Real-Time Detection of Atrial Fibrillation using a Low-Power ECG Monitor

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Abstract

A study was performed to determine the feasibility of a miniature, low-power ECG monitor capable of real time, automatic detection of atrial fibrillation. An original arrhythmia detection scheme was devised and tested using the MIT arrhythmia data available on PhysioNet. Five beat and five rhythm detectors were constructed and the regression values of each were passed onto two further classifiers for ultimate detection of atrial fibrillation. Tests showed that normal sinus rhythm could be detected with 93.06% sensitivity and 95.08% specificity and atrial fibrillation with 94.76% sensitivity and 92.48% specificity. The target device was constructed and fast, efficient algorithms were developed to carry out the signal processing and classification processes. Power consumption was measured at 30mW giving 96 hours of continuous operation. The computation time for the signal sub-band filtering and heart beat interval calculations was measured at 2.1ms per 8ms interval, and heart beat classification at 10.2ms per classifier per beat detected. This research demonstrates that the design of a low-powered, low-cost, miniature ECG monitor having the ability to automatically detect atrial fibrillation in real time is feasible.

1. Introduction

With an ageing population, health services create an ever increasing burden on a country's resources. A prominent cardiac condition that is having an increasing affect in society is atrial fibrillation (AF), a condition of the heart whereby the atria do not beat in synchronism with the ventricles. Although this condition is not necessarily life threatening, without careful management the sufferer is five times more likely to experience a stroke than normally [1] and long term cardiac damage can occur. It is usually the elderly that suffer from this condition, but there are a number of recognised elite sportsmen and sportswomen who are affected by paroxysmal AF, adversely affecting their ability to compete. Currently, AF is detected by visual inspection of the electrocardiograph (ECG) waveform by a cardiac specialist, be it in paper or electronic form. However there is increasing use of automated systems to carry out interpretation tasks.

Current technology such as the Holter monitor store the ECG waveform for later analysis. Some do basic arrhythmia detection but few go as far as classifying the arrhythmia type. An example of current technology is the Philips Medical DXL ECG Algorithm [2] used in a number of Philips products including high end ECG monitors and sophisticated ECG interpretation systems. Although automatic ECG interpretation software is now advanced, products are expensive and it is always recommended that an experienced cardiac physician "over-reads" the automated interpretation.

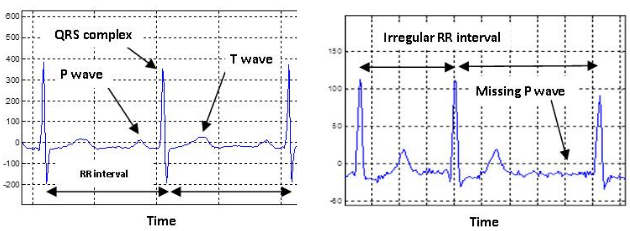
With advances in digital signal processing and electronic devices, an opportunity exists to develop a miniature, low power ECG monitor that can automatically detect AF for front line diagnostic purposes. This could have the desirable effects of lowering health care costs, improving patient management and detecting previously unknown cardiac issues in individuals.

In this paper we investigate other methods of determining whether or not a heart is in AF and propose novel algorithms that can be implemented in a miniature, low-power device. Section 3 describes the search for alternative methods and experiments carried out to validate them. Section 4 details the results of these experiments and gives a brief description of implementation in the target device. Section 5 provides concluding remarks.

2. Background

The heart, in simple terms, is a muscle much like other muscles in the body. However, it has some major physiological differences that allow it to carry out its primary function as a pump. It has a very sophisticated electrical system that controls the activities of the cardiac muscle, synchronising the two top chambers (the atria) with the two bottom chambers (the ventricles) to create an efficient pumping mechanism.

The pumping cycle is initiated by an electrical impulse generated within the sino-atrial node causing the atrial muscles to contract, thus pumping blood from the atria into the ventricles. This electrical impulse travels across the atria in a wavelike fashion and is detected by the atrio-ventricular node and channelled down the Bundle of His to the ventricles. A small delay in conduction allows the ventricles to fill with blood before contracting and pumping blood to the lungs and the rest of the body. When a heart suffers from AF, the atria do not function properly and the regular pulse generated by the sino-atrial node for normal sinus rhythm (NSR), (figure 1a) loses focus. Instead, random electrical activity of the atria take control causing widely varying heart beat intervals (see figure 1b).



(a) Normal Sinus Rhythm (b) Atrial fibrillation

Figure 1. ECG morphology.

This random electrical activity is manifest in the ECG giving three important diagnostic clues indicating a heart is in AF [3] . They are:

- Irregular RR interval.
- Missing P-wave.
- High frequency atrial activity.

These three physiological features are important prerequisites for the detection of AF, however in the case of the P-wave and the existence of high frequency atrial activity, they are difficult to detect and other methods are investigated here to determine the onset of AF.

Since the advent of Digital Signal Processing (DSP), much research has gone into using DSP techniques to automate diagnosis of cardiac health issues, including AF. Use of a Hidden Markov Model [4] enabled the ECG waveform to be broken down into segments for measuring the P-wave duration. It was concluded that the P-wave duration was not pertinent for detecting AF. Wavelets have also been used to segment the ECG waveform [5] but it was discovered that detection of the onset of the P-wave and T-wave was not a reliable indicator. However small variations in the ECG waveform have been detected [6] and used to indicate AF by applying the wavelet transform to the signal and analysing the resulting statistics. Success has been reported in detecting AF using the stationary wavelet transform [7], thereby eliminating the need for QRS cancellation and creating a set of features from the resulting statistics; this used "an efficient classifier to distinguish between AF and non AF segments" of the ECG signal. Methods for detecting the QRS complex include Slope Vector Waveform [8] in the time domain and using the Teager Energy operator [9]. In all of these reports, research was carried out purely to see if the ECG features were detectable, but none went as far as creating algorithms that could be implemented in devices to perform the detection task.

3. Methods

As mentioned above, the P-wave is an important clue as to whether a heart is in AF or not. The P-wave is difficult to detect because of its inconsistent morphology and variable amplitude. The presence of high frequency atrial activity can also be hard to detect because it is often masked by noise and other cardiac unrest. RR interval on the other hand is easy to track as long as the QRS complex is reliably detected. RR intervals for NSR are very regular with only small variations between beats. Contrast this with the RR interval during AF having greater RR interval variations. However, similar large variations can be seen when a heart is experiencing other arrhythmia such as bigeminy or trigeminy. Bigeminy is arrhythmia caused by premature Atrial (A) or Ventricular (V) contractions occurring every other beat; occurring every other two beats for trigeminy. To help improve the detection of A, N and V beats it was decided to also include detection of beats caused by right (R) and left (L) bundle branch blocks.

With this in mind, we considered that if the beat type and variability could be reliably detected, then the arrhythmia type could be better determined. By eliminating other causes of arrhythmia it then becomes more likely that AF is the cause. So, to detect AF we propose that the RR interval variations be determined and detection of beat type be carried out.

Beat and rhythm detection

For beat detection a six level discrete wavelet transform was implemented and 24 features created for training five classifiers, one each for the A, L, N, R, and V beat types using five Support Vector Machine (SVM) classifiers. The regression values from each of the learning machines were passed as features onto a final classification process for arrhythmia detection.

For rhythm detection the RR interval variability was calculated from the RR intervals. Five features were then generated from the RR interval variations to train five SVM rhythm classifiers, one each for atrial flutter (AFL) , atrial fibrillation (AFIB), Bigeminy (B), Normal sinus rhythm, (NSR) and Trigeminy (T). Again, the regression values from each of the learning machines were passed as features onto a final classification process for arrhythmia detection.

Final classification

For final arrhythmia classification, two more SVM's were constructed and trained, the first for detecting normal sinus rhythm and the second atrial fibrillation (see figure 2). The ten regression values produced by the preceding ten classifiers were passed on as features to this classifier and a simple voting scheme used to produce the final result.

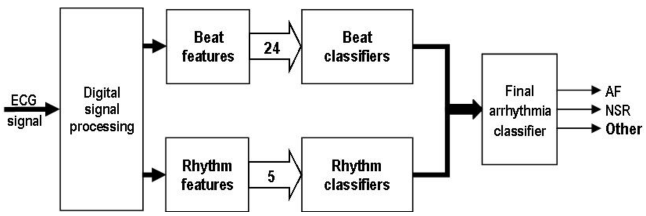


Figure 2. Classifier structure.

By combining the efforts of the beat and rhythm classifiers in this way, it was hoped to improve overall arrhythmia detection.

Testing

For testing of our alternative method, forty eight files from the MIT arrhythmia database on PhysioNet [10] were downloaded and two feature sets, one for each of the beat and rhythm classifiers, were extracted using various DSP techniques. This gave a total of 109494 beats each having 24 beat features and 5 rhythm features.

The 24 beat features and five rhythm features were presented to five beat classifiers and five rhythm classifiers for training and testing respectively. This produced 10 regression values that were then used as feature inputs to the final classifier. In total, 10% of the 109494 samples were randomly chosen for training, and the remaining 90% for classification testing as initial indicators of classification ability and reliability. Classifiers for the A, L, N, R, and V type beats (see table 1) and AFL, AFIB, B, NSR, and T type rhythms (see table 2) were created and used in the final arrhythmia detection process.

For interest, the 10 classes associated with the 10 regression values were also used for testing to see the difference between the two feature sets.

4. Results

Following is a summary of results obtained by using the proposed method of AF detection.

Beat and rhythm classifiers

Table 1 shows the classification ability of the beat classifiers. The number of support vectors retained ranged from 8% to 23% of those presented for training. The A type beat was the worst of the classifiers and this is not unsurprising as the A beat morphology is similar to the N type. What was surprising was the relative ease that the other classifiers identified their respective beat types considering they were set up for one-against-the-rest classification.

Beat Type		Se	Sp	C	σ
Premature atrial contract.	A	0.74	0.99	6	4
Left bundle branch block	L	0.97	0.99	6	4
Normal sinus beat	N	0.98	0.93	6	4
Right bundle branch block	R	0.98	0.99	6	4
Premature ventricular contract.	V	0.93	0.99	6	4

Table 1. Beat Classification. C and σ are radial basis function parameters, C being the box constraint whereby $0 \geq \alpha \geq C$. Se: sensitivity; Sp: specificity.

Table 2 shows the classification ability of the rhythm classifiers. The number of support vectors retained ranged from 15% to 30% of those presented for training. Most show sensitivity and specificity in the high 80% range with NSR being the worst case with sensitivity of 79%.

Rhythm Type		Se	Sp	C	σ
Atrial Fibrillation	(AFIB	0.90	0.90	1	0.5
Atrial Flutter	(AFL	0.88	0.88	1	1
Bigeminy	(B	0.88	0.94	1	1
Normal sinus rhythm	(NSR	0.79	0.89	3	0.5
Trigeminy	(T	0.89	0.88	1	2

Table 2. Rhythm Classification

Arrhythmia detection

Finally, the beat and rhythm regression values, and separately the classes, were passed to a decision algorithm in two tests to determine the likelihood of arrhythmia being caused by AF. See table 3 for the test results using the classes only and table 4 for the test results using the regression values only.

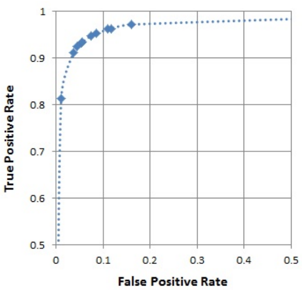
Final Rhythm Class		Se	Sp	C	σ
Atrial Fibrillation	(AFIB	0.91	0.91	1	3
Normal sinus rhythm	(NSR	0.91	0.92	1	3

Table 3. Overall Rhythm Classification using classes from previous classification stages.

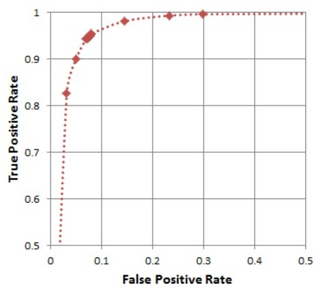
Final Rhythm Class		Se	Sp	C	σ
Atrial Fibrillation	(AFIB	0.95	0.93	1	3
Normal sinus rhythm	(NSR	0.93	0.95	1	3

Table 4. Overall Rhythm Classification using regression values from previous classification stages.

Receiver operating characteristics curves for the two final classifiers are shown in figure 3. Both exhibit good classification ability.



(a) Normal Sinus Rhythm



(b) Atrial fibrillation

Figure 3. Final Classifier ROC curves.

Target device

Power consumption was measured at 30mW with 96 hours of continuous operation using an 850mAH Li-Pol battery. Time to carry out the signal DWT sub-band filtering and RR interval calculations was measured at 2.1ms per 8ms intervals, and heartbeat classification by the SVM at 10.2ms per beat detected per classifier.

5. Conclusions

We have described a method of detecting AF based on two types of features: those based on beat type, and those based on rhythm type. The beat classifier resulted in better than expected classification accuracy. Detection of A type beat was worst but this was not unsurprising as the A beat morphology is similar to the N type. What was surprising was the relative ease with which the other classifiers identified their respective beat types considering they were set up for “one against all other” classification. The rhythm classifiers also produced acceptable accuracy. Even though sensitivity and specificity figures were below the 90% range, this was better than expected. By combining the outputs of the beat and rhythm classifiers as features for the arrhythmia classifier, overall detection rates were acceptable considering the simplistic feature extraction methods used and the intended application of the target device with its limited processing power. The chosen microcontroller has a hardware multiplier capable of carrying out the “multiply and accumulate” instruction desirable for DSP applications, but has a maximum operating clock rate of only 25MHz, considerably lower than specialised digital signal processors.

Algorithm development on the target device was carried out using its native assembly language. The only problematic implementation was the coding of the support vector machine in integer/fixed-point format. Further work is being carried out to overcome this difficulty. This research shows it is feasible to design a small, low-power ECG monitor capable of detecting atrial fibrillation in real time. Improved feature extraction methods will be investigated and fine tuning of the learning machines will be carried out to produce a monitor ready for field testing.

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