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Atrial Fibrillation detection based on ECG-Features Extraction in WBSN

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Abstract

Wireless Body Sensor Networks (WBSNs) and wearable technology are the new trends in healthcare applications. This technology can provide real-time monitoring of the patient's bio-signals and health condition. In this context, the analysis of ECG signals, reflecting the heart activity, is considered as key tool in diagnosing cardiac disorders such as Atrial Fibrillation (AF) that can lead to strokes and heart failure. Classical approaches for sensor-based AF detection require continuous transmission of ECG signals to a remote server which can rapidly exhaust the sensor energy and shortens the lifetime of the application. In this paper, we propose a new low-power scheme for AF episodes detection in ECG signal that is intended for implementation in WBSN. The paper details the design of this scheme and demonstrates its high accuracy for AF detection.

Peer-review under responsibility of the Conference Program Chairs.

Keywords: WBSN, ECG processing , Low energy processing, Atrial Fibrillation

1. Introduction

The use of Wireless Body Sensor Networks (WBSN) can enable real-time automated detection of AF. In depth, this technology of WBSN can be used to capture and transmit a raw ECG signals to a remote server that process the signal, extracts the most relevant ECG features and uses them for classification and AF episodes detection.

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However, applying this approach for full ECG signal transmission using body sensor node faces the problem of limited availably energy in these nodes. Indeed, it has been proved that the transmission of the full recorded signal is highly consuming power at the sensor node questioning the sensor life-time and consequently the validity of the approach [2]. Therefore, the main issue that faces the design sensor-based application for AF detection is to reduce the per-node energy consumption related to ECG data transmission through the wireless link. Radio energy consumption is proportional to the number of transmitted bits. The compression of the ECG signal might be an adequate solution for this issue. However, chae et al.[5] have shown that applying compressive sensing method is not an adequate solution for efficient Low-energy sensing. As an interesting new approach to reduce the volume of transmitted data, we propose an approach of on-sensor extraction of the relevant features from the ECG signal, analysing them for AF detection and then sending adequate notification to the remote server. This approach is intended to reduce the energy consumption related to the wireless data-transmission. Thus, we expect that it will increase the body sensor's life-time and consequently the application of remote ECG monitoring.

The approach of embedded ECG processing for relevant features extraction that helps to detect AF episodes is an active research area that still needs further efforts to bring out an efficient energy solution to be deployed in WBSN. Most of the developed schemes for AF detection use automated arrhythmia classification based on RR irregularity of the ECG segment [11]. A typical heart beat has a waveform composed by P wave followed by QRS complex and then a T as shown in Fig. 1. The extraction of the QRS complex represents the fundamental tasks that allows to determine the R peak in the ECG signal and consequently extracting the duration between two consecutive R peaks called RR intervals. For the AF episodes detection, it requires a combination of two ECG features that are the absence of P-wave and the irregularity in RR intervals. This combination would provide high accuracy of EF detection [15, 16]. However, the The main research challenge at this level is to accurately differentiate between AF episodes and other irregular heart rhythms[13] using an energy-aware and memory-efficient algorithm.

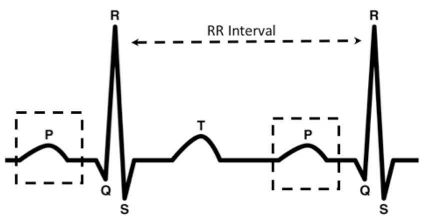


Figure 1 - General relevant ECG features

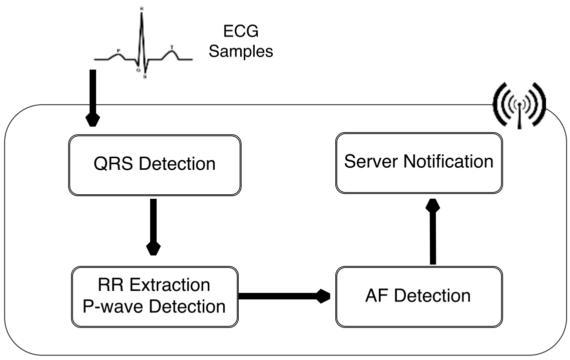


Figure 2 - Proposed AF detection scheme

The main contribution of this paper is to propose a new embedded scheme for the AF episodes detection with low energy consumption intended to be implemented in WBSN. The proposed scheme is based on an enhanced version of Dual Slope algorithm[1] capable to efficiently detect the QRS complex and to extract the measurement of RR interval. It is also extended to detect the P-wave in the ECG signal. The proposed scheme is designed to notify a remote server with the detection of AF symptoms in ECG signals. This papers presents the design of the AF detection scheme in ECG signal. It studies the performance analysis of the ECG sensing scheme to accurately detect the AF episodes in ECG segments and it shows its adequacy for low-power consumption when implemented in wireless sensors.

2. General approach for AF detection in ECG signal

The basic idea, adopted in this paper, is to reduce the amount of transmitted data to the diagnosis-control-point by extracting useful ECG features on the source sensor and analysing them for AF detection. The overall structure of the proposed scheme is summarized in Fig. 2.

AF episode detection is based on the processing of an ECG signal that has a length of 10 seconds. This length is an optimal recording length of the ECG signal that can contain a number of QRS complexes sufficient for checking the regularity of RR intervals and detection of p-wave presence or absence. From another side, the reduced set of samples in the processed ECG signal saves the memory in the wireless sensor.

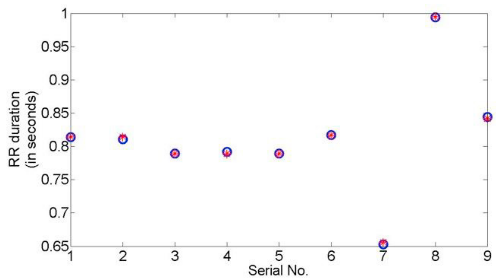
2.1 RR Interval Extraction

In our proposed scheme, we have used the Dual-Slope algorithm for R peak detection [18]. The Dual-Slope algorithm does not include any pre-processing or noise filtering phases. Thus, it requires less processing and lower buffer requirements. This is expected to reduce the amount of local signal processing and consequently its power consumption.

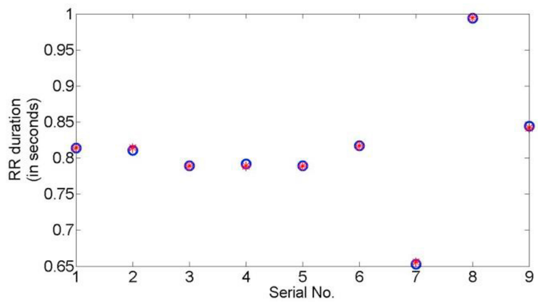
The dual slope algorithm does not require any QRS enhancement and directly starts detecting the QRS complex to localize the R peak. It focuses on calculating the slope of straight lines connecting two samples that are separated by a distance equal to the QRS width (60-100ms) [6] . The largest value of the slopes is expected to be found in the QRS complex. The largest slope change occurs at the peak. Therefore, for accurate R peak detection, the difference between the left and right slopes is compared with an adaptive threshold. The computational efficiency of the Dual Slope algorithm that is based on slope calculation and comparison makes it more appealing than R peak detection methods adopted in related work: two-stage QRS dection [10], morphological transforms [7] , and wavelet-based ECG delineation [4].

To analyse the reliability of the proposed ECG sensing scheme to efficiently extract the RR intervals we have used a Matlab tool to process a set of ECG test signals extracted from ECG databases available at Physionet [9]. The main idea is to check the capability of the dual slope to determine the RR intervals with accuracy compared to measurements available in the database annotations. Thus, we have been interested to evaluate the capability of the proposed scheme to extract the RR feature using ECG-signals recorded under different conditions. The following table sums up the main characteristics of the used test signals.

In Fig. 3. Plots, as red asterisk, the values of the extracted RR intervals using our proposed scheme and it plots also the annotated RR intervals as blue circles. This figure shows, through the intersection of asterisks and circles, that the measured RR intervals are very close to annotated RR intervals provided in the used ECG signal databases. Moreover, the results shown in this figure attest about the dual slope algorithm capability to extract accurate RR features under noise and different types of ECG signals (Fig.3(a) and Fig.3(b)).



(a) Clean signal from arrhythmia patient



(d) Noisy signal from arrhythmia patient

Figure 3. RR feature extraction

2.2 P-wave analysis and detection

The DS algorithm was basically designed to detect QRS that helps to extract the RR feature. We have extended the algorithm's features extraction capability by designing a low-complexity p-wave detection approach that detects the presence of a p-wave in the current heartbeat. For a segment of 10 sec, the number of QRS complexes present in this window depends on the heart rate. During a normal heart rhythm, referred to clinically as (Normal Sinus Rhythm) every QRS complex is proceeded by a normal p-wave [17]. However, during an AF episode p-waves are replaced by low-amplitude fibrillatory f-waves.

During a normal heart beat, a valid p-wave would typically occur in the second half of the RR interval (figure 1). To detect a p-wave we used a derivative-based technique inspired from the work proposed in [12]. This approach uses the derivative to count the number of local peaks in a specified search range. We optimized this approach to meet our p-wave analysis objectives. We limited the search range to only the second half of the RR interval and we based our peak detection method on the use of the first order difference (Eq. 1). In our method, a candidate point is defined as a down-ward zero crossing point where the derivative sign changes from positive to negative. The candidate point is a possible local peak if the derivative slope at that point is higher than a pre-set threshold. Section 3.3 explains how the threshold was defined.

$$\mathrm{Diff(i)} = -2\mathrm{ECG(i-2)} - \mathrm{ECG(i-1)} + \mathrm{ECG(i+1)} + 2\mathrm{ECG(i+2)} \qquad \mathrm{Eq.\,(1)}$$

The algorithm maintains the total number of processed segments (referred to as *n* in Eq.2) and the number of processed segments that did not include a p-wave (referred to as *m* in Eq.2). Finally, a weight factor (*w*) estimates the presence or the absence of p-waves over the total number of processed segments in the 10 seconds window. A high weight factor, accompanied by RR irregularity, indicates a symptom of an AF episode. On the other hand, a low weight factor, accompanied by regular RR intervals, indicates a normal heart rhythm. Fig. 4 shows the flowchart of the local peak detection process.

$$\mathrm{w} = {}^{\mathrm{m}}/_{\mathrm{n}} \qquad \mathrm{Eq.\,(2)}$$

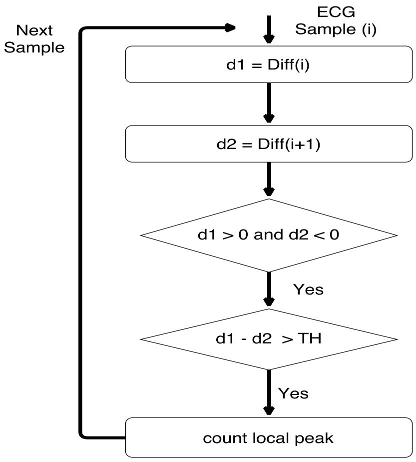


Figure 4. Local peak detection using derivative method

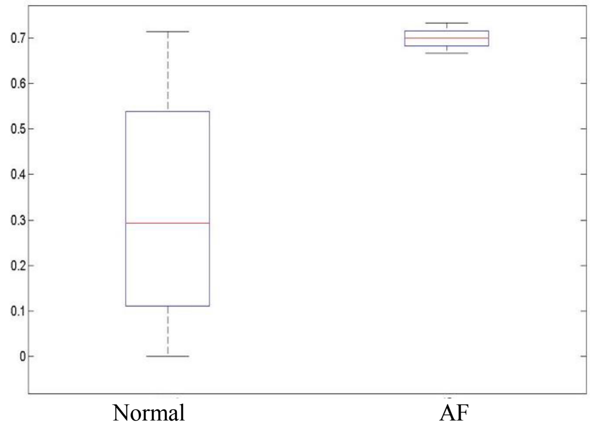


Figure 5. Estimated weight factors for normal and rhythm AF episodes

To calculate the value of the threshold (TH) we have used model of p-waves from the QT database [14]. The QT database is designed for evaluation of algorithms that detect waveform boundaries in ECG signals. Using the database annotations, we extracted a set of p-wave segments *Pw* from Normal Sinus Rhythm signals. For each segment in *Pw*, we calculated the derivative using (Eq. 1) and recorded the maximum derivative slope (*MaxSD*).

$$\mathrm{TH} = \mathrm{avg}\left(MaxSD\ (Pw) \right) \qquad \mathrm{Eq.\,(3)}$$

To evaluate the dual slope algorithm's capability in detecting the presence of p-waves in ECG segments of normal heart rhythm and the absence of p-waves in AF episodes. We used Matlab to test two sets of signals that are summarized in Table I: Normal Sinus Rhythm from the QT database and AF signals from the AF Termination Challenge database [9]. From each signal, we used a 10 seconds segment record. As previously explained in section 3, our proposed method analyses the ECG segment proceeding the current R peak to decide if a p-wave is present or absent. Then a weight factor (w) is calculated using Eq.2 to give an overall indicator on the absence or presence of p-wave in the 10 seconds window.

TABLE I. TEST SIGNALS (P-WAVE DETECTION)

	Signal Reference No.	*Reference Database*
Normal	sel16539, sel116786, sel16795, sel17453	QT
AF	s09, a09, b13, n06	AF Termination Challenge

The boxplots in Fig. 5 show that the median weight factor for normal segments is 0.3 whereas the median weight factor of AF episodes is 0.7. These results reflect that the proposed p-wave detection algorithm was capable to indicate the presence or absence in the set of tested signals.

2.3. Atrial Fibrillation Detection and Notification

The main objective of our proposed scheme is to raise suspicion of a probable AF episode. Using a simple decision tree that evaluates the locally extracted features, the sensor can decide if the 10 seconds segment is AF or not-AF. To apply the decision rules, the sensor needs first to calculate the peak-to-peak value $PP(RR_s)$ where RR_s is the set of RR intervals extracted from the 10 seconds segment. The PP value defines the maximum difference between any two RR intervals. PP values higher than 0.2 trigger AF-typical symptoms. To make the final decision, the p-wave weight factor is compared against a pre-set threshold. Weight factors higher than 0.3, are also considered AF symptoms. Fig.8 shows the decision rules of local AF detection. The sensor sends a 1-byte notification message along with the set of extracted RR intervals for further offline analysis using methods such as statistical analysis [8] and frequency domain analysis [16].

$$\mathrm{PP}(RR_s) = \max(\ RR_s\ ) - \min(\ RR_s\ ) \qquad \text{Eq. (4)}$$

Using the extended implementation of the dual slope method, a given ECG segment is classified as AF or not AF. The tested ECG segments (10 seconds) are described in Table II. Our objective in this section is to verify the AF decision rules and their accuracy in segments classification based on the extracted AF parameters (*PP* and *w*).

TABLE II. TEST SIGNALS (AF DETECTION)

	Signal Reference No.	*Reference Database*
Normal	sel16773, sel17453, sel16795, sel16786, sel16539	QT
AF	a07, b13, s02, t04, a09	AF Termination Challenge

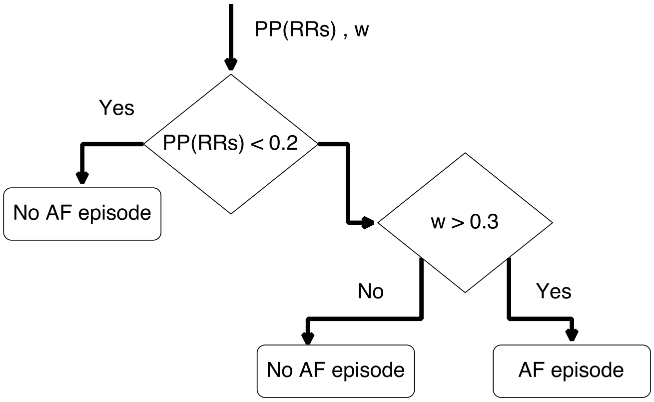
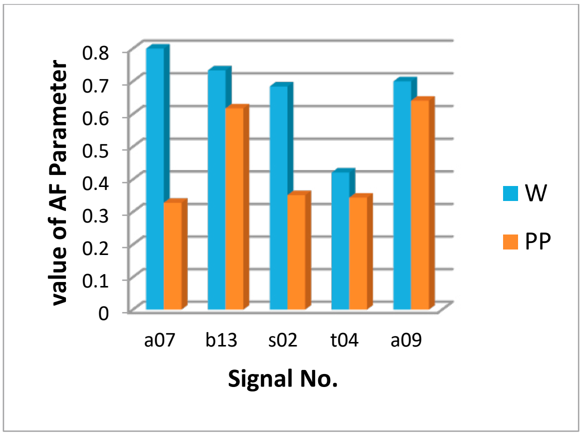


Figure 6. AF decision rules



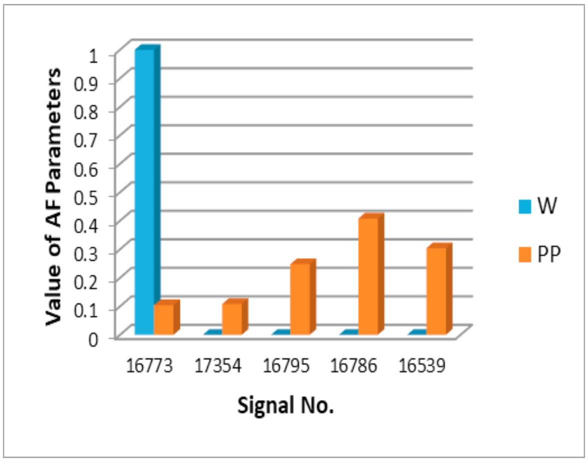


Figure 7. AF parameters for AF episodes

Figure 8. AF parameters for normal signal

The charts in Fig. 7 and Fig. 8 illustrate the AF parameter values for normal and AF ECG segments. For each test segment, the chart shows the value of *PP* and *w*. By applying the AF decision rules depicted in Fig.6, the scheme was accurately classifying each segment.

3. Sensor energy consumption

We evaluated the energy consumption related to the processing of this scheme in a sensor node using the Avrora simulator [2]. This tool allows us to evaluate the energy consumption related to the internal processing of a given algorithm implemented on sensors using TinyOS. It is capable of emulating the internal resources, processing requirements, and features for a set of sensor nodes such as MICA family sensors and TelosB sensors. In this evaluation, our objective is to estimate the energy related to the processing of the different steps of the proposed scheme including the notification to the remote server.

Table III lists the estimation of the energy cost for the different modules of the AF detection scheme. We note that this evaluation considers the worst algorithmic case of each module.

TABLE III. ENERGY CONSUMPTION OF THE PROPOSED SCHME ON MICA2 SENSOR

Component	*Description*	*Energy units (mJ)*	*Related task*
E_{sample}	energy per sample	0.03	R peak detection
E_R	energy per segment	75	
E_{RR}	energy per RR	0.01	RR interval extraction
E_P	energy per RR	0.13	p-wave detection
E_{FX}	energy per segment	2.1	RR extraction, p-wave detection
E_{AF}	energy per segment	0.016	AF detection
E_{radio}	energy per byte	0.3	Server Notification
$E_{radioSample}$ (2 bytes)	energy per sample	0.6	
$E_{radioRR}$ (4 bytes)	energy per RR	1.2	

The results presented in this table show that the energy consumption was kept low for MICA 2 sensor. It shows also that this method can be efficiently to save energy and to extend the network life time.

4. Conclusion

In this paper we proposed a new low-power scheme capable of detecting AF episodes and intended for implementation in WBSN. The basic idea is to reduce the amount of transmitted data by extracting ECG features on the source sensor and analysing them for AF episode's detection. Our proposed scheme is intended to raise suspicion of a probable AF episode. It uses a decision tree based on the combination of two ECG features: RR interval's duration and absence of the p-wave. The obtained results attest about the efficiency of the schemes in distinguishing AF ECG segments from normal rhythm segments. When implemented in Mica2 sensor, the scheme was capable to save energy.

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