Open Source Java-based ECG analysis Software and Android app for Atrial Fibrillation Screening

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Abstract

The development of mHealth applications could facilitate the decrease of the healthcare costs in both high income and low to middle income regions. However, it is essential that mHealth software is validated on public databases. Moreover, public scrutiny of the algorithms is likely to lead to faster and lower cost innovation. In this paper, we therefore present a novel Java-based Android application offering advanced Electrocardiogram (ECG) processing techniques, including signal quality analysis and Atrial Fibrillation (AF) screening.

The application connects the phone to a wireless ECG device for ECG signal recording. The application then processes the acquired signal in three stages. First a peak detector, based on peak energy-amplitude detection, is applied. The detector has been adapted to deal with high noise environments and frequent signal loss or saturation. A Signal Quality Index (SQI) is then computed. Finally, an AF detection algorithm, based on RR interval regularity is applied.

The peak detection achieved 99.8% sensitivity and 98.7% positive predictive value on the MIT-BIH arrhythmia database. The SQI had 96.9% accuracy on an extension of the CinC 2011 Competition database. The AF detector achieved a 92.7% sensitivity and 94.0% positive predictive value on the MIT-BIH AF database, on short 12 beat-length segments with as few as 10% of the beats being related to AF.

This application opens the way for advanced ECG analysis in the mHealth context and more specifically for the screening of AF in developing countries. The software will be released under the BSD Open Source License to increase the engagement of the user community in the use of the software.

1. Introduction

In recent years, the fields of telemedicine and mHealth, especially in the context of increasingly resource-constrained healthcare systems, have been rapidly evolving. Many reasons can be given for explaining this trend, but the two most important ones are 1) the need to reduce the cost of healthcare expenditure in developed countries, and 2) to facilitate access to a better healthcare for population in resource-scarce communities [1]. The development of robust mHealth applications may enable the early diagnosis or screening of pathologies, which today remain mainly undetected.

One of the most interesting targets amongst cardiovascular pathologies is Atrial Fibrillation (AF). AF is a heart rhythm abnormality and it is associated with an increased risk of stroke and heart failure, especially in women. The prevalence of AF is 0.4% to 1% in the general population and increases with age [2].

In this paper, we present a novel mHealth Android application aimed at screening for AF. This application records the Electrocardiogram (ECG) waveforms by connecting the phone with an ECG recording device via Bluetooth. The signal processing is then performed on the phone and the user is provided with essential feedback, such as an evaluation of the Signal Quality Index (SQI), in addition to the heart rate. For benchmarking, the analysis software was evaluated on public databases.

2. Material and methods

2.1. ECG device

The current version of the phone app was developed on the Android platform (4.2) in Java and communicates via Bluetooth to a Shimmer ECG device (Shimmer Research, Dublin, Ireland) [3,4]. This device provides two ECG lead recording during ambulatory situations. It is lightweight (28g) and therefore acceptable for wearable applications.

Streaming of the ECG signals can be initiated after Bluetooth pairing, and are acquired at a sampling frequency of 256 Hz. The traces of the two ECG leads are then plotted by the app, along with the estimated Heart Rate (HR) and the SQI of each ECG lead. Once the user is happy with the overall quality of the traces, the recording function can be invoked and the ECG data are saved as text files on the mobile phone or as binary files to a microSD card.

2.2. Signal processing

The signal processing consists of three consecutive stages: peak detection, quality and rhythm assessment.

2.2.1. Peak detection

Beat or peak detection is arguably the most important task for ECG signal processing. The R-peak is the most distinguishable feature in the signal, generated when the ventricle's cells are depolarized. Detection of these peaks allows HR or cardiac rhythm assessment.

R-peak detection has been thoroughly studied and several methods have been proposed. The method implemented in this app was originally developed in C by Clifford [5]. The algorithm is a modification of an approach first described by Nygârds and Sörnmo in 1983 [6] and subsequently updated by Hamilton, Pan and Tompkins in 1985 and 1986 [7, 8].

The detection method consists of two stages:

1. Pre-processing of the ECG signal: both linear and non-linear filtering methods are used in order to enhance highly energetic peaks with an approximate duration of 100ms. This stage is summarized in the flowchart on Figure 1
2. Post-processing decision rules: these operate on the processed ECG signal to identify the relevant sections containing R-peaks ('fiducial' points).

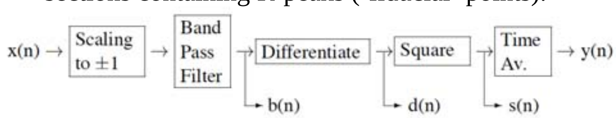

Figure 1. Four steps of the first stage of the R-peak detector.

Clifford added adaptive thresholding and initialization taking the median value of the first and third quartile of the time-averaged signal. This made the algorithm scale-independent, robust to large changes in amplitude, and have a rapid recovery time from gross artifacts [5]. Note that such gross artifacts do not often present in standard online databases, but are otherwise generally common.

The R-peak detection was evaluated on the MIT-BIH arrhythmia database, including 48 recordings of 30-minute ECG signals [9]. The different records included pathological cases, such as premature ventricular contraction, bundle branch blocks or atrial fibrillation (AF). The BxB tool from PhysioNet [10] was used for automatic evaluation of the beat detection by matching automated beats with the reference annotations, searching in a 150ms window. The implemented Java version of the QRS detector was compared with *eplimited* [7, 8], which is freely available [11].

2.2.2. Signal quality index

Ambulatory recordings are particularly prone to noise and artifacts. The software provides an estimation of the signal quality so that the user, who may not be familiar with physiological signals and may not be able to visually assess the quality of the ECG traces, can decide whether the current analysis is reliable or recording needs adjustment. The development of such indices is of interest in numerous applications and especially for mHealth applications [9]. Other studies were also performed to assess the influence of pathological rhythms and beats on the estimation of SQIs [10].

In Behar *et al.* [13] SQI estimation was based on a combination of several basic SQIs using a machine learning approach. The first basic SQI was a comparison between two R-peak detectors. The first detector was the one described in section 2.2.1. The second algorithm, *wQRS*, is based on the length-transform, which is designed to emphasize the QRS complexes [11,12]. The resulting metric, bSQI, is then calculated as follows:

$bSQI(k)=N_{matched}(\mathrm{k}.w)/N_{all}(\mathrm{k},w)$,

where N_{matched} is the number of beats that both algorithms detected (within 150 ms) and N_{all} is the number of all beats detected by either algorithm (without double counting the matched beats). In other words, $N_{\mathrm{all}} = N_{DF} + N_{LT} - N_{\mathrm{matched}}$, where N_{DF} was the number of beats detected by Clifford's method [5] and N_{LT} was the number of beats detected by the *wQRS* method [14,15].

bSQI was evaluated on an extension of the database provided for the Physionet/CinC Challenge 2011 [12], which consisted of set of manually labeled 10-second ECG segments. This set of data contained 10020 segments labeled 'good quality' and 8745 segments labeled 'bad quality'. This SQI was compared with other SQIs, which were based on previously described statistics (kurtosis- kSQI and skewness- sSQI) or spectrally band-limited measurements (pSQI and basSQI for assessing the energy in the baseline). See Behar *et al.* [13].

2.2.3. Atrial fibrillation detection

AF is a cardiovascular pathology, which is associated with irregular cardiac rhythm. The RR interval time-series is characterized by a succession of short and long intervals. This phenomenon can be explained by a random firing of the AV node due to the fibrillation of the atria. In such condition, the ECG traces show a substitution of the p-waves by f-waves, which present throughout the cardiac cycle. The determination of f-wave frequency can aid in the assessment of AF.

In our Android application, an AF detection method based on the regularity of the RR time series was initially implemented [16]. The measurement of this regularity, coefficient of sample entropy, was computed as follows:

$$COSEn = SampEn - \ln(2r) - \ln(\overline{RR}),$$

It is based on the sample entropy defined by

$$SampEn = -\ln(A/B) - \ln(B) - \ln(A),$$

where A is a total number of matches of length $m+1$ and B the total number of matches of length m, with a matching tolerance r, and $\overline{RR}$ is the mean RR interval.

The matching tolerance r was initialized at 30ms and was increased iteratively until $A \geq 5$. *COSEn* was computed on non-overlapping 12 beat-length segments. If *COSEn*>-1.4 on a segment, then AF was reported.

The AF detection algorithm was evaluated on the MIT-BIH AF database [10], which consisted of 25 long-term recordings (10 hours each) with subject exhibiting (mostly paroxysmal) AF. Each recording was divided in 12-beat segments, which were classified as AF if at least 10% of the beats were atrial in the segment. Results were compared with the method developed by Linker [17], which analyzed the signal over 10s windows.

2.2.4. Ventricular fibrillation detection

As an accurate detection of Ventricular Fibrillation (VF) and tachycardia (VT) is of the highest importance for patient monitoring, we have also included a machine learning approach for VF detection. The detector is based on Li *et al.*'s method [18]. This technique extracts two features from the ECG (related to spectral energy) on a 5-second window and combines them using a machine learning approach. These features were inspired from the literature and selected using a genetic algorithm.

The current implementation of the VF detector combines the two features by using a multi-layer perceptron, with a structure containing three layers and twelve nodes in the hidden layer. Tests (not reported here) have shown no significant difference between this implementation and the Support Vector Machine approach presented in [18]. The authors reported an accuracy, sensitivity and specificity of approximately 96% on a test set containing more than 20,000 events extracted from 67 subjects in three publicly available databases (the AHADB, CUDB and VFDB).

3. Results

3.1. Peak detection

The results of the beat detection evaluation are presented in Table **1**. Note that the results are only slightly inferior to those of Hamilton, Pan and Tompkins [7, 8] for both Sensitivity (Se) (0.8% lower) and positive predictive value (PPV) (1.1% lower). This is because our method was adapted to ambulatory signals and not specifically tuned to the MIT-BIH Arrhythmia Database.

Table 1. Beat detection evaluation on the MIT-BIH arrhythmia database.

Method	Se	PPV
Hamilton, Pan & Tompkins [7,8]	99.8%	99.8%
Proposed method	99.0%	98.7%

Table 2. Classification results on individual SQIs and the extended CinC challenge database (in %).

	bSQI	kSQI	sSQI	pSQI	basSQI	qSQI	pcaSQI
Ac	96.9	87.9	89.2	75.2	62.6	76.6	95.0
Se	98.3	91.1	94.4	80.6	67.9	80.5	94.5
Sp	95.3	84.2	83.1	69.0	56.4	72.1	95.6

Table 3. Atrial Fibrillation classification results on the MIT-BIH AF database.

Method	Se	Sp	PPV
Implemented method	92.7%	94.2%	92.2%
Linker [17]	96.6%	82.3%	80.0%

3.2. SQI

The evaluation of the individual SQIs on the extended CinC Challenge database is presented in **Error! Reference source not found.**. Note that bSQI achieves the best results on this database in terms of Accuracy (Ac), Sensitivity and Specificity (Sp) of all the univariate approaches.

3.3 Atrial Fibrillation

The evaluation of the atrial fibrillation method is given in **Error! Reference source not found.**. The overall accuracy of the implemented method [16] is relatively good. Even if Linker's technique has a better sensitivity (by 3.9%), the implemented method results in fewer false positives, which results in a better Specificity (+11.9%) and positive predictive value (+12.2%), essential in scaling up healthcare.

4. Discussion

The app presented in this paper provides a baseline tool for further development of open source ambulatory ECG analysis. The beat detection results showed that *eplimited* is slightly more accurate on the MIT-BIH arrhythmia database. Nevertheless, the implemented technique reitialization procedure makes it more robust for signals with low amplitude and frequent artifacts. Moreover, *eplimited* has a scan back procedure, which looks back in time if no beats have been detected during a certain period. This non-real-time processing approach and has therefore not been implemented in the app.

The current implementation of the SQI achieves the best results amongst the individual SQIs tested. However, Behar *et al.* [13] have shown that a combination of SQIs can give better results. Moreover, pathological ECGs can hamper the SQI method, which would be prejudicial for pathology screening. It should be noted though that AF does not affect the SQI classification [13].

The proposed AF detection has a better specificity and positive predictive value for short windows than previously reported algorithms. However, it is not the optimal AF detection algorithm, and its accuracy on other (out-of-sample) databases has been shown to be inferior [19]. Although it would also be interesting to compare with other methods, it is difficult because most methods for detecting AF use longer segments. There is also much disagreement on how many AF beats within a tracing are needed to trigger an AF classification. A deeper comparative study of algorithms, window size, and noise sensitivity can be found in Colloca et al [19].

Future work will include the implementation of the Support-Vector-Machine (SVM) approach for both the estimation of the SQI and the detection of AF episodes.

5. Conclusion

We have presented a novel Android application which allows the recording of ECG signals and the detection of AF. The app also provides a quality index for the assessment of analysis reliability and feedback to the user to allow quality improvement at point of care. The implemented software has been evaluated thoroughly on large and publicly available databases, and promising results have been presented. Such an application offers great promise for the development of ECG analysis in the mHealth context, and especially for the screening of AF in developing countries. The source code has been made freely available under an open source license and future improvements will be integrated into the algorithms.

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