Quality assessment of ECG signals based on Support Vector Machined and Binary Decision Trees

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***Abstract*—Abstract— The quality assessment of ECG signals has crucial importance for the automatic diagnosis of heart disease, especially for signals which heavily contaminated with several artifacts. Therefore, several SQA (signal quality assessment) techniques were presented based on ECG signal features and the machine learning classifiers or heuristic decision rules. This study presents an algorithm for accurate and offline detection of motion artifacts and noise in ECG signals. Our MN artifact detection approach involves two stages. The first stage involves extracting several non-fiducial features from ECG. The second stage of our approach uses Support Vector Machines and Binary Decision Trees to grade signals. The proposed method tested in the PhysioNet/Computing in Cardiology Challenge 2011 Database by comparing two different classifiers. The SVM provided the best classification accuracies of nearly 95% on the labeled data. (Labels which indicate the ECG signal is acceptable or not for clinical interpretation).**

Keywords*—ECG, Signal quality assessment, SVM, RMS

I. Giriş

ELECTROCARDIOGRAM (ECG) signals are widely used for many healthcare issues such as cardiovascular disease diagnosis, arrhythmias, physiological feedback, sleep apnea detection, chronic patient surveillance, sudden cardiac arrest prediction, biometric, emotional, and physical activity recognition systems. These ECG application systems highly demand high-quality signals, since feature extraction is the first step for many algorithms, and extracting features depends mostly on the quality of ECG. For this reason, signal quality assessment (SQA) of the ECG signal has crucial importance, and the importance of that is increasing with the rise of mHealth Apps. The current state-of-the-art SQA methods can be grouped into two. The first category uses the fiducial features [1]-[3] for the quality assessment of ECG. The second group uses non-fiducial features[4]-[6] in order to grade signals. However, fiducial features highly depend on reliable algorithms to detect several features (QRS complex, PQRST morphologies) under nonpathological and pathological noises that are still challenging tasks, especially by taking into consideration mobile ECG recorders are usually not intended to be used by uneducated personnel or by patients themselves. For this reason, we present a method that uses non-fiducial features of ECG. In our algorithm, we have extracted the root mean square value of every single lead of each record. After obtaining the RMS value of each lead, two features, which are the mean and standard deviation of the RMS, were derived and have used in order to categorize signal as acceptable or not by using SVM and Trees. All in all, we have produced two metrics for each channel (24 features in all) and presented to SVM and Trees for training on the provided labels.

This paper presents a comparison between SVM and Trees for classifying ECG signals by using extracted non-fiducial time-domain features. The extracted feature from ECG has particular importance since most of the applications which use signal quality metrics are real-time.

II. Methods

A. Databases

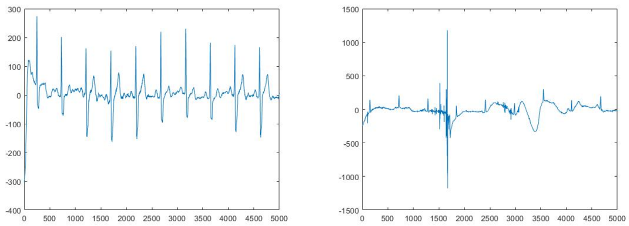
For this study, ECG records from PhysioNet/Computing in Cardiology (CinC) Challenge 2011 were used. This challenge data has composed of two sets, set-a and set-b. We have used set-a in order to train and test our algorithm since annotations of set-b is not announced to public. The training data were chosen randomly among 1000 record.

The PhysioNet/CinC set-a database includes 10 s records of standard 12-lead ECGs with full diagnostic bandwidth (0.05 – 100Hz), sampled at 500 Hz with 16-bit resolution. The training dataset has annotated by a group of annotators in a blinded fashion for grading. Less than one-third of the data were classified as unacceptable.

A third-order Butterworth bandpass filter with cut-off 0.7 – 100 Hz was performed on each channel individually. Then, RMS values of each single lead were calculated separately.

B. Moving Root Mean Square

The moving RMS value is calculated by using a sliding window over the each channel of the signal and taking the RMS at that window, whose definition is given below. When there is a large amplitude shifts, or device saturation in signal.The moving RMS increases as can be seen in 2

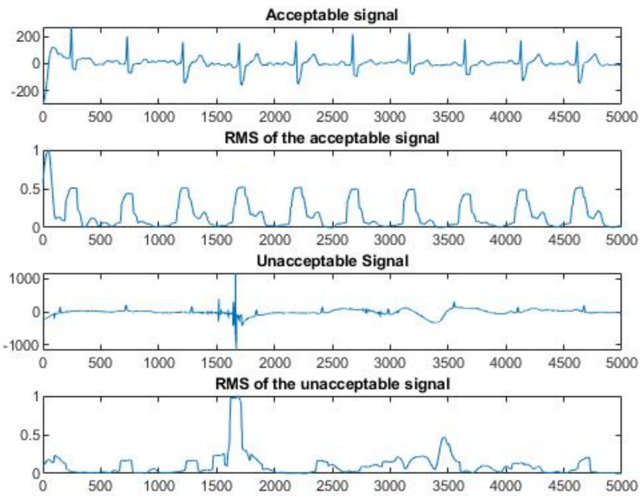


(a) acceptable (b) unacceptable

Şekil 1: Example for first lead of 'acceptable' and 'unacceptable' ECG recordings

$$X_{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}|x_n|^2}, \tag{1}$$

where N is the window length and x_n is the time sequence in that window. We have determined the length of the signal as one-tenth of sampling rate.



Şekil 2: RMS of the acceptable and unacceptable data

When we obtained the RMS values of the signal, we have normalized them in order to obtain mean and standard deviation values, since these features are fed to an SVM and Trees, and all features have the same importance according to each other.

C. Machine learning for classifying quality of ECG

For training SVM and Trees, we have chosen random 30 records from the labeled data for the CinC Challenge dataset. These records are composed of 12-lead each 10s record. After extracting features, we have used as the input features of a support vector machine (SVM) and Trees. While training classifiers, 5-fold cross-validation was performed in order to estimate accuracy and sensitivity on training data. The equation which is used for SVM is in 2

$$k(x_n, x_m) = exp\left(-\frac{||x_n - x_m||^2}{2\sigma^2}\right) \tag{2}$$

Where x_n and x_m are two vectors expressed in the initial feature space. The SVM with a Gaussian kernel has two parameters: C and σ, C is a constant that controls the trade-off between minimizing training errors and controlling the model, and σ controls the width of the Gaussian and plays a similar role as the degree of the polynomial kernel in controlling the flexibility of the resulting classifier. We then performed a tuning on these parameters in order to get the best hyperparameter.

When considering classification tasks for a tree, a decision tree T is a tree shaped classifier which consists of nodes t and edges. Any tree origins from a node without any incoming edge, called root node. The terminal nodes, i.e. nodes which do not possess any outcoming edges, are called leaves. The remaining nodes are called internal nodes. To each leaf a class or even a class probability is assigned. Each of the non-leave nodes represents a split regarding the input space. Such split is represented by a decision Φ(.). Most often, univariate decision, Φ(.)= Φ(x) of the from "$x \geq$ threshold" or "$x \in$ set" where x represents a single attribute, are considered.

The optimization parameters for trees(thresholds) was also implemented. The optimized tree has 11 children with a depth of 5, which is a reasonable quantity for real-time applications.

III. Results and Discussion

The performance of the proposed SQA method was evaluated using the three benchmark metrics. Sensitivity (Se), Accuracy (Ac) and specificity (Sp), which are defined as

$$Se = \frac{TP}{TP + FN} \qquad Sp = \frac{TN}{TN + FP} \tag{3}$$

$$Ac = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

where the true positive (TP) denotes a number of correctly identified unacceptable or noisy ECG signals by a SQA method, the false negative (FN) denotes a number of inadequate quality of ECG signals, which are identified as the adequate signal quality by the method, the true negative (TN) denotes a number of correctly identified acceptable ECG signals, and the false positive (FP) denotes a number of acceptable ECG quality signals which are identified as unacceptable quality by the SQA method.

The proposed method for estimating of acceptability of 12 lead ECG records achieved a score of 0.94 accuracies on the testing data set. The results are shown in Table I

TABLO I: Results of Method

Classification type	Sensitivity (Se)	Specifity (Sp)	Accuracy (Ac)
SVM	0.925	0.99	0.941
Tree	0.933	0.99	0.947

As can be seen from the results table, the specificity of the proposed algorithm is very high. The reason for the high specificity is coming from the low number of false positives, which means that in the presence of the noise and motion artifact, the algorithm is going to detect it with a high rate and mark it as an unacceptable signal before interpreting it. This property of the algorithm has crucial importance for mHealth applications since it can reduce the number of false alarms that are caused by noise and artifacts.

In the literature, there are several algorithms implemented on the same database and yield similar or higher accuracies. However, these algorithms mostly depend on a combination of several SQIs in an algorithm. Therefore, they are expensive for real-time applications. For example, Behar et al. [2] presented a method to assess the ECG quality with an accuracy of 99% for false arrhythmia alarm reduction by using seven SQIs. However, most of these SQIs requires higher computational cost. Also, [7] proposed an algorithm with an accuracy of 90.4% for grading ECG signals, which uses powers in different frequency bands as a feature of ensemble trees. However, frequency-domain based features are expensive for computational cost, and using the ensemble method, which combines several decision trees, is not efficient.

For these reasons, the proposed algorithm constitutes a strong solution for ECG signal quality assessment, especially for the mobile healthcare systems.

IV. Conclusion

This paper presents an algorithm for grading 12-Lead ECG signals as acceptable (to be used for further analysis) and unacceptable. We have taken Root Mean Square of each channel, then two features, which are the mean and standard deviation of the RMS, are extracted. Finally, these features have fed into SVM and Decision Trees in order to classify signals. The proposed algorithm was tested on the PhysioNet/Computing in Cardiology Challenge 2011 Database by comparing two different classifiers. The bot classifiers provided the best classification accuracies of nearly 95% on the dataset.

In contrast with most of the state-of-art signal quality assessment algorithms, our method requires no R-peak detection, delineation, alignment, QRS complex detection[9], or any higher level ECG processing tasks at all. Consequently, it is not dependent on the success of such tasks. In addition to that, the number of features we extract from the signal is lower compared to current algorithms. Also, the computational cost of our algorithm is better than other signal quality assessments[6-7] since it does not require any frequency-domain operation.

Kaynaklar

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