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Real-time Heartbeat Outlier Removal in Electrocardiogram (ECG) Biometric System

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***Abstract*—Electrocardiogram signal is prone to noise interference. Processing noisy signals in an automated system such as biometric systems negatively affects its performance. In this paper, we developed a real-time *abnormal* electrocardiogram heartbeat detection and removal. The proposed technique eliminates outliers in real-time while subjects data are being collected. We used Gaussian mixture model to model *normal* electrocardiogram heartbeat. A Gaussian mixture of 2 components achieved the least equal error rate of 12% in separating *normal* from *abnormal* heartbeats. We utilized this outlier removal method in a biometric system and examined it on a fingertip acquired ECG signals database. The designed biometric system had an equal error rate of 5.94% in comparison to 12.30% in a state of the art approach.**

I. Introduction

Electrocardiogram (ECG) is recording of the electrical activity in the heart. This signal has been widely used worldwide to diagnose heart problems. It is acquired using electrodes connected to the surface of the skin. The most common configuration to set up these electrodes is the 12-lead configuration which uses ten electrodes. Six of the ten electrodes are connected to the chest and four electrodes are connected to the limbs. Misplacing the electrodes affects the acquired ECG signal morphology [1]. Usually, *normal* ECG heartbeat consists of six main characteristic points, P, Q, R, S, T, and U, as shown in Figure 1.

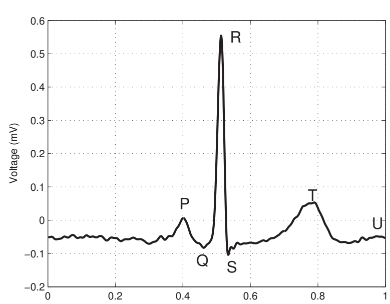

Fig. 1. ECG heartbeat with main characteristic points

The importance of ECG signal in the medical field has raised competition among manufactures producing ECG related devices, and this competition has led to inexpensive sensing acquisition devices. For this reason, ECG signal as biometrics can be a low-priced system to deploy. In verification ECG biometrics [2], heartbeats are fed to a classification module to make a decision on whether to accept or to reject the identity of a person. Having a noisy ECG acquisition negatively affects the biometric system performance.

Using 12-lead configuration in a biometric system may not be attractive due to the inconvenience associated with its electrodes set up. Other configurations, for example a 1-lead configuration [3], which collects ECG signals from fingertips using three electrodes, is more appealing. However, such configuration is prone to noise. As a result, developing an ECG signal quality measure system is crucial for ECG biometric systems.

In this paper, we propose a real-time ECG signal quality assessment to detect and eliminate *abnormal* ECG heartbeats in order to increase biometric system accuracy. The term real-time in this paper refers to the capability of instantly measuring the "goodness" of the shape of a heartbeat while being collected. We first applied a preprocessing stage to remove some types of noise, then we modelled *normal* heartbeats using a Gaussian mixture model (GMM), which is used to assess, thus, eliminate *abnormal* heartbeats in real-time. The term *normal* refers to ECG heartbeats that resemble Figure 1. Also, the term *abnormal* refers to any signal that is visually significantly different from *normal* heartbeats (i.e. a signal that does not have characteristic points).

Section II reviews the literature. Section III presents outlier elimination using GMM. Section IV provides experiments and results, and lastly Section V concludes this work.

II. Literature review

We categorize outliers removal as real-time and non-real-time systems categories. In the real-time system category, the outlier removal is subject invariant such that it does not require the information of a specific subject. Models and thresholds are designed from previously examined subjects. Real-time systems can be used on unseen before subjects; hence, they can be deployed for real-time applications. On the other hand, non-real-time systems are not subject invariant. They need to have information about the subjects they are applied on in order to design a model and a threshold. Afterwards, the model and the threshold are used on the subject again to remove outliers. Therefore, this category cannot be applied in real-time on an unseen before subjects.

The research in detecting anomaly in signals is directed towards either assessing quality of a signal or towards statistical

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outlier detection. The work in [4] measured the quality of ECG signal through three stages. The first stage was a preprocessing stage to remove baseline wanders and high frequency disturbances. The second stage was related to measuring the energy of the signal. Finally, the third stage measured the quality of the signal by applying correlation. In [3], [5], autocorrelation was utilized to eliminate heartbeats that were above a pre-set threshold from the median autocorrelation value.

The research in [6] proposed using four flags to assess ECG signal quality: one flag detected ECG misplacement, second flag detected large impulse, another flag detected the existence of Gaussian noise, then the last flag measured QRS waveform detection error. A quantitative assessment was reported based on the values of these flags. In [7], seven simple measurements were used to report an ECG signal quality measure. Six of the measurements were frequency components of ECG signal while the seventh measurement measured electrodes movements. In [8], ECG heartbeat were extracted as the duration of [-200, 400] milliseconds around the R peak. The mean (or median) of consecutive heartbeats were used to calculate a template, then Euclidean or cosine distance to decide whether the signal was *normal* or *abnormal* were utilized. All the aforementioned techniques were evaluated on ECG signals.

The essential problem with the techniques explained in this section, and most other techniques in the literature, is that their performance deteriorates when they are used in real-time on new, unseen before subjects. An experiments in Section IV compares and demonstrates that.

III. Methodology

The developed method to achieve a real-time ECG signal outlier detection consisted of three main stages: filtration, segmentation, and modelling.

A. Preprocessing

There are several sources of artifacts that interfere with ECG signal acquisition including: electromyogram, power line, baseline wander, and electrodes movement interferences. ECG signal spans frequencies between 0.05Hz or 1Hz to 40Hz or 100Hz [9]. There is no intrinsic ECG signal above 100Hz frequency. As a result, a fourth order Butterworth band-pass filter with frequencies between 0.5Hz to 40Hz was deployed to reduce the effect of noise [10].

In order to segment ECG signal into isolated heartbeats segments, R peaks were detected using Pan-Tompkins algorithm [11]. The heartbeat segment was then constructed as the interval of [-500, 500] milliseconds centred at the detected R peak.

B. Gaussian mixture model (GMM)

GMM is usually used as an unsupervised clustering method. However, in this paper it was used to model *normal* ECG heartbeats. GMM is a sum of M weighted Gaussian densities [12] given by

$$P(\boldsymbol{x}) = \sum_{m}^{M} w_m b(\boldsymbol{x}, \mu_m, C_m) \tag{1}$$

where w_m is the weight of the Gaussian densities, $\sum_m^M = 1$. $\boldsymbol{x}$ is a k dimensional features vector. Therefore, the pdf, $b(\boldsymbol{x}, \mu_m, C_m)$, is

$$b(\boldsymbol{x}, \mu_m, C_m) = \frac{1}{(2\pi)^{\frac{k}{2}} (|C_m|)^{\frac{1}{2}}} e^{-\frac{1}{2}(\boldsymbol{x}-\mu_m)^T C_m^{-1} (\boldsymbol{x}-\mu_m)} \tag{2}$$

where μ_m, C_m are the mean vector and the covariance matrix respectively.

Consequently, if we have 200 features (i.e. k=200), then each Gaussian has 200 dimensions. The motivation behind using the GMM was the assumption that *normal* ECG heartbeats could be modelled into M Gaussian densities with k dimensions for each Gaussian.

Expectation Maximization (EM) [13] algorithm was used to construct the GMM. EM considers all training examples and tries to fit a Gaussian distribution on it. After obtaining the Gaussian models from training data, the evaluation was based on measuring the log-likelihood.

C. Database

For the experiments, University of Toronto Database (UofTDB) [3] was used. UofTDB was collected at the University of Toronto. It was gathered over six sessions that spanned a six month period. It is a 1-lead configuration with three electrodes, and it is acquired from fingertips. It has a sampling rate of 200Hz. In the database, 1,012 subjects had their ECG collected for 2-3 minutes each.

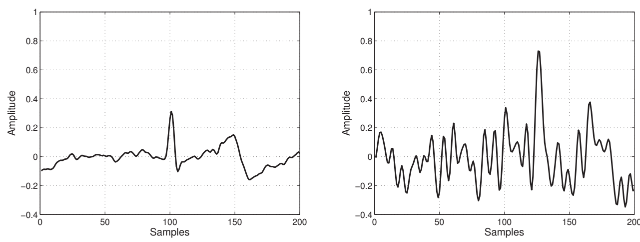
The preprocessing stages explained in Section III-A was applied to each subject's ECG signal. From the 1,012 subjects, a total of 158,984 heartbeats segments were available for experimentation.

D. Modelling normal heartbeats

It is desired to achieve a real-time outlier removal system. We approached this problem by creating a generic model that is trained offline and is capable to distinguish *normal* from *abnormal* heartbeats. The model is subjects invariant; hence, it can be used in biometric system without requiring subjects' specific data. Here we study the feasibility of using GMM to detect *abnormal* heartbeats. Also, we examine the influence of different number of Gaussian components.

If we model *normal* heartbeats then any heartbeat with statistics significantly different from the *normal* heartbeat can be classified as an *abnormal* heartbeat. Hence, we constructed a *normal* heartbeats model. For the task, *normal* heartbeats segments were collected to train the GMM. From the database of 158,984 heartbeats, 1,330 heartbeats were separated into *normal* and *abnormal* heartbeats. Out of the 1,330 heartbeats, 930 heartbeats were *normal* heartbeats while the other 400 heartbeats were *abnormal* heartbeats. It is worth mentioning that the subjects whose *normal* and *abnormal* heartbeats were used in constructing the GMM model were removed from the database examined in the experiments. As a result, the experimentation database consists of 943 subjects.

The criteria to separate *normal* and *abnormal* heartbeats was based on achieving two purposes: first, we needed to eliminate the obviously *abnormal* heartbeats, and second, we should allow interclass and intraclass variations. Consequently, the strategy we followed was that a heartbeat was considered as *abnormal* if it visually looked significantly different than the ECG heartbeat in Figure 1. Figure 2 illustrates an example of a *normal* and an *abnormal* ECG heartbeats.



(a) *Normal* heartbeat (b) *Abnormal* heartbeat

Fig. 2. Example of a *normal* and an *abnormal* heartbeat

Out of the 930 *normal* heartbeats, 800 heartbeats were used to train a GMM model while the other heartbeats were used for model validation. Figure 3 presents the equal error rate (EER) for different models. EER was calculated as the percentage where $FRR = FAR$. FRR and FAR are the false rejection rate and false acceptance rate, respectively.

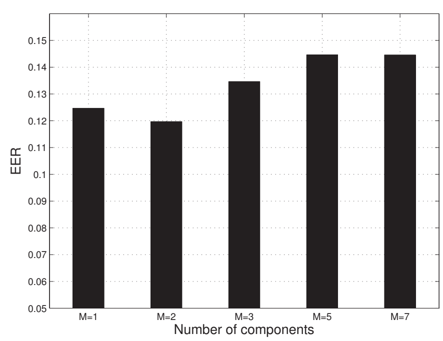
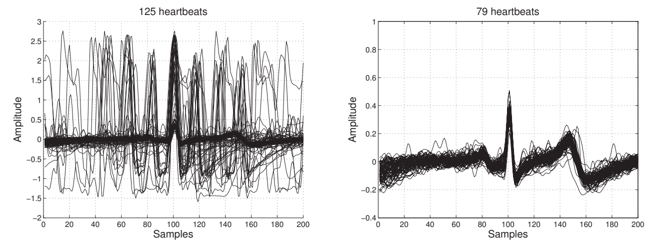


Fig. 3. Heartbeats classification error using GMM

It can be noticed from Figure 3 that when *normal* data were modelled with 2 Gaussian mixtures, it achieved the best results. All available 930 *normal* heartbeats were used in training a new Gaussian model with 2 mixtures for the experiments. An example of a subject's heartbeats before and after applying outlier removal using GMM with 2 components (GMM, M=2) can be observed from Figure 4. Forty-six heartbeats out of the 125 heartbeats were removed.

IV. Experimentations

We suggested a method to achieve a heartbeat outlier elimination by modelling *normal* heartbeats with density estimation using GMM statistics. In this section we examined the viability of such approach. This experiment intended to demonstrate the influence of outlier removal on a verification biometric system. Three biometric systems were implemented and their ROC



(a) Before outliers removal (b) After applying GMM, M=2 outlier removal

Fig. 4. GMM,M=2 model outlier removal

curves were compared. One of the biometric systems utilized the GMM, M=2 outlier removal. Another biometric system had Interquartile Range (IQR) outlier removal, and the third biometric system was based on a state of the art AC/LDA [5] biometric system that uses autocorrelation threshold for outlier removal.

Bootstrap Aggregating (bagging) was used as a classification stage in GMM, M=2 and in IQR based systems. Bagging [14] is a machine learning technique that generates weak classifiers. The weak classifiers were decision trees with 50 learners. The aggregated average of these weak classifiers decide on the class of the data. Bagging was used in particular because we observed an "unstable" classifier prediction when we applied predictors to the ECG heartbeats data. It is unstable in a sense that slight change in the training data led to a significant change in the constructed classifier model and a significant change in accuracy. Bagging usually reduces this issue [14].

Verification biometric system is a two-class classification problem. From the 943 subjects, two non-overlapping databases were constructed: training and testing. The training database consisted of 80% of the data of each subject while the other 20% constructed the testing database. For each subject, bagging was used to create a model, and for that, we required positive and negative data. The positive data were the subject's training data while the negative data were randomly selected from other subjects. The number of negative data was same as the number of positive data.

The IQR outlier [15] removal criterion is a statistical method that removed any heartbeat with R peak amplitude greater than $U_{outlier}$ or less than $L_{outlier}$ where:

$$\begin{aligned} U_{outlier} =& Q_3 + 1.5 \times IQR \\ L_{outlier} =& Q_1 - 1.5 \times IQR \end{aligned} \tag{3}$$

Q_1 and Q_3 are the 25^{th} and 75^{th} quantiles, respectively. Also, $IQR = Q_3 - Q_1$.

We implemented two types of IQR outlier removal: real-time and non-real-time implementations. The difference between them is that the former had the parameters $U_{outlier}$ and $L_{outlier}$ pre-set by calculating their values from the 1,330 heartbeats used in Section III-D. Hence, similar to this paper's approach, it can be used to remove outliers in real-time and for any subject, seen or unseen before. On the other hand, the non-real-time implementation calculated $U_{outlier}$ and $L_{outlier}$ for each subject. The non-real-time system requires calculating parameters from each subject before examining it again to remove its outliers. Therefore, it is not suitable for real-time applications when unseen before subjects can be encountered.

We compared the implemented verification system to a state of the art biometric verification system AC/LDA [5]. AC/LDA system does not require signal segmentation, and it uses autocorrelation (AC) as features. It then applies LDA for dimensionality reduction. Lastly, it uses Euclidean distance for classification. ROC curves for the biometric systems are presented in Figure 5. From Figure 5 and Table I, improvement is apparent in GMM, M=2 in comparison to other biometric systems. It is pertinent to mention that AC/LDA pre-sets its autocorrelation value for outliers removal. Hence, based on real-time versus non-real-time categories, we would categorize it as a real-time outlier removal system.

Despite the fact that GMM, M=2 outlier removal performance was close to IQR non-real-time outlier removal, the latter is not suitable for our intended real-time application. However, when IQR non-real-time outlier removal implementation was changed to perform in real-time, its performance deteriorated due to the large inter-subjects variation in R peak amplitudes.

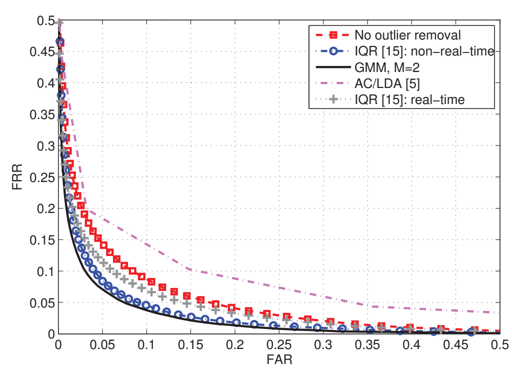


Fig. 5. ROC curves for the biometric systems

Method	EER (%)
AC/LDA [5]	12.30
No outlier removal	9.44
IQR [15]: real-time	8.25
IQR [15]: non-real-time	6.35
GMM, M=2	**5.94**

TABLE I
EER FOR THE BIOMETRIC SYSTEMS

V. Conclusion

Gaussian mixture model (GMM) provided a viable approach to successfully classify *normal* and *abnormal* heartbeats. Hence, it was used as ECG outlier removal to reduce the number of *abnormal* ECG heartbeats that may otherwise jeopardize biometric system decision if not eliminated. This outlier removal method does not require prior knowledge about the tested subject, and it can be implemented as a real-time outlier removal within ECG acquisition devices. Additionally, this technique can provide an instant feedback about the quality of the signal being collected. The biometric system that used GMM with 2 mixtures for outlier removal outperformed the AC/LDA state of the art biometric system by achieving 5.94% EER in comparison to 12.30% EER in the latter. Also, when this biometric system, GMM of 2 mixtures, was compared to a biometric system that uses IQR outlier removal, the latter achieved an EER of 8.25%

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