Real-time ECG monitoring and arrhythmia detection using Android-based mobile devices

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***Abstract*— We developed an application for *Android*™-based mobile devices that allows real-time electrocardiogram (ECG) monitoring and automated arrhythmia detection by analyzing ECG parameters. ECG data provided by pre-recorded files or acquired live by accessing a *Shimmer*™ sensor node via *Bluetooth*™ can be processed and evaluated. The application is based on the Pan-Tompkins algorithm for QRS-detection and contains further algorithm blocks to detect abnormal heart-beats. The algorithm was validated using the *MIT-BIH Arrhythmia* and *MIT-BIH Supraventricular Arrhythmia* databases. More than 99% of all QRS complexes were detected correctly by the algorithm. Overall sensitivity for abnormal beat detection was 89.5% with a specificity of 80.6%. The application is available for download and may be used for real-time ECG-monitoring on mobile devices.**

I. INTRODUCTION

Arrhythmia is a common medical condition which includes a broad range of heart-related pathologies [1]. Although not all of them are permanent or require medical attention, they may provide hints to the development of serious heart diseases. The ECG has been a cornerstone for the detection and diagnosis of such conditions for a long time. However, its interpretation is mostly based on medical experts or specialized hardware only available in clinical environments. This is especially problematic in developing countries, where the availability of clinics and medical experts is low [2]. There is a definite need for automatic, low-cost physiological monitoring solutions that are easy to use, accurate, and can be used in home or ambulatory settings.

Mobile devices like smartphones and tablet computers continuously grow in processing power and become an integral part of daily life, even in developing countries [2]. Recently, such mobile devices are also used for biomedical signal processing and ECG analysis [3], [4], [5]. In 2011, *PhysioNet/Computing in Cardiology* [2], [6] arranged a challenge to develop efficient algorithms to improve the quality of ECG recordings using mobile devices and to improve efficiency of ECG diagnosis. Scully et al. [7] demonstrated that physiological features like heart rate, breathing rate and blood-oxygen saturation can be extracted using camera recordings from mobile phones. The authors concluded that all processing could be performed on modern mobile devices. However, they did not share their software implementation. Furthermore, algorithms for arrhythmia detection were developed and assessed that were capable of handling the hardware restrictions of mobile devices [1]. However, they needed medical expert intervention in order to operate. In summary, the previous work in the literature focused on developing algorithms for ECG monitoring either did not share an actual software implementation, did not specifically evaluate arrhythmia detection on mobile devices, or needed expert intervention in order to operate.

Our contribution in this paper is threefold. Firstly, we provide an algorithm for real-time detection of QRS complexes and automated, intervention free normal/abnormal heart beat classification, which extends well-known analysis methods [8], [1]. Secondly, we present an implementation of the algorithm in an Android-based ECG monitoring application[3], which can process ECG signals in real-time by accessing a *Shimmer*™ sensor node via Bluetooth or by using a database of pre-recorded data. Thirdly, we conduct a detailed evaluation of the application and the implemented algorithms in respect to QRS detection and abnormal beat classification using pre-recorded data of the *MIT-BIH Arrhythmia* [9] and *MIT-BIH Supraventricular Arrhythmia* [10] databases.

II. METHODS

The algorithm consists of four major steps: (A) QRS detection; (B) template formation and adaptation; (C) feature extraction; (D) beat classification. Fig. 1 depicts an overview of the algorithm.

A. QRS detection

As a first processing step, the raw ECG lead II signals were processed with digital filters for noise rejection and QRS detection as proposed by Pan & Tompkins [8]. The processing steps were in order of application: (i) a bandpass filter (output denoted *Band*) composed of cascaded low-pass and high-pass filters, (ii) a five-point differentiation, (iii) a squaring operation, point-by-point, and (iv) a moving window integration (output denoted *Int*).

Single QRS complexes were isolated using a threshold T computed from *Int* by applying a moving average filter with a window size of 150 ms. If either *Int* or *Band* reached the threshold, a search for the R-deflection was initiated using a 3-point peak-detector on *Band*. For each peak candidate, *Int* was again compared to T to ensure that the detected peak was a valid R-deflection.

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[3]The precompiled Android *apk* can be downloaded at http://tinyurl.com/Hearty-zip. The source code is available on request.

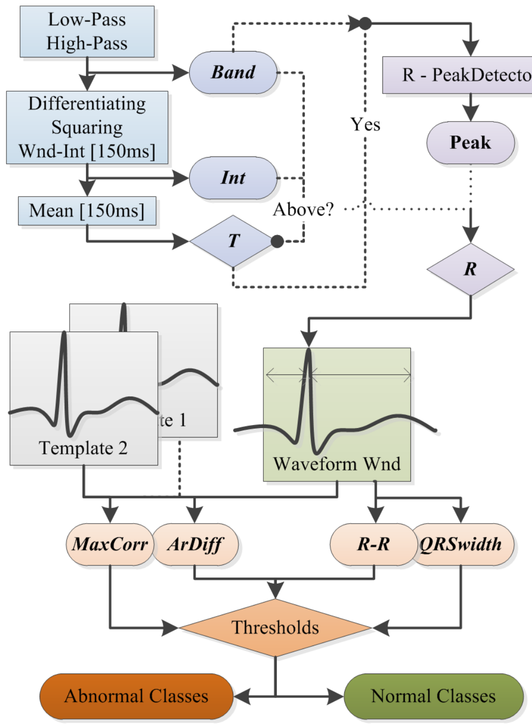

Fig. 1. Overview of the algorithm for heartbeat detection and classification.

B. Template Formation and Adaptation

To facilitate subsequent feature computation and heart beat classification, two QRS-complex templates were required. As a fully autonomous approach was desired, these templates were not selected by a supervising cardiologist like in [1], but derived automatically from the ECG signal and adapted over time.

For the template generation, a selection process was conducted at the beginning of every ECG acquisition to determine the first templates. For this, computations were performed on 400 ms windows centered on the first six validly detected R-peaks. The QRS complexes in these six windows were used as candidates for the templates. In order to assign the candidates to the two template slots, two criteria were used: (i) smallest difference of the individual waveform area to the average waveform area of the six candidates; (ii) Pearson correlation between the candidates of more than 0.95. The candidates were first split in two groups according to their individual waveform area, where beats with area lower than the average were considered first. Within each group the beats were ranked according to (i). Using this ranking, the first two consecutive candidates that satisfied (ii) were chosen as templates. If such a pair could not be identified, the first two ranked candidates were chosen.

With our approach not relying on expert-supervised selection of normal beats, we refrained from having a fixed set of templates for an entire ECG recording. Therefore, the two templates were both updated during ECG processing. Every time a heart beat was classified as normal (see below), it replaced the template that had the higher correlation with the classified beat. This progressively rotated new normal beats through the template slots and provided the same behavior described in the QRS template matching procedures in [1].

C. Feature Extraction

For subsequent beat classification, four heart beat features as defined by Krasteva & Jekova [1] were used. The features with respect to the templates were: (i) difference in absolute area (*ArDiff*, using normalized waveform area) and (ii) maximal cross-correlation coefficient (*MaxCorr*). Again, 400 ms windows centered on every detected R-peak were used for this computation. Furthermore, the width of detected QRS complexes *QRSwidth* was computed using the Pan-Tompkins integrator output [8]. The last computed feature was the R-R-interval *R-R*. The computed features are shown as rounded shapes in Fig. 2.

D. Beat Classification

Beats were classified using two different characteristics:

- the WAVEFORM characteristic, which distinguished normal and abnormal beats. The abnormal beats class had the subclasses {premature ventricular contraction (PVC), PVC/aberrant, bundle branch block, escape beat (generic), atrial premature contraction (APC), aberrant},
- the PACE/RHYTHM characteristic, which distinguished normal and abnormal pace. The abnormal pace class had the subclasses {fusion of two beats, AV-block, tachycardia, bradycardia}.

Discrimination of the different subclasses was performed by a decision tree (Fig. 2) as proposed in [1]. The different beat classes are shown in rectangular boxes in Fig. 2.

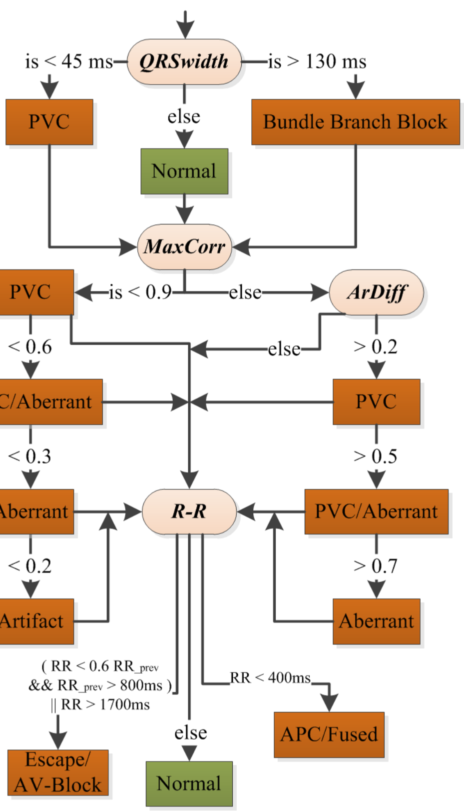

Fig. 2. Decision tree for heart beat classification.

III. IMPLEMENTATION

The software framework was implemented in *Java*™ using the *Android SDK 2.3.3* (Google Inc.). Android was used because of its open nature, widespread use and the portability of the code. Additionally it allowed simple integration of external ECG sensors via Bluetooth.

The software framework consisted of three components: (A) a *Data Delivery Service* that provided data streaming from a Bluetooth connection or pre-recorded database files, (B) a *Signal Processing Service* that implemented the above mentioned algorithms, and (C) a *Graphical User Interface* (GUI) that displayed the results.

A. Data Delivery Service

The Data Delivery Service allowed provisioning of ECG data to the actual processing algorithms in real-time. Implementation was realized as an Android background service. Using a service allowed to manage the Bluetooth connection to the sensor node independently of any foreground process, allowing the user to switch between applications without loosing the connection. Furthermore the service provided a consistent interface to the processing application for live and pre-recorded data.

Data were either provided in *live mode* or *database mode*. In live mode, the service allowed acquisition of ECG lead II data via a Bluetooth connection to a *Shimmer* ECG sensor node. *Shimmer* (Shimmer Research Ltd., Dublin, Ireland) is a small, lightweight wireless sensor platform consisting of a low-power microcontroller and a wireless network module as well as expansion modules providing sampled ECG, EMG or GSR signal data in real-time. In database mode, the service supported reading of pre-recorded ECG lead II data from database files. In this case real-time sampling was simulated by the service. If available, the service additionally supported annotation characters for evaluation.

B. Signal Processing Service

The signal data provided by the Data Delivery Service were passed to the Signal Processing Service, which implemented the processing steps. To realize processing in real-time, the implementation was optimized with respect to computational requirements and memory footprint. Circular buffers were used for all buffering operations during signal processing to avoid overhead and function calls were kept at a minimum. All digital filters were automatically adapted to the sampling interval of the incoming data.

C. Graphical User Interface

A GUI was implemented, which allowed starting and stopping the processing and visualization of the results (Fig. 3). To allow efficient plotting of signal data with high sampling rates, a specialized plotting component was implemented. Line-plots representing the raw ECG signal, extracted QRS complexes and variation of heart rate were displayed in the bottom area. Every time a QRS complex was detected and classified, it was marked either in green (normal beat) or red (abnormal beat). Additionally the current value of different features like heart rate, *R*-*R* interval in ms and number of recognized QRS complexes was displayed in the upper area. Upon closing an overview of the classification results was displayed.

Fig. 3. Screenshot showing the main interface of the application

IV. EVALUATION

For evaluation, the MIT-BIH Arrhythmia [9] and the MIT-BIH Supraventricular Arrhythmia [10] databases were used. Using a PC, the records of both databases were downloaded and converted to a format readable by the application. The data were then uploaded to the memory card of different mobile phones. The mobile phones used were: *Samsung™ GT-I9000*, *Samsung™ GT-N7000*, *HTC™ Wildfire S A510e*.

For the evaluation, the currently valid annotation character supplied with the MIT-BIH records (if available) was compared with the result of the classification of every detected beat. The results were stored by the application to provide statistics about matches and mismatches. After processing of all MIT-BIH records, the results were evaluated on a PC.

For the presentation of the results, the normal/abnormal beat classifications were evaluated. The measures to describe the performance of the classification were:

- TRUE NEGATIVE: correctly classified as normal
- TRUE POSITIVE: correctly classified as abnormal
- FALSE NEGATIVE: incorrectly classified as normal
- FALSE POSITIVE: incorrectly classified as abnormal
- MEDIAN FN: median of false negatives over all records

V. RESULTS

Tab. I presents the results for real-time classification of the MIT-BIH Arrhythmia and the MIT-BIH Supraventricular databases. $256,014$ unique beat annotations (MIT-BIH Arrhythmia: $90,116$ in 39 records, MIT-BIH Supraventricular: $165,898$ in 72 records) were processed, and 0.42% were not recognized. Overall sensitivity for abnormal beat detection was 89.5% with a specificity of 80.6%. The results of the application were identical on all employed mobile phones.

Several records (MIT-BIH Arrhythmia: 104, 109, 111, 118, 124, 203, 214, 231, 232; MIT-BIH Supraventricular 845, 848, 850, 855, 888, 890) had to be omitted, as they only contained exclusively paced, left/right bundle branch block, abnormal beats or severe noise within the fist ten beats.

Live operation of the application was tested with one healthy individual. The application worked as expected, providing a continuously monitored ECG signal with no abnormally detected beats.

TABLE I
EVALUATION RESULTS FOR ALL DETECTED BEATS

	MIT-BIH Arrhythmia	MIT-BIH Supraventricular
Detected Beats	99.59%	99.58%
True Positive	11 224	16 474
True Negative	65 855	114 606
False Positive	10 987	32 567
False Negative	1 680	1 556
Median FN	3	3

VI. DISCUSSION

The results demonstrated that the proposed implementation works well on the MIT-BIH databases. Especially the high sensitivity and the low number of false negatives evidenced that the approach was applicable, while the number of false positives could still be reduced.

For those database records where the first beats and hence the template was conditioned well, detailed analysis showed a high classification accuracy. This also showed that most of the false negative or false positive decisions were made on isolated records. In most cases this was the result of poorly conditioned templates due to either noisy data or ectopic beats at the beginning of a record.

Automated selection of the first templates relied on a simple algorithm, which requires that the first 10 beats are of high quality. This needs to be improved in further work, especially as several records in the databases could not be used because of this limitation. To provide more consistent results, a further step in the selection algorithm could be implemented to evaluate the signal quality/level of noise, present at the beginning of the recording and delay the first template selection accordingly. It might also be a viable option to extract accurate templates over the course of an entire ECG recording, store them associated with the current mobile phone user, and reuse them in subsequent ECG evaluations of the same user. It would allow the template selection to still be entirely unsupervised while opening up the opportunity for more accurate templates.

The algorithm ran in real-time on all tested phones, but created high computational load. Analysis showed that the computation of the maximal correlation coefficient was the most resource-intensive step. It might be applicable to only use a single correlation coefficient and assume it to be maximal when computed around the R-deflection. Using the free resources, analysis of features in the frequency domain or of the secondary lead could be performed, which might increase classification performance.

Live recording and processing was only tested with one healthy individual. It could be shown that the implementation works stable with live data, indicating the applicability in the home or ambulatory setting. As an equally important matter it has to be assessed how long-term ECG monitoring on mobile phones will be affected by the limited battery power available. Also, additional sensor platforms will be considered to avoid having the Shimmer node as a mandatory component. This will be evaluated in future studies.

VII. CONCLUSION

We provided an implementation of a software framework for monitoring ECG and providing automated arrhythmia detection on mobile devices. Our main goal was to avoid expert supervision and to assess the resulting performance of such an approach. Using template based processing and beat classification, these tasks could be achieved and the resulting application may be used for real-time ECG-monitoring on mobile devices. The evaluation of two MIT-BIH databases showed that the algorithm can detect the QRS complex with high reliability and classify between normal and abnormal beats with high sensitivity. However, some improvements are still required, especially with respect to template generation. As a next step we are going to further evaluate our approach in this regard, using long-term ECG data of patients with cardiac pathologies.

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