A Statistical Approach for Accurate Detection of Atrial Fibrillation and Flutter

S Dash[1], E Raeder[2], S Merchant[3], K Chon[4]

[1]Department of Biomedical Engineering, State University of New York at Stony Brook, Stony Brook, NY, USA
[2]Department of Medicine, Division of Cardiology, State University of New York at Stony Brook, Stony Brook, NY, USA
[3]ScottCare Corporation, Cleveland, OH, USA
[4]Department of Biomedical Engineering, State University of New York at Stony Brook, Stony Brook, NY, USA

Abstract

We have developed an algorithm for real-time detection of atrial fibrillation (AF) and flutter (AFL) that relies on 4 statistical techniques (root mean square of successive differences, turning point ratio and Shannon entropy). For AFL detection we use a time-frequency based method via the complex demodulation technique to recognize a characteristic rhythm of AFL. We used the MIT-BIH Atrial Fibrillation database to train the algorithm and then tested it on the MIT-BIH Arrhythmia database. We achieved sensitivity (specificity) of 94% (95%) on the training set and 90 % (91%) on the test database for AF detection. We further tested the AF performance on 36 actual Holter files obtained from The ScottCare Corporation and achieved sensitivity and specificity of 95% and 95% respectively. AFL detection was tested on 2 files of the AFIB database and we achieved 97% sensitivity and 95% specificity. The ease of implementation and minimal memory and speed requirements make this algorithm ideal for on-chip or similar usage.

1. Introduction

AF is the most common clinical cardiac arrhythmia afflicting 2-3 million Americans. Since it is a major risk factor for stroke, early detection od AF should be a public health priority to mitigate its deleterious consequences. However, this is difficult because of the frequent occurrence of asymptomatic AF (~20% of AF found incidentally on clinical examination is asymptomatic [1,2]). Thus there has been a concerted effort to develop computational methods to tackle the problem of AF detection.

There are 2 broad categories of AF detection: (1) algorithms based on detecting the absence of P-wave in the ECG and (2) algorithms based on detecting randomness in the RR interval (RRI) time-series. Our method is a category 2 algorithm since we try to quantify the RRI randomness using established HRV statistics such as the root mean square of successive differences (RMSSD), the Turning Point Ratio (TPR) and the Shannon Entropy (SE).

We also address the related problem of detection AFL which is clinically related to AF. Krummen et al [3] have shown that atypical flutter rhythms are difficult to separate from AF rhythms since both are random. However, we found that typical (type I) flutter can be detected using a time-frequency method as described below.

The algorithms have been tested on the MIT-BIH Atrial Fibrillation database [4], MIT-BIH Arrhythmia database [4] and a ScottCare database of 36 Holter recordings.

2. Methods

The RR interval time-series (MIT-BIH database) is first inspected to detect ectopic beats which may confound the AF algorithm. This is accomplished by a method based on percentiles of successive RRI ratios which exhibit distinct patterns for ectopic beats. A detailed description of the algorithm may be found in [5]. For Holter database, we used pre-annotated instances of ectopy that are available in Holter software to morphologically compare with the beats acquired.

AF Detection Algorithm:
<u>Step 1</u>: Root Mean Square of Successive Differences

(RMSSD) was calculated using the following formula:

$$RMSSD = \left(\frac{1}{l-1} \sum_{j=1}^{l-1} \left(a(j+1) - a(j) \right)^2 \right)^{\frac{1}{2}} \quad (1)$$

We divide the RMSSD value by the mean RRI in order to account for the beat-beat variations in HR. This ratio is then compared to a threshold (RmsThresh).

Step 2: Turning Point Ratio (TPR) is based on the non-parametric "Runs Test" used to measure the degree of randomness in a particular time-series. Each beat in a RRI segment is compared to its 2 nearest neighbors and is designated a Turning Point (TP) if it is greater or less than both. The expected number of TP's in a segment of length l is given by

$$\mu_{TP} = \frac{2l-4}{3} \quad (2)$$

$$\sigma_{TP} = \sqrt{\frac{16l-29}{90}} \quad (3)$$

A beat segment is considered random if the number of turning points (or TPR, if it is normalized against the length l) falls within some threshold confidence interval (TprThresh) of the expected TPR.

Step 3: Shannon Entropy (SE) is a metric used to measure the level of uncertainty in a random variable by quantifying the probability that runs of patterns exhibiting regularity over some duration of data exhibit similar patters over the next duration of data. It is calculated from a histogram of RR intervals in a segment of length l using 16 equally spaced bins. We can define a probability distribution for the RRI segment using:

$$p(i) = \frac{N_{bin\,(i)}}{l - N_{outliers}} \quad (4)$$

Here, $N_{bin\,(i)}$ is the number of beats in the ith bin and $N_{outliers}$ is the number of outliers (16 in or case) and $p(i)$ is the probability associated with all beats falling in the ith bin. The SE is then calculated as

$$SE = -\sum_{i=1}^{16} \frac{p(i)\log(p(i))}{\log\left(\frac{1}{16}\right)} \quad (5)$$

The SE is compared to a threshold (SeThresh) to be derived after tuning using the ROC curve.

Step 4: After all the above statistics are calculated, a simple AND condition is applied. The beat segment is considered AF only if all the above statistics cross their respective thresholds.

Atrial Flutter Detection Algorithm:

Detection of Atrial Flutter (AFL) was done using a time-frequency method via the variable frequency complex demodulation method (VFCDM), which consists of two steps [5]. The VFCDM method involves a two step procedure. The first step is to use the CDM or what we termed the fixed frequency CDM (FFCDM) to obtain an estimate of the time-frequency spectrum (TFS), and the second step is to select only the dominant frequencies of interest for further refinement of the time-frequency resolution using the VFCDM approach. In the first step of the VFCDM method, a bank of lowpass filters is used to decompose the signal into a suite of band-limited signals. The analytic signals that are obtained from these, through use of the Hilbert transform, then provide estimates of instantaneous amplitude, frequency, and phase within each frequency band.

Using the above method, we obtained the TFS of every l-beat RRI segment (after resampling the l-beat segment at 4 Hz). Based on the observation that RRI series during Type I Atrial Flutter showed somewhat regular high-frequency oscillations, we formulated an algorithm to quantify this distinctive rhythm. We first detect the frequency at which the highest spectral peak occurs for every time point in the TFS. The number of such "peak frequencies" greater than a certain frequency threshold (say f_{thresh}Hz) is counted and converted to a percentage of the total number of time points in the TFS. If this percentage is greater than a given threshold (say p_{fthr}%), we annotate the RRI-segment as a Type I flutter segment. We note that similar methods of quantifying the proportion of HF-oscillations may also be used if desired; we use this particular method since we found it to be most accurate for the current study.

All thresholds were obtained using the Receiver Operating Characteristic (ROC) curve method which utilizes the sensitivity and specificity metrics. Tuning was done using the MIT-BIH Atrial Fibrillation database available from www.physionet.org [4]. Testing of the AF algorithm was done on the MIT-BIH Arrhythmia Database [4] and on a separate 24-hour Holter database consisting of 36 files from ScottCare Corporation (Cleveland, Ohio). The Flutter detection algorithm was tested on 2 files of the MIT-BIH Atrial Fibrillation database that contained approximately 80 minutes of type I flutter.

3. Results

The optimum segment length for AF/AFL detection was 128 beats, calculated using the ROC curves as described below. Figure 1 shows example ROC curves for different segment lengths for the AF detection algorithm. Similar ROC curves were obtained by varying other parameters as described below. We have previously reported the AF detection results on the MIT-BIH databases in [6].

The ROC curve [7] is used to find the threshold set that provides the optimal sensitivity and specificity based on "area under the curve" calculations. For each combination of the thresholds ([RmsThresh, TprThresh, SeThresh] for AF detection or $[f_{thresh}, p_{fthr}]$ for AFL detection), we calculated the number of detections that were True Positives (TP), True Negatives (TN), False Positives (FP) or False Negatives (FN). Sensitivity was calculated as TP/(TP+FN) and plotted against specificity (calculated as TN/(TN+FP)) and the threshold combination that gave the highest area under the curve was chosen as the optimal threshold parameter set.

Tables 1 and 2 give the optimal thresholds for AF and AFL detection algorithms respectively along with the corresponding sensitivity and specificity values for different databases. Figure 1 shows an example ROC curve showing the variation of sensitivity and specificity for AF detection as the threshold parameter SeThresh is changed while RmsThresh and TprThresh are kept constant.

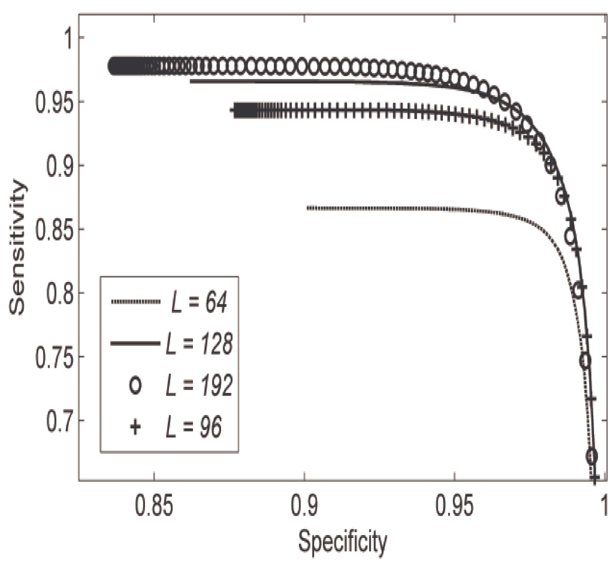

Figure 1. Representative Receiver Operating Characteristic Curves for different RRI segment lengths. RmsThresh and TprThresh are kept constant while SeThresh is varied from 0.01 to 1.00 in steps of 0.01. Similar curves may be obtained by varying other threshold parameters. It was observed that L=128 gave best results and longer segment length did not contribute significant increases to accuracy.

4. Discussion and conclusions

In this study we report on the application of a recently developed real-time atrial fibrillation detection algorithm [6] while further extending the results to a separate Holter monitored ECG database provided by ScottCare. We also present a recently developed atrial flutter detection algorithm that has shown promising results.

Table 1. AF detection algorithm threshold values and accuracy measures for the test (AFIB) and training (Arrhythmia and Holter) databases.

Threshold Parameters		*Optimum values*	
RmsThresh TprThresh SeThresh		RMSSD > 0.1 * mean RRI 0.54 < TPR < 0.77 SE > 0.7	
Database	*N*	*Sensitivity*	*Specificity*
MIT-BIH AFIB	23	94 %	95%
MIT-BIH Arrhythmia (200 series)	25	90%	91%
Holter (ScottCare)	36	95%	95%

Table 2. Atrial Flutter detection algorithm threshold values and accuracy measures for the test (AFIB) database (here we considered 2 files which had significant AFL).

Threshold Parameters		*Optimum values*	
f_{thresh} p_{fthr}		0.72 Hz 19%	
Database	*N*	*Sensitivity*	*Specificity*
MIT-BIH AFIB	2	97%	95%

We were able to achieve high sensitivity and specificity when we considered beat-to-beat as well as episodic detection of the aforementioned rhythms.

As described in the "Introduction" section, there have been several attempts to characterize atrial fibrillation with an eye towards early diagnosis. There are two notable effects of AF on the ECG: (a) the absence of the P-wave (obscured by the fibrillatory waves) and (b) the "irregularly irregular" nature of the RR interval (or the heart-rate time series). Our algorithm focuses on the latter primarily because P-wave are difficult to identify, particularly in the case of Holter monitoring which is quite susceptible to motion or other artifacts. Moreover, detection of the QRS complex from the ECG is fairly easy considering that it has the highest amplitude as well as the steepest slopes.

We quantify the randomness of the RRI time series during AF by using 3 well-established statistical measures, namely the root mean square of successive differences (RMSSD), the turning point ratio (TPR) and the Shannon entropy (SE). Of these the RMSSD and the SE are already widely used in HRV studies. We have earlier reported [5] accurate performance statistics (sensitivity and specificity) on the MIT-BIH AFIB and Arrhythmia databases [4]. On the same databases, a similar study done by Tateno and Glass [8,9] reported high sensitivity and specificity using their own algorithm that compared histograms of successive differences in RR intervals during AF or non-AF. However, a drawback of this algorithm is the large memory capacity required in storing banks of test histograms. By comparison, our algorithm needs to store only 3 threshold values and is also quite computationally efficient because of the usage of the AND condition in deciding whether segments are AF or not.

We have now tested the AF detection algorithm on a new database of 36 24-hour Holter recordings that were provided by the ScottCare Corporation. We were able to obtain very good sensitivity (95%) and specificity (95%) values. We have initially found the specificity value to be 69% but after accounting for annotation errors in classification of AF rhythms as normal sinus beats by scanning technician and excluding atrial flutter beats we were able to increase the specificity to 95%.

The second part of the study was devoted to the development and (preliminary) testing of a flutter-detection algorithm. We have used a time-frequency spectral analysis method called the VFCDM [5] that has previously been shown to have very high concomitant time-frequency resolution. The overall objective is to quantify the proportion of the RRI segment that shows "flutter-like" regularity. The MIT-BIH AFIB database contains two files that have type I flutter, and these are characterised by significant high-frequency oscillations. The details of the quantification algorithm have been specified under the "Methods" section and the initial results have been encouraging.

Krummen et al [3] have shown that the irregularity of RR intervals is not very successful in distinguishing atrial fibrillation and flutter rhythms, especially when the flutter is of type II, which is characteristically more irregular that type I flutter. This was one of the reasons we chose to concentrate on type I flutter which tends to show up as regular "saw-tooth" like oscillations and is relatively easier to identify. We are currently working on separate methods to detect and classify type II AFL, something that we have encountered frequently in 24-hour Holter monitoring data.

Another important point is the removal of the ectopic beats from the RR interval series. We have dealt with this potentially tricky problem extensively in our previous publication [5]. We have observed that the accuracy of the AF and AFL detection suffers significantly if ectopic beats and compensatory pauses are not removed from the RR segment. This is expected since the presence of ectopy generally contributes to the random nature of the segment and may erroneously classify non-AF/AFL beats.

We have thus demonstrated the feasibility of automatic real-time classification of two types of irregular cardiac rhythms, namely atrial fibrillation and type I atrial flutter. We believe the ease of use and speed of the algorithms facilitates easy on-chip implementation without compromising significantly on the accuracy.

References

[1] Humphries KH, Kerr CR, Connolly SJ, Klein G, Boone JA, Green M, et al. New-onset atrial fibrillation: sex differences in presentation, treatment, and outcome. Circulation. 2001 May 15;103(19):2365-70.

[2] Kerr C, Boone J, Connolly S, Greene M, Klein G, Sheldon R, et al. Follow-up of atrial fibrillation: The initial experience of the Canadian Registry of Atrial Fibrillation. Eur Heart J. 1996 Jul;17 Suppl C:48-51.

[3] Krummen DE, Feld GK, Narayan SM. Diagnostic accuracy of irregularly irregular RR intervals in separating atrial fibrillation from atrial flutter. Am J Cardiol. 2006 Jul 15;98(2):209-14.

[4] Goldberger AL, Amaral LA, Glass L, Hausdorff JM, Ivanov PC, Mark RG, et al. PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals. Circulation. 2000 Jun 13;101(23):E215-20.

[5] Wang H, Siu K, Ju K, Chon KH. A high resolution approach to estimating time-frequency spectra and their amplitudes. Ann Biomed Eng. 2006 Feb;34(2):326-38.

[6] Dash S, Chon KH, Lu S, Raeder EA. Automatic Real Time Detection of Atrial Fibrillation. Ann Biomed Eng. 2009 Sept; 37(9):1701-1709.

[7] Zou KH, O'Malley AJ, Mauri L. Receiver-operating characteristic analysis for evaluating diagnostic tests and predictive models. Circulation. 2007 Feb 6;115(5):654-7.

[8] Tateno K, Glass L, editors. A method for detection of atrial fibrillation using RR intervals. Computers in Cardiology 2000.

[9] Tateno K, Glass L. Automatic detection of atrial fibrillation using the coefficient of variation and density histograms of RR and ΔRR intervals. Medical and Biological Engineering and Computing. 2001;39(6):664-71.

Address for correspondence

Ki H. Chon
Department of Biomedical Engineering
State University of New York at Stony Brook
Stony Brook, NY
ki.chon@sunysb.edu