A Novel Single-Channel Real-Time Event Monitoring Software for Extremely Hardware-Limited ECG Devices

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Abstract

In this paper a reliable single-lead real-time cardiac monitoring algorithm for extremely limited hardware platforms is presented. The algorithm performs robust detection and classification for QRS complexes as well as a trusted recognition method for certain cardiac events including life-threatening arrhythmias. The ECG analyzing software is developed for clinical and home care applications, validated in real environments and implemented in a portable battery-powered device with up to seven-day operating time and low-power consumption. The whole ECG software implementation requires only 537 Bytes of RAM memory and round 20 kilobyte of ROM flash memory. The QRS detector achieved a sensitivity (Se) of 99.48% and a positive predictivity (P+) of 99.67 % after analyzing the first channel of all MIT-BIH Arrhythmia Database records, while a Se of 99.50% and a P+ of 99.33% were attained after considering the first lead of all records provided by AHA Arrhythmia Database.

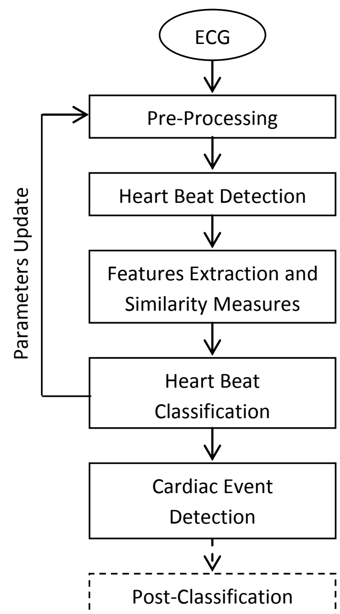

Figure 1. The workflow diagram for the single-channel ECG portable monitoring process implemented in this work.

1. Introduction

Cardiac monitoring continuously provides instant assessment of the patients' heart rhythm. In this work, an ECG monitoring algorithm is designed and implemented on an single-channel portable ECG device with up to seven-day operating time. The device is supported with an extra feature allowing transmission of selected ECG segments using bluetooth technology. This device is powered by a micro-controller with 56KB ROM, 2KB RAM, 200 Hz A/D converter and 8 MHz clock speed. The algorithm software occupies only 20 KB of flash ROM and uses 537 Bytes from the memory RAM. Therefore, the design and the implementation of the corresponding analyzing software were quite challenging.

Many efforts were made so far to provide robust mobile cardiac real-time monitoring systems. González et. al [1] have developed an algorithm for two-lead ECG monitoring system supported by the same micro-controller used in this work. However, the validation of this algorithm was carried out on another database than conventional MIT/AHA databases. Another work done by Valenza et. al [2] implemented a Kohonnen Self Organizing Map (KSOM)-based algorithm in a wearable real-time system for detection of significant cardiac arrhythmias. The system presented by [2] requires a long off-line training phase and relatively high memory usage. Furthermore, the implemented algorithm was validated using part of MIT database signals. In the work presented in [3], a single-channel QRS detector was developed on a micro-controller with even more limited resources than we used in this work. The performance of this algorithm for QRS complex detection was tested on MIT and AHA databases and the corresponding results

were very promising . However, in [3] no real-time classification or cardiac event method was provided along with the QRS detection implemented.
The monitoring algorithm presented in this paper is able to localize and classify cardiac cycles as well as to detect different cardiac events including life-threatening ventricular tachycardia in real time.

2. Methods

2.1. Motivation

The single-channel ECG portable monitoring software algorithm developed in this work consists of five major stages, namely ECG signal pre-processing, heart beat detection, similarity and dissimilarity feature extraction, heart beat classification and cardiac event detection including post-classification, see figure 1.

2.2. Pre-processing

In order to reduce the effect of the baseline wander in ECG signal and to provide high response for steep slopes like QRS complexes, one stage moving window median filter with $300msec$ window length was applied. Thus, the complexes can be distinguished more easily from other low-frequency components of ECG, like T and P waves. Due to the modest resources of the hardware platform, it was not possible to employ additional digital filters, for instance to remove high-frequency noise components and so on. Figure 2 presents the output of a one stage moving window median filter on an arbitrary input ECG signal. As illustrated in this figure, the baseline wander distortion in the raw ECG signal is completely removed in the output signal. Besides, the low-frequency components of P and T waves are highly suppressed compared to the high-frequency components of QRS complexes.

2.3. Heart beat detection

The procedure of heart beat detection implemented in this analyzing software is adopted from the idea of localization algorithm used originally by *Hannover ECG System* (HES) [4]. Detecting the ventricular activities in the input ECG signal is accomplished in three main steps, namely signal transformation, signal conditioning and signal thresholding. This process is carried out on the output signal of the preprocessing step, presented in section 2.2.
• *Signal Transformation*: It implies a so-called spatial-velocity method for the detection of QRS slopes. The spatial velocity signal SV is defined as the rate of change in an input signal with respect to time. In a given digital signal, each sample of the spatial velocity signal can be derived from a set of samples, i.e. a time window of n elements,

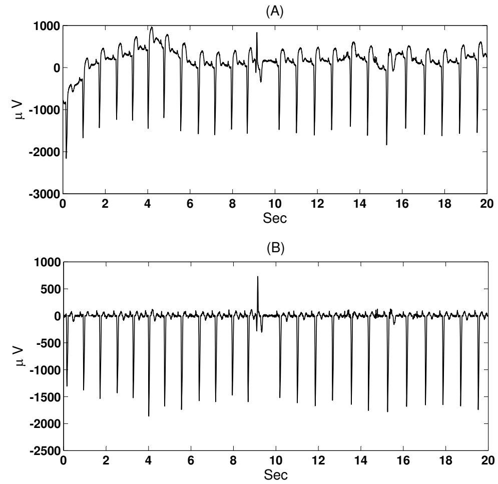

Figure 2. (A): raw single-channel ECG signal (B): the corresponding output signal after using single stage moving window median filter with $300msec$ window length.

from the input signal Y after carrying out certain calculation procedure. Considering $t_1, t_2, ..., t_n$ as the time instances for the corresponding sample values $y_1, y_2, ..., y_n$ within a specific time window in the input signal under study, SV for a specific sample k, $SV(k)$, can be calculated as follows:

$$SV(k) = \frac{\frac{1}{n}\sum_{i=1}^{n}(t_i - \bar{t})(y_i - \bar{y})}{\frac{1}{n}\sum_{i=1}^{n}(t_i - \bar{t})^2} \quad (1)$$

where $\bar{t}$ and $\bar{y}$ are the mean values of all time instances $t_1, ..., t_n$ and all the corresponding sample values $y_1, ..., y_n$, respectively. In order to optimize SV output signal for a given input signal, the moving window technique using suitable overlapping percentage and scanning window size is to be considered.
• *Signal Conditioning*: Due to the median filter used in the preprocessing step and to the spatial-velocity method, P wave and T wave frequency components represented in SV signal are significantly reduced. However, in order to reduce the number of false positive detections, an enhancement procedure for high-frequency components of QRS complex in SV was carried out by means of squaring operation. Accordingly, large QRS components will be much emphasized and small T wave and P wave low-frequency components will be highly suppressed in the same time. An optimized moving window integration filter was also implemented after the squaring operation to smooth the output signal. An example of the output signal at this step is shown in figure 2-C. This final conditioned spatial-velocity signal denotes as S.
• *Signal Thresholding*: As the value of the signal S ex-

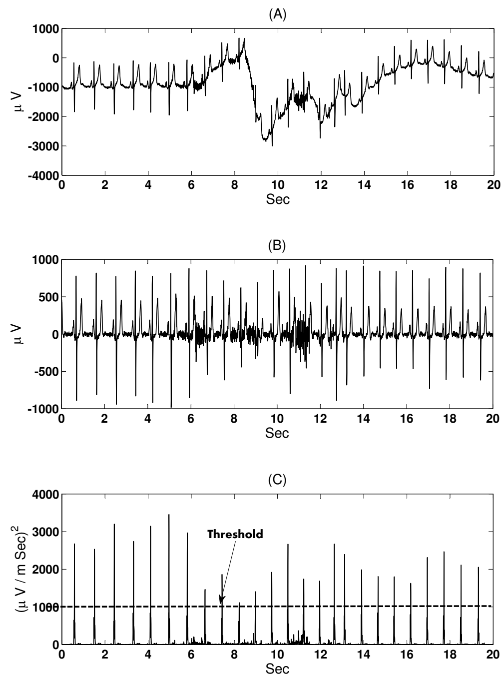

Figure 3. (A): raw ECG input signal (B): the corresponding output signal after the median filter illustrated in section 2.2 (C): the corresponding final conditioned spatial-velocity signal.

ceeds a certain adaptive threshold Thr, the corresponding time instance is registered. A window, starting from the detected time instance with specific length, will be then projected on the raw ECG signal to capture the new QRS complex candidate. In order to confirm the possible new heart beat, a set of plausibility checks have to take place on the candidate QRS complex. A so-called QRS complex template, defined as representative QRS complex for all detected dominant QRS complexes, is used to compute the adaptive threshold Thr. The conditioned spatial-velocity signal S_{Temp} for the QRS complex template is calculated using the same methods presented in the last two steps (*Signal Transformation* and *Signal Conditioning*). The calculation of the adaptive threshold Thr is done using the following equation:

$$Thr = \alpha \times S_{Temp}, \tag{2}$$

where α is a constant and $\alpha \in [0.20, 0.35]$. The value of α was optimized empirically. Figure 3 illustrates an ECG input segment, its corresponding output after using the median filter represented in section 2.2 and its corresponding signal S. As shown in this figure, only QRS components are emphasized allowing sensitive detection of heart beat using a suitable adaptive threshold.

2.4. Feature extraction and similarity measures

In this algorithm, different features were extracted from each detected heart beat by means of three main similarity measures. The extracted features were further analyzed in order to classify the detected beat. The adaptive QRS complex template was considered as reference QRS complex to compare with. The number of samples in the template beat and each detected beat have to be identical. $Beat_{Temp}$ and $Beat_{Actual}$ are defined as two row vectors of length n. They are normalized between +1 and -1 and representing the QRS complex template and the actual detected QRS complex respectively. Thus, the three measures are calculated as follows:

1. *Morphology Difference Measure*: At any given index i, a row vector B_i of length m is defined as follows:

$$B_i = [b(1)b(2)b(3)\cdots b(m)], \tag{3}$$

where $b(k)$, at index k, can be computed as:

$$b(k) = Beat_{Temp}(i) - Beat_{Actual}(i - (\frac{m+1}{2}) + k) \tag{4}$$

Finally, the minimal absolute value of the row vector B_i can be obtained. By repeating the same procedure for each sample in $Beat_{Temp}$, a set of values will be produced. Giving that, $MeanSet$ is defined as the average of this set of values, the *morphology difference Measure* $MorphDiffMeas$ will be calculated as:

$$MorphDiffMeas = (1 - MeanSet) \times 100\% \tag{5}$$

2. *Base-To-Peak Measure*: $MaxAbs_{Temp}$ and $MaxAbs_{Actual}$ denote the maximal absolute values in $Beat_{Temp}$ and $Beat_{Actual}$ respectively. Based on that, the *Base-to-peak measure* $B2PMeas$ will be given as follows:

$$B2PMeas = (1 - abs((MaxAbs_{Temp} - MaxAbs_{Actual})) \times 100\% \tag{6}$$

3. *Peak-To-Peak Measure*: Giving Max_{Temp}, Max_{Actual}, Min_{Temp} and Min_{Actual} as the maximal and minimal values in $Beat_{Temp}$ and $Beat_{Actual}$ respectively, the *peak-to-peak measure* $P2PMeas$ can be yielded using the following equation:

$$P2PMeas = (1 - abs(Max_{Actual} - Min_{Actual} - Max_{Temp} + Min_{Temp})) \times 100\% \tag{7}$$

2.5. Heart beat classification

The classification algorithm implies a complex decision tree model along with a particular case analysis for the corresponding nodes. The classification tree algorithm is able to analyze all independent variables presented in the section 2.4 as well as additional variables like RR interval and heart rate for the actual detected heart beat. As result, the beat cycle will be clustered into one of the four available given classes, namely normal (NOR), premature ventricular contraction (PVC), supra ventricular premature beat (SVPB) or non-defined type (NDT). By comparing the set of independent variables in a given node with their corresponding thresholds, two possible action decisions can be made. That is, the corresponding node will be then able to decide whether additional checking procedures run by other tree nodes are still required or the detected beat can be directly classified in one of the available main classes. Necessary checking procedures in different tree nodes are realized until a final decision about heart beat type can be taken. After the heart cycle was classified successfully, the heart beat template along with all required thresholds and algorithm parameters will be updated.

2.6. Cardiac event detection

This software is able to detect heart rhythm disturbances in real-time, like bigeminy, couplet, triplet, cardiac pause, asystoly and ventricular tachycardia. A major drawback of many existing ventricular tachycardia (VT) monitoring methods is the high incidence of false alarms. This is mainly due to the difficulty in discriminating between VT signal and strong moving artifact signal in real application. In order to enhance the detection precision, i.e positive predictivity, of VT in this work, a so-called post-classification method is being developed and optimized. It is based on re-analyzing the morphology and heart rhythm features of the actual beat in relation with corresponding features of the previous heart beats. Cardiac event detection including VT with and without post-classification method were validated on AHA Arrhythmia Database using the run-by-run performance statistic tool (RxR) available on *PhysioNet.org*.

3. Results

Regarding the QRS detector, a sensitivity (Se) of 99.48% and a positive predictivity (P+) of 99.67% were yielded using the first channel of all MIT-BIH Arrhythmia Database records [5], while a Se of 99.50% and a P+ of 99.33% were obtained employing the first lead of all records provided by AHA Arrhythmia Database [6]. For PVC detection, the Se and P+ after analyzing the first channel of both databases are greater than 92% and 76%, respectively. Without using the post-classification method, the Se and P+ of Couplet and short run detection on AHA Database are greater than 85% and 82%, respectively. Se and P+ of long run detection are equal to 43% and 76%. By using the post-classification method, the P+ for all kind of run detections were increased by 12% in average, while the Se were decreased by round 35% in average.

4. Discussion and conclusions

The results obtained by the post-classification method using AHA Database and a number of other real-time long-term ECG recordings show that the precision of cardiac rhythm detections especially for VT has been noticeably improved, that is, the number of VT false warnings has been extremely decreased. As already mentioned, an optimization process is still being carried out on the post-classification method in order to increase the loss in detection sensitivity. It is mainly based on improving heart beat classification part by implementing an extra feature for P wave detection. Accordingly, more arithmetic power and working memory usage will be highly required. However, further performance improvement of the monitoring algorithm will be one of the main objectives of this work in the near future. The overall results achieved in this work show that a sensitive QRS complex detector and classifier as well as well-trusted monitoring algorithm for cardiac events with very low rate of false alarms can be accomplished even with limited hardware resources.

References

[1] Gonzalez R, Jimenez D, Vargas O. WalkECG: a mobile cardiac care device. In Computers in Cardiology, 2005. Lyon,, September 2005; 371–374.

[2] Valenza G, Lanata A, Ferro M, Scilingo EP. Real-time discrimination of multiple cardiac arrhythmias for wearable systems based on neural networks. In Computers in Cardiology, 2008. Bologna,. ISSN 0276-6547, September 2008; 1053–1056.

[3] Hamilton P. Open source ECG analysis. 2002 Computers in Cardiology September 2002;101–104. ISSN 0276-6547.

[4] Zywietz C, Borovsky D, Faltinat D, Klusmeier S, Schiemann W. The Hannover EKG System HES. Trend in Computer Processed Electrocardiograms 1977;159–167.

[5] Moody GB, Mark RG. The MIT-BIH arrhythmia database on CD-ROM and software for use withit. In Computers in Cardiology 1990, Proceedings. Chicago, IL, USA, September 1990; 185–188.

[6] American heart association ECG database DVD, 1997;available from www.ecri.org.

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