2012 IEEE INTERNATIONAL WORKSHOP ON MACHINE LEARNING FOR SIGNAL PROCESSING, SEPT. 23–26, 2012, SANTANDER, SPAIN

ECG-BASED BIOMETRICS: A REAL TIME CLASSIFICATION APPROACH

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ABSTRACT

Behavioral biometrics is one of the areas with growing interest within the biosignal research community. A recent trend in the field is ECG-based biometrics, where electrocardiographic (ECG) signals are used as input to the biometric system. Previous work has shown this to be a promising trait, with the potential to serve as a good complement to other existing, and already more established modalities, due to its intrinsic characteristics. In this paper, we propose a system for ECG biometrics centered on signals acquired at the subject's hand. Our work is based on a previously developed custom, non-intrusive sensing apparatus for data acquisition at the hands, and involved the pre-processing of the ECG signals, and evaluation of two classification approaches targeted at real-time or near real-time applications. Preliminary results show that this system leads to competitive results both for authentication and identification, and further validate the potential of ECG signals as a complementary modality in the toolbox of the biometric system designer.

***Index Terms*—** Biometric Systems, ECG signal, Real Time Recognition Systems, SVM classifiers

1. INTRODUCTION

Recent developments within the biosignal research community have found electrocardiographic (ECG) signals to hold relevant subject-dependent information. Biometrics is therefore emerging as one of the novel application fields for ECG signals [1, 2]. Due to its intrinsic nature, ECG signals possess several highly desirable features, such as the fact that it is originated in the body by a vital and live organ, it is permanently available, and it is difficult to mimic since there is no association to reproducible external physical landmarks.

The acceptance of ECG based methods requires real-time or near real-time processing to enable practical identity recognition scenarios. Therefore, within the field of ECG biometrics, recent research work has focused on usability and computational efficiency aspects; namely, on the design of non-intrusive acquisition methods, and on the improvement of signal processing and pattern recognition algorithms, making them more suitable for regular use and widespread applications.

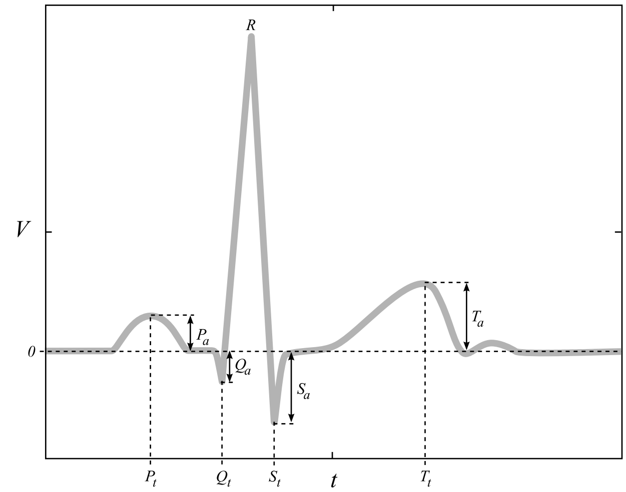

Fig. 1. Features measured from the ECG waveform. After the filtering process the ECG baseline is fairly zero centered, and therefore the amplitude measurements are taken with respect to the zero centered line. The temporal measurements are generally relative measures taken with respect to the R-peak.

Within ECG-based biometrics, current methods can be classified as either fiducial or non-fiducial. The former, describes approaches based on fiducial points found in signals such as the heartbeat waveforms and/or specific features related to complexes therein (illustrated in Fig. 1) [3, 4]. The latter, generally refers to techniques which rely on information extracted from the ECG signals without having any particular cues within the signal as a reference [5, 6]. Partially fiducial, or combination methods have also started to appear, where fiducial information is only used for ECG segmentation [7].

*work was partially funded by FCT under grant SFRH /PROTEC/49512/2009 by the ADEETC from Instituto Superior de Engenharia de Lisboa

†work was partially funded by FCT under grant SFRH/BD/65248/2009

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In this paper, we present a novel approach to ECG biometric systems, with the purpose of reducing the acquisition time and computational complexity. The proposed system is comprised by: a) *A non-intrusive acquisition setup for hand palms ECG*; b) *Real-time preprocessing of the ECG waveform using an adaptation of the Engelse-Zeelenberg algorithm [8] and the online R-peak detection by Christov [9]*; and c) *A classification architecture devised for real-time or near real-time applications*.

We evaluate Nearest Neighbor (NN) classifiers and Support Vector Machines (SVMs) in a partially fiducial framework. The rest of the paper is organized as follows: Section 2 provides an overview of the state-of-the-art on ECG based biometric systems; Section 3 describes the proposed approach; Section 4 presents the experimental setup and main results; and Section 5 outlines the main findings and overall conclusions.

2. ECG BIOMETRIC SYSTEMS

In [10], seven factors are described to assess the suitability of physical or behavioral traits for biometric applications, which are defined as: a) *Universality*; b) *Uniqueness*; c) *Permanence*; d) *Measurability*; e) *Performance*; f) *Acceptability*; and g) *Circumvention*. State-of-the-art work on ECG-based biometrics, has found ECG signals share these characteristics.

As a vital sign, the ECG or a related signal (e.g. the electrical signature of a pacemaker), can be measured in the generality of living subjects , it is easily acquirable using modern wearable techniques [11], and it has been shown to perform accurately for biometric purposes. Furthermore, two key aspects make the ECG particularly interesting as a biometric modality, namely the fact that signals are continuously available, and that they can be acquired in real-time through minimally-intrusive devices [12, 13].

These characteristics are especially appealing for real-time biometric applications, for which current modalities present limitations, mainly due to the technical constraints regarding the interaction between the subjects and the biometric reader. The generality of modern biometric techniques, such as face recognition, hand geometry, or keystroke dynamics, require direct contact or close proximity to a reader bound to a fixed physical location. Moreover, the underlying sensing principles that provide the input data, are difficult to integrate in a convenient way within a routine activity scenario.

Figure 2 depicts the typical block diagram of a biometric system adapted to the approach followed on our work. Raw data is acquired through an ECG sensor, and submitted to a preprocessing block which performs data filtering. A pattern extraction block takes the preprocessed input signals and extracts the segmented individual heartbeat waveforms. In the end, a classifier uses the extracted patterns to produce a decision.

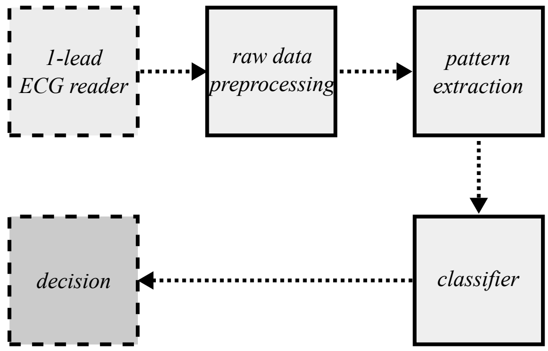


Fig. 2. Architecture of the biometric system.

3. PROPOSED APPROACH

3.1. Pre-processing

Within the scope of our work, we consider a pattern, x, to be the single heartbeat waveform data comprised between the interval $[t_R - 200; t_R + 400]ms$, t_R being the time instant of the $R-$peak reference complex (in ms), see Fig. 1.

For $R-$peak detection, we build on the work by [8] and [9], according to which the raw ECG signals, $r[n]$, are band-pass filtered to the $[1; 30]Hz$ bandwidth, passed through a differentiator Eq. (1), and the resulting signal is filtered through a low pass filter Eq. (2):

$$y_1[n] = r[n] - r[n-4], \tag{1}$$

$$y_2[n] = \sum_{i=0}^{4} c_i . y_1[n-i], \text{ where } c_i = [1, 4, 6, 4, 1] \tag{2}$$

The $R-$peaks are identified by thresholding two lobes of the differentiated version of the raw signal, for which an adaptive threshold is used over the so called complex lead signal, $y_3[n]$, obtained by averaging the absolute value of the differentiated signal, $y_2[n]$.

As adaptive threshold we chose the Steep-slope threshold (M) of [9]. M is computed using a temporal sliding window of $5s$, consisting of a buffer $MM = M_1, M_2, M_3, M_4, M_5$, obtained by the concatenation of 5 partial thresholds, M_i, determined by equation 3 in each $5s$ sliding window; M is obtained according to equation 4.

$$M_i = 0.6 \max(y_3[n]), \tag{3}$$

$$M = \begin{cases} M_i & \text{during the initial } 5s \\ \frac{1}{5}\sum_{i=1}^{5} M_i & \text{rest of acquisition} \end{cases} \tag{4}$$

The partial thresholds are continuously updated, overriding the previous threshold, left shifting the intermediate thresholds and calculating a new M_5. This new partial threshold, M_5^{new}, can become quite high, due to premature ventricular contraction, so if $M_5^{new} > 1.5M_5$, it takes the value $1.1M_5$.

Figure 3 presents an example of the segmentation of ECG signals acquired at the hands and pre-processed using this method.

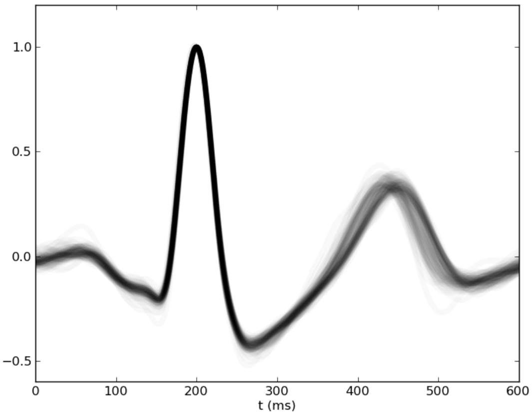


Fig. 3. Example of single heartbeat waveforms, x, after segmentation of hand palms ECG readings. The dark gray wave results of the superimposition of several single heartbeats, in light gray.

3.2. Nearest Neighbor

Classifiers based on the k-NN rule are among the simplest in terms of overall concept and implementation. For a given instance x, an estimated class prediction w_x is produced by determining the most represented class or grouping among the neighborhood of the k nearest patterns from the data set $\mathbb{D}_{NN}$ collected during the enrollment stage, according to a given distance metric, $D(,)$. We call this the training set, and denoting N as the number of classes, and n the number of training templates, it is defined as:

$$\mathbb{D}_{NN} = \{(x_i, w^{x_i}) | x_i \in \mathbb{R}^p, w^{x_i} \in 1, \cdots, N\}_{i=1}^{n}. \quad (5)$$

For experimental purposes, the 1-NN classifier was used, in which case the class w^{x_u} assigned to an unknown sample x_u is the one of the training set instance closest to x_u:

$$w^{x_u} = w^{x_k} : x_k = \arg \min_{i=1,\cdots,n} D(x_u, x_i). \quad (6)$$

In our approach, the Euclidean distance was chosen as distance metric,

$$D(x_u, x_k) = \sqrt{\sum_{i=1}^{p} (x_u(i) - x_k(i))^2}. \quad (7)$$

A distance matrix was computed, describing distances between each instance from the test set and each of the classes.

For identification purposes, the class prediction is defined as the class label of the closest pattern, Eq. (6).

For authentication, a user is accepted if the distance to its NN templates is smaller than a given threshold; the number of falsely accepted and falsely rejected patterns are determined in order to compute the False Acceptance Rate (FAR), and False Rejection Rate (FRR). From these, we compute the Equal Error Rate (EER), which is then used to assess the performance of the system.

3.3. Support Vector Machines

Support Vector Machines (SVM) are one of the most actively developed classification methodologies [14, 15], being successfully applied in many application domains. It is especially suited for high-dimensionality feature spaces.

Consider the binary classification setup with training set $\mathbb{D}_{SVM}$, composed by l instances, a subset of the complete training set, comprising only the training samples of two classes, here denoted as $w = -1$ or $w = 1$:

$$\mathbb{D}_{SVM} = \{(x_i, w^{x_i}) | x_i \in \mathbb{R}^p, w^{x_i} \in -1, 1\}_{i=1}^{n}. \quad (8)$$

SVM find the classes separating hyperplane ($v \cdot x = b$), maximizing the margin. In order to deal with the case where the hyperplane splitting introduces misclassifications, the concept of "soft" margin is used. The method introduces slack variables, ξ_i, which measure the degree of misclassification of sample x_i, weighted by the parameter C, leading to the following primal formulation:

$$\min_{w,\xi,b} \frac{1}{2}||v||^2 + C \sum_{i=1}^{n} \xi_i \quad (9)$$

$$s.t. \ \ w^{x_i}(v \cdot x - b) \geq 1 - \xi_i. \quad (10)$$

The learning process is assumed to be performed offline. Once the model is computed (v and b), the class prediction, w^{x_u}, for an unknown object, x_u, is determined by

$$w^{x_u} = sgn(v \cdot x + b). \quad (11)$$

In order to deal with the multiclass problem of classifying N subjects into $\mathbb{C} = \{1, ..N\}$ classes, we followed the dominant approach of reducing the multiclass problem (*one-versus-many*) into multiple binary classification problems (*one-versus-one*). In our approach we built $N - 1$ models for each individual, each model enables the comparison of individual j with all the other. As an example, consider the model f_{jk}, trained for individuals j and k,

$$f_{jk}(x_u) : x_u \in \mathbb{R}^p \rightarrow w_{x_{jk}} \in j, k, \quad (12)$$

it computes a decision over instance x, deciding if it is classified as individual j or k.

In authentication, the strategy consists in testing all the $N - 1$ trained models, $f_{j\cdot}$, where j is the class of the individual trying to guarantee authentication, and accepting only a situation where all the models positively classify the testing instance.

In identification, the strategy consists in the selection of the individual, for which the majority of the trained models is well classified,

$$w^{x_u} = \arg\max_{j} \sum_{k=1,k\neq j}^{N} \mathbb{I}\big(f_{jk}(x_u) = 1\big), \qquad (13)$$

where $\mathbb{I}$ is the indicator function (equal to one if its argument is a true proposition, and equal to zero if it is a false proposition).

3.4. Real Time Considerations

The proposed approach is focused on real time applications. Being based on a partially fiducial approach, it only requires the segmentation of the ECG waveform. Our approach for segmentation is based on an algorithm adapted for real time R-peak detection, as previously described in Section 3.1. Each of the proposed approaches has a different computational complexity, with respect to the classification strategy.

In the identification scenario, the 1-NN classifier requires the computation of n Euclidean distances, between the unknown sample x_u, and the n instances of the training set $\mathbb{D}_{NN}$. In authentication, it requires only the computation of k Euclidean distances between x_u, and the k training templates of a given class w_j that the subject claims to be. The computational cost of an unitary Euclidean distance is $3p$ floating point operations, Eq. (7). In the SVM classifier, the proposed architecture, requires for identification, N comparisons, between the unknown sample x_u, and the $N-1$ models, where N is the number of classes. For authentication, it requires the comparison with $N-1$ models. Each comparison is obtained with an inner product, therefore requiring $2p$ floating point operations, Eq. (11).

Table 1 summarizes the computational complexities of both approaches. For authentication, both approaches exhibit linear complexity: in the 1-NN case it is a function of the number of instances of a given class from the training set; and in the case of SVM it is a function of the number of individuals. For identification, the 1-NN approach also has linear complexity, which is a function of the total number of instances in the training set, while the SVM approach has quadratic complexity, which is a function of the total number of classes or individuals.

Both approaches seem suitable for real time computation, and the SVM method is computationally more efficient when $k \geq (N-1)\times 2/3$ or $n \geq N\times(N-1)\times 2/3$. Regarding the spatial complexity, the 1-NN approach requires the storage of the n templates from the training set, while SVM requires the storage of $N \times (N-1)$ models. Whenever $k \geq N-1$ and $j \geq N-1$, the SVM approach is spatially less demanding, while the 1-NN is otherwise more advantageous.

Table 1. Computational complexity in terms of floating point operations: k and n represents the number of training instances of class i and all training set $\mathbb{D}_{NN}$, respectively; N the number of individuals; p floating point operation.

	Authentication	**Identification**
1-NN	$k \times 3p$	$n \times 3p$
SVM	$(N-1)\times 2p$	$N \times (N-1) \times 2p$

The selection of the classification method is dependent on the application and constrains of the target device where the system will run. On a computer, both memory and computational resources are generally available in abundance, making the differences between both approaches less pronounced. A mobile device, has more limited resources, and a scenario where typically only a restricted number of subjects is recognized, in which case the SVM's are less demanding. On the other hand, on a dedicated device for access control to facilities involving a the recognition of a large number of users, the 1-NN approach could be more appropriate.

4. RESULTS AND DISCUSSION

4.1. Experimental Setup

To evaluate the proposed approach, we performed an extensive data collection in 32 subjects (25 males and 7 females), with an average age of 31.1±9.46 years. Subjects were only asked to rest their left/right hands as indicated in the device for a 5 minutes period.

A custom ECG sensor arrangement was used for signal acquisition [13], where dry Ag/AgCl electrodes are placed at the hand palms level as depicted in Figure 4. This arrangement is built as a flexible and malleable mat, allowing it to be used together with multiple input devices.

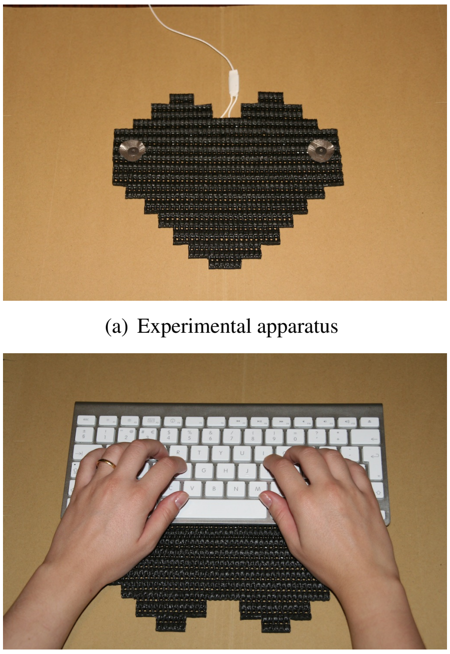
The ECG sensor has a differential operating principle, with a virtual ground, enabling the use of only two contact leads. The signal conditioning circuitry includes a preamplifier with total gain of 1000, and an analog band pass filtering between the 1-30Hz bandwidth.

For signal processing, Python was used, together with the standard modules for scientific computing, and the novel MILK [1] and LIBSVM [16] toolboxes.

4.2. Results

For experimental evaluation purposes, raw signals were processed according to the proposed approach, and 30 independent test runs were performed; each run consisted of two randomly selected exclusive datasets, where the training set contained 30% of the total collected patterns as the templates database, and a test set the remaining 70% of the patterns.

[1] `http://packages.python.org/milk/`



(a) Experimental apparatus

(b) Data acquisition

Fig. 4. Experimental setup for data acquisition.

We evaluated the authentication and identification potential of ECG signals collected at the hand palms using individual heartbeat waveforms directly, and also means of m waves. We summarize the authentication results in terms of mean equal error rate (EER), and the identification results in terms of mean identification error (Eid). For the SVM approach, in the authentication scenario, we do not calculate the EER, but instead present a fixed operation point, presenting the authentication error, false acceptance rate (FAR), and false rejection rate (FRR). This operation point is fixed by the C parameter of equation 9, which in the presented case corresponds to $C = 1$, trading off the generalization capability and the misclassification errors.

Table 2 highlights the main results. For the NN approach, if individual heartbeat waveforms are used, a mean EER of $9.39\%\pm0.19$ and a mean identification error of $17.62\%\pm0.59$ were achieved, which decreases to $2.75\%\pm0.29$ and $5.61\%\pm 0.94$ when averages of 5 heartbeat waveforms are considered as representative pattern. These correspond respectively to $1s$ and $5s$ of acquired signals approximately. For the SVM approach, the chosen operation point enables a FAR of 0% on every situation, while the FRR decreases from $51.55\% \pm 6.61$ to $13.91\% \pm 4.55$, when only an individual heartbeat waveform, or an average of 5 heartbeat waveforms are used, respectively.

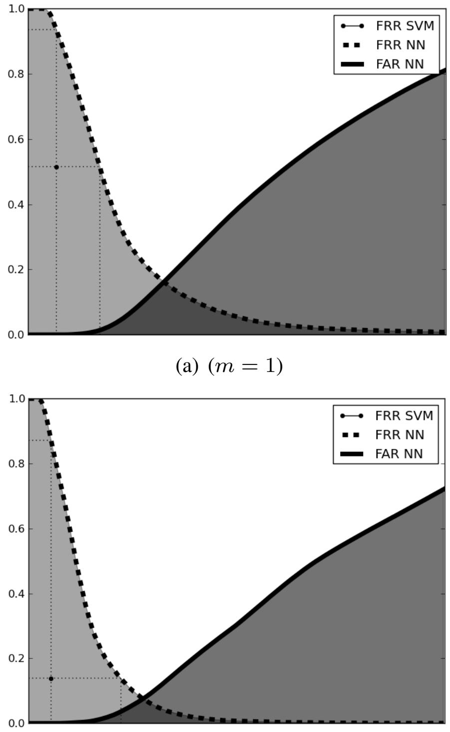
These results are within the confidence intervals of what is reported in literature for chest and finger signals, which for identification results are in the order of $\sim [5-10]\%$ respectively, and for authentication are in the order of $\sim [2-5]\%$

Table 2. Obtained results.

	1-NN		SVM		
m	EER	Eid	Err	FRR	Eid
1	$9.39\%\pm 0.19$	$17.62\%\pm 0.59$	$0.06\%\pm 0.04$	$51.55\%\pm 6.61$	$28.07\%\pm 3.88$
2	$6.05\%\pm 0.36$	$11.94\%\pm 0.96$	$0.01\%\pm 0.03$	$27.06\%\pm 6.36$	$16.57\%\pm 4.05$
3	$4.55\%\pm 0.41$	$8.71\%\pm 0.85$	$0.01\%\pm 0.03$	$19.73\%\pm 6.04$	$12.02\%\pm 2.67$
4	$3.13\%\pm 0.41$	$6.72\%\pm 0.82$	$0.00\%\pm 0.04$	$19.61\%\pm 6.76$	$10.93\%\pm 3.91$
5	$2.75\%\pm 0.29$	$5.61\%\pm 0.94$	$0.00\%\pm 0.04$	$13.91\%\pm 4.55$	$8.87\%\pm 3.35$

[12, 17, 1].

Figure 5 presents the SVM operating point over the



(a) $(m = 1)$

(b) $(m = 5)$

Fig. 5. FAR and FRR curves over different thresholds for the 1-NN classifier. The circle marker identifies the FRR value for the operating point of the SVM classifier (corresponding to FAR=0.0).

FAR/FRR curve of the 1-NN classifier. As is possible to see, the obtained FRR, for the equivalent point in the 1-NN classifier, leads to FAR values several orders of magnitude higher. Regarding the Eid it consistently leads to a higher number of misclassifications when compared with the 1-NN approach, which in the best case scenario leads to a $8.87\% \pm 3.35$, when an average of 5 heartbeat waveforms is used.

5. CONCLUSION

Biometric systems are moving towards multimodal approaches, where several modalities combined are able to overcome some of the limitations exhibited by each modality separately. Current approaches are still mostly based on physical properties of the subjects, which, despite the high accuracies, present constraints regarding the interaction with the readers, the periodicity of identity recognition, and other aspects as liveliness detection in the subject or latent templates.

Some behavioral biometrics modalities have the potential to complement existing approaches due to their intrinsic nature, and the ECG is one such case. In this paper we have presented and evaluated a novel approach to ECG-based biometric systems recurring to Support Vector Machines (SVM), and compared it to the performance of the commonly used Nearest Neighbor (NN) classifier. It led to quite interesting results for the cases where the FAR=0. We computed the computational complexity of both approaches showing their potential of application on real time operation.

Experimental results have shown that our approach enables high recognition rates, further validating ECG-based behavioral biometrics as an interesting complement to other modalities. Each method presented advantages depending on whether identification or authentication is performed, therefore contributing to further expand the set of tools that are available for the biometric system designer.

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