

Simple Scoring System for ECG Quality Assessment on Android Platform

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Abstract

Work presented in this paper was undertaken in response to the PhysioNet/CinC Challenge 2011: Improving the quality of ECGs collected using mobile phones. For the purpose of this challenge we have developed an algorithm that uses five simple rules, detecting the most common distortions of the ECG signal in the out of hospital environment. Using five if-then rules arranges for easy implementation and reasonably swift code on the mobile device. Our results on test set B were well-outside the top ten algorithms (Best score: 0.932; Our score: 0.828). Nevertheless our algorithm placed second among those providing open-source code for evaluation on the data set C, where neither data nor scores were released to the participants before the end of the challenge. The difference in the scores of the top two algorithms was minimal (Best score: 0.873; Our score: 0.872). As a consequence, relative success of simple algorithm on undisclosed set C raises questions about the over-fitting of more sophisticated algorithms – question that is hovering above many recently published results of automated methods for medical applications.

1. Introduction

Cardiovascular diseases are the leading cause of death worldwide. With fast spread of different types of mobile solutions for recording of physiological signals outside hospital, the amount of data that needs to be processed is increasing significantly.

Many tasks envisioned during development of mobile-based measurement devices still need a clinician's input to make final decision. Therefore what starts as an helping tool for clinician, may turn into added burden on the clinician's time schedule. To ease such a burden on clinicians, automatic preprocessing of signals can be used to evaluate the basic signal parameters such as signal quality. Only signals with sufficient quality are then presented to the clinician. Additionally, as in the case of 2011 PhysioNet/CinC Challenge [1], the mobile phone can be used as an extension of the clinicians reach. It is useful especially to the areas without developed infrastructure, where

specialized medical services are sparse. Information about the quality of the signal, presented readily on-site, enables reacquisition of the signal at nearly no cost.

The question about how to assess the signal quality was asked many times before. Let us cite at least some of the papers, that tried to determine if the ECG signal is of sufficient quality or not [2–4]. In our approach we have focused on the easily interpretable rules that can describe the signal quality without excessive computational burden on the mobile device.

2. Method

From the very beginning, after our first review of data, we have focused on the development of set of rules that would distinguish between two classes (Acceptable, Unacceptable) of recordings from the training set A. We had two reasons for our approach. First one was the existence of third – middle (Undecided) – class in the test set B, which from our experience tends to punish algorithms, that are over-fitted to the initial data set. The second reason was that without cardiologist in our team we had difficulties to find out why some of the records, even though they shared many if not all their characteristics, were assigned to opposite classes. We will present some of these pairs further in this section.

In the following subsections all five rules are described with graphical depiction of their most interesting errors. The thresholds used in the rules were determined heuristically.

2.1. Rule I – Missing lead

The first rule was designed to exclude all the records where at least one lead was missing. If the sum over the whole lead was less than 0, the recording was excluded.

2.2. Rule II – Poor contact

Second rule should fire, when there was distortion of the signal caused most likely by poor electrode contact. The rule looks for the amplitude change of limited time

duration. Interesting pair of recordings is depicted on the Figure 1.

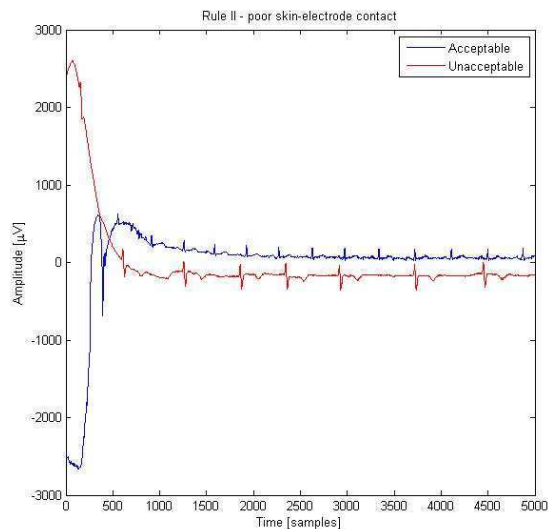


Figure 1. Poor skin contact. Acceptable [record 427] and Unacceptable [record 661] records in class A. Both records classified as unacceptable.

2.3. Rule III – High amplitude artefact – disconnected lead

Rule III is tightly related to the Rule II, it looks for the high amplitude peak – the absolute value of the maxima is significant for this rule – not the time duration. Interesting pair of recordings is depicted on the Figure 2.

2.4. Rule IV – Isoline drift

Fourth rule assigned unacceptable class to all recordings where the isoline was drifting. It did not have significant impact on the training data A, but without it the performance on the class B was slightly worse.

2.5. Rule V – Noisy lead

Final rule focused on detection of noisy signals. We have used threshold for standard deviation normalized to amplitude of the lead. Final picture of a pair of recordings where this rule fired, although the recordings are from opposite classes can be seen on Figure 3.

2.6. Using the rules in Android

In general if any lead of the record fulfilled any of the five rules the whole recording was classified as unacceptable. The use of rules described above was sequential.

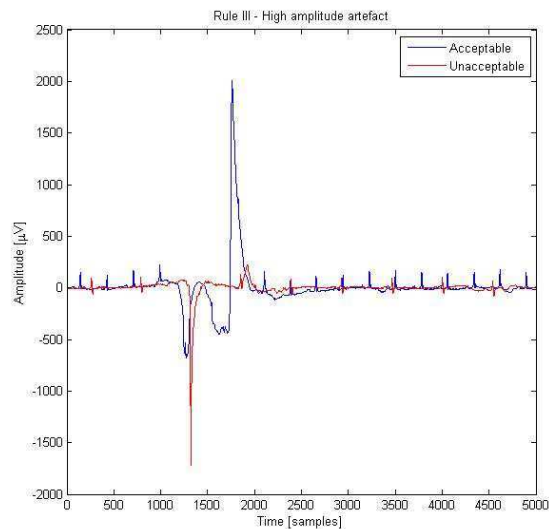


Figure 2. High amplitude artefact. Both records classified as Unacceptable although the class A annotation says Acceptable [record 82] and Unacceptable [record 662].

We have taken the first lead of the recording and run it through the first rule. If the rule’s decision was to classify that lead as unacceptable, the algorithm continued with the next record. Otherwise the algorithm would continue to next rule, next lead as long as there were any left.

We did no significant tweaks when transforming the code from Matlab to Android’s Java. The code is open-source and should be accessible from the Physionet/CinC Challenge site.

3. Results

The overall results of our method as computed on different CinC 2011 Challenge databases are presented in the Table 1. As described in the previous section the rules were applied sequentially until any rule was fulfilled on any lead of the recording. This is partially expressed in the Table 2, where the first three rules were responsible for detection of most of the unacceptable recordings. Nevertheless thanks to the five iterations (submissions) on the testing set B, we found out that the last two rules also improved the results slightly.

Table 1. Overall results of the five-rule method

Training data set A	0.903
Testing data set B	0.833
Evaluation data set C	0.872

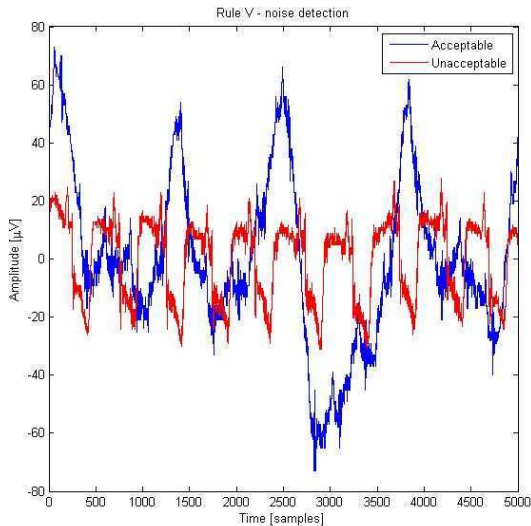


Figure 3. Noise was detected in both recordings although the class A annotation says Acceptable [record 568] and Unacceptable [record 800].

Table 2. Number of records assigned to the unacceptable class on the training data set A.

Rule	Class 1 as 1	Class 0 as 1
I - missing lead	124	0
II - poor contact	92	1
III - high amp. artefact	94	19
IV - isoline drift	5	0
V - noisy lead	3	4

4. Discussion and conclusions

Our approach to the task of 2011 PhysioNet/CinC Challenge was to develop simple rule based algorithm, which tries to detect the most common distortions of the signal.

There are definitely some types of distortions that our algorithm was unable to deal with. Swapped leads can be mentioned as an example. Even though we have implemented simple, and fairly precise, R-detection algorithm we were unable to come up with any text-book related algorithm for detection of swapped leads, where the amount of false positives would not exceed number of correctly detected records.

We tried to estimate, based on the training set A, some of the parameters that annotators might consider important. We think in general sufficient quality during the whole recording on all leads was of importance, even though the ECG curve was less important than the rhythm recording (thus low amplitude recordings were ok, but one high-amplitude burst could render whole recording unaccept-

able).

The Challenge results are very interesting from the point of view of the classifier over-fitting. Even though we know very little about exact set selection, from our experience [5], possible classifier over-fitting is often neglected in the discussions about the algorithm evaluation.

The fact is that even though the classifier is properly trained – the training and testing sets are randomized, and cross validation is used – we can end up with a fairly over-fitted classifier. It is usually due to the unideal database, or its annotation, which is then responsible for the low ability of the algorithm to generalize in the conditions of the real world. We think that such an observation is clearly supported by the comparison of results on the test set C.

Acknowledgements

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