A Method for Detection of Atrial Fibrillation Using RR Intervals

K Tateno, L Glass

Department of Physiology and Centre for Nonlinear Dynamics, McGill University
Montreal, Quebec, Canada

Abstract

This work describes a method for automatic detection of atrial fibrillation (AF) based on RR intervals. We define ΔRR to be the difference between successive RR intervals. The standard density histograms of RR and ΔRR intervals are determined from data in the MIT-BIH atrial fibrillation/flutter database. The present method estimates the similarity between the standard density histograms and a test density histogram by the Kolmogorov-Smirnov (KS) test. The algorithm returns significance (p) of difference between given histograms. If the p value is smaller than a value (P_c), the test density histogram is significantly different from the standard density histogram. If the test density histogram is not significantly different from the standard density histogram, we say the data is AF. Using the standard density histogram of ΔRR with $P_c = 0.01$, the average sensitivity is 93.2% and the average specificity is 96.7%.

1. Introduction

It is difficult to detect AF based solely on the RR intervals as recorded for example by a portable monitor [1, 2, 3, 4].

Several different methods for detection of AF based on RR intervals have been reported [5, 6, 7, 8, 9]. Moody and Mark [8] classify RR intervals as short, long or regular. They then construct a Markov model for the probabilities for transitions between RR intervals in each of the three different length classes. AF data has typical transition probabilities not shared by normal rhythms or other arrhythmias. Pinciroli and Castelli have investigated the morphology of histograms of RR intervals collected during atrial fibrillation and other arrhythmias [3]. They show that the histograms of the ratio between successive RR intervals show characteristic differences between normal rhythm and AF, but do not develop quantitative tests for AF.

Various statistical properties of AF have been analyzed in the past. The coefficient of variation (CV) of RR intervals is ~0.23 during AF [10]. Further, the density histogram of RR intervals during AF is skewed right [11]. Pinciroli and Castelli have also reported that a histogram of the ratio between successive RR intervals is symmetrical to the mean value [3]. Their report indicates that density histograms based on RR intervals during other arrhythmias than AF, differ from those collected during AF, and can therefore be used to detect AF. However, they do not provide a quantitative algorithm.

We define ΔRR to be the difference between successive RR intervals. Here we present a preliminary report of a method for AF detection based on determination of standard density histograms of RR and ΔRR intervals. These histograms are used as a template for detection of AF and the differences between the standard histograms and a test sample are quantitatively evaluated.

2. Methods

Figure 1 shows a typical time series of RR intervals from a patient with paroxysmal AF. When AF occurs this marker line is set to AF; otherwise it is set to N, which signifies a rhythm that is not AF (non-AF). Paroxysmal AF is often interrupted by another arrhythmia or normal sinus rhythm.

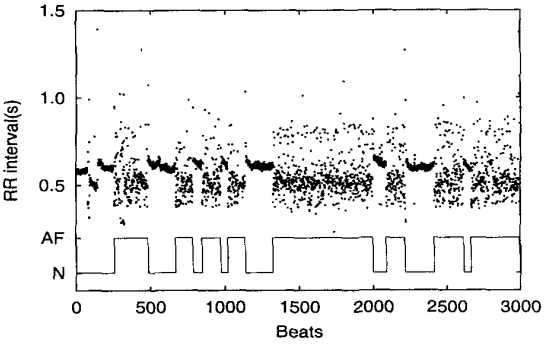

Figure 1. Time series showing the RR intervals from subject 04043 from the MIT-BIH atrial fibrillation/flutter database. The solid line directly under the time series of RR intervals shows the assessment of AF as reported in the database.

Data was obtained from the MIT-BIH atrial fibrillation/ flutter database

(http://www.physionet.org/physiobank/database/afdb). The data contains 300 AF episodes, sampled at 250 Hz for 10 hours from Holter tapes of 25 subjects. During AF, we consider blocks of 100 successive beats. The mean value of RR intervals in each 100 beats block is determined. The mean value identifies the set of 100 beats as falling into one of 9 different classes, corresponding to mean values between 300-399ms, 400-499ms, 500-599ms, etc. For each class, a density histogram of RR and ΔRR is compiled by lumping data together from all patients. The resulting density histograms are taken to be the standard density histograms for AF, sorted by the mean RR interval.

In order to test for AF in a test record, we consider the 100 beat segment centered on each beat in the record. For each beat we determine the density histograms of RR and ΔRR and compare these with the standard density histograms. Similarity of the given density histograms was evaluated using the Kolmogorov-Smirnov (KS) test [12]. In the KS test, one assesses if two given distributions are different from each other. This test returns a p value. If the p value is greater than certain value, P_c, then we say that the distributions are not significantly different from one another. In the current case, since the standard density histograms represent AF, a value of $p > P_c$ is associated with a positive identification of AF (or more accurately failure to reject the hypothesis that the test distribution is not AF). We assumed $P_c = 0.01$ throughout the present work.

For each beat, the identification of AF in the test record is compared with the documented rhythm in the data base and can be classified in one of four categories [13]: true positive (TP) – AF is classified as AF; true negative (TN) – non-AF is classified as non-AF; false negative (FN) – AF is classified as non-AF; false positive (FP) – non-AF is classified as AF. Sensitivity and specificity are defined by TP/(TP+FN) and TN/(TN+FP), respectively. The predictive value of a positive test (PV+) and the predictive value of a negative test (PV-) are defined by TP/(TP+FP) and TN/(TN+FN), respectively.

3. Results

Figure 2 shows an example of the result of the KS test based on the standard density histograms of RR and ΔRR. AF often shows paroxysmal stopping and starting. Using the standard density histograms based on the RR intervals, there are many false negative leading to a low sensitivity. The long stretch of AF extending from beats $\sim$1400 to $\sim$2000 is not detected using the histograms based on the RR intervals. The assessment based on ΔRR functions is much better. However, since the assessment is based on histograms collected over 100 beats, AF is not accurately detected at the time of transitions between AF and sinus rhythm, and for AF of short duration.

We first applied the KS test to the MIT-BIH atrial fibrillation/flutter database that was used to construct the standard histograms. Using the standard density histogram of RR intervals, we find the sensitivity is 53.9%, and the specificity is 98.9%. A decrease in P_c increases the sensitivity, while it decreases the specificity. The assessment of AF based on ΔRR works much better. From the total number of beats assessed in table 1, the sensitivity is 93.2%, and the specificity is 96.7%. The PV+ and PV- are both 95.2% .

Table 1. Beat by beat assessment of AF based on ΔRR using data in the MIT-BIH atrial fibrillation/flutter database

Subjects	TP	TN	FN	FP
00735	313	39849	19	0
03665	10667	41501	390	155
04015	444	40542	81	2886
04043	10520	47156	4114	73
04048	503	39007	310	62
04126	2789	38335	504	1180
04746	30660	16945	213	3
04908	5482	55452	328	446
04936	32828	13330	6853	583
05091	56	35117	1525	43
05121	28004	15504	1765	4556
05261	695	44319	239	229
06426	52603	1352	481	667
06453	243	34322	202	18
06995	26505	25298	969	2365
07162	36546	0	2700	0
07859	48436	0	11797	0
07879	39833	16468	202	39
07910	6597	29826	123	1
08215	32999	10224	81	0
08219	13814	42951	380	2096
08378	1760	35377	195	8131
08405	44350	13727	695	32
08434	2283	37386	27	102
08455	43991	15286	223	0
total	472921	689274	34416	23667

We further applied the KS test to another database which was not used to construct the standard density histograms. The AF database was obtained from 200 series (subjects 201, 202, 203, 210, 217, 219, 221, and 222) of the MIT-BIH arrhythmia database (http://www.physionet.org/physiobank/database/mitdb). Using the standard density histogram of RR intervals, we find the sensitivity is 25.9%, and the specificity is 93.2%. The many false negatives lead to low sensitivity. Using the standard density histograms of ΔRR, the sensitivity is

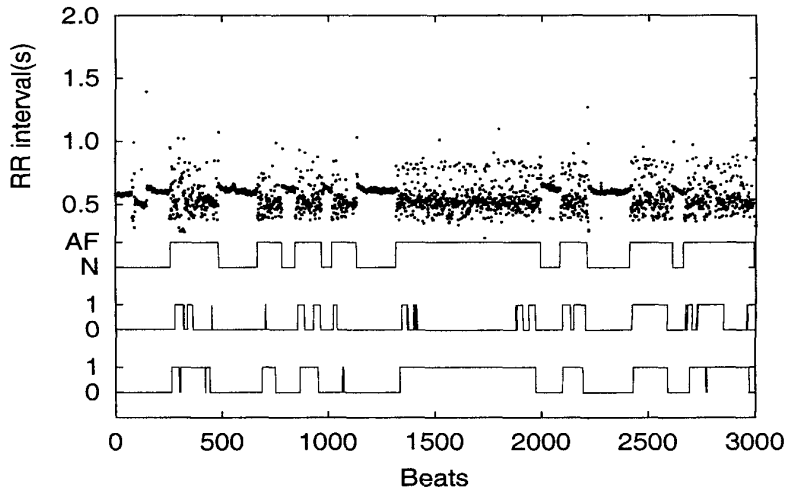

Figure 2. The KS test for subject 04043 of the MIT-BIH atrial fibrillation/flutter database. Time series showing the RR intervals from subject 04043 from the MIT-BIH atrial fibrillation/flutter database. The solid line directly under the time series of RR intervals shows the assessment of AF as reported in the database. The solid line under that represents the assessment of AF, indicated by 1, and non-AF, indicated by 0, based on the density histogram of RR intervals. The solid line at the bottom of the figure shows the assessment of AF, indicated by 1, and non-AF, indicated by 0, based on ΔRR.

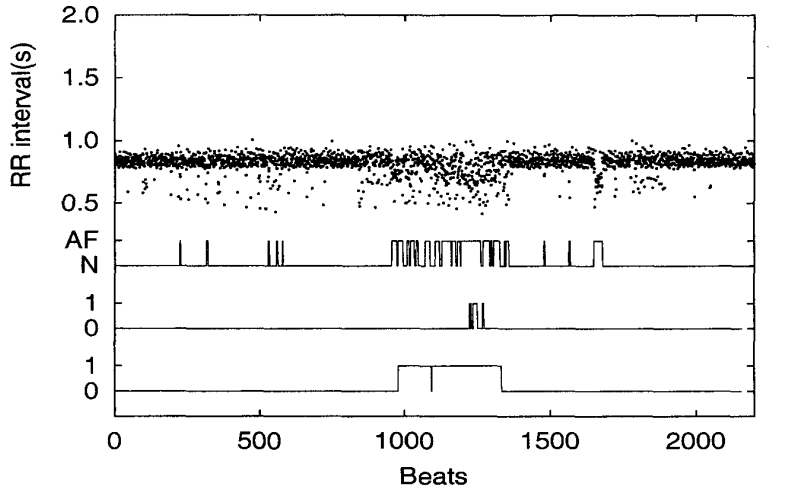

Figure 3. The KS test for subject 217 of the MIT-BIH arrhythmia database. The three solid lines underneath the data have the same meanings as in figure 2.

88.8%, and the specificity is 64.1% (from table 2). In this case, a relatively large number of false positive leads to low specificity.

4. Discussion

The current paper presents results on determination of AF by comparing test records with standard density histograms based on RR and ΔRR. When the analysis is carried out using the RR intervals density histograms there were many false negatives leading to a low sensitivity and a low PV-. In contrast, The assessment based on the standard density histograms of ΔRR is more accurate for most subjects. However, subjects 05091 and 06453 have many false negatives. In subject 06453 the AF is frequently of short duration. Since the current method is based on sequences of 100 beats, AF of short duration is not well detected. This deficiency might be corrected

Table 2. Beat by beat assessment of AF based on ΔRR using data in the MIT-BIH arrhythmia database

Subjects	TP	TN	FN	FP
201	840	411	31	629
202	719	1130	171	64
203	1659	194	380	691
210	2461	0	79	58
217	246	1713	92	105
219	1695	226	55	126
221	1878	7	427	63
222	786	800	66	779
total	10284	4481	1301	2515

by constructing test histograms based on fewer than 100 beats. Further work is needed to determine the optimal number of beats for AF detection.

Figure 3 illustrates the problems involved with detecting AF with short duration using the current method. When AF of short duration occurs, this leads to both false negatives and false positives (around beats 957 to 1358). The false positives lead to a low specificity. Although this lowers the quantitative evaluation of the algorithm, the method does adequately show that the predominant rhythm from beats 957 to 1358 is AF.

In some of the records, our analysis leads us to question the assessment in the database. For example, subject 203 is an example of a atrial flutter-atrial fibrillation patient with frequent transitions between the two rhythms. However, the irregular ventricular response combined with the variability of morphology of the atrial waves, leads us to conclude that some of the atrial identifications in this patient may be more appropriately classified as a coarse AF. Thus, the AF detection algorithm here may be helpful in reexamination of the rhythm identification in the MIT-BIH database.

In the present work, we assume $P_c = 0.01$. A decrease in P_c improves the sensitivity and an increase in P_c improves the specificity. Depending on the particular usage, other values of P_c might be optimal.

Acknowledgements

This work has been partially supported by the MITACS, National Center of Excellence funded by Natural Sciences and Engineering Research Council of Canada, the Medical Research Council (Canada) and the National Center for Research Resources of the National Institutes of Health (P41 RR13622) (USA). We thank George Moody, Rahul Mehra, and David Ritscher for helpful conversations.

References

[1] Andresen D, Brüggemann T. Heart rate variability preceding onset of atrial fibrillation. Journal of Cardiovascular Electrophysiology Supplement 1998; 9:S26–S29.

[2] Murgatroyd F, Xie B, Copie X, Blankoff I, Camm A, Malik M. Identification of atrial fibrillation episodes in ambulatory electrocardiographic recordings: validation of a method for obtaining labeled R-R interval files. Pacing and Clinical Electrophysiology 1995;18:1315–1320.

[3] Pinciroli F, Castelli A. Pre-clinical experimentation of a quantitative synthesis of the local variability in the original R-R interval sequence in the presence of arrhythmia. Automedica 1986;6:295–317.

[4] Slocum J, Sahakian A, Swiryn S. Computer detection of atrial fibrillation on the surface electrocardiogram. Computers in Cardiology 1987;253–254.

[5] Artis S, Mark R, Moody G. Detection of atrial fibrillation using atrial neural networks. Computers in Cardiology 1992;173–176.

[6] Gersch W, Eddy D, Dong Jr E. Cardiac arrhythmia classification: a heart-beat interval-Markov chain approach. Computers and Biomedical Research 1970;4:385–392.

[7] Hnatkova K, Murgatroyd F, Guo X, Camm A, Malik M. Atrial premature beats preceding episodes of paroxysmal atrial fibrillation: factorial analysis of a prediction system. Pacing and Clinical Electrophysiology 1997;20:2003–2007.

[8] Moody G, Mark R. A new method for detecting atrial fibrillation using R-R intervals. Computers in Cardiology 1983;227–230.

[9] Pinciroli F, Rossi R, Valenza P. PAFHPI: self-monitoring of paroxysmal atrial fibrillation episodes in ambulatory patients. Computers in Cardiology 1993;503–506.

[10] Meijler F, Wittkampf F. Role of the atrioventricular node in atrial fibrillation. In Falk R, Podrid P (eds.), Atrial Fibrillation: Mechanisms and Management, 2nd. Philadelphia: Loppincott-Raven Pulishers, 1997; 109–131.

[11] Goldstein R, Barnett G. A statistical study of the ventricular irregularity of atrial fibrillation. Computers and Biomedical Research 1967;1:146–161.

[12] Press W, Teukolsky S, Vetterling W, Flannery B (eds.). Numerical recipes in C: The art of scientific computing. Cambride University Press, 1992.

[13] Hulley S, Cumming S (eds.). Designing clinical research. Williams & Wilkins, 1988.

Address for correspondence:

Leon Glass
Dept. of Physiology and Centre for Nonlinear Dynamics,
McGill University
3655 Drummond Street, Montreal, Quebec, Canada
tel.: +1-514-398-4338, fax: +1-514-398-7452
glass@cnd.mcgill.ca