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ECG R-R Peak Detection on Mobile Phones

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Abstract— **Mobile phones have become an integral part of modern life. Due to the ever increasing processing power, mobile phones are rapidly expanding its arena from a sole device of telecommunication to organizer, calculator, gaming device, web browser, music player, audio/video recording device, navigator etc. The processing power of modern mobile phones has been utilized by many innovative purposes. In this paper, we are proposing the utilization of mobile phones for monitoring and analysis of biosignal. The computation performed inside the mobile phone's processor will now be exploited for healthcare delivery. We performed literature review on RR interval detection from ECG and selected few PC based algorithms. Then, three of those existing RR interval detection algorithms were programmed on Java™ platform. Performance monitoring and comparison studies were carried out on three different mobile devices to determine their application on a realtime telemonitoring scenario.**

I. INTRODUCTION

RECENT research in mobile phone based remote monitoring is proven to be beneficial for patient monitoring (acute, chronic, disaster affected patients), senior or elderly monitoring and even performance monitoring of army, military, police, fire fighters, adventurer, and rescuer [1]-[2]. Small Java™ programs (MIDlets) running on the mobile phones are capable of performing detection of specific diseases by analysing the biosignals received from the acquisition devices like blood pressure cuffs, ambulatory ECG monitor, portable diabetes checker etc. [1]-[2]. Most of the mobile phones now support compact Java™ runtime called Kilobyte Virtual Machine (KVM). Unlike Java runtime for PC, KVM is a miniature run time that is capable of running Java™ software or MIDlets. To the application developer of a mobile phone, Java 2 Micro Edition (J2ME) architecture presents Application Programming Interfaces (APIs) and functionalities supported by the KVM. Compared with a desktop PC, mobile phones have limited computational power to execute complex programs, e.g., the majority of mobile phones don't support floating point operations and multi-dimension arrays which make the implementation of complex algorithm rather difficult. Almost all of the existing studies of biosignal monitoring, detection and analysis were purely based on PCs and PDAs [3]-[9]. Since utilization of the processing power of mobile phones for biosignal analysis is an innovative and novel idea, detailed experimentation needs to be performed to demonstrate its applicability.

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Detection of ECG RR interval and QRS complex is crucial for a sustainable health monitoring scenario, since a wide range of heart diseases like tachycardia, bradycardia, arrhythmia, palpitations etc. can be efficiently diagnosed utilizing the resultant RR interval. Hence, in this paper, we selected a few preferred algorithms, which were previously executed only on PC environment for RR detection of ECG signals in real-time, and deployed them in mobile phones to ascertain their performances. Results from the experimentation suggest that mobile phones can be used to detect abnormality from biosignals in realtime.

II. BACKGROUND OF RR DETECTION ALGORITHM

Electrocardiogram or ECG is the record containing electrical activities of the heart. ECG is widely used to diagnose different heart abnormalities. Different patterns of a normal ECG graph are denoted by the letters P, Q, R, S and T (Fig. 1). RR interval and the QRS complex reveal crucial heart condition of a monitored person.

Generally, a person suffering heart abnormality is needed to be monitored on a regular basis. Therefore, RR interval detection and other biosignal surveillance have to be tested on abnormal ECGs. Fig. 2 shows an abnormal ECG recording representing the first 899 samples (2.5 seconds) of entry 232 of MIT-BIH arrhythmia database [10].

12 ECG entries each with 60 seconds measurement from MIT-BIH arrhythmia database were used for our experimentation. MIT-BIH database has been extensively used in literature for performance monitoring and comparison of different algorithms that perform ECG signal processing [3]-[4]. In this research three fundamental QRS detection algorithms namely Amplitude Based, First

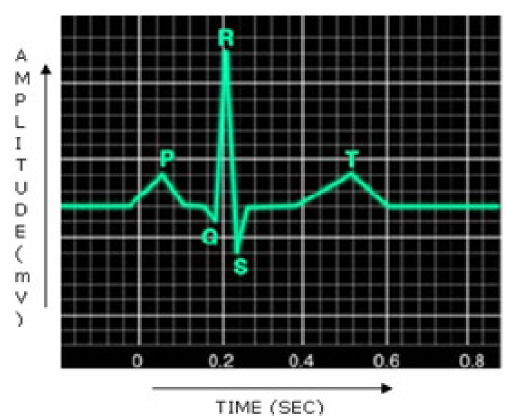

Fig. 1. A sample of normal ECG signal

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Derivative Based and Secondary Derivative Based techniques [3], have been chosen as a pioneering effort to implement ECG R-R peak detection on mobile phone.

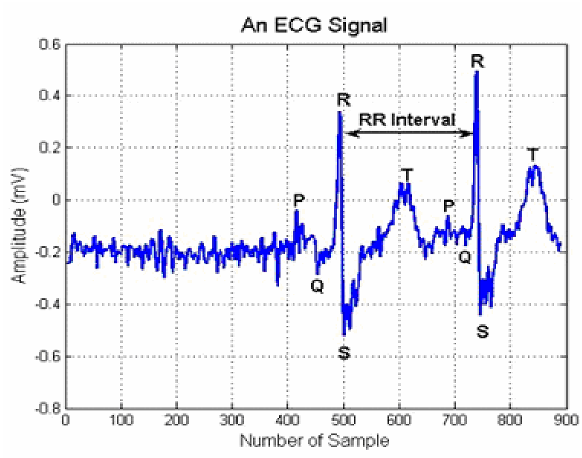

Fig. 2. A sample abnormal ECG signal from MIT-BIH arrhythmia database

A. Amplitude Based Technique (ABT)

The Amplitude based technique (ABT) performs very simple comparison where the ranges of sample ECG points falling beyond an amplitude threshold are determined to be a QRS complex candidate. For Fig. 2, the amplitude threshold can be 0.2. After the QRS complex is detected, the highest amplitude of the detected QRS is ascertained to be R peak. Equation (1)-(4) generalises the amplitude based method. The original ECG signal, xn, from the patient body is given by (1).

$$\mathbf{x}_n = x_1, x_2, ..., x_N \tag{1}$$

where, n=1, 2,…, N and N is the length of the signal.

$$(x_r, x_{r+1}, x_{r+2}, ..., x_{r+k}), ..., \\ (x_l, x_{l+1}, x_{+2}, ..., x_{N-c}) > amplitude\ threshold \tag{2}$$

where, 1<r<l<N, x_{N-c} is the last value greater than the threshold and both x_{r+k+1} and x_{n-c+1} are less than the amplitude threshold.

Each of the section enclosed by the parenthesis of (2) (left side of the equation) is QRS complex candidate.

$$R\ peak = Max(QRS\ Complex) \tag{3}$$

$$RR\ Interval > \frac{n_r}{f} \tag{4}$$

where, n_r is the number of samples between two corresponding R peaks and f is the sampling frequency of the ECG.

B. First Derivative Based Technique (FDBT)

These techniques predominantly revolve around the values, obtained by performing first derivatives of the ECG samples. RR interval can be measured by several first derivatives based QRS detection techniques described in the literature [5]-[7] followed by the application of (3)-(4).

To measure the performance of FDBTs in mobile phone platform, slightly modified version of [4] was adopted.

The first derivative, y_n was calculated at each sample point of x_n such that

$$y_d = x_{n+1} - x_{n-1} \tag{5}$$

where, d = 1, 3, …, N-1

A QRS complex is detected whenever three consecutive first derivative values are greater than a positive slope threshold, followed within next ten samples by two consecutive first derivative values less than a negative slope threshold. Equation (6)-(8) describes the process.

$$y_i, y_{i+1}, y_{i+2} > 0.1375 \tag{6}$$

$$y_j, y_{j+1} < -0.2 \tag{7}$$

$$j - i < 10 \tag{8}$$

After the detection of the QRS complex, (3)-(4) is used to derive the RR interval.

C. Second Derivative Based Technique (SDBT)

Previous research reveals several second derivative based QRS detection algorithms [8, 9]. For performance comparison, a modified version of [8] was used in this investigation. At first, (9)-(10) were used to evaluate the absolute values of first (y0) and second (y1) derivative.

$$y0_d = ABS(x_{n+1} - x_{n-1}) \tag{9}$$

$$y1_s = ABS(y0_{d+2} - 2 * y0_d + y0_{d-2}) \tag{10}$$

where, s=1, 2, 3…, N-3

A scaling value, y2 is obtained from (11).

$$y2_s = 1.3 * y0_d - 1.1 * y1_s \tag{11}$$

For all values exceeding a threshold, are determined to be the start of a QRS candidate (12).

$$y2_s >= 0.9 \tag{12}$$

Values from x_{s-3} to x_{s+3} is passed to (3) as the QRS Complex to compute R peak and finally, (4) is used to calculate the RR interval. After locating a single R peak, the next seven $y2_s$ values are ignored, since most of time there are few $y2_s$ values greater than the threshold surrounding a single R peak.

III. System & Method

The overall idea was a complete mobile phone based telemonitoring platform, where the patient wears an ambulatory device that monitors the patient's biosignal such as ECG. Then the biosignal is sent from the ambulatory acquisition device to the mobile phone of the patient using Bluetooth. The mobile phone then processes the biosignal to detect any abnormality and notifies the rescuer at any life threatening events. The whole system architecture is presented in Fig. 3.

Since, low end mobile phones are constrained with hardware limitations and capable of executing only 3000 to

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10000 operations per second, selection of RR detection algorithms was focused mainly on lower complexity level.

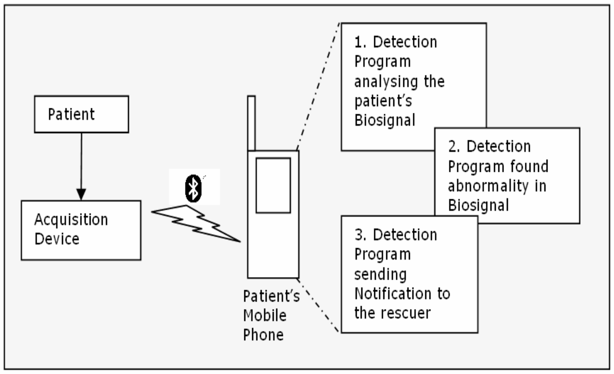

Fig. 3. System architecture: mobile phone based realtime abnormality detection & biosignal analysis

Three different RR detection algorithms representing three pioneering classifications namely amplitude based, first derivative based and second derivative based RR detection algorithms, were selected for running inside the mobile phones [4]. The RR detection algorithms were then programmed for java based mobile phones. Sun Java Wireless Toolkit 2.5 was used for programming MIDlets in regular mobile phones. Fig. 4 shows the deployment of different RR detection algorithms in Java™.

Performances were noted for three different mobile phones (Nokia 91, Nokia 6280 and Siemens C75) using different randomly selected ECG entries of MIT-BIH Arrhythmia database [10]. These three models are all popular regular mobile phones within middle price range.

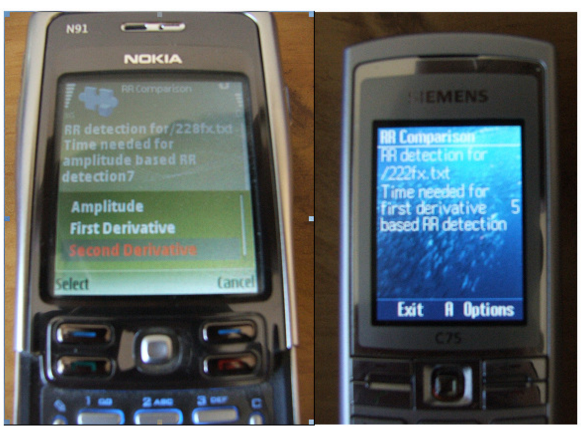

Fig. 4. Deployment of RR detection programs in Java KVM

The ECG entries of MIT-BIH were kept inside the mobile phones during the testing and performance monitoring of the RR detection algorithms. Therefore, during that period Bluetooth was not used for sending ECG to the mobile phone from the acquisition device. The ECG signal has single channel, 11 bit resolution with 360 Hz sampling frequency and yields a step size of 5 microvolts. They contained 60 seconds ECG signal meaning each of the selected MIT-BIH entries had 21600 (360*60) samples.

IV. RESULTS

Table I demonstrates the processing time requirement for different RR detection algorithms using different randomly selected ECG files on three different mobile phones.

A realtime factor, R_f was calculated using (13).

$$R_f = \frac{P_t}{measurement\ window} \quad (13)$$

where, P_t is the processing time needed to run the RR detection algorithm for an individual ECG entry within one measurement window and the window is 60 seconds in this

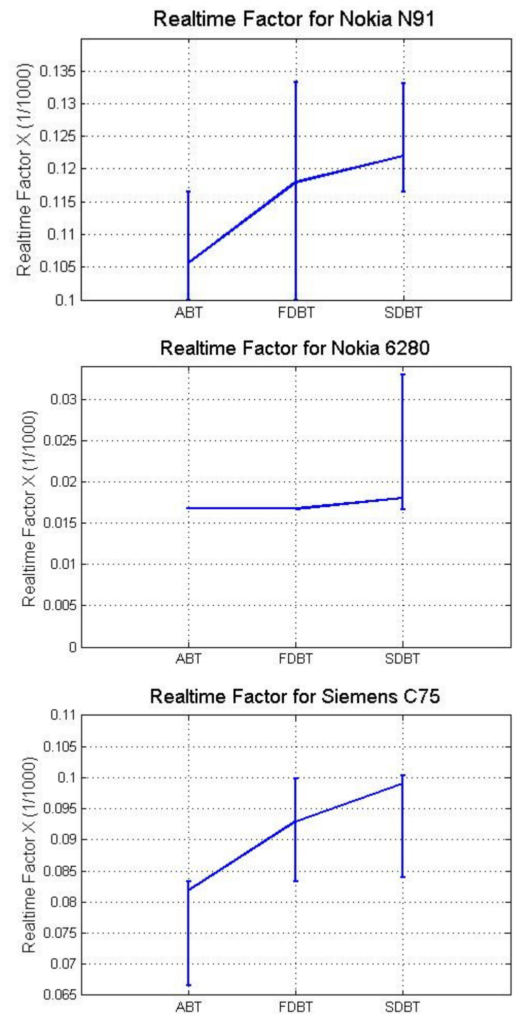

Fig. 5. Realtime factors for different mobile phones and RR detection methods

study. P_t is measured by time stamps embedded in the beginning and the ending of the implementation codes.

Whenever (14) is true, the algorithm is classified as realtime for mobile phone based processing.

$$R_f << 1 \quad (14)$$

Equation (14) basically exemplifies the simple fact that to operate the algorithm in realtime, the processing time required to process 1 seconds ECG data must be much less than 1 second..

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TABLE I
PERFORMANCE COMPARISON OF THE RR INTERVAL ALGORITHMS AMONG DIFFERENT MOBILE PHONES

MIT BIH Entry	Nokia N91			Siemens C75			Nokia 6280		
	ABT (ms)	FDBT (ms)	SDBT (ms)	ABT (ms)	FDBT (ms)	SDBT (ms)	ABT (ms)	FDBT (ms)	SDBT (ms)
100	6	8	8	5	6	6	1	1	2
102	6	7	7	5	6	6	1	1	1
105	6	6	8	5	5	6	1	1	1
114	6	7	7	5	6	6	1	1	1
117	7	8	7	6	6	6	1	1	1
201	6	7	7	4	5	5	1	1	1
213	7	7	8	4	5	6	1	1	1
219	6	7	7	4	6	6	1	1	1
222	6	7	7	5	5	6	1	1	1
228	7	7	8	6	6	6	1	1	1
231	6	7	7	5	6	6	1	1	1
234	7	7	7	5	5	6	1	1	1

Fig. 5 illustrates the realtime factors for Amplitude Based Technique (ABT), First Derivative Based Technique (FDBT) and Second Derivative Based Technique for three different mobile devices. It can be shown that the value of R_f ranged from 1.6×10^{-5} to 13.3×10^{-5} which are much less than 1 during the entire experimentation process. Therefore, for all the mobile phones tested, realtime operations were achieved and Nokia 6280 was found to consume the least processing time

These figures (Fig. 5) also depict the variations of processing times within a particular algorithm (ABT/FDBT/SDBT) while experimenting with different MIT-BIH ECG entries.

V. DISCUSSION & CONCLUSION

The Java implementation of three ECG R-R peak detection algorithms are deployed on three different regular mobile phone handsets. The experiment results with 12 MIT-BIH arrhythmia database indicates the realtime detection was achieved based on the realtime criteria set in this paper. Though the data acquisition program isn't integrated into the detection program yet, it will unlikely affect the experiment result due to multi-thread supporting of J2ME.

The research of realtime RR peak detection on mobile phone is the foundation step for the future research of mobile phone based abnormality monitoring from realtime acquired ECG data. Mobile phones based RR detection is certainly a cheaper solution since expensive PCs are not required for data processing anymore. In addition, a mobile phone based system provides a true ambulatory and wireless connectivity for the patient and other needed user groups. The monitoring and pre-analysis results can be easily transmitted to remote locations using 3G, GPRS, SMS, CBS, MMS, Email, HTTP etc. or even it can be simply displayed on the mobile phone screen.

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