ECG Biometrics: a robust short-time frequency analysis

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***Abstract*—In this paper, we present the results of an analysis of the electrocardiogram (ECG) as a biometric using a novel short-time frequency method with robust feature selection. Our proposed method incorporates heartbeats from multiple days and fuses information. Single lead ECG signals from a comparatively large sample of 269 subjects that were sampled from the general population were collected on three separate occasions over a seven-month period. We studied the impact of long-term variability, health status, data fusion, the number of training and testing heartbeats, and database size on ECG biometric performance. The proposed method achieves 5.58% equal error rate (EER) in verification, 76.9% accuracy in rank-1 recognition, and 93.5% accuracy in rank-15 recognition when training and testing heartbeats are from different days. If training and testing heartbeats are collected on the same day, we achieve 0.37% EER and 99% recognition accuracy for decisions based on a single heartbeat.**

I. Introduction

Since the work of Biel *et. al.* [1], [2] and Kyoso [3], there has been increased interest in biometrics based on the Electrocardiogram (ECG). ECG as a biometric has three key properties:

- ECG signals are difficult to counterfeit.
- The ECG signal is present in all living individuals.
- It provides additional information related to psychological states and physiological status, which may be of interest for certain applications.

A number of methods and analyses have been proposed under several operational scenarios. For example, fiducial-based methods, autocorrelation, and time-frequency methods using 12-leads ECG signals from healthy subjects under normal resting conditions have been examined extensively [4], [5], [6], [7], [8], [9], [10], [11]. ECG as a biometric based on a single lead has also been studied [7], [8]. Chan *et. al.* studied the biometric performance of one lead ECG signals recorded from subjects' thumbs. Israel *et.al.* [5] studied the effects of mental stress on biometric performance by requiring healthy subjects to perform various tasks while the ECG signal was recorded. Wübbeler *et. al.* specifically studied the effect of temporal variability by using training and testing ECG signals recorded on different days [12]. In the work of [13], the possibility of using ECG as a biometric on subjects with two specific heart diseases, premature ventricular contraction (PVC) and atrial premature contraction (APC), was studied. In the work of [14], a large dataset comprising 502 subjects was used, with training and testing heartbeats taken consecutively on the same day.

Here, we propose a novel robust time-frequency method for ECG biometrics, applying a large dataset of one lead ECG signals from 269 subjects, representing different demographic groups and health status. We focus on contributing to the development of ECG as a biometric with respect to:

- *Analyses on a large representative database*. Most previous results are based on ECG signals selected from only healthy subjects or only unhealthy subjects with specific diseases from three major databases, the MIT-BIH Normal Sinus Rhythm, MIT-BIH Arrhythmia, and PTB databases. In studies that have used these databases, strict subject selection criteria were applied. The present report is based on a large sample ($n = 269$) drawn from the general population.
- *A novel robust method for signal variability and information fusion*. Using fusion over multiple training sessions, we propose an information theoretic method to select features based on their distinguishability and stability. We have previously shown this approach to be useful in another cardiovascular based biometric using Laser Doppler Vibrometry measurements [15], [16], [17], [18], [19].
- *More acceptable electrode placement*. We use a simple recording montage, with electrodes placed bilaterally on the lower rib cage, so that subjects are not required to undress. Despite the lack of electrode placement standard-

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ization, we show that our performance is still comparable with performance reported in other studies.

- *The effects of sample size*. To understand the utility of ECG as a biometric, we examine the ECG biometric performances using different number of training and testing heartbeats, as well as number of subjects in the database.

We focus on ECG biometric performance under two scenarios: acquiring training and testing heartbeats on the same day, and acquiring testing heartbeats from one week to several months after the training heartbeats have been obtained. For both scenarios, we study the effects of the number of training and testing heartbeats used on the ECG biometric performance. Furthermore, we show how to improve performance through robust feature selection and the fusion of training information from different days. Both authentication and recognition performances are studied. For within session analysis, the proposed method achieves 0.37% equal error rate (EER) based on a single heartbeat, and 0.02% based on multiple test heartbeats, which is comparable to the best existing methods. Moreover, based on multiple test heartbeats, the recognition accuracy is 99.2%. In particular, for healthy subjects, we achieve a recognition accuracy of 99.67%, which is one of the best existing results.

This paper addresses a method of scientific analysis of ECG signals as a biometric. It does not suggest ways to implement and deploy the proposed ECG biometric system.

The paper is organized as follows. Section II introduces the experimental dataset and ECG signal preprocessing methods. In section III, we discuss the operational scenarios studied in the paper. The novel short-time frequency method is introduced in section IV, with simulation results given in section V, and conclusion in section VI.

II. ECG DATASET AND PREPROCESSING

The ECG signals were obtained from a single channel, with the electrodes placed bilaterally on the lower rib cage. Signals were recorded with a Biopac TEL-100 system, using a 0.5 Hz high pass filter and 500 Hz low pass filter. The ECG signal acquired at this location has a strong R-wave and is less affected by movement artifact than some of the conventional ECG leads. The subjects were asked to sit for five minutes as the recording took place. Each of the 269 subjects had ECG recorded on three different days, which we call sessions 1, 2, and 3, where the separation between recording days ranges from two weeks to six months. The ages of the subjects varied from 18 to 66 years, with mean and standard deviation of 38.8 and 14.1 years respectively. 40.15% of the subjects had some heart-related disease, including hypertension. 46.84% of the subjects used medicines or other substances that may affect the ECG signal. 27.88% of the subjects were healthy and did not use substances that may affect the ECG signal. Moreover, 53.9% of the subjects were females, and 72.12%, Caucasians.

The ECG signals, which were originally sampled at 10 kHz, were subsequently down-sampled to 1 kHz and digitally notch filtered at 60 Hz to remove power line interference. The resulting ECG signal was reduced to individual 700 msec segments aligned to the respective R-wave peak, beginning 200 msec prior to the peak. The segment (heart pulse) duration was chosen to ensure that all of the major components (P, Q, R, S, and T-waves of a single heartbeat) were included while minimizing the possibility of including portions of adjacent beats. Each ECG heart pulse was normalized by subtracting the sample mean of the pulse, and dividing by the sample standard deviation.

In order to align the ECG segments to the peak of the R-wave, the peak has to be detected. For each study participant, the data were first high-pass filtered using an IIR elliptical filter (5 Hz cutoff, 90 dB attenuation). An artifact-free calibration epoch of 15 sec was selected. All positive inflection points (peaks) within this epoch were then determined. Only peaks whose amplitude was at least 75% of the amplitude of the maximum detected peak were retained for further analysis. An initial detection template, individualized for each study participant, was created by averaging periods of ECG activity (epoch duration = 750 msec) time-locked to each peak (epoch onset = 250 msec prior to detected peaks). This initial detection template generally represented an accurate model of an individual's typical heart beat; however, such averages can be inappropriately influenced by factors such as noise spikes in the data, or abnormally large amplitude T-waves. In order to reduce the impact of such influences, a final detection template was constructed according to the following procedure. The initial detection template was cross-correlated with the 15 sec calibration epoch. The resulting cross-correlation function was then examined for inflection points whose values represented correlations greater than or equal to 0.35. Each resulting peak in the cross-correlation function was assumed to indicate a detected heart beat. The peak of the R-wave associated with each detected beat was determined by finding the maximum value in the filtered ECG data in a 100 msec window beginning 50 msec prior to the peak in the associated cross-correlation function. A final detection template was then created by averaging 750 msec ECG epochs beginning 250 msec prior to the peak of each detected R-wave in the calibration epoch. R-waves in the entire ECG recording were then detected by cross-correlating the final detection template with the complete ECG data vector. In a manner analogous to that used to create the final detection template, detected heart beats were defined as peaks in the cross-correlation function whose value exceeded 0.35. R-wave peaks were estimated by determining the time of the maximum value in the ECG signal within a 100 msec window centered on the time at which the heart beat detection peak occurred in the cross-correlation function.

III. BIOMETRIC PERFORMANCE EVALUATION SCENARIOS

In addition to having a database of diverse subjects, we are interested in evaluating ECG biometric performances under the effects of temporal variability due to different data acquisition dates, differences in the number of heartbeats used in the testing and training sets, and varying the number of subjects in the database. To study the temporal effects, there were three

testing scenarios, one of which involved using training and testing heartbeats from the same day, and two of which involve training and testing heartbeats from different days:

- *Within session tests*. For a given session, ECG recordings from each subject are separated into two parts. The training heartbeats comprise subsets of the first half of the recordings, while the testing heartbeats comprise subsets of the second half of the recordings.
- *Across sessions tests: single training session*. In this case, training heartbeats consist of subsets of heartbeats from a session, whereas the testing heartbeats come from another session. This study focuses on the effects of ECG time variability.
- *Across sessions tests: multiple training sessions*. In this case, the training heartbeats come from two sessions while the testing heartbeats come from the third session. This study focuses on how to train a classifier using heartbeats from multiple days, and how much performance increases by doing such.

We evaluate performance based on verification (authentication) and recognition (identification). In verification, the system is designed to verify a claimed identity using the biometric trait. In recognition, the system is required to infer the subject's identity based on the biometric trait. For each test and task, different numbers of heartbeats ranging from 1 to 256 are used for training and testing. This helps to understand the sample size effect on ECG biometric performance, and for operational purposes, to optimize data acquisition time. For recognition, we further investigate the performance when the database includes different numbers of subjects. To do so, we simulate databases consisting of 20 to 260 subjects, in steps of 20, by selecting contiguous subsets of subjects from our original dataset.

IV. The time-frequency method and robust feature selection

From each ECG pulse signal, we compute a spectrogram which is the logarithm of the square of the magnitude of the short-time Fourier transform of a normalized ECG heart pulse. In computing the short-time Fourier transform (STFT), we use a Hamming window of size 64ms, with a step size (the distance between the beginnings of two consecutive windows) of 10ms. Thus, there is an overlap of size 54ms between consecutive time frames. This window size was chosen empirically so that it yields robust and good single-heartbeat authentication performance in terms of equal error rate (EER). After computing the STFT, the frequency content was truncated at 250Hz to reduce boundary effects. The spectrogram is then computed as the logarithm of the squared-magnitude of the truncated STFT. We refer to the index of each point of the spectrogram as a time-frequency bin. Thus each ECG heart pulse can be represented by $L = 2048$ time-frequency components denoted as $Y(l)$. To build a generative classifier, we use independent normal distributions to model the time-frequency bins of each subject. During training, only the means and variances have to be estimated. For each bin l of subject i, we use the maximum likelihood (ML) estimates which are the sample means and variances denoted as $\hat{\theta}_i(l) = (\mu_{il}, \sigma^2_{il})$.

It is known that feature selection or dimensionality reduction often improves performance of classification problems [20] (and many other papers) and cardiovascular based biometrics [15], [16], [17], [19]. We use a robust informative feature selection method to select informative time-frequency bins for verification and recognition. The two key elements considered in our feature selection method are distinguishability and stability. The feature should help distinguish the subject from a reasonably large subset of other subjects, and it should be stable across sessions. The l-th feature of the i-th subject is selected if the symmetric relative entropy, i.e. the symmetric Kullback-Leibler divergence, between $\mathcal{N}(\mu_{il}, \sigma^2_{il})$ and the nominal distribution $\mathcal{N}(\mu_{0l}, \sigma^2_{0l})$ is larger than a threshold $\kappa > 0$. The relative entropy between two densities p and q is defined by

$$D(p\|q) = \int p \log \frac{p}{q} \tag{1}$$

where the integral is taken over the support set of p. The symmetric relative entropy between the two densities is defined as

$$d(p, q) = D(p\|q) + D(q\|p) \tag{2}$$

For the Gaussian distributions used in our model, the symmetric relative entropy between $\mathcal{N}(\mu_{il}, \sigma^2_{il})$ and $\mathcal{N}(\mu_{0l}, \sigma^2_{0l})$ is

$$d(\hat{\theta}_i(l), \hat{\theta}_0(l)) = \frac{\sigma^2_{il} + (\mu_{il} - \mu_{0l})^2}{2\sigma^2_{0l}} + \frac{\sigma^2_{0l} + (\mu_{il} - \mu_{0l})^2}{2\sigma^2_{il}} - 1 \tag{3}$$

where the nominal model is obtained by using the spectrograms of all the subjects in the database. Using the symmetric relative entropy for feature selection ensures that only those bins whose distributions are far from the nominal are selected for each subject, thereby ensuring distinguishability. Moreover, stability of features is enforced by the variance of the subject's bin σ^2_{il}. It follows from the construction of the nominal model that for the most part, $\sigma^2_{il} < \sigma^2_{0l}$, so that the second term in equation (3), with σ^2_{il} in the denominator, increases as σ^2_{il} decreases; for subject bins with small variances, the symmetric relative entropy tends to be large.

The score of a test heartbeat using the i-th subject's model is given by the log-likelihood ratio (LLR):

$$\Lambda_i = \sum_{l=1}^{L} \log \left[\frac{p_i(Y(l)|\hat{\theta}_i(l))}{p_0(Y(l)|\hat{\theta}_0(l))} \right] I_{d(\hat{\theta}_i(l), \hat{\theta_0}(l)) > \kappa} \tag{4}$$

where $I_{\{\cdot\}}$ is the truth function indicating which time-frequency bins are selected; l is the index of the bins. For verification, the LLR given in equation (4) is compared with a threshold τ, so that if $\Lambda_i > \tau$, the heartbeat with the claimed identity is accepted, otherwise the heartbeat is rejected. For recognition, the LLR is computed for every subject model, and the subject whose model gives the largest score is declared. For rank-k recognition, subjects with models yielding the top k scores are declared. For across session verification, the

score function was modified so as to disregard the role of the variances of the time-frequency bins. That is, we set $\hat{\theta}_i(l)$ and $\hat{\theta}_0(l)$ to a constant θ.

In recognition, to ensure that a variable number of time-frequency bins can be selected for each subject's model, the score obtained from comparing a test heartbeat to a subject's model is normalized by a score obtained from comparing the heartbeat to the nominal model. This normalization ensures that there is no direct relationship between the number of bins used in a subject's model, and the value of the computed score [20]; more selected bins does not mean higher scores.

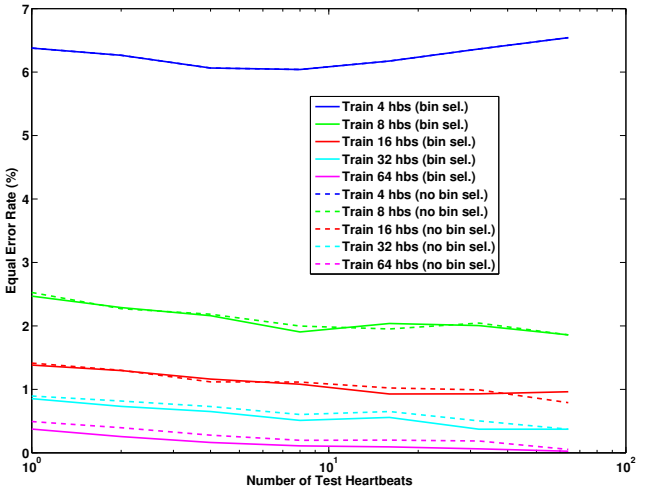

Fig. 1. EER curves for training on 4, 8, 16, 32, 64 heartbeats and testing on 1, 2, 4, 8, 16, 32, and 64 heartbeats, with and without feature selection.

V. Results

A. Within session analysis

In this analysis, ECG signals of each subject collected on the same day are separated into various sizes of the training and testing sets. The number of ECG signals used in training ranges from 4 to 64, in powers of 2. After training each model - which includes feature selection, we tested on 1, 2, 4, 8, 16, 32, and 64 pulses. For each trained model and a given number of testing pulses *t*, we performed *n*-independent tests, where *n* is the number of non-overlapping pulse blocks of size *t* there are in 64 pulses; $n = \lfloor \frac{64}{t} \rfloor$. For recognition, the number of subjects in the database was varied from 20 to 260, in steps of 20, and the analysis was repeated for contiguous blocks of size *m*, where $m = 20 \times i, i = 1, 2, 3, \ldots, 13$. Figure 1 shows the authentication performances, represented by the equal error rates (EERs), for all the training and testing sets. The solid lines represent the cases of using feature selection. We see that an EER as low as 0.37% is attained when decisions are based on a single test heartbeat. As the number of test heartbeats increases, the EERs tend to decrease, reaching a nadir of 0.02%. Figure 2 shows the k-Rank recognition accuracy for training on 4, 8, 16, 32, 64 heartbeats and testing on a single heartbeat. A rank-1 recognition accuracy of 99% can be obtained, when decisions are based on a single heartbeat. As expected, the recognition accuracy increases, as the rank increases. In general, recognition accuracy increases as the number of subjects in the database decreases. This is in agreement with our expectation; fewer subjects to choose from yield fewer opportunities for misclassification.

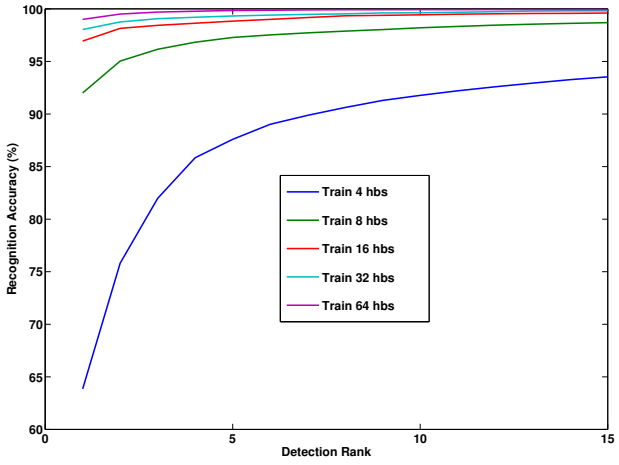

Fig. 2. k-Rank recognition accuracy for training on 4, 8, 16, 32, 64 heartbeats and testing on 1 heartbeat, with feature selection and 260 subjects in the database.

B. Cross session analysis I: one training session

In this analysis, training heartbeats are obtained from one session and testing, from another. The number of ECG signals used in training ranges from 4 to 128, in powers of 2. After training each model - which includes feature selection, we tested on 1, 2, 4, 8, 16, 32, 64, and 128 pulses. For each trained model and a given number of testing pulses *t*, we performed *n*-independent tests, where *n* is the number of non-overlapping pulse blocks of size *t* there are in 128 pulses; $n = \lfloor \frac{128}{t} \rfloor$. The biometric performances obtained by training on the first session, and testing on either the second or the third session are shown in Figure 3. We see that the performance based on testing on heartbeats from the second session tends to be better; ECG performance is negatively affected by the amount of time between training and testing heartbeats. This difference in ECG performance between testing on heartbeats from the second and third sessions might also be due to differences in electrode placement on the different days. To single out time variability as the cause of the ECG performance differences, a study, were the electrode placement is highly standardized in all sessions, has to be performed.

C. Cross session analysis II: Two training sessions

In this analysis, training heartbeats are obtained from two days, and testing, from the third. Simple data fusion that trains a combined model for each subject's bin is used. The number of ECG heartbeats used in training ranges from 8 to 256, where

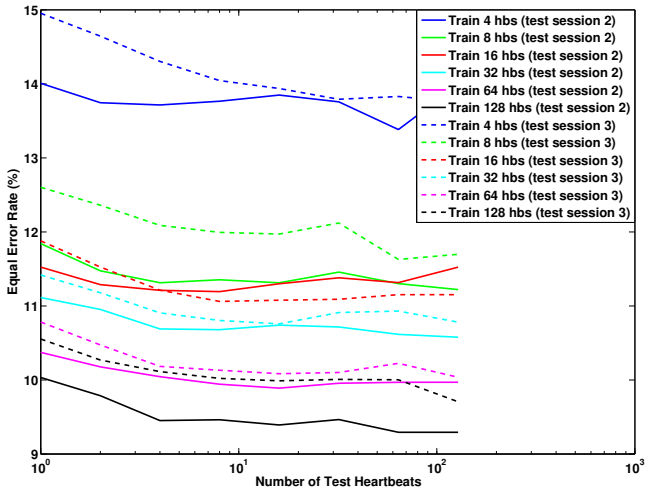

Fig. 3. EER curves for training on 4, 8, 16, 32, 64, 128 heartbeats and testing on 1, 2, 4, 8, 16, 32, 64, and 128 heartbeats, using feature selection, when testing on session 2 (solid lines) and session 3 data.

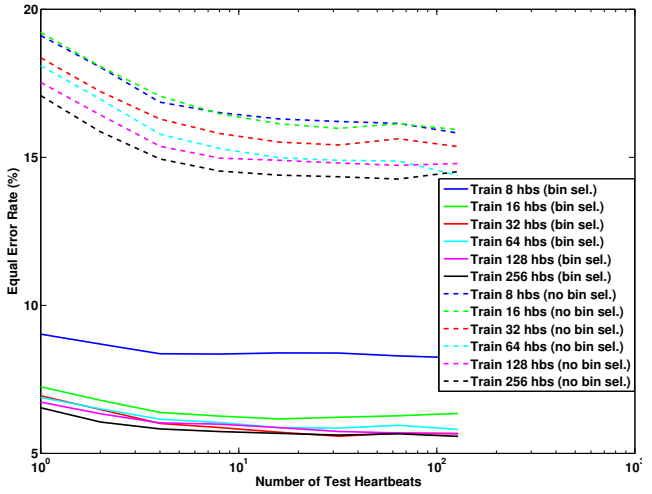

Fig. 4. EER curves for training on 8, 16, 32, 64, 128, 256 heartbeats and testing on 1, 2, 4, 8, 16, 32, 64, and 128 heartbeats, with and without feature selection.

half of the heartbeats come from one day, and the remaining from another. Figure 4 shows the EERs for all the training and testing sets, with (solid lines) and without feature selection. It is evident that feature selection improves the authentication performance in all cases. We see that an EER as low as 5.58% is attained when decisions are based on multiple test heartbeats. Figure 5 shows the EERs for testing on a session, when training is performed on heartbeats from either two or a single previous session. We observe a two-fold improvement in authentication performance due to data fusion. Figure 6 shows the k-Rank recognition accuracy for training on 8, 16, 32, 64, 128, 256 heartbeats from two training sessions and testing on half the number of training heartbeat, respectively. A rank-1 recognition accuracy of 76.9% can be obtained, when decisions are based on multiple heartbeats. As expected, the recognition accuracy increases, as the rank increases, reaching a rank-15 value of 93.5%. When a verification analysis is performed on a database including only people of good health, a 4.75% EER is achieved, when training and testing on 256 and 32 heartbeats respectively. Similarly, when the analysis is performed on a database including only unhealthy people, a 5.7% EER is achieved. The performed based on a database including only people of good health or only unhealthy people is comparable to the performance using the database including both health statuses. This shows that our proposed method is robust to different health statuses.

VI. Conclusion

In this paper, a novel short-time frequency method with robust feature selection is proposed for use as an ECG biometric. This approach does not require extraction of fiducial points. Rather, a systematic approach to feature generation and selection of informative features is presented.

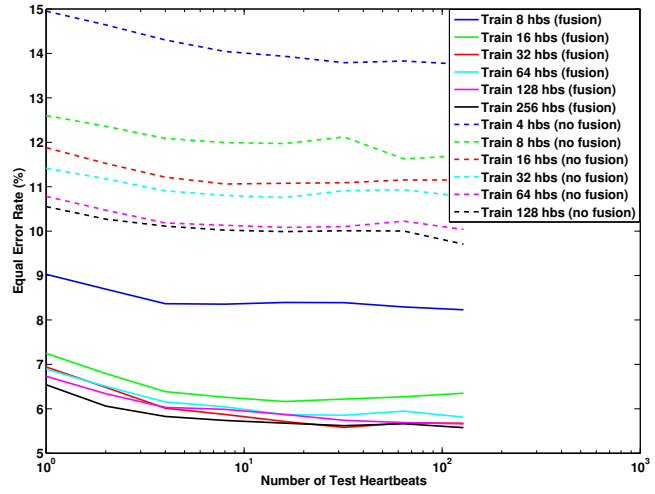

Fig. 5. EER curves for testing on 1, 2, 4, 8, 16, 32, 64, and 128 heartbeats, using feature selection, when training on two sessions (solid line) and a session.

Since the data comprises single lead ECG signals from 269 subjects that represent different demographic groups and health statuses, and were collected on three separate occasions over a seven-month period, we are able to study the impact of long-term variability, health status, data fusion, the number of training and testing heartbeats, and database size on ECG biometric performance. The method uses informative feature selection via symmetric relative entropy, and fuses heartbeats from two training occasions to achieve 5.58% EER in verification, 76.9% accuracy in rank-1 recognition, and 93.5% accuracy in rank-15 recognition when testing heartbeats come from another day. When the heartbeats used for training and testing are recorded on the same day, an EER of 0.37% and a

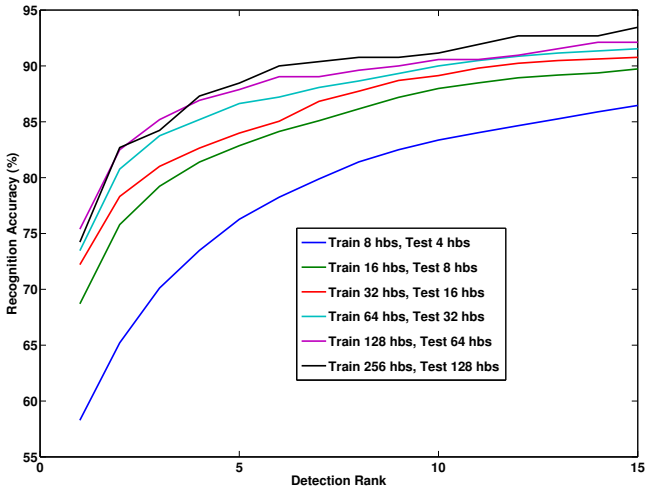

Fig. 6. k-Rank recognition accuracy for training on 8, 16, 32, 64, 128, 256 heartbeats from two training session, and testing on half the number of training heartbeats respectively, using feature selection, with 260 subjects in the database.

recognition accuracy of 99% is attained, for decisions based on a single heartbeat. When a similar analysis is performed on a database including only people of good health, or only unhealthy people, the authentication performance and recognition accuracy are comparable to what we obtain using the database including both health statuses. This shows that our proposed method is robust to different health statuses.

The major contributions of this work are by way of analyzing a large realistic dataset comprising several races, genders, age groups, and health statuses, proposing a novel robust method for capturing signal variability and information fusion, proposing a method that performs well under poor electrode placement and signal quality, and demonstrating the effects of sample size on the authentication performance and recognition accuracy of ECG biometrics.

The MIT databases have ECG recordings from a single day for each subject, permitting only within session analysis. On the other hand, the PTB database has ECG recordings from multiple days for some, but not all subjects. Since the ECG recordings from the MIT and PTB databases do not directly lend themselves to our multiple sessions data protocol, it will be easier to apply the methods proposed by authors of previous ECG biometric papers to our database, in order to compare the biometric performance of our proposed method to those of other authors.

In the future, we intend to apply the methods proposed by other authors to our database. Also, we plan to analyze the applicability of the proposed method to bicycle exercise and gender dichotomized ECG signals.

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