Robust Detection of Atrial Fibrillation for a Long Term Telemonitoring System

B Logan, J Healey

Hewlett Packard Labs, Cambridge, USA

Abstract

We present a method to automatically detect Atrial Fibrillation (AF) for ambulatory monitoring with arbitrary lead placements. We aim for robust AF detection in the face of significant muscle artifact and potentially changing morphology. Our approach is based on the variance of R-R intervals since the QRS spike is the most prominent feature of an ambulatory ECG and the least confounded by muscle noise. Specifically, we use the morphology-independent QRS detector wqrs *to compute R-R intervals and variance and then smooth the resulting classifications for further robustness. Experiments on the MIT-BIH AF database (AFDB) show our AF detection algorithm has sensitivity 0.96 with specificity 0.89 which is sufficient for AF screening.*

1. Introduction

Healthcare spending is increasing at alarming rates in most industrialized countries. At-home care and prevention promise to reduce costs and improve availability of healthcare to aging populations. Cardiac arrhythmias are one of the major health care issues facing an aging population and, in particular, atrial fibrillation (AF) is reported to be responsible for 15-20% of all strokes[1] and is predicted to be associated with over 3 million hospitalizations by 2025[2].

AF is a cardiac arrhythmia that causes the heart to beat irregularly, leading to inefficient pumping of blood and ultimately blood clots and strokes. The early detection and diagnosis of this condition is problematic however since AF can be asymptomatic. Ambulatory monitoring provides a way of detecting AF in these cases. However, the ECGs collected by Holter monitors and the like can contain significant muscle artifact, as demonstrated in Figure 1, and may be from non-standard electrode placements. This paper presents an algorithm to automatically detect AF in the face of these challenges. Our aim is to estimate patients' daily AF burden and thus perform well enough to screen for the disease. Our algorithm is based on the robust open source QRS detector *wqrs*[3] and analysis of R-R intervariation.

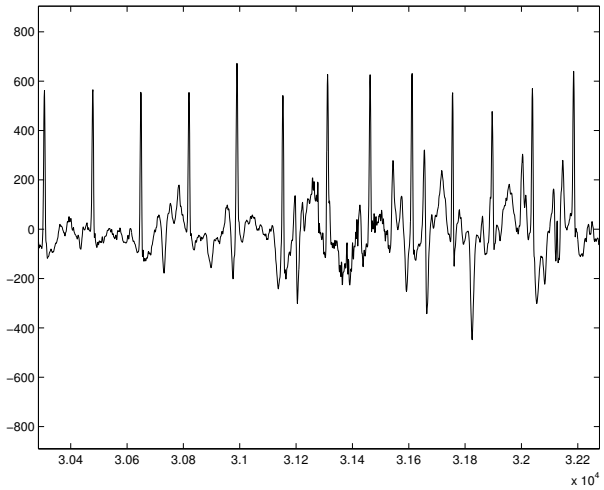

Figure 1. ECG signal collected during a period with significant movement. Note that while the QRS spikes are prominent, other features are less so. The plot shows signal amplitude *vs* sample number.

This paper is organized as follows. In Section 2 we describe our algorithm for AF detection. We next present experiments demonstrating its efficacy. In Section 4 we discuss implementation issues. Finally we present conclusions in Section 5.

2. Methods

Our method relies on combining three key insights. First is the fact that the variance of R-R intervals is a good indicator of AF. This can be seen in Figures 2 and 3 below. Here we show histograms of the variance of R-R intervals calculated over 10 second windows for heart data from the MIT-BIH AF database (AFDB)[4]. Figure 2 shows the histogram for data labeled as AF and Figure 3 shows the histogram for normal heart data. Clearly the two conditions exhibit different characteristics which can be used to clas-

sify unseen signals as normal or AF.

The second key insight is that *wqrs* provides a morphology independent QRS detector which allows accurate calculation of R-R intervals regardless of lead placement. As shown in Figure 4 the shape of the QRS complex in an electrocardiogram differs depending on where the electrodes are placed on the body. The R-wave spike can either be upwards pointing, downwards pointing, or can have both up and down components. Using a technique similar to that found in *wqrs*, we implement a linear transform of the ECG signal where, for each time window, w, the length of the line of the ECG signal over that time is calculated. The result is a line transform of the ECG where each point represents a successive line integral of a sliding window, w. The effect of the line transform on three ECG morphologies: upward, downward and cross is shown in the lower half of Figure 4 . We see that regardless of morphology, the line transform peaks at the QRS complex allowing it to be found.

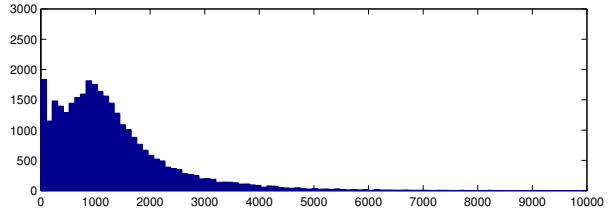

Figure 2. Histogram of R-R intervals calculated over 10s windows for AF ECG data from the MIT-BIH AF database.

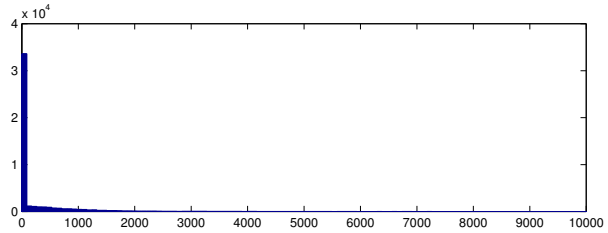

Figure 3. Histogram of R-R intervals calculated over 10s windows for normal ECG data from the MIT-BIH AF database.

The third key insight used is that the QRS spike is the most prominent feature in an ECG and the least affected by muscle noise. Figure 1 shows an example of an ECG signal collected during a period of significant movement. Note that while the QRS spikes are very prominent, other features of the ECG wave are difficult to distinguish.

Based on the three key insights described above, our AF detector is constructed as follows.

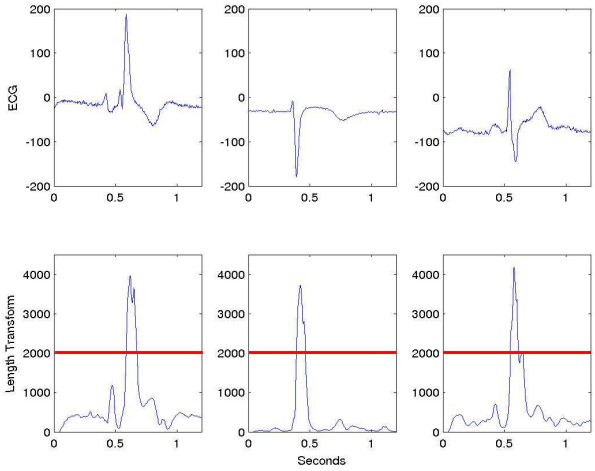

Figure 4. Demonstration of the effect of the length transform on three ECG morphologies.

1. We first use $wqrs$ to determine R-R intervals.
2. We then normalize the R-R intervals according to the following equation:

$$RR_{norm} = \frac{RR}{\bar{RR}} * 100 \quad (1)$$

where $\bar{RR} = 0.75\bar{RR} + 0.25RR$ where RR is the current R-R interval.
This method is inspired by the feature normalization by Moody and Mark [5] and compensates for different patient resting heartrates.
3. The variance of the RR_{norm} statistic is then computed over 10 second sliding windows.
4. An initial AF detection is computed according to whether the variance over each 10s window is greater than a settable threshold. A typical threshold is 200.
5. These initial classifications are then smoothed to eliminate spurious errors. Any of the many smoothing algorithms can be applied. Our system uses a simple majority voting scheme over 600 beat windows.

3. Experiments

We tested the performance of our algorithm on the MIT-BIH AF database (AFDB) [4]. This database contains 10 hour ambulatory recordings from 25 patients using 2-lead electrodes in a standard configuration. We only used the 23 patients for which signal files are available. The data is labeled as AF, normal or in rare cases with other arrhythmias by experts. For the purposes of scoring, we considered all non-normal heart data to be AF.

Figure 5 shows ROC curves for three variants of our algorithm. The first, denoted "R-R Var", is without beat normalization or smoothing (steps 2 and 5 above). The sec-

ond, denoted "%R-R Mean Var", incorporates beat normalization and the third "Smoothed %R-R Mean Var" is the full algorithm. The figure shows that the R-R interval normalization and smoothing steps improve performance. A typical operating point of the full algorithm is sensitivity 0.96 with specificity 0.89. This is acceptable for AF screening and estimating AF burden.

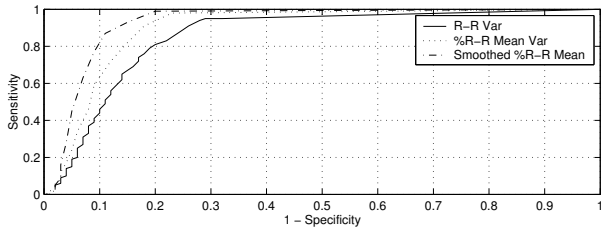

Figure 5. Results for 3 variants of our AF detection algorithm.

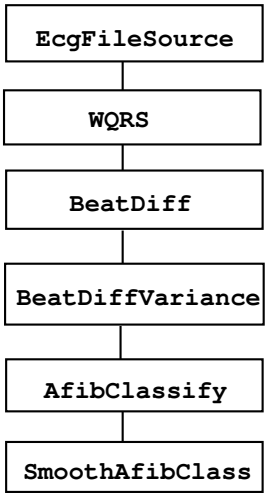

Figure 6. *BioStream* plan for AF detection. Each box represents an *operator* which processes streaming ECG data.

4. Implementation issues

We have implemented our AF detection algorithm as a *plan* in *BioStream*, our architecture for real-time processing of streaming physiological signals [6]. *BioStream* processes data using plug-in analysis components that can be easily composed into plans using a graphical programming environment. The architecture is scalable, allowing implementation on systems ranging from desktops to server farms. It guarantees real-time response and data persistence in a distributed environment.

The use of *BioStream* implies "start-up" delays as the input streams to each module of the system fill. Figure 6 shows a graphical representation of the plan for our AF detection algorithm. Each box on this diagram represents a *BioStream operator* which processes streaming data.

The first operator, *EcgFileSource* reads a stored ECG file. In a real-time implementation, this operator is replaced by an operator to obtain the ECG from a ECG monitor. The next operator *WQRS* implements the line-integral based QRS detector. It has an 8 second start-up delay as various thresholds are set.

The next two operators *BeatDiff* and *BeatDiffVariance* compute the difference between beats as defined by Equation 1 and then the variance of this. *BeatDiff* has a start-up time of 2 beats. *BeatDiffVariance* operates over sliding windows, currently set to 10s. Hence it has a start-up time of 10s.

The *AfibClassify* operator makes an initial threshold-based decision as to whether each beat is part of an AF sequence. It has no start-up delay. The *SmoothAfibClassify* operator smoothes classification by voting over a settable sliding window. This is currently set to 600 beats hence it has a start-up delay of 600 beats.

Thus the main start-up delay introduced by our implementation is that of *SmoothAfibClassify*. For a heartrate of 60 beats per minute, this would be of the order of 10 minutes. Since AF is not immediately life threatening, a 10 minute delay is not problematic.

5. Conclusions

We have developed an algorithm that can reliably detect AF using only the analysis of R-R intervals. Since the QRS complex is the most prominent feature of an ambulatory ECG and the least sensitive to muscle noise, we anticipate our algorithm will perform well in many ambulatory monitoring situations. Our algorithm is also morphology-independent, giving good performance for arbitrary lead placements. Experiments on the MIT-BIH database showed our approach correctly identifies AF with sensitivity 0.96 and specificity 0.89 on the MIT-BIH database. This is sufficient accuracy for AF screening.

Acknowledgments

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Address for correspondence:

Beth Logan
Hewlett Packard Labs
One Cambridge Center
Cambridge MA 02142
USA
btlogan@ieee.org
jennifer.a.healey@gmail.com