ECG Quality Assessment for Patient Empowerment in mHealth Applications

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Abstract

State-of-the-art mobile ECG recorders are usually not intended to be used by untrained personnel or by patients themselves. For that purpose, a suitable graphical user interface that provides real-time feedback concerning the signal quality is required.

We have developed a measure for mobile ECG quality assessment based on a) basic signal quality properties (amplitude, spikes, constant signal portions), b) number of crossing points in between different leads, and c) QRS-amplitude vs. noise-amplitude ratio. An advanced algorithm and a simplified Android algorithm were implemented and evaluated by taking part in the Computing in Cardiology Challenge 2011.

Our advanced algorithm achieved a score of 0.916 (4th place) in Event 1 of the Computing in Cardiology Challenge 2011. The simplified Android algorithm achieved a score of 0.834 (6th place) in Event 2 and a score of the 0.873 (1st place) in Event 3 of the challenge.

1. Introduction

1.1. ECG self recording

Today, ECG recorders are a common diagnostic tool that is normally used by specially trained personnel. However, mobile ECG recording sets are becoming more and more common, and in many situations self-recording of ECGs by patients themselves is required. Unfortunately, ECG recorders currently available lack a suitable graphical user interface that provides real-time feedback concerning the signal quality and, therefore, high-quality ECGs can hardly be recorded by untrained personnel or patients [1, 2].

1.2. eT-study – Single lead ECG quality assessment and RFID-Bluetooth coupling

In a previous project we have developed a mobile phone based eHealth Terminal (eT) for self-recording of ECGs at the patient's home [3]. A high level of usability was achieved by utilizing a combination of Bluetooth and Radio Frequency Identification (RFID) technology: We had found that Bluetooth's major disadvantage is the complicated pairing procedure, while our easy-to-use RFID approaches for data acquisition lacked sufficient data transmission rates for ECG recordings. Therefore, Bluetooth pairing information was written on an RFID-tag that was placed besides the display of the ECG recorder. Additionally, a field detector was developed, which switched-on the ECG recorder's Bluetooth module, as soon as an RFID reader was close enough to the field detector. This setup enabled ECG transmission from the ECG recorder to the eHealth Terminal simply by putting the eHealth Terminal close to the ECG recorder.

On the mobile phone a Java 2 Micro Edition application (J2ME – Sun Microsystems, Inc, Santa Clara, CA 95054, USA) controlled the ECG recording and – in real-time – detected the QRS complexes and displayed the present ECG signal quality based on the confidence level of the QRS detector.

In autumn 2010 a study was conducted, in which the use of the eHealth Terminal was evaluated in a group of 21 heart failure patients [4]. All patients were equipped with mobile ECG recording sets using RFID-Bluetooth coupling for one week and were asked to record two approx. 30 s ECGs per day. During the eT-study we found that self-recording was feasible for 20 out of 21 patients. Each ECG was validated by three independent specialists. 12.3 % of 211 ECGs were classified as "atrial and ventricular rhythm can be determined", 55.4 % as "ventricular rhythm can be determined" and 44.6 % as "unacceptable".

1.3. Aim of the present work

The eT-study showed, that single lead ECG recordings done by the patients themselves are feasible for most patients – using RFID-Bluetooth coupling and giving feedback about the present ECG quality via the mobile phone. Anyway, the eHealth Terminal described above was designed for single lead ECG recordings, only.

Therefore, it was the aim of the present work to develop an algorithm expanding this approach to a standard 12 lead ECG and to implement parts of this algorithm on an Android (Donut, Google Inc, Mountain View, Ca, USA) mobile phone – consuming as little resources as possible.

2. Methods

2.1. ECG quality assessment – From single lead to 12 lead ECGs

The algorithm developed in the eT study was adapted to 12 lead ECG signals. This advanced algorithm was implemented in Matlab (MathWorks Inc., Natick, Massachusetts, USA) and extended using several additional criteria for ECG quality assessment.

In our analyses we skipped the first 800 ms of the signals, since several ECGs showed transient onset characteristics. For the remaining signal, each single channel of each ECG was analysed using four criteria concerning the basic signal properties (A1-A4) and three additional criteria (B, C and D):

Criterion A1 – Signal amplitude

Criterion A1 was fulfilled if the portion of samples that showed amplitudes of more than +- 2 mV was higher than 40 % of the analysed signal.

Criterion A2 – Spike detection

Criterion A2 was fulfilled, if the portion of samples situated close to spikes (first derivative of the signal > 0.2 mV / sample) was higher than 40 % of the analysed signal.

Criterion A3 – Zero line detection

Criterion A3 was fulfilled, if the portion of samples featuring equal amplitudes with their preceding sample was higher than 80 %. Using this criterion, signal portions with zero line as well as completely overpowered portions could be detected.

Criterion A4 – Total length of remaining signal

Signal portions that exceeded any of the thresholds of criteria A1-A3 were classified as “potentially bad”. Criterion A4 was fulfilled, if the portion of “potentially bad” samples was higher than 68.5 %.

Criterion B – Number of lead crossing points

One common method for displaying 12 lead ECG signals is plotting one lead underneath the other (see Fig. 1). Using this type of view, it may happen that the signal of one lead is plotted over those of other leads, especially when the ECG of one of the leads drifts a lot – but not far enough to “drift out of view”. In this case, not only the drifting lead is hard to analyse, but also other leads may be obscured.

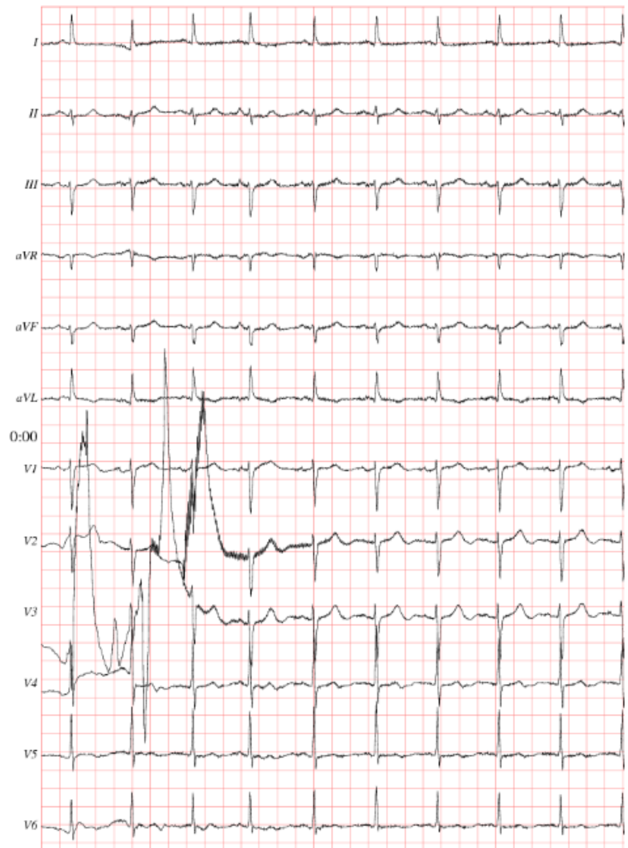

Figure 1 – ECG representation plotting one lead underneath the other illustrating the effect of drifting leads (V2, V3) on the quality of the plot (screenshot taken from PhysioNet [5]).

Therefore, we counted the number of crossing points in between the signals of different leads. If the maximum number of crossing points of one lead with any of the other leads was higher than 49, the signal was classified as “not acceptable”.

Criterion C – Quality of QRS detection

A quality measure for QRS detection was calculated based on three parameters determined during QRS detection: a) Signal to noise ratio (amplitude of the lowest QRS complex detected divided by the highest amplitude of none-QRS-signal-portions), b) maximum QRS amplitude, and c) regularity of the detected rhythm. Criterion C was fulfilled, if the measure was < 0.2.

Criterion D – Quality of second worst channel

Criterion D was fulfilled, if the number of lead crossing points of the second worst channel (sorted by the number of lead crossing points) was higher than 23 or the quality measure of the second worst channel (sorted by the quality measure) was lower than 0.065.

Final signal classification

An ECG was classified as "unacceptable" if

a) Criterion B was fulfilled, or if
b) Criterion C was fulfilled, or if
c) any of criteria A1-A4 was fulfilled for any channel AND criterion D was fulfilled.

2.2. Simplified Android application

In order to run the classificator with minimal resources (as demanded in event 3 of the Computing in Cardiology Challenge 2011) we transferred only parts of the advanced algorithm described in Section 2.1 to a simplified algorithm running on a mobile Android phone – skipping the computationally expensive QRS detector. Signal amplitude, spike and zero line analyses on the one hand, as well as crossing point detection in between leads on the other hand, can be done within a few computational steps per sample. Therefore, criteria A1-A4 and B were implemented within the Android application.

Finally, the whole simplified Android source code for ECG classification consisted of 64 lines, only.

2.3. Validation – CiC Challenge 2011

Our algorithms have been validated by taking part in the Computing in Cardiology Challenge 2011 [6]. The Challenge consisted of three events: Event 1: Best classification results with any kind of algorithm (number of correctly classified signals divided by the total number of signals). Event 2: Best classification results with an open source algorithm running on an Android mobile phone taking no more than 30 s per 10 s 12 lead ECG. Event 3: Best classification results with minimal computation time running on an Android mobile phone (weighted score combining both measures).

3. Results

3.1. Validation of the full algorithm

The advanced algorithm classified 204 out of 1000 ECGs of the trainings-set (set a) and 114 out of 500 ECGs in test-set (set b) as "not acceptable". The remaining signals were classified as "acceptable". The portion of correctly classified ECGs was 0.933 in the trainings-set and 0.916 in the test-set. This was the fourth best result of the Computing in Cardiology Challenge in Event 1 (the total number of participants was 49, the winner's score was 0.932).

3.2. Validation of the simplified Android application

Using our simplified Android algorithm we achieved a score of 0.834 (sixth place) in Event 2 and a score of 0.873 (first place) in Event 3 of the Computing in Cardiology Challenge 2011.

4. Discussion

From a technical point of few, the performance of our algorithms has been tested by taking part in the Computing in Cardiology Challenge 2011. Additionally, in the course of the eT study (see section 1.2 and [3, 4]) we could show that such algorithms are a valuable tool for ECG recordings done by untrained personnel or patients themselves. While in the eT study single lead ECGs were analyzed, in the present work the algorithms were extended and validated for 12 lead ECGs. We expect, that the benefits from ECG quality assessment during recording and direct feedback to the recording person will be beneficial for 12 lead ECGs as well.

Based on our experiences with the single lead algorithm of the eT-study we expect that our advanced multi lead algorithm will be fast enough to validate 12-lead ECG signals in real time as well. Anyway, the advanced algorithm has not been implemented on an Android phone yet.

The simplified algorithm is currently implemented in Android. Combined with our algorithm of the eT study, it could also run on any mobile phone supporting J2ME. Therefore, it is suitable for most mobile phones (not only smartphones) currently available.

The simplified algorithm's classification results were significantly worse than those of the advanced algorithm (score 0.916 vs. 0.834). Nevertheless, since the simplified algorithm was extremely compact and fast, it was the best performing algorithm in Event 3 of the CiC Challenge 2011, where both classification accuracy and computation time were relevant. In a real-life scenario, computation times up to real-time (e.g. 1 s computation time per 1 s ECG) would probably be sufficient for giving feedback to the person recording the ECG. Since our algorithm is much faster than that, most of the mobile phone's computational power is not occupied during ECG recording. Therefore, additional tasks could simultaneously be performed by the phone, such as real-time signal compression and transmission, advanced ECG analyses (e.g. QT measurement) or audio or video phone calls to physicians.

5. Conclusion

Real-time ECG quality assessment during recording is feasible and usable and can help untrained personnel and patients. The required accuracy level of quality assessment depends on the use case. While high accuracy algorithms can provide valuable feedback to the recording person, simple and efficient algorithms may be preferred if limited computational power is available.

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