ECG-BASED AUTHENTICATION
Bayesian vs. Nearest Neighbour Classifiers

Carla Oliveira and Ana Fred
Instituto de Telecomunicações, Instituto Superior Técnico, Tech. University of Lisbon, Lisbon, Portugal

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Abstract: This paper presents an approach for human authentication based on electrocardiogram (ECG) waveforms. ECG data was collected from 24 individuals during the realization of cognitive tests, where subjects held a surface mount triode placed on the V2 pre cordial derivation. Authentication is based on MAP, One-Class and 1-NN classifiers. Results show that ECG-based authentication may be a feasible tool for biometric systems. The One-Class classifier with class normalization has presented enhanced performance, with an equal error rate of 3.5%.

1 INTRODUCTION

Biometric authentication is a promising tool for security applications, attesting that the user of a system is who he claims to be through the use of some of its physical or behaviour characteristics (*e.g.*, a fingerprint). Recent work, (Biel et al., 2001) and (Israel et al., 2005), suggests that the human heartbeat is a characteristic that can be used in biometric authentication schemes, as it exhibits features that are unique to an individual. Electrocardiogram (ECG) is the typical method to measure heartbeat, being extensively used in medicine. Figure 1 illustrates a typical ECG trace.

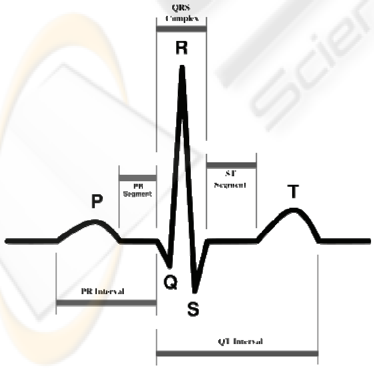

Figure 1: A typical heartbeat waveform (adapted from (Wikipedia, 2008)). The R R interval indicates the duration of a heartbeat. P, QRS, and T indicate the major ECG complexes comprising one heartbeat.

Some feasibility studies on the potential of ECG for biometrical applications are found in the literature. For example, in the identification scheme presented in (Wübbeler et al., 2007), authors use 234 ECG recordings of 10 s length, obtained during several months up to several years. Records were taken from 74 subjects in a supine position in a resting state, from the three Einthoven leads. Classification is based on the heart vector and a simple distance measure, standard nearest neighbour, and threshold schemes being used. For verification, an error rate of 2.8% was achieved; while a rate of 98.1% was obtained for identification. Other study is presented in (Chan et al., 2008), where ECG data was collected from 50 subjects during 3 sessions on different days, from two electrodes on the pads of their thumbs using their thumb and index fingers. Classification was performed using percent residual difference, correlation coefficient, and a novel distance measure based on wavelet transform. The wavelet distance measure has a classification accuracy of 89%, outperforming the other methods by nearly 10%.

In this work we have addressed the problem of user authentication from ECG records using a single lead montage, while the subjects were performing cognitive tests on a computer. Classification is based on two Bayesian classifiers, the *maximum a posteriori* (MAP) (Duda et al., 2001) and the One-Class (Tax, 2001) classifiers, and also on a distance based method, the 1-Nearest Neighbour (1-NN) (Duda et al., 2001) classifier. The MAP

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classifier assigns an object x to the class k with the largest *a posteriori* probability $p(\omega_k|x)$. In One-Class classification only $p(x|\omega_k)$, the probability density of the target class, ω_k, is known. Estimating the probability density from the training data and given a threshold, the classifier accepts or rejects the test samples. The 1-NN classifier assigns an object x to its nearest class, with closeness measured by the Euclidean distance between the vectors of inputs.

This paper is composed of 4 sections, besides the current one. The next section presents the data acquisition system from which ECG records were obtained. Section 3 describes the authentication system, detailing the implementation of the classifiers. An overview and discussion of results is provided in Section 4. Section 5 finalises the paper, drawing the main conclusions.

2 DATA ACQUISITION AND PROCESSING

The ECG data analysed in this work was acquired within the scope of the HiMotion Project (HiMotion, 2008). The HiMotion Project consisted on the design, implementation and administration of a set of computer based experiments with cognitive tests related to memory, concentration, association, intelligence and insight (discovery). The underlining idea is that these activities produce noticeable changes in the physiological characteristics of subjects, which, on one hand, are task dependent, and therefore global task-related dynamics/features can be recognized, and, on the other hand, individual behavioural traits may be present in the acquired data, and thus contribute for human authentication. A set of physiologic signals was continuously acquired during the realization of the tests: electrodermal activity, blood volume pressure, electroencephalography and ECG. A population of 24 male and female volunteers, with a mean age of 23.4±2.5 years, was asked to complete the series of tests in individual sessions, designed to take, in average, 30 minutes.

ECG measurements were taken using a surface mount triode placed on the V2 pre-cordial derivation. Each heartbeat waveform was sequentially segmented from the full recording, and then all individual waveforms were aligned by their R peaks in segments of equal temporal length. The mean wave for groups of 10 heartbeat waveforms (without overlapping), was computed to minimize the effect of outliers. A labelled database composed by 137 samples was compiled, in which each pattern corresponds to a mean wave. For each mean waveform (Figure 1), the latency and amplitude for each of the P QRS T peaks were extracted, along with a sub sampling of the waveform itself, providing a feature representation space of 53 features. In this work, only the latencies and amplitudes of P, Q, S and T complexes were used, resulting in 8 features, Table 1.

Table 1: Description of features.

Feature	Description
1	Latency of P complex
2	Latency of Q complex
3	Latency of S complex
4	Latency of T complex
5	Amplitude of P complex
6	Amplitude of Q complex
7	Amplitude of S complex
8	Amplitude of T complex

Concluding, the available ECG data comprises 24 classes (each corresponding to each one of the subjects under test) and 8 features.

3 AUTHENTICATION SYSTEM

The purpose of ECG-based authentication systems is to attest that the user of a system is who he claims to be, through the monitoring of its ECG records. In this work, three classifiers were implemented using Matlab (Matlab, 2007): MAP classifier, One-Class classifier and 1-NN classifier.

The MAP classifier algorithm was constructed as follows. Two mutually exclusive sub-sets from the 137 sample set are created, with 1 pattern for test and the remaining 136 for training ("leave-one-out" method). Then, density of the training data, $p(x|\omega_k)$, is estimated according to a maximum likelihood technique later explained. $p(\omega_k|x)$ is subsequently computed for each test sample according to (1) and the classifier decides on accepting test samples if (2) is verified. This process is repeated for all the 137 samples. It is important to state that a Naive Bayes model is considered for used features, thus assuming statistical independence between them, (3). Also, classes are assumed to be equiprobable, (4).

$$p(\omega_k \mid x) = \frac{p(x \mid \omega_k)\,p(\omega_k)}{p(x)} = \frac{p(x \mid \omega_k)\,p(\omega_k)}{\sum_{i=1}^{24} p(x \mid \omega_i)\,p(\omega_i)} \quad (1)$$

$$p(\omega_k \mid x) > \lambda \quad (2)$$

$$p(x \mid \omega_k) = \prod_{j=1}^{8} p(x^j \mid \omega_k) = \prod_{j=1}^{8} N(\mu_k^j, \sigma_k^j) \quad (3)$$

$$p(\omega_i) = p(\omega_k) = \frac{1}{24} \quad (4)$$

For the One-Class classifier, a similar algorithm was adopted. The algorithm starts to estimate the distribution of training data. Then, the probability density of the target class, $p(x|\omega_k)$, is estimated and normalized within a factor F_{class}, which is the maximum value within each class, (5). Afterwards, given a threshold λ, the classifier accepts the test samples included in the acceptance region defined by threshold according to (6). This process is repeated for all the 137 samples. For comparison purposes, another version of the One-Class classifier was implemented, using a different normalization factor, F_{all}, which is the maximum $p(x|\omega_k)$ value found over all classes, (7).

$$F_{class} = \max(p(x \mid \omega_k)) \quad (5)$$

$$p(x \mid \omega_k) > \lambda \quad (6)$$

$$F_{all} = \max_k(p(x \mid \omega_k)) \quad (7)$$

Note that, regarding these two Bayesian classifiers, the density model of the training data was estimated based on its histogram plots, Figure 2. A Gaussian distribution, with mean μ and variance σ^2, was assumed for each feature. It is important to state that this is a simplistic approach (*e.g.*, feature 2 in Figure 2 is a Dirac function), with implicit drawbacks on the performance of the authentication system. A mixture of Gaussians will probably provide refined results, but has the additional complexity drawback.

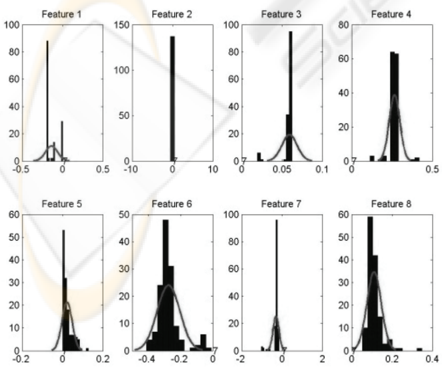

Figure 2: Histogram plots for subject id 10.

The 1-NN classifier algorithm starts to compute and store the Euclidean distances between all data samples, and then normalizes the computed values to F_{dis}, which is the maximum distance found between two samples x_a and x_b, (8). After the creation of training and test sets, the minimum distances for the training set within each class are found and classification is based on that. Test samples are accepted if (9) is verified. This process is repeated 137 times, one per sample.

$$F_{dis} = \max(d(x_a, x_b)) \quad (8)$$

$$d_{\min}(x \mid \omega_k) < \lambda \quad (9)$$

4 RESULTS AND DISCUSSION

In what concerns the MAP classifier, the confusion matrix (average values obtained for the 137 runs) is presented in Figure 3. It is clear from this figure that test samples from different individuals are extremely uncorrelated, thus being correctly classified. About 60% of the test samples achieve $p(\omega_k|x) > 0.85$. In Figure 4 and Figure 5 one may observe the average Receiving Operating Characteristic (ROC) and the False Acceptance Rate (FAR) / False Rejection Rate (FRR) curves, respectively, for the 137 runs. It is observed that FAR and FRR are dependant on the adjustable chosen threshold. If the threshold value is increased, FAR decreases, while FRR increases. When the value of threshold is decreased, the proportion FRR will decrease, while FAR increases. FAR lies between 5% and 17%, while FRR achieves values between 4% and 9%. The equal error rate (EER) occurs for $\lambda \sim 2.6\text{E-04}$, corresponding to FAR=FRR=7%. For this value of the threshold, FAR and FRR values were analysed within each class (see Figure 6). It is observed that classes 1, 18 and 22 present the worst results. In order to determine EER within each class, the respective FAR and FRR values were computed. Table 2 presents the λ_k values corresponding to the EER for each class k. An average EER of 5.9% was estimated, being lower to the one obtained for the MAP classifier with a global threshold. Thus, one concludes that specific thresholds per class will enhance the performance of the classifier.

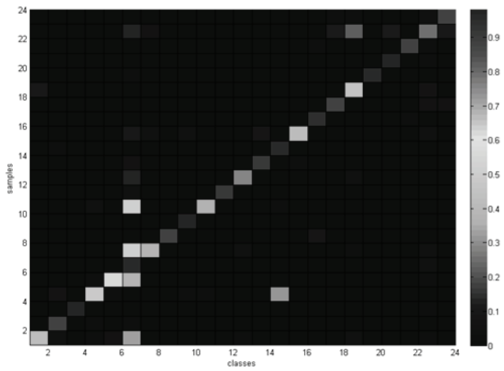

Figure 3: Confusion matrix for the MAP classifier (average values).

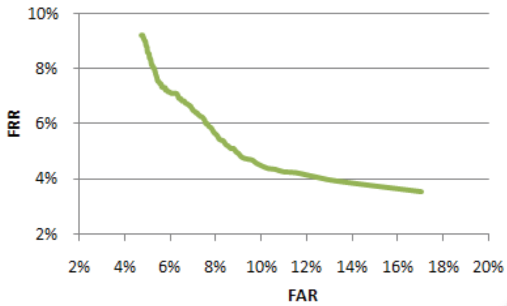

Figure 4: ROC curve for the MAP classifier.

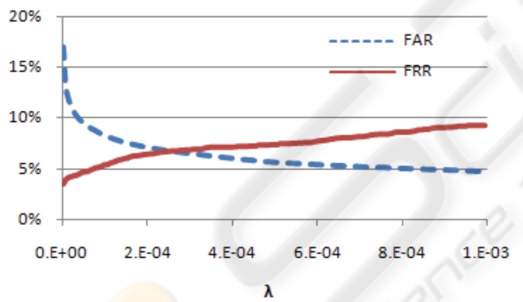

Figure 5: FAR/FRR(λ) curves for the MAP classifier.

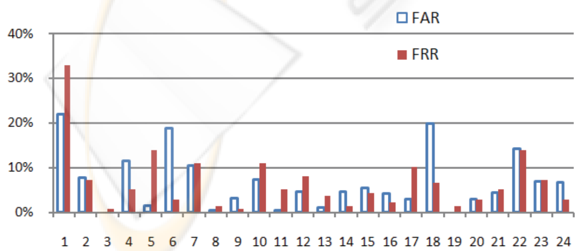

Figure 6: FAR/FRR curves for each class, with $\lambda \sim 2.6E\text{-}04$ (MAP classifier).

Table 2: ERR within each class (MAP classifier).

Class, k	λ_k	ERR
1	1.51E-04	27%
2	4.66E-04	7%
3	2.00E-09	0%
4	6.40E-03	6%
5	6.45E-06	4%
6	9.90E-01	5%
7	1.91E-06	11%
8	3.00E-06	1%
9	2.00E-03	1%
10	1.56E-04	8%
11	2.06E-08	2%
12	2.10E-05	7%
13	2.80E-10	2%
14	1.60E-01	3%
15	3.86E-04	4%
16	3.30E-03	2%
17	3.48E-06	9%
18	4.70E-03	10%
19	2.00E-08	0%
20	1.56E-04	3%
21	1.71E-04	5%
22	3.11E-04	15%
23	2.66E-04	7%
24	2.03E-03	4%
	average	6%

Regarding the One-Class classifier, the confusion matrix (average values) obtained for the 137 runs, is presented in Figure 7. Again, it is observed that samples are extremely uncorrelated and almost all are correctly classified. 75% of the test samples achieve $p(x|\omega_k) > 0.85$. ROC and FAR/FRR(λ) curves for the One-Class classifier (with normalization within each class) are represented in Figures 8 and 9, respectively. One observes better results for this classifier when compared to MAP, with FAR ranging from 3% and 13%, while FRR lies between 7% and 13%. EER happens for $\lambda \sim 1.4E\text{-}03$, corresponding to FAR=FRR=3.5%. Worse results were obtained for the version of One-Class classifier with normalization to the maximum $p(x|\omega_k)$. In this case, FAR lies between 5% and 15%, while FRR ranges from 8% to 16%. EER occurs for $\lambda \sim 2.5E\text{-}08$, corresponding to FAR=FRR=10%.

Regarding the 1-NN classifier, Figure 10 and Figure 11 represent the ROC and FAR/FRR(λ) curves for this classifier. For 1-NN, a symmetric trend is verified when compared to the Bayesian classifiers. With higher threshold levels, FAR will increase, while FRR decreases. This is intuitive, as increasing the distance threshold will lead the system to accept more users, thus increasing FAR and decreasing FRR. Poor performances were obtained for 1-NN, with EER occurring for $\lambda \sim 2.9E\text{-}02$, corresponding to FAR=FRR=8%.

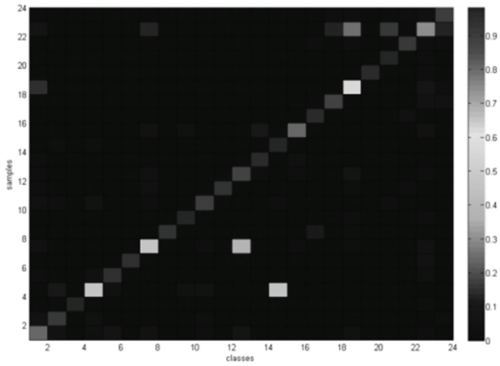

Figure 7: Confusion matrix for the One-Class classifier with class normalization (average values).

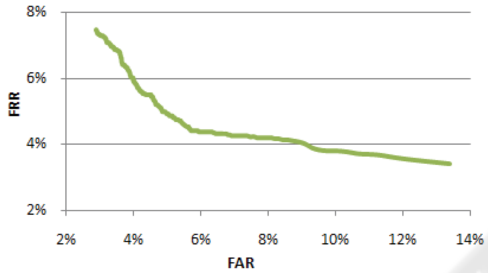

Figure 8: ROC curve for the One-Class classifier.

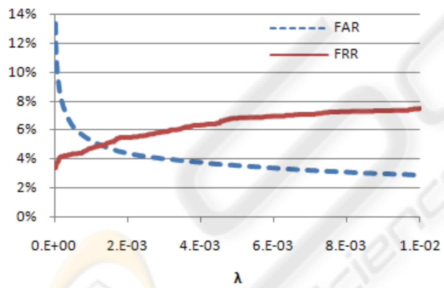

Figure 9: FAR/FRR(λ) curves for the One-Class classifier.

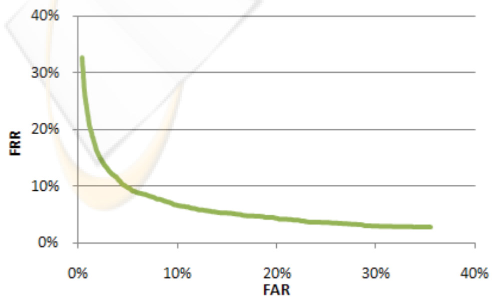

Figure 10: ROC curve for the 1-NN classifier.

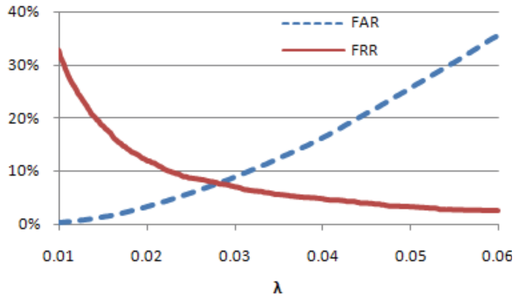

Figure 11: FAR/FRR(λ) curves for the 1-NN classifier.

An overview of the obtained results is presented in Table 3, from which one concludes that all the implemented classifiers are promising for an ECG-based authentication scheme.

Table 3: Overview of classifiers.

Classifier	EER
MAP	7%
One-Class (class normalization)	3.5%
One-Class (maximum normalization)	10%
1-NN	8%

5 CONCLUSIONS

This paper exploits possible approaches for ECG-based authentication schemes, using real data obtained by the HiMotion Project. ECG records from 24 individuals were gathered during realization of cognitive tests, where subjects held a surface mount triode placed on the V2 pre cordial derivation. Two Bayesian classifiers, MAP and One-Class, and a standard 1-NN were implemented using Matlab. Results show that the three schemes achieve feasible performances for an authentication system, with statistical classifiers presenting better results.

Regarding the Bayesian classifiers, Gaussian distributions were assumed to estimate $p(x|\omega_k)$. In the MAP classifier, decision is based on posterior probabilities, given a global threshold for the 24 classes. This assumption results in an EER of 7%. It was shown that enhanced performance could be obtained, if one considers specific thresholds per class. The same conclusion is valid for the One Class classifier, which, in a first approach, considers class normalization factors, leading to an error rate of 3.5%. Without normalization to the maximum

$p(x|\omega_k)$ within each class, performance degrades to error rates of 10%. Regarding the 1-NN classifier, which is based on distance measure, a slight worse performance was achieved with EER of 8%.

It is concluded that the ECG biometric does provide a simple method for human authentication, which may be appropriate in some applications (*e.g.*, sensor authentication in body area networks). Moreover, ECG may be a good source of additional information in a multi-biometrics approach, as well as integrated in health surveillance systems.

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