TOWARDS A FINGER BASED ECG BIOMETRIC SYSTEM

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Abstract: The ECG signal has been shown to contain relevant information for human identification. Even though results validate the potential of these signals, data acquisition methods and apparatus explored so far compromise user acceptability. In this paper we propose an ECG based biometric system that uses signals collected at the fingers through a minimally intrusive 1-lead ECG setup. Time domain ECG signal processing is performed, following the usual steps of filtering, peak detection, heartbeat waveform segmentation, and amplitude normalization. We introduce two additional steps of synthetic waves generation and time normalization. Through a simple one nearest neighbor classifier, results have revealed this to be a promising technique.

1 INTRODUCTION

As a biometric trait, electrocardiographic (ECG) signals have very appealing intrinsic characteristics as they provide intrinsic liveliness detection, and are strongly correlated to the subjects arousal level (Malik and Camm, 2004). Therefore, the application of ECG for biometric purposes has been studied for long, both under controlled and unrestrained scenarios (Riera et al., 2008; Shen et al., 2002).

Recent work has shown the validity of the ECG signal for human identification (Coutinho et al., 2010; Li and Narayanan, 2010; Silva et al., 2007b). While results enhance the potential of these signals, user acceptance may be limited by the data acquisition methods and apparatus. State-of-the art research has revealed that, for biometric applications, a 1-lead setup suffices; nonetheless, a chest-mounted sensor apparatus with pre-gelled electrodes is typically used (Shen and Tompkins, 2005; Silva et al., 2007a).

We propose an ECG based biometric system for human identification, that recurs to a minimally intrusive 1-lead setup for signal acquisition at the fingers. Our apparatus uses dry electrodes as interface with the skin, further improving its usability.

This work relies on time domain processing of the ECG signal. Due to the inherent heartbeat waveform variability, normalization must be performed in order to obtain invariant characteristics usable for identification. The typical steps consist of filtering, peak detection, heartbeat waveform segmentation, and amplitude normalization; our approach further improves on prior art by adding two additional steps in the final part of the process that consists of adding synthetic waves to the collected signals and performing time-normalization of the features.

The rest of the paper is organized as follows: Section 2 introduces an overview of the system; Section 3 presents the proposed signal acquisition apparatus; Section 4 details the signal processing; Section 5 shows the experimental evaluation; and finally Section 6 outlines the main results and conclusions.

2 SYSTEM OVERVIEW

The system architecture is depicted in figure 1. At the hardware level we have the 1-lead ECG sensor setup connected to the signal acquisition unit, that transmits the data through a Bluetooth wireless connection to a base station (PC).

At the base station, Matlab was used for data acquisition, processing, and storage. A specific API, BioMLab, was implemented to interface Matlab with the wireless acquisition unit, handling the low-level communication and signal acquisition tasks.

A signal processing block implements the signal

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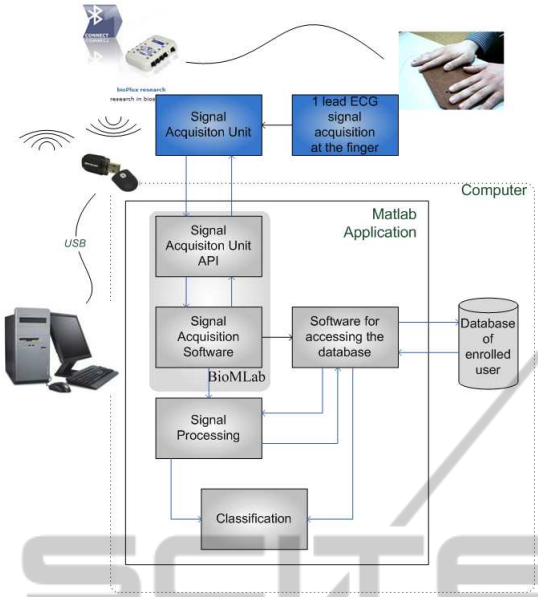
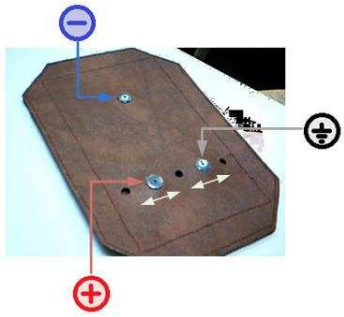
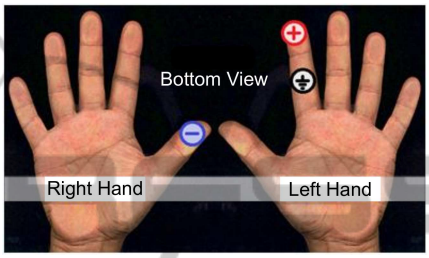


Figure 1: System Architecture.



(a) Adjustable sensor mount.



(b) Hands placement.

Figure 2: Signal acquisition setup.

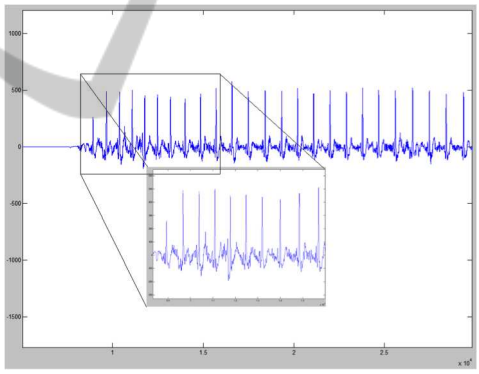


Figure 3: Sample of an ECG signal collected at the fingers.

analysis algorithms and feature extraction. Classification is performed using the features provided by the signal processing stage, and a database is used for data persistence.

A simple set of functions was implemented to handle the data storage and retrieval from the database. The database itself is based on text files containing the set of features collected from each user during the enrollment.

3 DATA ACQUISITION

3.1 Measurement Apparatus

Advances in biosignal acquisition have led to wireless, wearable and unobtrusive technologies for collecting ECG signals (Gamboa et al., 2010; Leonov, 2009; Cunha et al., 2007). Still, current systems are mostly targeted at wellness and medical applications, requiring physical contact with the subjects body at the trunk and/or legs level. Furthermore, conductive paste or pre-gelled electrodes are generally required.

We propose a method and apparatus for ECG signal acquisition, through a single lead setup at the fingers, recurring to dry electrodes. This setup intends to bring the usability of ECG based biometric systems to the level of other biometric traits, in terms of signals acquisition (Duta et al., 2002; Jain et al., 1999).

Our adjustable sensor mount and measurement apparatus prototype is depicted in Figure 2(a). A rigid base integrates three leads which, due to the underlying sensor design correspond to the ground, positive and negative poles. The right hand thumb is used as negative active pole, and the left hand index finger simultaneously as the positive electrode and ground, as illustrated in figure 2(b).

The base sensor is an ecgPLUX active ECG triode, and its specifications are listed in Table 1. The interface with the skin is done through dry AgCl electrodes without the need of any gel or conductive paste.

For signal acquisition and transmission we used a Bluetooth wireless bioPLUX research biosignal acquisition unit. Table 2 describes the main specifications of this system.

Figure 3 shows an example of the signals acquired at the fingers using the proposed setup, where the ex-

Table 1: ecgPLUX sensor specifications.

Gain	1000
Filtering	0.05-30Hz
CMRR	110dB
Input Impedance	>1MOhm

Table 2: bioPLUX research specifications.

Connectivity	Bluetooth Class II
Sampling Rate	1000Hz
Channels	8 An. + 1 Dig.
Size	84x53x18mm
Weight	86g

istence of the different complexes can be easily observed.

3.2 Heartbeat Waveform Segmentation

The first step consists of a band pass digital filtering of the signal, in the $[0.5, 30]$ Hz band using a FIR filter. Theses frequencies retain the necessary information for the proposed task while eliminating both the baseline wander and eventual high frequency noise.

The QRS detection is performed following an adaptation of the Englese and Zeelenberg algorithm (Englese and Zeelenberg, 1979), found to be one of the more robust for this purpose (Friesen et al., 1990).

The filtered ECG signal is passed through a differentiator (eq. 1), and then by the sequence of filters (eq. 2 and 3)

$$y_0[n] = x[n] - x[n-1], \quad (1)$$

$$y_1[n] = y_0[n] - y_0[n-4], \quad (2)$$

$$y_2[n] = \sum_{i=0}^{4} c_i . y_1[n-i], \text{ where } c_i = [1,4,6,4,1] \quad (3)$$

In figure 4 we illustrate $x[n]$ (in blue) and $y_2[n]$ (in red). The presence of an R spike will induce a pronounced negative lob and two positive lobs with lower amplitude in $y_2[n]$.

The R peaks detection is based on two thresholds masking the amplitude of these positive and negative lobs. Instead of using the ones proposed in (Friesen et al., 1990), we calculated thresholds through experimental analysis of the data.

The masking the "real" R spikes, is concluded by computing the RR intervals based on neighbor R spike, and using an additional verification based on knowledge of the physiological limits of these intervals (Chung, 2001). We consider as valid R spikes, the ones whose neighbor R spikes rhythm is

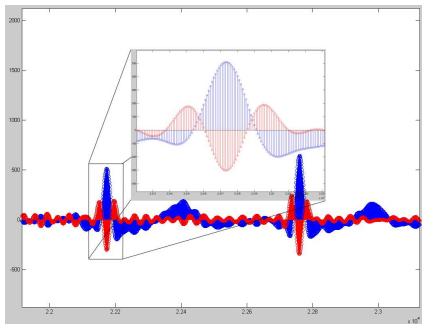


Figure 4: Peak detection using an adaptation of (Englese and Zeelenberg, 1979) algorithm.

within the interval $[minLatency, maxLatency]$, where $minLatency$ corresponds to $150BPM$ and $maxLatency$ to $30BPM$.

After the determination of the R spikes we continue with the segmentation of the ECG signal, identifying the Q and S complexes. For the identification of these complexes we continue to use $y_2[n]$.

Taking as reference the identified R spike, we analyze the $y_2[n]$ signal within its neighborhood, determining the time instants were it starts to be positive and comes down to negative again, determining the intervals $[iStartQ, iEndQ]$ and $[iStartS, iEndS]$. Within these intervals we take the minimum value of $x[n]$ as the Q and S complexes.

The final step for determining the heartbeat waveform is finding the P and T complexes. For the P complex, we look for the maximum value of $x[n]$ in the interval $[leftMostIndex, iStartQ]$, where the $leftMostIndex$ was determined as the R spike time subtracted by the typical PQR latency interval upper bound.

For the determination of the T complex we follow a similar process, finding the maximum value of $x[n]$ in the interval $[iEndS, rightMostIndex]$, where $rightMostIndex$ was determined as the R spike time plus the typical RST latency upper bound.

We consider as valid P+QRS+T complexes, sequences of signals, where: a) P and T peak values are higher than zero amplitude; and b) the P complex starts at least within 30ms before the Q complex.

4 SIGNAL PROCESSING

4.1 Time Normalization

Changes in the heart rate typically result in the time compression/expansion of the heartbeat waveform. The normalization of the segmented heartbeat signal

will ensure that the variability of the latencies of each complex is reduced. Figure 5 illustrates one example of an acquisition where the subject presented a computed heart-rate of 133 beats per minute (BPM) at the beginning the acquisition, and 70 BPM at the end, showing the expansion/compression effect on the waveform caused by different heart rate values.

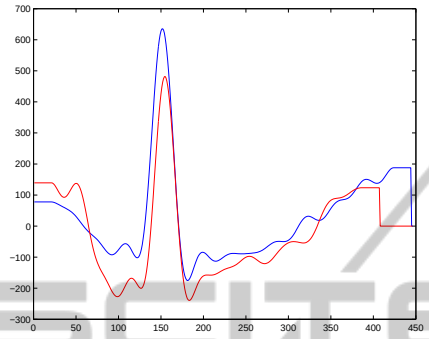


Figure 5: Hearbeat waveforms at different heart rates (133 BPM and 70 BPM).

Usually, the normalization of the segmented signals is performed decimating the signal in between a fixed window centered around the R spikes. In this work we followed a non-uniform decimation procedure which doesn't use fixed time windows, but the ECG signal fiducial points themselves. This procedure is divided in two parts: decimation of the interval between the beginning of the P complex until the R spike; decimation of the interval between the R spike and the end of the T complex.

The devised algorithm samples these intervals so that each pattern has the same number of samples independently of the expansion/compression of the heartbeat waveforms. The resulting normalized signals will all have the same number of samples and the R peak in the same time instant. In figure 6 we present an example of the time normalized signals obtained during one acquisition.

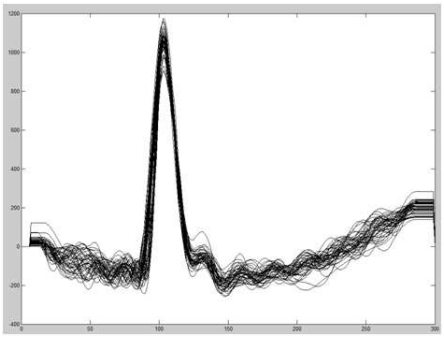


Figure 6: Example of time normalized signals.

4.2 Mean Waves vs. Synthetic Waves

In previous works (Coutinho et al., 2010; Silva et al., 2007b), in order to minimize the effect of outliers, the mean wave computed from 10 consecutive segmented heartbeat waveforms was used.

We propose an approach based on the generation of synthetic waves based on the waves already segmented. This procedure generates synthetic waves with increasing amplitudes between the envelope delimited by the amplitudes of two consecutive waves collected from the signal. Figure 7 illustrates in red synthetic waves generated between two original waves.

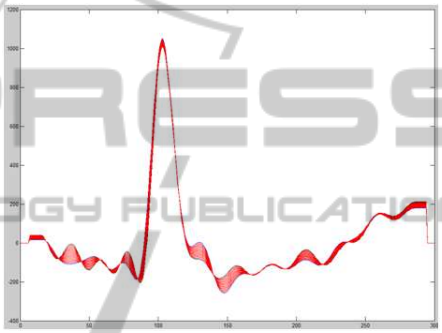


Figure 7: Synthetic wave generation.

4.3 Amplitude Normalization

The ECG signal processing is only concluded with the amplitude normalization step. We followed two different approaches. In the first approach we take the segmented time-normalized signals and normalize it to a constant amplitude. We use as normalization factor the average of the amplitude of the obtained R peaks.

In the second approach we start with the previous procedure, but followed by the addition of a constant with the value of 10% of the normalization factor. This value normalizes the intra-subject heartbeat amplitude while preserving the inter-subject amplitude differences. The percentage was empirically determined by experimentally analyzing the data.

5 EXPERIMENTAL EVALUATION

5.1 Classification

Our identification system is based on pattern matching; the individual heartbeat waveforms are extracted from the ECG signal trace, added together, and the

amplitudes from each sample of the normalized heartbeat waveforms are the features used by the classifier.

We recurred to a simple $1-$NN classifier with the Euclidean distance as a metric function. In the identification stage, the distance between the unknown pattern, X_u, and each pattern, X_i, in the database is computed, and the unknown pattern is considered to belong to the same class w_i of the pattern X_i with lower Euclidean distance.

$$\hat{w}_u = w_i : i = \underset{i}{\operatorname{argmin}} |X_u - X_i| \quad (4)$$

For the evaluation of the system we populated a database with acquisitions of 11 subjects. For each user we collected 2 minutes of ECG signal at the fingers using the proposed apparatus. The first minute was used for enrolment and the second for test.

5.2 Results

Different experiments were conducted evaluating the different possible combinations of signal processing. Due to space limitation we present only two:

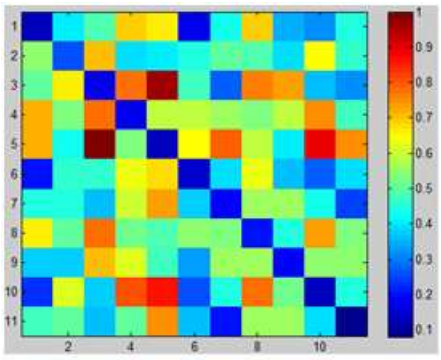
Experiment (A). Non-uniform time normalization of the segmented heartbeat; normalization in amplitude; mean wave; no synthetic waves generation; as features we consider the full wave.

Experiment (B). Non-uniform time normalization of the segmented heartbeat; normalization in amplitude; addition of synthetic waves; as features we consider the full wave.

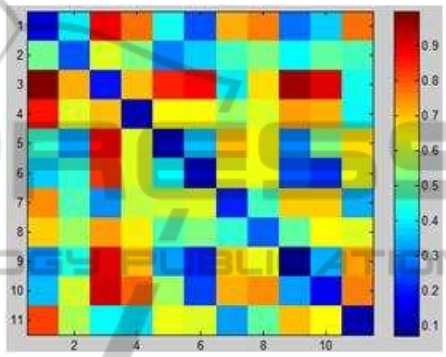
Figure 8 presents the distance matrices obtained with the proposed methodology for experiments (A) and (B). The element i, j of the matrix represents the distance from the subject i to the subject j, according to the set of features used. In the presented color scheme, blue is attributed to values close to zero, representing subjects with very similar features, and red is attributed to values close to one, representing subjects very dissimilar.

In the matrices of Figure 8 we see that there are very few entries with blue color, except in the diagonal, which represents the distance from the subject to himself. This characteristic is important in order to have a high true positive rate (TPR). The main difference from figure 8(a) to figure 8(b) is that in the later the diagonal matrix is closer to one giving better results concerning the TPR.

If we use as threshold for decision $th = 0.87$ over figure 8(a), we obtain as decision the matrix found in figure 9, corresponding to the situation of equal error rate (EER) of 9,09%, and to a true positive rate of (TPR) 90,91 %.



(a) Experiment (A).



(b) Experiment (B).

Figure 8: Distance matrix for the performed experiments.

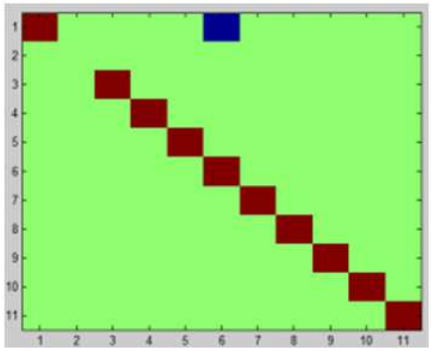


Figure 9: Decision for the experiment (A) using as threshold 0.87.

In Figure 10 we show the ROC curve for experiments (A) and (B), summarizing the performance of the proposed system.

6 CONCLUSIONS

This paper describes a methodology and apparatus for human biometric identification based on $1-$lead finger ECG signals. Our goal was to provide the building

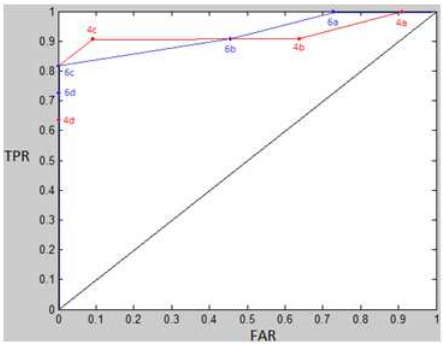


Figure 10: ROC curve.

blocks for an unintrusive real-time biometric system based on the ECG.

We have devised a measurement apparatus that only requires contact with the subject hands without the need of pre-gelled electrodes or conductive paste, providing a signal acquisition setup similar to the ones already used by other, largely accepted, biometric traits.

Experimental evaluation has shown promising results, as the proposed approach allowed us to obtain a 9.09% EER and 90.91% TPR on a group of 11 subjects, from the signals collected at the fingers.

Future work will focus on extending the subject base and experimenting alternative feature analysis and classification methods, targeting a continuous real-time system.

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