Prediction of Paroxysmal Atrial Fibrillation by Analysis of Atrial Premature Complexes

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***Abstract*—Currently, no reliable method exists to predict the onset of paroxysmal atrial fibrillation (PAF). We propose a predictor that includes an analysis of the R-R time series. The predictor uses three criteria: the number of premature atrial complexes (PAC) not followed by a regular R-R interval, runs of atrial bigeminy and trigeminy, and the length of any short run of paroxysmal atrial tachycardia. An increase in activity detected by any of these three criteria is an indication of an imminent episode of PAF. Using the Physionet database of the Computers in Cardiology 2001 Challenge, the predictor achieved a sensitivity of 89% and a specificity of 91%.**

***Index Terms*—APC, atrial fibrillation, atrial tachycardia, ECG, electrocardiogram, PAC, PAF, paroxysmal atrial fibrillation, prediction.**

I. Introduction

ATRIAL fibrillation (AF) is the most common sustained tachyarrhythmia. In the United States alone, AF affects an estimated 2.2 million people, with an increased incidence in the elderly population [1]. Although not life-threatening, AF may severely impact the quality of life and increase the risk of stroke. Based upon clinical history, AF may be classified as paroxysmal or chronic [2]. Paroxysmal AF (PAF) is defined as attacks of AF lasting from 2 min to less than 7 days. Chronic AF is defined as lasting more than 7 days. Chronic AF may be the end result of PAF in about 30% of the group of PAF patients [3].

With advances in pacing therapy such as dual-site pacing [4], [5], bi-atrial pacing [6], [7], and high rate atrial pacing [5], the incidence of PAF may be significantly reduced. But the increased pacing load, whether it is from pacing two anatomic sites [8] and/or pacing at a higher rate than normal, coupled with higher pacing voltages in the case of bi-atrial pacing, means that the longevity of the battery-driven implanted pacing devices (either a pacemaker or an implantable cardioverter-defibrillator) is diminished. Thus, in terms of device longevity, advanced pacing modes turned on only when an episode of PAF is imminent would be advantageous.

In 2001, the Computers in Cardiology (CinC) Conference issued the PAF Prediction Challenge [9], [10]. In cooperation with Physionet [11] a set of electrocardiogram (ECG) records [12] were made available for analysis. The PAF Prediction Challenge was closed in September 2001 and the final classification released in September 2002. The authors of the paper did not participate in the original challenge, and, at the time the analyses were completed, did not have knowledge of the correct classification. The methods used by seven of the teams [13]–[19] who participated in the Challenge were presented at the 2001 CinC Conference in Rotterdam. Other teams did not document their methods.

In this paper, we present an approach to the prediction of PAF that is based on the analysis of the R-R time series. We found that our approach predicted the onset of PAF more accurately than the methods reported at the conference.

II. Database

For the PAF Prediction Challenge, Physionet provided 100 sets of ECG records from 98 subjects [12]. Each set consisted of two records, each 30 min long. The subjects were divided into two groups of roughly equal size. All the subjects in the first group, the "arrhythmic" group, had a history of PAF. The two ECG records per set provided in this first group of subjects consisted of one record immediately prior to an episode of PAF, and the other record distant ($\geq$45 min) from any such episode. The other group of "normal" subjects had no history of PAF, and two ECG records were also provided for each set in this group.

The dataset was split into a learning set and a test set. The learning set consisted of 50 sets of ECGs, 25 of them from PAF subjects, and 25 from normal subjects. These ECGs were recorded from 48 subjects, with 2 extra sets from the group to make up the total of 50 sets. Physionet provided labels with the learning set, indicating whether the record immediately preceded a PAF episode. The test set consisted of 50 sets of ECG records from 50 subjects, which were provided without labels. The number of PAF subjects in the test set was 28.

The challenge consisted of two events. For the first event, entrants were asked to determine which of the 50 test records were acquired from each of the two subject groups; namely, the Arrhythmic group and the Normal group. Entries were given a score that was equal to the number of correctly classified records (0–50). For the second event, entrants were asked to determine which of the two records from each subject preceded a PAF episode. Subjects in the Normal group were always considered correctly classified, thus the score was from 22 to 50.

Each ECG record consisted of two-channel traces from a Holter recording. Physionet provided the time of the R peaks in

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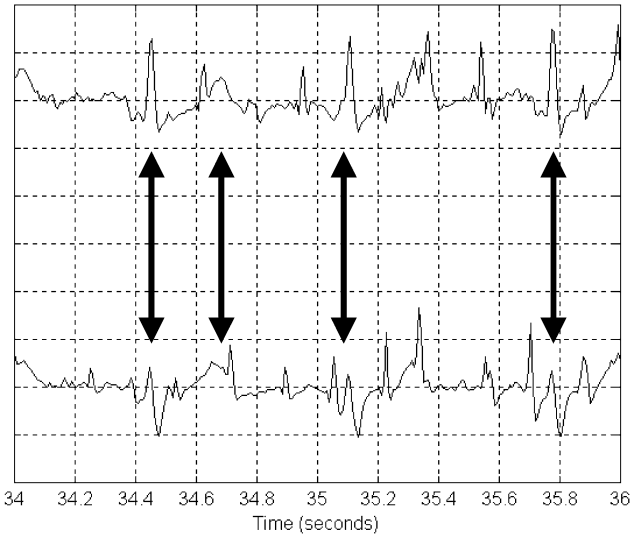

Fig. 1. Example of oversensing due to noise. The arrows point to the detected R waves. The second detected R wave is noise.

each record. These annotations were generated by an automatic algorithm and were known to contain errors. An example of an annotation error is illustrated in Fig. 1.

Although the detection of the P-waves would be useful in predicting PAF, automatic extraction of this feature from the ECG requires advanced software [16], [18] not available to the authors. Thus, we limited our analysis to interbeat (R-R) intervals. To make up for our lack of advanced software to differentiate between atrial and other premature complexes, the two-channel ECG traces were used to visually verify that a premature complex was of atrial origin and not from the atrioventricular (AV) junction nor from the ventricle (a premature ventricular contraction or PVC). In any implementation in an implantable device [4]–[8], P-wave detection from sensing electrodes in the (right) atrium is a given fact. Thus, our manual step in this paper does not impact any implementation in an implantable device.

III. Methods

We hypothesized that prediction of PAF could be predicated on a change from a "normal" state to an "at risk for PAF" state. The physiologic changes that made the subjects more susceptible to PAF are not addressed in this paper. The indicators in the (R-R) rhythm predictive of this change are at the center of this study.

It was necessary to assume that the state change took place minutes prior to the episode of PAF, else preventive therapy would not be effective. In this study, the rhythm far from any episode of PAF is taken as the reference or normal state. The goal is to detect a change in rhythm that favors the development of PAF.

Since approximately 93% of episodes of PAF are triggered by premature atrial complexes (PACs) [20], the identification of PACs from the R-R time series was required. A PAC complex was defined to be the PAC itself and the following atrial event,[1]

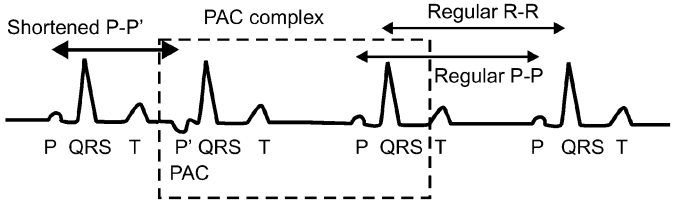

Fig. 2. Normal PAC and definition of PAC complex to include both the PAC and the next P wave and its associated QRS.

as illustrated in Fig. 2. An Isolated PAC is preceded and followed by two cycles of the prevalent rhythm. We identified four separate categories of isolated PACs based on their PAC complexes.

1) PAC with sinus node reset, Fig. 3(a). The ectopic P' wave resets the sinus node within normal conduction time. Thus, the next R-R interval is within 100 ms of the prevalent R-R interval.
2) Interpolated PAC, Fig. 3(b). The associated QRS complex occurs in the middle of a normal series of QRS, without disrupting the prevalent rhythm. The sinus node is not reset in this case.
3) PAC with delayed sinus node reset, Fig. 3(c). The ectopic P' wave is delayed in the path to the sinus node. Thus, the next R-R interval is longer than the prevalent R-R interval by >100 ms
4) PAC with full compensatory pause, Fig. 3(d). In this case the PAC causes the AV junction to be refractory, preventing the next sinus node P-wave from being conducted down to the ventricle. Due to conduction delay, the sinus node is not reset. Thus, the time interval from the previous R wave to the R wave following the QRS complex generated by the PAC is equal to twice the prevalent R-R interval.

The R-R patterns associated with categories 2)–4) are not unique to PACs. They have PVC counterparts: interpolated PVC [21]; PVC with retrograde atrial conduction; and PVC with full compensatory pause. Examples of these PVCs are illustrated in Fig. 4. Thus, in the absence of a P wave detector, ECGs were used to visually ascertain that a premature complex of interest, as determined by the R-R time series, was indeed a PAC.

In the following tests, the two records of a set are compared. When one of the tests detects a difference between the two records a rhythm change is declared.

We counted the number of isolated PACs in categories 2–4 for each of the 30-min records of a subject. The following criteria were used to determine which records preceded a PAF.

A. PAC Test

- If the difference in the number of PACs between the two records of a subject was ≥ 2, a rhythm change was

[1]In this paper, which is R-wave based, we have to exclude patients with third-degree (complete) AV block. Then each P generates a QRS, provided the AV junction is not refractory due to the conduction of an earlier P or P'. The definition here is then applied to the associated QRS. second-degree AV block, which was found in a number of the subjects, is not a problem because the intervals associated are long and are not easily confused with premature complexes.

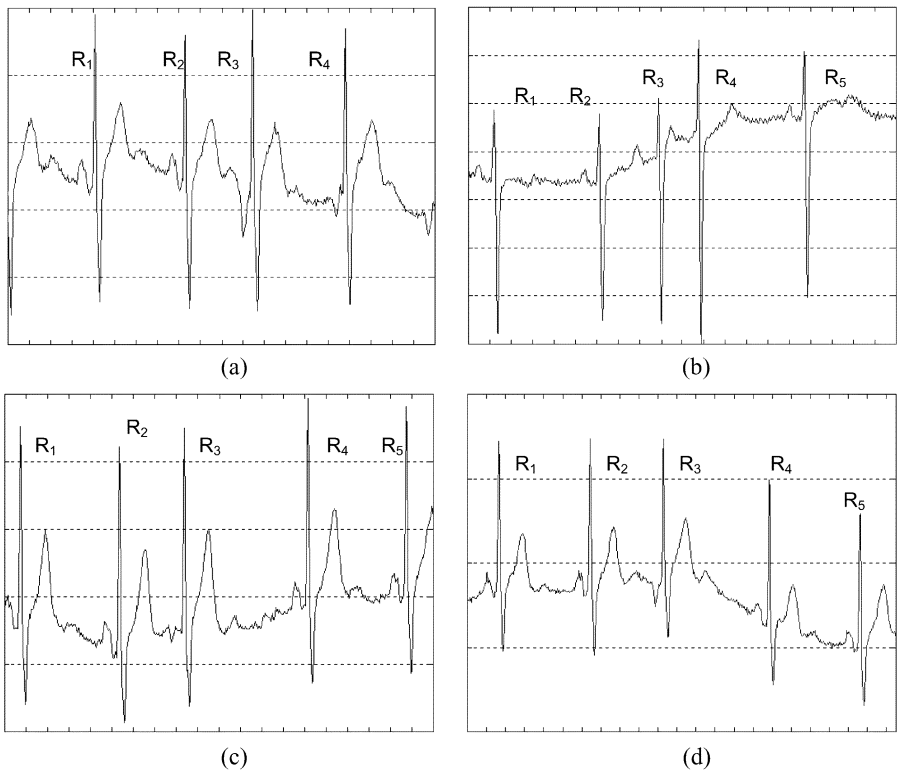

Fig. 3. ECGs of various types of PACs (third QRS). (a). PAC with sinus reset, $R_3R_4 = R_1R_2$. (b). Interpolated PAC, $R_2R_4 = R_1R_2$. (c). PAC with delayed sinus node reset, $R_3R_4 > R_1R_2$. (d). PAC with full compensatory pause, $R_2R_4 = 2\ R_1R_2$. QRS of PACs are similar to other QRS. R-R timing is used to differentiate the four types of PACs. Note inverted P' waves in (a), (c), (d). Horizontal tick marks are 200 ms apart.

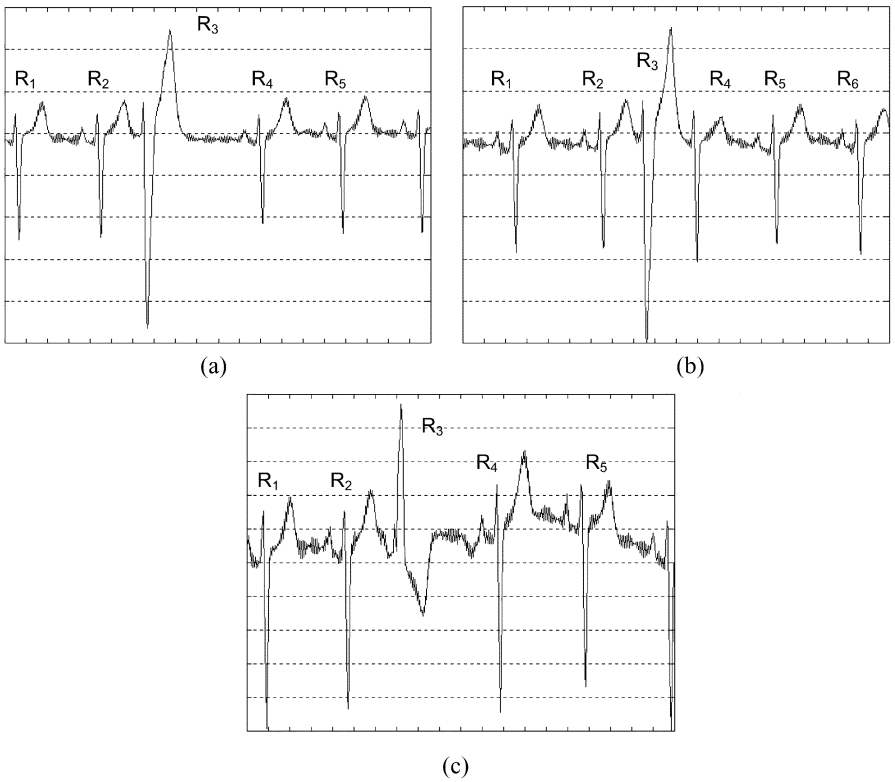

Fig. 4. ECGs of various types of PVCs (third QRS). (a) PVC with full compensatory pause, $R_2R_4 = 2\ R_1R_2$. (b) Interpolated PVC, $R_2R_4 = R_1R_2$. (c) PVC with retrograde conduction into the atrium, $R_3R_4 > R_1R_2$. QRS of PVCs are significantly wider than normal QRS. R-R timing is used to differentiate the three types of PVCs. Horizontal tick marks are 200 ms apart.

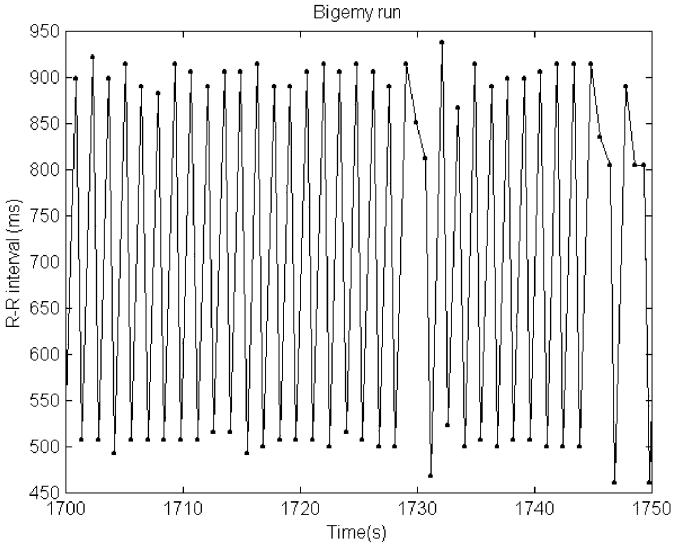

Fig. 5. Tachogram of run of atrial bigeminies.

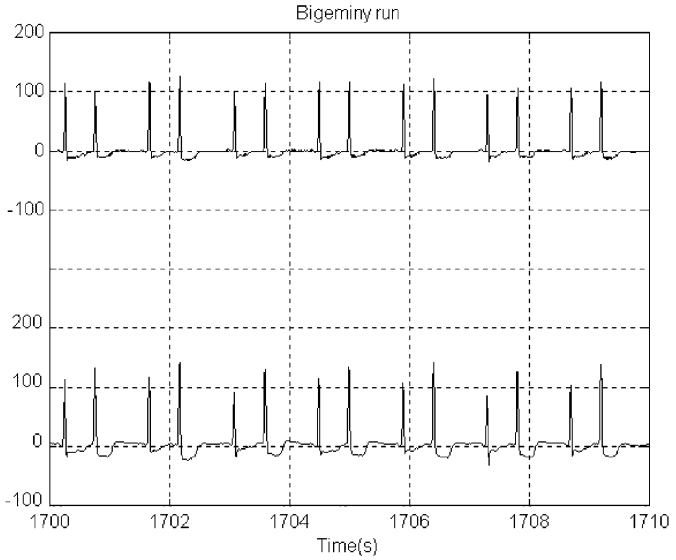

Fig. 6. Holter ECGs of run of atrial bigeminies.

detected. We declared the record with the larger number of PACs as the one preceding the episode of PAF.

- If the difference was <2, no rhythm change was detected. Further tests would be needed to diagnose this subject.

The PAC test was applied to isolated PACs. To account for atrial bigeminies and trigeminies the PAC test must be supplemented with a bigeminy test. The bigeminy tests described below account for both bigeminies and trigeminies.

B. Global Bigeminy Test

1) Identify changes in R-R of greater than 70 ms.
2) Filter the R-R intervals with a 10-point boxcar

$$y(n) = \sum_{1=0}^{9} x(n-i) \tag{1}$$

where $x(n)$ is an indicator that is 1 if the R-R interval delta is greater than 70 ms and 0 otherwise.

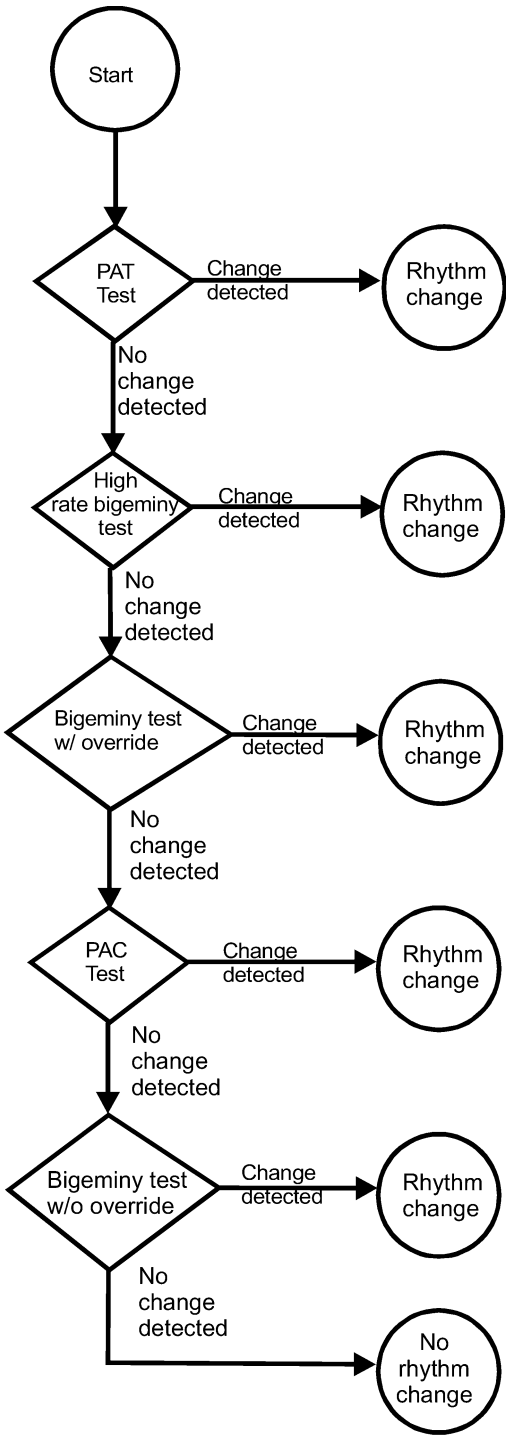

Fig. 7. Test flow diagram.

3) Compute the average power of the filtered signal

$$p = \frac{1}{N} \sum_{N} y(n)^2 \tag{2}$$

where N is the record length.[2]

4) The bigeminy test was applied to a subject only if the average power in at least one record was >9.5.[3] Otherwise, it was not applicable.

[2]Since y(n) is positive, the squaring operation was not absolutely required. It was used to give additional weight to large values of $y(n)$.

[3]Number determined experimentally.

TABLE I
PAF LEARNING SET RAW RESULTS

Subject	PAC Test			PAT Test		Bigeminy Test		
	Correct	Incorrect	Normal (B/T-G overrides)	Correct	Incorrect	Correct	Incorrect	High bigeminy rate
1	√					●		
2	●							
3			√			●		
4	√			●		√		
5		◆						
6	●			√		√		
7		◆						
8	√					●		
9			√			●		
10	√					●		
11		◆					√	
12	●							
13	●						√	
14	●						√	
15	●					√		
16			√			●		
17		√			√	√		●
18			√			●		
19	●					√		
20		√		●			√	
21		√						●
22			√			●		
23	●							
24	●					√		
25	●					√		
PAF	14	6	5	3	1	15	4	2

Legend: Correct: 2nd record identified as preceding PAF. Incorrect: 1st record identified as preceding PAF.
●: correct result used; ◆ : incorrect result used; √: test result not used in diagnosis due to lower priority.

5) The average powers of eligible subjects, per the criterion in #4 above, were compared. If one power was greater than the other by a factor of at least 1.5, a rhythm change is declared.
6) Normally the bigeminy test was not allowed to override the results of a positive PAC test. It was used only when the PAC test yielded an inconclusive result (i.e., a difference in PACs of 0 or 1). However, if the ratio in Step 5) was ≥ 4, the PAC test was overridden.
7) Similarly if the largest power in Step 4) was >20, the PAC test was overridden. An example of such a rhythm is illustrated in Figs. 5 and 6. The average powers due to PACs were then compared as in Step 5). This was labeled as the high bigeminy rate criterion.

The above bigeminy test was global (i.e., over 30 min). Frequently, the changes were more localized.

C. Local Bigeminy Test

- Each record was divided into adjacent segments 100 intervals long.
- In each segment, steps 1)–3) of the global bigeminy test were performed. N is now 100.
- The threshold in Step 4) was changed to 6.
- The ratio threshold was changed to 3.5.

D. End of Record Bigeminy Test

To account for a sudden burst of bigeminies at the end of the record, another subtest was applied when the two subtests above failed to detect a rhythm change.

- A rhythm change was detected if the end value of filtered values given by (1) was ≥ 5 (the filter output maximum is $= 10$).

From a prevention point of view, this rhythm change detection was too late for effective intervention.

Kolb *et al.* [20] reported that about 7.1% of PAF episodes were triggered by either atrial flutters or atrial tachycardias. Thus, our algorithm included a paroxysmal atrial tachycardia (PAT) component. This PAT test also detected atrial flutter since the analysis was based on QRS complexes. With typical 2:1 or 3:1 or even 4:1 AV block, an episode of atrial flutter would exhibit a QRS rhythm similar to that of an episode of PAT.

TABLE II
NORMAL LEARNING SET RAW RESULTS

Subject	PAC Test			PAT Test		Bigeminy Test		
	Correct	Wrong record	Arrhythmia	Correct	Incorrect	Correct	Incorrect	High bigeminy rate
1	●							
2	●							
3	●							
4	●							
5	●							
6			◆					
7	●							
8			√		◆			
9	●							
10	●							
11	●							
12			√		◆			
13	●							
14	●							
15	●							
16	●							
17	●							
18	●							
19	●							
20	●							
21	●							
22	●							
23	●							
24			◆					
25	●							
Normal	21	0	4	0	2	0	0	0

Legend: Correct: 2nd record identified as preceding PAF. Incorrect: 1st record identified as preceding PAF.
●: correct result used; ◆ : incorrect result used; √: test result not used in diagnosis due to lower priority.

E. PAT Test

- Three or more consecutive PACs, without any intervening long intervals were considered to meet the PAT criterion.

The flow diagram to combine the above tests is presented in Fig. 7. The global bigeminy test, when conditions 6) and 7) were not met, the local bigeminy test, and the end of record bigeminy test were all combined together in the last block "Bigeminy test without override." If a change was detected in any of these tests, then a rhythm change was declared.

IV. RESULTS

The prediction algorithm was developed using the learning set. The results are summarized in Tables I–III. The tables showed that a combination of tests was required to achieve good sensitivity without greatly compromising specificity. On the PAF learning set, the predictor was able to detect a rhythm change in all the record sets. When applied to the normal learning set, the predictor only successfully identified no change in rhythm in 84% of the record sets.

TABLE III
LEARNING SET RESULT SUMMARY

Dataset	Correct PAF diagnostic	Incorrect PAF diagnostic
PAF	22	3 (1st record selected)
Normal	21	4 (PAF patient)

When the challenge set was evaluated, the results in Tables IV and V were obtained. Using the published classifications [23], the algorithm achieved a sensitivity of 89% and a specificity of 91%.

V. DISCUSSION

The CinC 2001 scores for our algorithm were 45 (out of 50) and 25 (out of 28) for events I and II, respectively.[4] These scores were higher than those achieved by the other participants in the

[4]Before the final classification was released, we had submitted 17 entries for event I, and 13 entries for event II. We started with scores of 36/50 and 22/28 with our initial entries.

TABLE IV
CHALLENGE SET TEST UTILIZATION

Subject	PAC Tests	Bigeminy Tests		PAT Tests	Subject	PAC Tests	Bigeminy Tests		PAT Tests
		Normal	High rate				Normal	High rate	
1				●	26				●
2	●				27		●		
3		●			28	●			
4	●				29	●			
5				●	30	●			
6	●				31	●			
7	●				32	●			
8	●				33		●		
9	●				34	●			
10	●				35	●			
11	●				36		●		
12		●			37	●			
13	●				38	●			
14		●			39		●		
15		●			40		●		
16	●				41	●			
17	●				42	●			
18	●				43	●			
19	●				44	●			
20				●	45	●			
21			●		46	●			
22			●		47	●			
23			●		48	●			
24	●				49	●			
25	●				50	●			

Note: only test used for diagnosis shown.

challenge [13]–[19], [22]. The best results [23] in event I was achieved by Schreier, *et al.* [18] with a score of 41/50.[5] For the second event, Zong and Mark [16] achieved the highest score. Their scores were 40/50 and 22/28.[6]

Of the eight published algorithms [13]–[19], [22] developed using the 2001 CinC Challenge dataset, the simplest one was the one by Zong and Mark [16]. They used the frequency of PAC as their main discriminator.[7] Their initial score for event I was 35/50. This is similar to our performance by the PAC test alone; namely, 36/50.

The algorithm presented in the current study is most similar to the one reported by Hickey and Heneghan [22]. Their algorithm was based on R-R intervals and QRS morphology. They used the number of premature complexes, the number of PACs with and without sinus node reset and two spectral measures. They reported a score of 38/50 in the first Challenge. These results were close to what was achieved with just the PAC set of tests; namely, 36/50.

[5]This score was following their 8th entry. For event II, they submitted 2 entries and scored 20/28.

[6]These scores were following their seventh and first entries, respectively.

[7]They used an automated arrhythmia detection algorithm that identifies beat types (normal, PAC, PVC, etc.). The threshold for the predictor was derived from the learning dataset.

The results of Zong and then Hickey and confirmed by the PAC test here, indicated that to achieve a sensitivity greater than 75%, it was necessary to look beyond isolated PACs. The overall method for predicting PAF in this paper paralleled the findings of Kolb, *et al.* [20] and Hnatkova, *et al.* [24]. Hnatkova [24] reported that PAF was initiated by a solitary ectopic beat in more than 50% of the cases. Consistent with this result, the PAC test was the most effective at identifying the records prior to the PAF episodes. Kolb [20] reported that 93% of PAF episodes were initiated by PACs, and 7% by atrial flutter and tachycardia. To account for the 93%, the bigeminy tests were added to supplement our PAC test. The PAT test was used to address the initiations by atrial flutter and atrial tachycardia. As expected, the PAT criterion was invoked in only a small fraction of the cases.

VI. CONCLUSION

We have presented a method for predicting PAF that paralleled the mechanisms for PAF initiation [20], [24]. The overall sensitivity to rhythm change was 89% with a specificity of 91%. The key component of this method was an analysis of isolated PACs not followed by a regular R-R interval.

The duration of monitoring remains an open issue. In this study the monitoring duration was fixed at 30 min. In five of the

TABLE V
SUMMARY OF CHALLENGE SET CLASSIFICATIONS

Subject	ECG	Classification		PAF record		Subject	ECG	Classification		PAF record	
		Eval	True	Eval	True			Eval	True	Eval	True
1	1, 2	A	A	2	2	26	51, 52	A	A	51	51
2	3, 4	N	N	4	N/A	27	53, 54	A	A	53	53
3	5, 6	A	A	5	5	28	55, 56	A	N	56	N/A
4	7, 8	A	A	8	8	29	57, 58	A	A	58	58
5	9, 10	A	A	9	9	30	59, 60	N	N	59	N/A
6	11, 12	A	A	12	12	31	61, 62	N	A	61	62
7	13, 14	N	N	13	N/A	32	63, 64	N	N	63	N/A
8	15, 16	N	N	15	N/A	33	65, 66	A	A	65	65
9	17, 18	A	A	17	17	34	67, 68	N	N	67	N/A
10	19, 20	N	N	20	N/A	35	69, 70	N	N	70	N/A
11	21, 22	A	A	22	22	36	71, 72	A	A	72	72
12	23, 24	A	A	23	23	37	73, 74	N	N	74	N/A
13	25, 26	N	N	25	N/A	38	75, 76	N	A	76	76
14	27, 28	A	A	27	27	39	77, 78	A	A	77	77
15	29, 30	A	A	30	30	40	79, 80	A	A	79	79
16	31, 32	N	N	32	N/A	41	81, 82	A	A	81	81
17	33, 34	A	N	33	N/A	42	83, 84	N	N	83	N/A
18	35, 36	N	N	36	N/A	43	85, 86	N	A	85	86
19	37, 38	N	N	38	N/A	44	87, 88	A	A	87	87
20	39, 40	A	A	39	39	45	89, 90	A	A	90	90
21	41, 42	N	N	42	N/A	46	91, 92	N	N	91	N/A
22	43, 44	N	N	43	N/A	47	93, 94	N	N	93	N/A
23	45, 46	N	N	45	N/A	48	95, 96	N	N	96	N/A
24	47, 48	A	A	47	47	49	97, 98	A	A	98	98
25	49, 50	A	A	50	49	50	99, 100	A	A	99	99

Legend: Eval: diagnosis per method presented in paper. True: released classification. A: PAF patient, N: normal patient. N/A: for normal patient, neither record precedes any episode of PAF. Incorrect classifications are highlighted.

six patients of the challenge dataset that were incorrectly classified in Table V, the number of PACs was relatively low. We speculate that a longer monitoring duration may alter the diagnoses. Based on our experience with ventricular tachyarrhythmia prediction [25], doubling the monitoring duration to one hour might help in these cases.

At the cellular level, a possible model of PAF initiation is action potential duration (APD) heterogeinity [26]. Increased vagal activity may create nonuniform shortenings of the APD. This APD nonuniformity may cause the prolonged P-wave. When certain regions of the atria reach a critical shortening of APD due to increased vagal activities, then re-entry circuits may occur. During the transition from the normal state to PAF, these regions with critical shortening may not be large enough to sustain re-entry but they may cause an increase in the number of PACs not followed by regular R-R intervals, due to unusual conduction delay. These are the type 2–4 PACs that are detected by the PAC test. Note that a type 1 PAC, which causes a sinus node reset within normal conduction time, does not suffer any unusual delay in its path to reset the sinus node.

The results presented here are based on $\sim$100 hours of ECG recording. Extensive prospective studies are needed to fully validate the predictor presented in this paper. In particular, additional data from PAF patients to confirm the specificity[8] of the algorithm is required. The duration of the rhythm change is another parameter of interest. While additional small adjustments are likely required to further improve performance, we believe that the algorithm presented in this study is robust and can serve as the basis for future studies.

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