Early Detection of Myocardial Infarction Using WBAN

Medina Hadjem, Osman Salem, Farid Naït Abdesselam and Ahmed Mehaoua
LIPADE Laboratory, University of Paris Descartes, France
{firstname.lastname}@parisdescartes.fr

***Abstract*—Cardiovascular diseases are the leading cause of death in the world, and Myocardial Infarction (MI) is the most serious one among those diseases. Patient monitoring for an early detection of MI is important to alert medical assistance and increase the vital prognostic of patients. With the development of wearable sensor devices having wireless transmission capabilities, there is a need to develop real-time applications that are able to accurately detect MI non-invasively. In this paper, we propose a new approach for early detection of MI using wireless body area networks. The proposed approach analyzes the patient electrocardiogram (ECG) in real time and extracts from each ECG cycle the ST elevation which is a significant indicator of an upcoming MI. We use the sequential change point detection algorithm CUmulative SUM (CUSUM) to early detect any deviation in ST elevation time series, and to raise an alarm for healthcare professionals. The experimental results on the ECG of real patients show that our proposed approach can detect MI with low delay and high accuracy.**

***Index Terms*—Wireless Body Area Networks, Mycardial Infarction, ECG, ST elevation, Anomaly detection, CUSUM**

I. Introduction

Cardiovascular diseases are the leading causes of death worldwide, and Myocardial Infarction (MI), commonly known as heart attack, is the most serious one. Only a quarter of patients are able to recognize the symptoms of MI immediately. According to specialists, emergency aid is most effective if it is given over the next 4 hours after MI. In fact, it is during this period that we can prevent serious complications and damage of heart by early detection of MI in order to alert doctors in real time, especially for patients with high risk.

Recent technological advances in wireless networks, sensors integration and miniaturization allow fundamentally modernizing and changing the way healthcare services are deployed and delivered. Specific Wireless Sensor Networks (WSNs) for medical applications, known as Wireless Body Area Networks (WBAN), or Personal Area Networks (PAN) have been developed and deployed.

These networks consist of several sensors operating on or inside the human body, and transmit collected data to a gateway device that acts as a base station (e.g. smart phone, tablet, PDA, etc.) for real time processing, in order to send medical information and alarms to healthcare providers if an anomaly is detected. An example of a WBAN architecture is shown in figure 1. Many types of sensor devices are already available in the market, and they can capture various vital metrics like Heart Rate (HR), Respiration Rate (RR), Temperature (T), Oxygen Saturation (SpO2), Blood Pressure (BP), ElectroMyoGram (EMG) and ElectroCardioGram (ECG), etc.

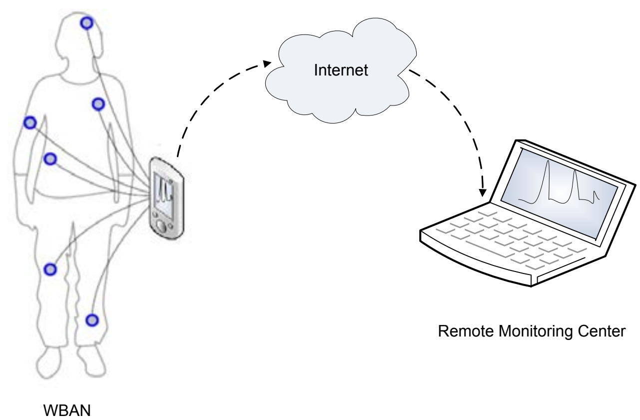

Fig. 1. An example of Wireless Body Area Network

Using WBAN in order to detect MI is an important issue, especially with expected benefits in term of life saving and cost reduction. According to the third global definition of Myocardial Infarction [1], ECG is an integral part of the diagnostic process of MI and should be acquired and interpreted correctly within 10 minutes after first symptoms.

The Electrocardiogram (ECG) is a waveform that represents the propagation of electric potentials through the heart muscle with respect to time. The propagation of these potentials results in the quasi-periodic contraction of the heart muscle. Each part of the cardiogram refers to a depolarization or a re-polarization of some region in the heart. The cardiogram consists of five major waves, also known as deflections in the cardiology literature, the P, Q, R, S, and T waves. Figure 2(a) illustrates the basic features and intervals of a one-cycle ECG waveform.

The ECG provides a non-invasive method for investigating heart function. Standard ECG measurements utilize 12 leads or views of the electrical activity of the heart (as shown in figure 3). However, ECG measurements using wireless sensors are generally for ambulatory applications and will typically utilize a subset of these leads. Several ECG sensors were proposed and designed by researchers like in [2]–[4]. There are also a plenty of devices in the market that propose portable ECG monitoring, called Holter ECG which can capture ECG

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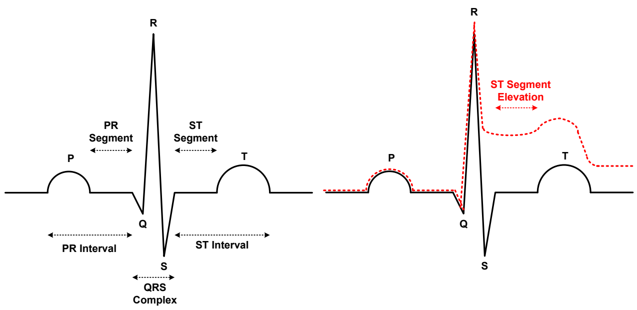


(a) One-cycle ECG tracing (b) ST Elevation ECG

Fig. 2. Normal ECG and ST elevation ECG

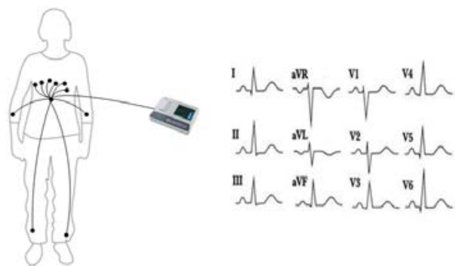


Fig. 3. A Standard 12-lead ECG measurement

during a long period (24h or 48h) like CardioDay proposed by getemed [5].

Myocardial Infarction is an acute ischemic heart disease characterized by a necrosis (death) of a portion of the heart muscle because of deprivation from oxygen. MI causes a serious disturbance of the cardiovascular system that leads to a direct threat for life.

MI is typically characterized by an elevation in the ST segment of ECG (as shown in figure 2(b)) which is normally iso-electric for healthy subjects (described in figure 2(a)). ST segment elevation is generally one of the first symptom of MI and is usually accompanied by chest pain. But in order to be more specific to MI (or suspicious of MI), the ST elevation must be significant in amplitude (up to 0.2 mV) and prolonged in time (several minutes) as indicated in [1].

The objective of this paper is to propose an efficient method to detect the deviation in "ST segment" time series based on prolonged ECG recording or real time capture of ECG using WBAN technology.

The rest of this paper is organized as follows. Section II surveys related work. Section III briefly reviews related techniques and presents our approach for early detection of MI. Section IV presents our experimental results. Finally, Section V concludes the paper.

II. Related work

Various ECG monitoring systems were proposed in the literature. MEDiSN [6] is a WSN for monitoring patients physiological data including ECG, in hospitals and during disaster events. MEDiSN comprises Physiological Monitors (PMs) and Relay Points (RPs) that self-organize into a multi-hop wireless backbone for carrying physiological data. RECAD [7] is a real-time continuous arrhythmias detection system based on WSNs technology. It uses Ambulatory Wireless ECG Sensor (AWES) to provide all time cardiac monitoring services.

Many ECG monitoring devices are available on the market, like CardioNet [8], a Mobile Cardiac Outpatient Telemetry™ (MCOT™) which offers a real time monitoring of ECG and wireless transmission of collected data to the monitoring center. Another example, Medtonic Reveal TX [9] which is a subcutaneous arrhythmia detection device.

In order to detect ECG anomalies, classification algorithms are generally proposed and used. The purpose of these algorithms is to classify measurements into 2 classes : normal or abnormal. In particular for MI classification, several methods were explored. In [10], Pei-Chann Chang et al. proposed a classification method of MI based on Hidden Markov Model (HMM) and Gaussian Mixture Models (GMM). Their accuracy was 82.5% with specificity of 79.82% and sensitivity 85.71%. Muhammad Arif et al. [11] used K-Nearest Neighbor (KNN) classifier and got an accuracy of 98.3%, sensitivity of 97% and specificity of 99.6%. In [12], Akshay Dhawan et al. used Multilayer Support Vector Machine (SVM) and Genetic Algorithm (GA) to detect MI. They obtained a sensitivity of 86.82% and a specificity of 91.05%. E. S. Jayachandran et al. [13] obtained an accuracy of 95% using Discrete Wavelet Transform (DWT).

Yang et al. in [14] transformed linearly a 12-lead ECG signals into 3-lead vector-cardiogram using Dower transformation, and then radial basis neural networks are used for classification. The detection accuracy of MI cases was 97% and accuracy of normal cases was 75%. In [15], Henrik Haraldssona et al. decomposed 12-lead ECG using hermite Basis functions and the resulting coefficients were used as inputs to a Bayesian ANN Classifier that were trained to detect MI. The accuracy obtained for MI cases was 94% and 93.3% for patients without MI. Zheng et al. [16] used SVM, Naïve Bayes (NB) and Random Forecast (RF) methods. Accuracies obtained for these classifiers were 81.9% for NB, 82.8% for SVM and 84.5% for RF.

These algorithms are generally quite complex and are not adequate for an implementation on a WBAN whose main restrictions are limitation in terms of reduced processing capacity, limited storage and power. The main contribution of this paper is the proposition of:

- A Real-time method for early detection of MI
- Autonomy of patients and remote capture of ECG using WBAN
- A low power consumption algorithm adapted to WBAN using CUSUM Method

III. Proposed approach

Our proposed system is composed of 3 modules :

- ECG sensors that can capture ECG and transmit it wirelessly like those proposed in [2]–[4]
- A Cell phone playing the role of a gateway that will receive the digitized ECG wirelessly, pre-processes it, extracts ECG features (P, Q, R, S, T) and analyzes the extracted features to detect reliable ST elevation in order to send an alert to healthcare professionals along with the ECG captured and the position of the patient
- A remote healthcare professionals (hospital or medical center) that will receive alerts and patients data in real time and take appropriate decisions about the patient condition

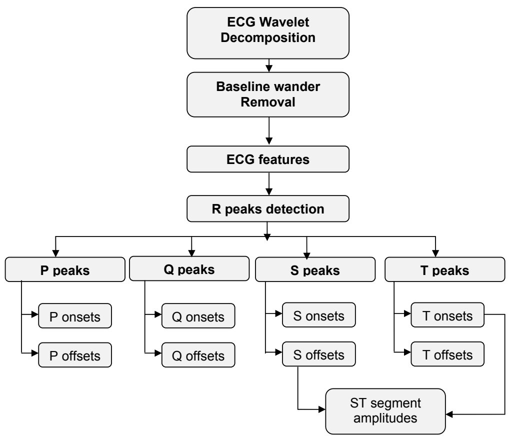


Fig. 4. ECG signal processing and features extraction

We consider a real deployment scenario where sensors send ECG measurements to a smart phone in real time. The main steps performed by our system consist of : pre-processing the received signal, extraction ECG features and detection of significant ST elevation that indicates a potential MI.

ECG Signal received from sensors is digitized but some steps are necessary in order to extract ECG parameters. The diagram in figure 4 details these steps. First, Wavelet decomposition is used in order to clean and denoise the original signal. The process of wavelet decomposition consists of taking the samples at a much lower frequency than the original signal, in order to reduce noise and preserve the QRS complex of the ECG, this technique is detailed in [17]. Then we carry out a baseline wandering removal, which is generally caused by patient movements, dirty or loose sensors and a variety of other reasons. The baseline wandering consists of changes in iso-electric line position and causes an artefactual data when measuring ECG. The removal is achieved by subtracting the first sample, which is generally the reference point, from the rest of signal. Finally, we extract the main ECG features by first detecting the R peaks and their positions in the signal, then we can extract the other peaks (P, Q, S, T) respectively and their onsets and offsets based on the R peaks. ST segment amplitude can be calculated from S-offset and T-Onset.

The result of the 2 steps described above is a time series of ST segment amplitudes per cycle of ECG. We consider only positive amplitudes of ST in our system, because ST elevation is more specific to MI than a ST depression [1]. As described in section I, the diagnostic of MI is complex and we can't consider any ST elevation as a sign of MI, this is why we use a change detection algorithm in order to detect new and significant ST elevation changes in ECG. Moreover, we define a window size and a minimum number of deviations that need to be detected within this window before raising an alarm, the aim is to ensure that the detected deviations are sufficiently prolonged to avoid false alarms.

Our proposed algorithm is based on Cumulative Sum (CUSUM) algorithm, which is a sequential analysis statistical tool that is particularly suited for the identification of deviations with the lowest delay.

To detect change point in the sequence of observations $ST = (ST_1, ST_2, \ldots, ST_n)$, the CUSUM algorithm uses the log-likelihood ratio of the observation ST_i:

$$S_n = \sum_{i=1}^{n} s_i \qquad \text{where} \qquad s_i = \log \frac{p_{\theta_1}(ST_i)}{p_{\theta_0}(ST_i)} \tag{1}$$

Where $p_\theta(ST_i)$ is the probability density function (PDF) of ST with parameter θ. CUSUM uses hypothesis testing and assumes that data follows a PDF with parameter θ_0 before the change occurrence (hypothesis H_0), and with parameter θ_1 after the change (hypothesis H_1).

$$H_0 : \theta = \theta_0 \qquad and \qquad H_1 : \theta = \theta_1 \tag{2}$$

In fact, the log likelihood ratio s_i is more likely to be negative in hypothesis H_0 (normal patient state) and positive after the change H_1 (sick or abnormal). To detect change, the relevant information lies in the difference between the value of the log-likelihood ratio and its minimum value:

$$g_n = S_n - m_n \qquad and \qquad m_n = \min_{1 \leq j \leq n} (S_j) \tag{3}$$

A threshold h is used to reject hypothesis H_0 (if $g_n \geq h$) and to raise an alarm. The value of the threshold must be chosen subject to low false alarm probability. If ST is normally distributed with variance σ^2 in both hypothesis, and with mean μ_0 in H_0, and μ_1 in H_1, g_n becomes:

$$g_n = \left[g_{n-1} + \frac{\mu_1 - \mu_0}{\sigma^2} \left(ST_n - \frac{\mu_1 + \mu_0}{2} \right) \right]^+ \tag{4}$$

μ_1 cannot be known before the change, and we approximate its value by $\mu_1 = \alpha \times \mu_0$. Equation 4 becomes:

$$g_n = \left[g_{n-1} + \frac{\mu_0(\alpha - 1)}{\sigma^2} \left(ST_n - \frac{\mu_0(\alpha + 1)}{2} \right) \right]^+ \tag{5}$$

Where $\{y\}^+ = \max(0, y)$. Our CUSUM detection method is described in algorithm 1, where we consider the sequence $ST = (ST_1, ST_2, \ldots, ST_n)$ as the extracted ST elevation values, and we use a threshold $h \geq 2$. In order to reduce false alarms, we introduce two new parameters to CUSUM algorithm:

- A sliding windows w (as shown in figure 5) that contains the last values of ST elevation to calculate the number of deviations

- The parameter k that indicates the minimum number of deviations ($A_i = 1$ in figure 5) that must be detected in the sliding window w before raising an alarm

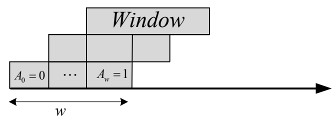


Fig. 5. Sliding window containing the number of deviations

Algorithm 1 ST elevation detection algorithm

Set the windows size w;
G=0;
Calculate the initial value of variance σ^2;
Calculate the initial value of mean μ;
for $i = 1 \rightarrow$n **do**
  Save the value of actual G in tmp;
  Calculate the new value of G;
  if ($G \geq h$) **then**
    The detected deviation is stored ($A_i = 1$);
    Calculate the sum of A_i in the sliding window;
    if (sum($A_i \geq k$) **then**
      Raise an alarm ;
      G=0 ;
    else
      G=tmp;
    end if
  else if (G <= 0) **then**
    G=0;
  end if
  Calculate μ using ST_i values with $A_i = 0$;
  Remove the first element in the window;
  Shift whole values by one case to the left;
  Insert the new ST_i value in the last case;
end for

IV. EXPERIMENTAL RESULTS

In order to evaluate our proposed approach for the early detection of MI, we use the EDB medical database from the Physionet [18]. This database consists of 90 annotated ambulatory ECG recordings from 79 subjects. These subjects have various heart anomalies (vessel disease, hypertension, coronary artery disease, ventricular dyskinesia, and myocardial infarction). Each data trace is two hours in duration and contains two signals (2-lead ECG), each sampled at 250 samples per second with 12-bit resolution over a nominal 20 millivolt input range. The sample values were rescaled after digitization with reference to calibration signals in the original analog recordings, in order to obtain a uniform scale of 200 ADC units per millivolt for all signals.

Figures 6(a) shows the original ECG signal of a patient with MI for a period of 4 seconds before filtering & denoising to illustrate ST elevation, Although the signal is not denoised yet we can visually see that the ST segment is elevated relatively to the PR segment which indicates the iso-electric level.

Figure 6(b) shows the result of wavelet decomposition and baseline wonder removing. The frequency bands of the original signal were separated in four levels. The second level decomposition of the signal was considered as the ideal ECG signal for the features extraction because it is the least noisy. Figure 6(c) is the final result of filtering and base line correction.

Figure 7 shows the variation of ST elevation amplitudes extracted for a complete ECG record (2 hours) of a patient with MI. Figure 8 shows the raised alarms by the modified version of CUSUM algorithm, when the threshold $h \geq 2$, the windows size $w = 100$ samples and the minimum deviations $k = 3$. In this case, 41 deviations were detected but only 5 alarms are raised for 3310 ST elevation extracted from the MI ECG. If we change the threshold $h = 1$, the number of deviations increases to 96 and the number of alarms to 9. Also, if we decrease the minimum changes k to 1 for a threshold $h = 2$, the number of alarms doubles to 10. Furthermore, the size of the windows w is also an important parameter, if the size of w is too large, we may miss important new ST elevation episodes, and if it is too small, we increase the sensitivity of the algorithm to new changes and then increase false alarms. The choice of the right values of parameters h, k and w is then a tradeoff between false alarms and miss detection.

To evaluate the performance of our proposed ST detection algorithm, we apply our algorithm on a subset of 50 records of the EDB Physionet database which contains MI ECG and other cardiac abnormalities ECG. Each record is 2 hours corresponding approximately to 7200 heart beats per record. We use the Receiver Operating Characteristic (ROC) curve in order to represent the fraction of True Positive Rate (TPR) vs. the False Positive Rate (FPR) with various values of the threshold h. The ROC curve is presented in figure 9.

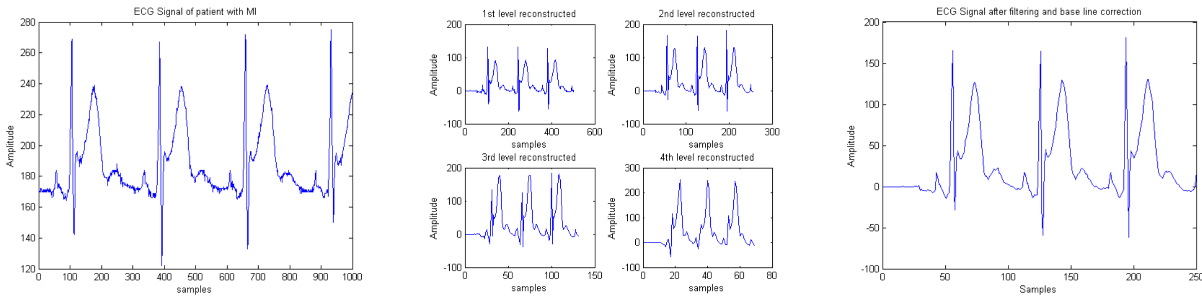
$$\text{Detection Rate} = \frac{TP}{TP + FN} \tag{6}$$

$$\text{False alarm rate} = \frac{FP}{FP + TN} \tag{7}$$

Where TP, FP, TN, FN are respectively, the number of true positives, false positives, true negatives and false negatives. The results obtained show that the optimal rates of DR and FAR are DR=73% and FAR=5% respectively.

V. CONCLUSION

In this paper, we proposed a new approach for early detection of Myocardial Infarction (MI) in real time manner. The proposed approach is based on the detection of deviations in ST segment elevation in the ECG. We combined Wavelet decomposition and Cumulative Sum Method (CUSUM) for a low power detection system adapted to WBAN. The Wavelet decomposition technique is first used to denoise and filter the original ECG signal and extract the values of ST segments, then the CUSUM algorithm is applied on these extracted values to detect significant deviations of ST elevation in order to



(a) MI ECG signal from the edb database (b) MI ECG signal after Wavelet Decomposition (c) ECG after filtering and base line correction

Fig. 6. ECG signal pre-processing

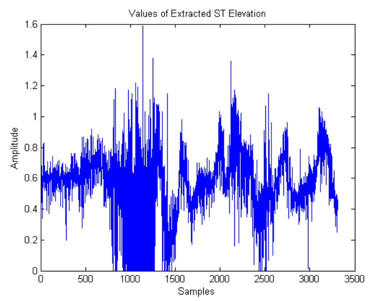


Fig. 7. Extracted ST Elevation amplitudes

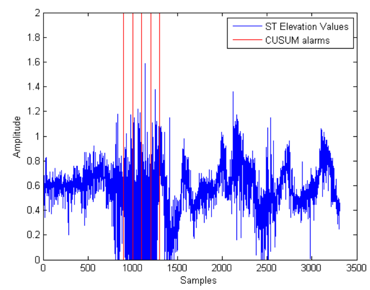


Fig. 8. Raised alarms by CUSUM algorithm

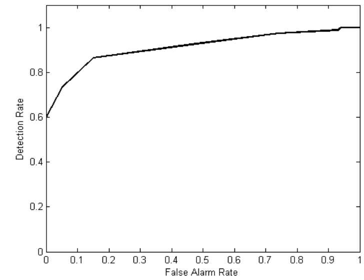


Fig. 9. Receiver Operating Characteristic

raise alarms. To reduce the probability of false alarms, we adapted the CUSUM algorithm by introducing a sliding window with fixed size, to hold the number of deviations that must be detected before raising an alarm. Finally, we applied our proposed approach on a real medical database (the Physionet EDB database) using MI and other cardiac problems ECG. Our experimental results show that our proposed approach can achieve a detection rate of 73% with a false alarm rate of 5%.

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