The Impact of Noise Removal on a Compression-based ECG Biometric Identification System

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Abstract

Several ECG (electrocardiographic) applications, both in the field of health, or even other subjects, like biometric identification, achieve better results when the signal is cleaned, i.e., without noise. In this paper, we have extended a method based in the *Hamming Distance*, that has proved able to find noise on an ECG signal. We study its effect in the accuracy results while performing ECG biometric identification, using a compression-based approach. We start by explaining how the method works, and then show the results on the experiments we performed, using real ECG data.

1 Introduction

ECG signals reflect an individual's cardiac electrical activity over a period of time. It has the advantage of being a unique aliveness indicator as it is difficult to be spoofed and falsified [3], which makes it desirable for biometric authentication purposes. However, this signal is prone to irregularities that are originated from several sources: pathological, psychological, noise, artifacts, among others [1, 2, 4, 5, 6, 12].

In a previous work [7], a method for finding noise has been proposed. However, it was only tested in synthetic ECG data. In this paper, we aim at extending that work, by using real data, and exploring the consequences of noise removal on a compression-based biometric identification system. The method is tested by using finite-context models (FCM) of different context depths k, as well as a mixture of FCMs.

1.1 Database

The database used in our experiments, and in previous works, was collected *in house* [4], where 25 participants were exposed to different external stimuli – *disgust*, *fear* and *neutral*. Data were collected on three different days (once per week), at the University of Aveiro, using a different stimulus per day.

The data signals were collected during 25 minutes on each day, giving a total of around 75 minutes of ECG signal per participant. Before being exposed to the stimuli, during the first 4 minutes of each data acquisition, the participants watched a movie with a beach sunset and an acoustic guitar soundtrack, and were instructed to try to relax as much as possible.

The ECG was sampled at 1000 Hz, using the MP100 system and the software AcqKnowledge (Biopac Systems, Inc.). During the preparation phase, the adhesive disposable Ag/AgCL-electrodes were fixed in the right hand, as well as in the right and left foot. We are aware that such an intrusive set-up is not desirable for a real biometric identification system. However, for testing purposes, it seems appropriate, as this approach is more reliable – produces less noise.

2 Method

2.1 R-peak detection

The development of a robust automatic *R-peak* detector is essential, but it is still a challenging task, due to irregular heart rates, various amplitude levels and *QRS* morphologies, as well as all kinds of noise and artifacts [10].

We have decided to use a *partially fiducial* method for segmenting the ECG signal and, since this was not the major focus of the work, we used a preexisting implementation to detect *R-peaks*, based on [10]. This method detects the *R-peak* by calculating the average point between the Q and S peaks (from the *QRS complex*) – this may not give the real local maximum of the *R-peak*, but it produces a very close point. Some evaluations were

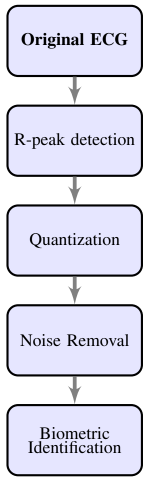

Figure 1: Overview of the different steps of the method proposed for biometric identification with noise removal.

done using *R-peak* detection performed by humans, in order to validate this step.

2.2 Quantization

We consider that the signal is already discrete in the time domain, i.e., that it is already sampled. However, we perform re-sampling using the previously detected R-peaks.

The design of the *quantizer* has a significant impact on the amount of compression obtained and loss incurred in a lossy compression scheme. We have used the widely known Symbolic Aggregate ApproXimation [11], SAX, in order to quantize the ECG values into a discrete alphabet.

There is a fundamental trade-off to take into account while performing the choice of the *alphabet size*: the quality produced versus the amount of data necessary to represent the sequence. From previous experiments, we found that using an alphabet size of 6 and 200 symbols per each R-R segment (per "heartbeat") produced good results for biometric identification. However, this result does not guarantee that the same will hold true for a different dataset or application.

2.3 Noise Removal

The idea of our proposed approach is to store all the n *words* (*SAX-words*) of an ECG on a size n array, compute the $n-1$ Hamming-distances between those consecutive n *words* and remove the *words* that correspond to an Hamming-distance greater than $\bar{x}+\delta\sigma$, were δ is a parameter of the method.

The distance i is given by the distance of the word i to the word $i+1$ (see Fig. 2) and, therefore, if it is greater than the threshold, both words i and $i+1$ are removed.

2.4 Parameter Tuning

In order to tune the parameter δ, we ran nearly 100 simulations, changing the parameter from 0.5 up to 3. Since the purpose of this experiment was only to tune the parameter, and not to obtain an optimal biometric identification accuracy, we used an extended-alphabet FCM based compressor (xaFCM) [9].

Because of this result, whenever we use "noise removal" on the results section, a value of $\delta = 1.1$ was used.

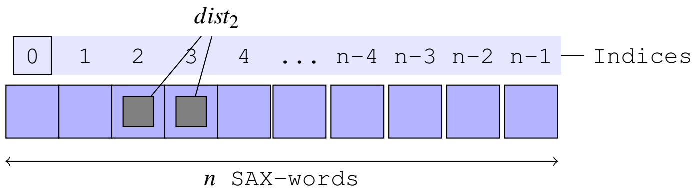

Figure 2: Array representation of SAX-words used to calculate Hamming-distances.

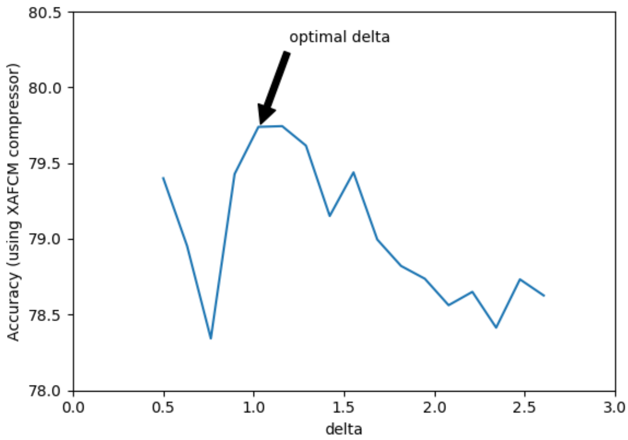

Figure 3: Parameter δ tuning.

3 Results

In order to simulate a real biometric identification system, whenever we test the system, we only use the other two days as reference (training). All tests were performed by using only 10 heartbeats as target (test).

From the results shown in Table 1, it is possible to notice that the noise removal slightly enhances biometric identification when using a single context FCM, specially when that context k is low ($k = 10$ or $k = 13$). For high order FCMs, the noise removal does not seem to have much impact ($k = 20$) and, when using a mixture of FCMs, it even seems to be counter productive – which makes us think that these type of models are highly robust to noise, being able to capture some useful information, even when great amounts of noise are present.

4 Conclusions and Future Work

In order to improve ECG biometric identification, we plan on improving the compression of the ECG, by enhancing the mixture of FCMs to a "smart" one – this is possible to do by using a machine learning algorithm, like neural networks, on top of the compressors. We expect to do this in the near future and publish the results.

Table 1: Biometric identification accuracy using different sizes of finite-context models, with noise removal (NR) and without removal (WR). The Mixture used the contexts $k = 2, 4, 8, 12, 16, 20$ with $\alpha = 1, 1, 0.5, 0.1, 0.1, 0.001$, respectively, with a forgetting factor $= 0.99$.

	Day for Target		
FCM context(s)	Day 1	Day 2	Day 3
$k = 10$ (WR)	77.94%	78.78%	78.22%
$k = 10$ (NR)	79.32%	80.31%	77.60%
$k = 13$ (WR)	79.697%	82.320%	79.102%
$k = 13$ (NR)	80.678%	82.720%	79.364%
$k = 16$ (WR)	79.93%	84.33%	80.76%
$k = 16$ (NR)	80.60%	83.73%	81.87%
$k = 20$ (WR)	79.36%	84.61%	81.79%
$k = 20$ (NR)	80.08%	84.36%	82.11%
Mixture (WR)	82.45%	84.98%	83.13%
Mixture (NR)	83.36%	84.93%	81.96%

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