Computer Algorithms for Evaluating the Quality of ECGs in Real Time

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Abstract

ECG, measuring body-surface electrical waves generated in the heart, is the golden standard for diagnosis of various cardiovascular diseases. The 2011 Physionet challenge visions mobile phones that can be used to collect and analyse ECG records. Such devices are particularly useful in underdeveloped regions, which have a large population size but lack adequate primary care capacity. Signals collected using mobile phones can be sent via mobile network to experienced doctors for further diagnosis. In response to Physionet 2011 challenge, we explore various time series techniques for their potentials in evaluating quality of an ECG, including time domain analysis, frequency domain analysis, joint time-frequency analysis, self correlation, cross correlation, and entropy analysis. Two algorithms are developed based on these techniques. The first algorithm consists of multi-stage tests. A record that passes all tests is regarded as of acceptable quality. In the second algorithm, results from various analyses are assembled into a matrix, which measures the regularity of the ECG. The quality of the ECG is then measured by the spectrum radius of the Matrix of Regularity. Since spectrum radius is continuous, the results can lead to continuous grades of ECGs. The algorithms are tested using training data from Physionet. Influences of various parameters are examined.

1. Introduction

Cardiovascular diseases are the number one killer worldwide [1]. Many countries face high and increasing rate of cardiovascular disease. Among the deaths caused by the heart diseases, 82% happen in developing countries. For diagnosis of normal cardiac rhythm, dysrhythmias, and myocardial ischemia, the standard 12-lead Electrocardiography (ECG) is considered as the noninvasive golden standard.

The heart is comprised of myocardium that is rhythmically driven to contract and hence drive the circulation of blood throughout the body. The electrical wave that drives the muscle propagates over the heart in a coordinated pattern. Thus the potential difference on the body surface of the subject is measureable and the resultant amplified and filtered signal is known as an ECG, which is considered as the best way to measure and diagnose abnormal rhythms of the heart [2].

Rural areas of developing countries lack experienced cardiologists. To improve the quality of health care for such patients, techniques based on telemedicine have been developed, in which a nurse or a patient himself can collect physiological information such as ECGs and transmit such signals to doctors, who are hundreds or thousands miles away for diagnosis [3]. One potential problem for a handheld ECG device is quality control of the collected signals especially when the collection is conducted by inexperienced paramedic or patient himself. The goal of this work is to develop a computer algorithm that can determine whether the quality of a signal is good or not. Moreover, when a record is decided to be unacceptable, the algorithm may also give advice as to how to correct the problems. This algorithm has potential applications in telemedicine and can help to improve the performance of such devices.

2. Method

2.1. Data

Physionet Challenge 2011 [4] provides several data sets for training and test. The training set consists of 1000 records. The challenge data are standard 12-lead ECG recordings (leads I, II, II, aVR, aVL, aVF, V1, V2, V3, V4, V5, and V6) with full diagnostic bandwidth (0.05 through 100 Hz) [5]. The leads are recorded simultaneously for a minimum of 10 seconds; each lead is sampled at 500 Hz with 16-bit resolution.

These data are recorded by nurses, technicians and volunteers with different amounts of training. The training set includes 775 records that are labelled as acceptable, 223 labelled as unacceptable, and 2 records labelled as indeterminate. Algorithms developed in this work are tested using the training data set.

off chart in channel V6.

At the third stage, each channel is divided into several segments and the standard deviation is calculated for each segment. If the standard deviation in some channel differs

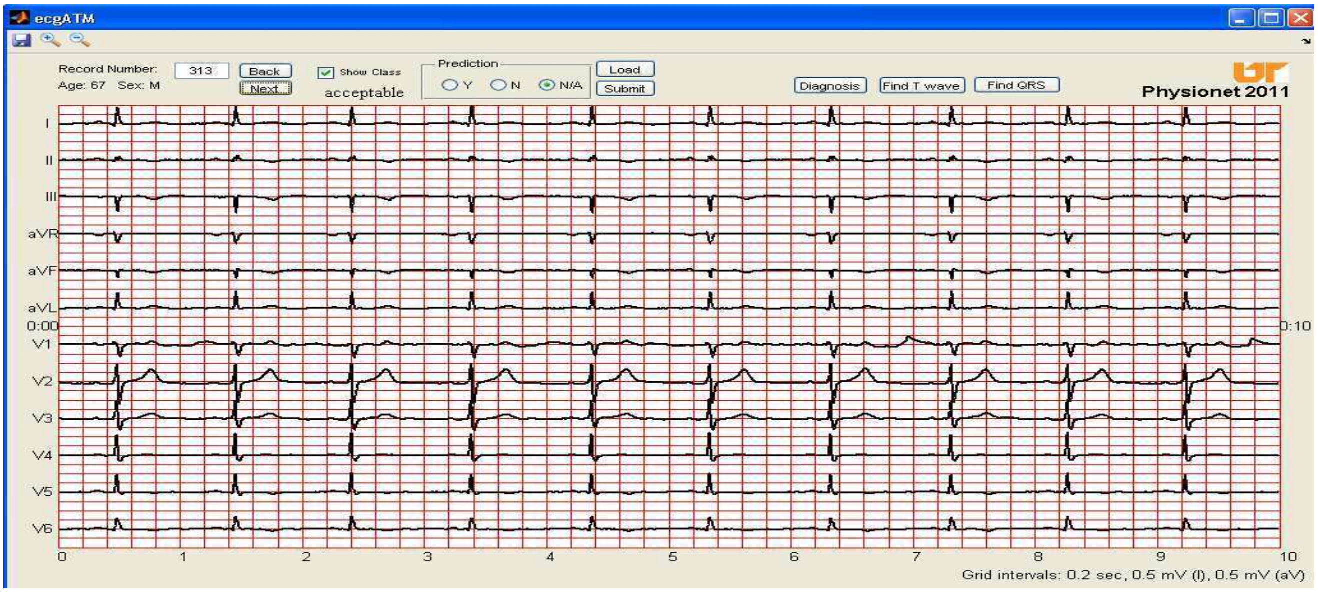

Figure 1：An example of the MATLAB GUI displaying a record.

too much, exceeding a certain threshold, the signal is determined to be poor. Figure 6 shows an example of this.

Then at the fourth stage, the cross correlation is computed for different channels of a record. The record is also first divided into several segments and the cross correlation of each segment is computed among the different leads. If the correlation coefficient is smaller than a certain threshold, the quality of the signal is determined to be poor. Figure 7 shows an example of this.

Finally, if the signal passes all the 5 steps, it is determined to be good.

A MATLAB GUI is developed to visualize and analyse the records. Figure 1 shows a snapshot of the MATLAB GUI displaying a record. The GUI allows users to browse through all records in a data set. If meta information such as age and sex are available, they will be shown on the GUI. For the training data set, users can choose whether to show the reference classification. This program can also allow users to load previously generated prediction results or manually make predictions. Moreover, simple statistical analyses are also implemented in the GUI.

2.2. A multistage test algorithm

We have developed a multistage algorithm for the classification of the ECG signals. The flowchart of the algorithm is shown in figure 2.

The first stage is to check whether a record has any flat channels. If any flat channel is found, the signal is determined to be unacceptable. In figure 3, the channel V6 shows an example of the flat channel.

Next, we check whether the record has any missing channels. A channel is said to be missing if its signal values are out of the range of the MATLAB GUI such that we can’t view it in the GUI. In figure 4, channel V1 is missing. Also we check whether a channel is partially off the chart. If the amplitude is too large or too small, the signal may be partially off the chart of the MATLAB GUI, as shown in figure 5, and in that case, the signal will be determined as poor. In figure 5, the signal is partially

2.3. Matrix of regularity

In the second approach, we represent the state of an ECG using a 12x12 matrix of regularity, denoted by R. Diagonal elements of R represent quality of the 12 channels of the ECG and off diagonal elements represent the quality of correlations between channels. For an ECG of perfect quality, all elements of the matrix R are set to zero. We carry out various tests to evaluate the quality of an ECG. Artefacts and disturbances of the channels are represented by positive numbers at the corresponding elements of R. Finally, the overall quality of the ECG is represented by the spectrum radius of the matrix of regularity.

2.4 Android implementation

In this project, the previous algorithms are implemented on an Android phone. Android is a software stack for mobile devices that includes an operating system, middleware and key applications, now belonging to the Google Inc [6].

The process of scoring a record involves loading ECG files and the five steps described in the previous section. Table 1 shows the average performance of key steps in processing a single record.

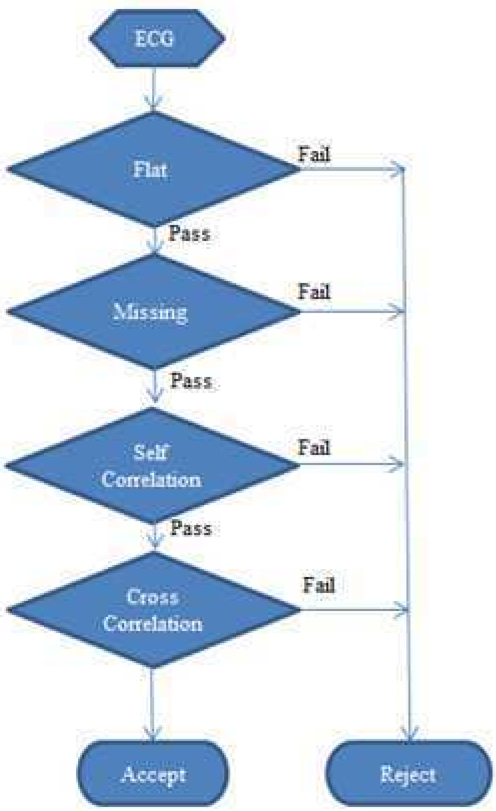

Figure 2. Flowchart of the algorithm. A record is classified as acceptable if it passes all the tests.

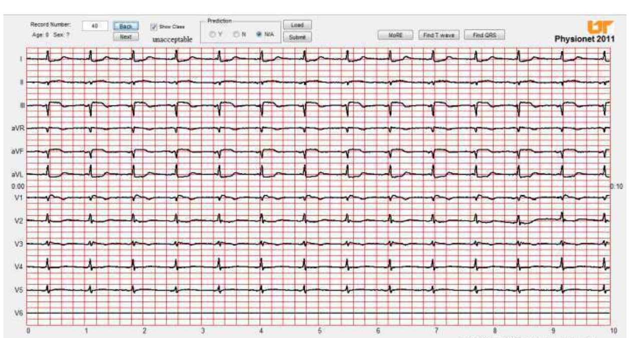

Figure 3. An ECG with a flatline in V6 channel.

3. Results and discussion

Results of the training set using the multi-state algorithm are shown in Table 2. The specificity measures the percentage of acceptable records that are correctly identified as acceptable whereas the sensitivity measures the proportion of poor signals which are correctly identified as poor. Table 3 shows the specific sensitivity and specificity of each test. Note that, when calculating the performance for correlation tests, we exclude those records with a flat or missing channel since they can be easily identified using the first two tests. Another data set provided by the Physionet 2011 challenge is used for test. The multi-stage test algorithm yields an accuracy of about 85%.

The method of regularity matrix yields more promising results. The best accuracy for the training set using this method is about 93.5%. The accuracy for the test set using this method is 90.0%. More importantly, this method generates scores, which continuously range between 0 and 1. On the other hand, the multi-stage test produces a yes/no type of output. The continuous scores can help to more accurately classify ECG according to their qualities.

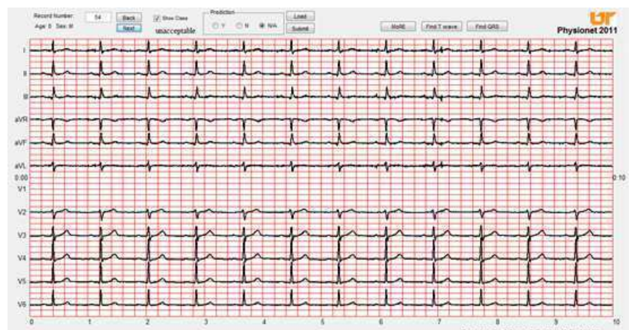

Figure 4. An ECG, for which channel V1 is missing.

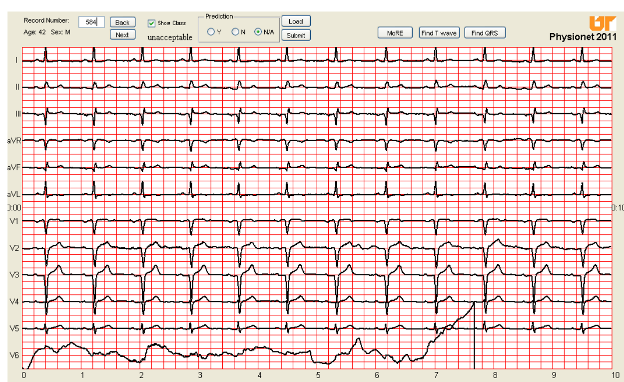

Figure 5. An ECG, in which channel V6 is partially off the chart.

4. Conclusion

In this work, we have developed a multi-stage test algorithm as well as a method based on Matrix of

Regularity to evaluate whether an ECG signal is acceptable for diagnosis or not. Various criteria have been adopted to test the quality of an ECG, Including the test for flat channels, missing segments, cross correlation between channels and self-correlation within a channel. An ECG that passes all the tests is labeled as acceptable; otherwise, unacceptable. The algorithms achieve good accuracy using a set of training data provided by Physionet.

The algorithms are also implemented in an android program and the efficiencies of the tests are studied. Overall, the computation is efficient. This application will enable inexperienced people to collect ECG signals from patients and to check whether the signals are usable or not with a cell phone, and then the signal can be transmitted to a cardiologist in a city hospital for diagnosis. Thus it will be of value for application.

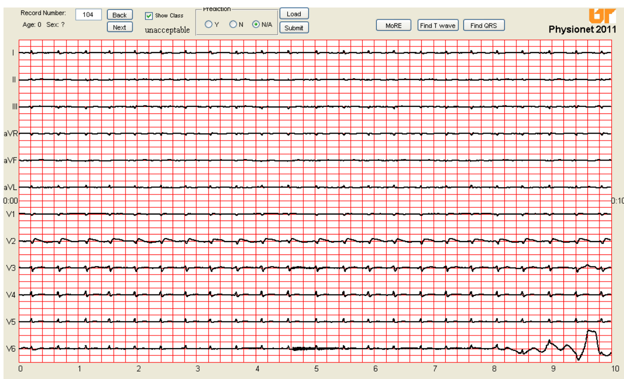

Figure 6. Example of a record with inconsistent standard deviations in different segments. The last 2 seconds in channel V6 is significantly different from previous signals in the same channel.

Table 1. Average time used for each step in processing a single record.

Step	Time/ms
Loading record	2270
Flat/Missing Channel	Negligible
Partially Off Chart	43
Bad Correlation	168
Bad Cross-Correlation	3652

Table 2. Accuracy, specificity, and sensitivity.

Accuracy	0.859
Sensitivity	0.9511
Specificity	0.8322

Table 3. Specificity and sensitivity of each stage.

Test	Sensitivity	Specificity
Flatline	0.57333	0.99226
Missing Channel	0.47556	0.99355
Partially missing	0.65778	0.97419
Self Correlation	0.85778	0.88774
Cross Correlation	0.40444	0.87613

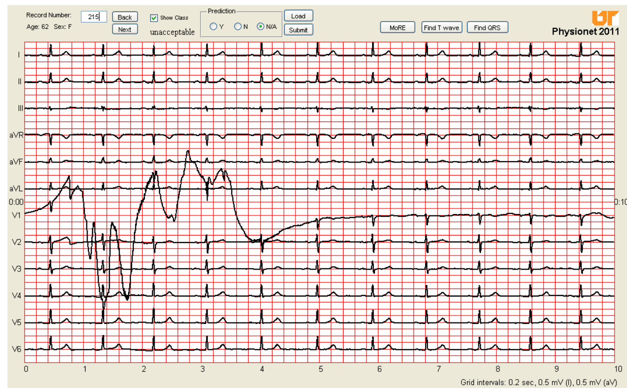

Figure 7. Example of a record with poor cross correlation among leads. In this example, the cross correlations between lead V1 and other leads are poor.

Acknowledgements

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