise peaks increases. On the other hand, a greater value of TH may erroneously filter the event peak and cause some of the AF episodes to go undetected. Since the latter is unacceptable for detection of AF, a smaller value of TH is prone to be used. At the value of 0.375, the average computation time for dealing one beat is about 1.2 μs. Out of the total 299 AF episodes of the MIT-BIH AF database, 267 episodes were correctly detected. The remaining 32 episodes were not detected mainly because of the short duration of AF, which is from 4 to 62 beats. In the Step 1–2, we used a detection

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blank of 20 beats to reduce the influence of noise peak. Thus, the shortest AF episode that the algorithm can detect is 20 beats. However, since the accuracy decreases with the number of RR intervals, AF of short duration, which is just longer than 20 beats may also go undetected.

In Step 2, we used 50 beats to classify the event type for three reasons. First, the number of beats used for the classification process determines the detection delay, and thus, the balance between accuracy and timeliness was considered. In this study, the delay was about 70 beats (nearly 1.2 min) because of using the blank of 20 beats. Second, previous analysis using the K–S test has discussed that the results of using the segment length of 50 beats are already approach to that of using 100 beats or more [17]. Finally, considering the complexity for programming in practice, we used the same value as the value used for calculating the dRDDC.

Further, in the optional steps of the classification process, we used several optimal values for discrimination between the *none* and *onset* event. Note that the purpose of using these steps is to filter some apparent *none* events, these values should be set strictly and kept constant. Otherwise, it would misclassify the *onset* event to the *none* event easily, and thus, influence the accuracy of algorithm significantly. For example, in Step 2–3, if the threshold of correlation coefficient is changed to 0.99, the SE will substantially reduce to 90.3% and the SP will moderately increase to 98.8%, when using the *all-steps* method ($P_c = 0.1$) applied to the MIT-BIH AF database.

V. Conclusion

In this study, we proposed a novel method for detection of the transition between AF and sinus rhythm, and achieved high performance for the validation databases. The algorithm has been integrated into a Holter system for the automatic detection of AF and it is also suitable for applying to the continuous AF monitoring situations.

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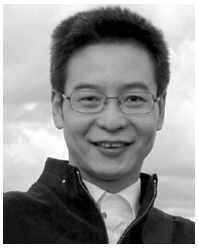
Chao Huang received the B.S. degree in biomedical engineering from the Zhejiang University (ZJU), Hangzhou, China, in 2008, where he is currently working toward the Ph.D. degree in the Department of Biomedical Engineering.

He is currently a Research Fellow with the Key Laboratory of Biomedical Engineering of Education Ministry, ZJU. His research interests include biomedical signal processing, with special emphasis on the automatic detection of ECG wave boundary and the automatic analysis of atrial fibrillation.



Shuming Ye received the Ph.D. degree in mechanical engineering from the Zhejiang University (ZJU), Hangzhou, China, in 1997.

From 1997 to 2005, he was an Associate Professor with the College of Life Science, ZJU. He is currently an Associate Professor with the Key Laboratory of Biomedical Engineering of Education Ministry, ZJU. His research interests include biomedical signal processing, cardiac arrhythmia analysis, biomedical signal acquisition and instrumentation, sensor and detecting method research, and *in situ* environment instrumentation.

Hang Chen received the Ph.D. degree in biomedical engineering from the Zhejiang University (ZJU), Hangzhou, China, in 2007.

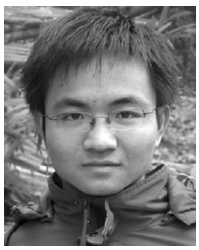
From 1994 to 2005, she was an Associate Professor with the College of Life Science, ZJU, where she has been the Assistant Dean of the College of Biomedical Engineering and Instrument Science since 2005. She is currently a Full Professor with the Key Laboratory of Biomedical Engineering of Education Ministry, ZJU. Her research interests include biomedical signal processing, biomedical instrumentation, and cardiac arrhythmia analysis.

Dingli Li received the Ph.D. degree in biomedical engineering from Zhejiang University (ZJU), Hangzhou, China, in 2008.

He is currently a Postdoctoral Researcher with the Department of Biomedical Engineering, ZJU. His research interests include embedded control systems, biomedical signal acquisition and instrumentation, and biomedical signal processing with main interest in ECG and photoplethysmography signals.

Fangtian He received the B.S. degree in clinical medicine from the Hanzhou Normal University, Hangzhou, China, in 2009.

During 1996 to 2004, he was a Committeeman with the Zhejiang Medical Association, China, where he has been the Editorial Member of two journals: *Journal of Eletrocardiology (China)* and *Journal of Clinical Electrocardiology* since 2005. He is currently a Technologist-in-Charge with the Department of Electrocardiographic, Sir Sun Sun Shaw Hospital, Hangzhou, China. His research interests include atrial fibrillation, clinical ECG diagnosis, and cardiac pacing analysis.



Yuewen Tu received the B.S. degree in biomedical engineering from the Zhejiang University (ZJU), Hangzhou, China, in 2008, where he is currently working toward the Ph.D. degree in the Department of Biomedical Engineering.

He is currently a Research Fellow with the Key Laboratory of Biomedical Engineering of Education Ministry, ZJU. His research interests include biomedical signal processing, computerized arrhythmia analysis, and ventricular late potentials analysis.

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