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Autenticação Multibiométrica utilizando ECG

Multimbiometric Authentication using ECG

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Resumo

Este artigo apresenta uma proposta para um sistema de autenticação multibiométrico utilizando sinais de Eletrocardiograma (ECG). São apresentadas as definições básicas da utilização do ECG como identificador biométrico assim como alguns sistemas propostos na literatura. A base de dados HiMotion, Gamboa et al. (2014), é utilizada para a realização dos experimentos utilizando métodos fiduciais e não-fiduciais, ainda consideram-se toda a base de dados e amostragens com um corte em 6 minutos. Os resultados obtidos mostram que o xxxxxxxxxx(EER) reduz de 0.70% para 0.36% ao utilizar toda a base de dados com o método fiducial. A acurácia aumenta, quando utilizado o método não-fiducial, de 60.49% para 95.28%.

Palavras-chave: Sinais ECG; biometria; HiMotion; multibiometria.

Abstract

In this paper, we present a proposal for a multi-biometric authentication system using ECG signals. This paper presents basic definitions on the ECG usage as a biometric identifier as some proposed systems in the reviewed literature. The HiMotion dataset, Gamboa et al. (2014), is used to perform the evaluation using fiducial and non-fiducial approaches considering all the sample and the dataset with a 6 min cut. The obtained results show that the EER reduces from 0.70% to 0.36% using the whole dataset using the fiducial approach. The accuracy increases using the non-fiducial approach from 60.49% to 95.28%.

Key-words: ECG signals; biometrics; HiMotion; multi-biometric.

1. Introduction

Security has been growing over the last years. Discussions about how to improve this systems point to several topics (BOUMBAROV et al. 2009). One of these topics is Biometric Systems, which are systems that identify persons using his/her physiological and/or behavioural characteristics such as fingerprints, retinal patterns, facial images, ECG. These traits must satisfy some requirements like universality, distinctiveness, permanence, collectability, and also other issues like performance, acceptability, and circumvention must be considered (HEGDE et al. 2011).

Internal body characteristics, such as ECG, have attracted attention among authentication systems researches. The ECG is a representation of the graphical electrical activity of the heart and is believed to be distinctive among individuals and stable for an extended time SAFIE et al. (2011).

Improve the accuracy of biometrics systems using ECG is challenge. Several authors like Agrafioti (2011), Agrafioti et al. (2012), Boumbarov et al. (2009), Canento et al. (2013), Carreiras et al. (2013), Coutinho et al. (2013) have been working to achieve this goal.

Our work takes Coutinho et al. (2013) as a foundation focusing on the potential of personal authentication using a diminished number of heartbeat waveforms. It uses fiducial, and non-fiducial methods, it also evaluates the recognition rate of an average heartbeat waveform in terms of discriminative authentication potential.

This paper is structured as follows: Section 2 presents an overview about (ECG) as biometric traits, in Section 3 we show how the methods used in our work, Section 4 presents the results obtained, and Section 5 bring our conclusions.

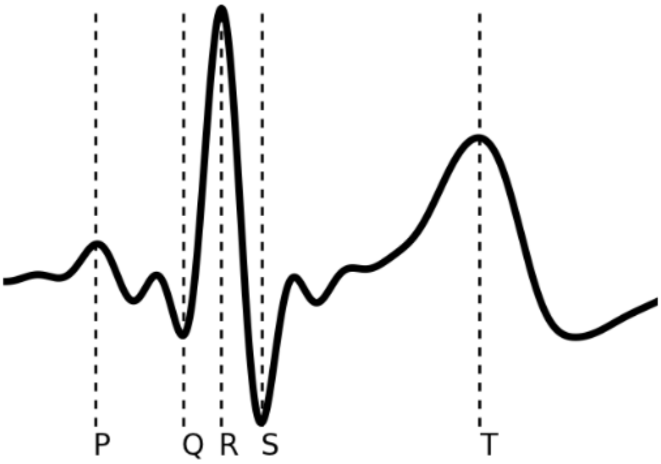
2. ECG

The main challenge of implementing ECG is that it is very time-dependent. It is challenging to obtain always the same ECG characteristic even from the same user. This variation comes, mostly, from the effect of heart rate variability and electrode placement (SAFIE et al. 2011).

The ECG signal is directly related to the physiology of each person. Some factors such as skin conductance, body mass, congenital disorders, genetic singularities, position, shape and size of the heart and chest cavity can make this information vary among individuals. Irrespective of what factors originate these differences, there are subject-specific physiological features in the ECG signal that suggests its applicability to the context of biometric systems (COUTINHO et al. 2013).

There are two types of ECG based biometrics methods concerning feature extraction: fiducial and non-fiducial methods. Fiducial methods try to correctly extract information from the ECG to detect each of the heartbeats. Their points of interest in a single heartbeat waveform, such as local maxima or minima; are used as a reference to allow the definition of several features like time and amplitude (CANENTO et al. 2013). Complementing, Gao et al. (2011), states that fiducial points of interest on a heartbeat, such as the onsets and offsets of P and T waves, or the QRS complex. These points represent the sequential depolarization and repolarization of the cardiac muscle (AGRAFIOTI et al. 2012).

Figure 1 – ECG heart beat example with points of interest. from Canento et al. (2013)



Source: Canento et al. (2013)

The non-fiducial methods extract discriminative information without the help of reference points in the ECG waveform as shows Figure 1. A global pattern from heartbeat waveforms is usable as a feature (CANENTO et al. (2013).

3. Methodology

This section describes the process taken to obtain the data, to treat it, and how we proceed with our evaluation strategy.

3. 1 Data Sources

Our data sources come from HiMotion[1] dataset, which took the ECG from 26 healthy volunteers performing activities at the computer, without posture or motion limitations simulating a regular computer usage scenario.

As the data acquisition had no time limitations to complete the proposed task, and therefore, the heartbeat waveform collection of each subject vary in time over all the subjects. So we took the dataset truncated at ~6 min, which corresponds to the fastest completion time of the proposed task, and also without any time limitation.

[1] HiMotion is a research project designed to create a multimodal database and tools to study human behavior, cognition, and emotion. In the context of computer-based tasks, it aims to elicit cognitive load and specialized affective responses. The database includes both human-computer interaction (HCI) and psychophysiological data, collected through an experimental setup devised for a synchronized recording of the keyboard, mouse, and central/ peripheral nervous system measurements (GAMBOA et al., 2014).

An algorithm separated these two sets, randomly to each subject, in two portions: test data and train data, respectively, with 70% and 30% of the total dataset size of each subject.

```
for key in testData:
np.savetxt(base_dir+'/TesteBioINESC/files/'+subDir+'/'+'%d_testData'  key +
subDir+'.txt', testData[key], fmt='%.18e')
for key in trainData:
np.savetxt(base_dir+'/TesteBioINESC/files/'+subDir+'/'+'%d_trainData'  key +
subDir+'.txt', trainData[key], fmt='%.18e'
```

3. 2 Evaluation Strategies

As described in the previous subsection, we worked with HiMotion dataset in two versions (all collected data, and with ~6min cut). Our evaluation of this dataset uses fiducial and non-fiducial methods.

We submitted these two versions of the dataset to our algorithm using 1-NN classifier and fiducial method. The implemented algorithm uses BiometricsPyKit. We tested each dataset version in five runs with a random selection of test and train data. At the end of each test, we saved two subsets of the version under test in a test data and train data files. These files had respectively 70% and 30% of the total dataset size of each subject.

The resultant files were used to make the quantisation of the values; we encoded with a quantiser associated with the subject the selected heartbeat waveforms. After this, we applied the cross-parsing algorithm. The non-fiducial method was evaluated running both versions datasets. The quantisation and cross-parsing functions used was implemented by Coutinho et al. (2013) in Matlab. Our algorithm tests, for each subject in the dataset, the authentication process using these functions and the obtained results are stored. The cross-parsing function was applied to compare test data and train data files of the same subject and comparing different subjects.

All results obtained, fiducial and non-fiducial, were stored in text files to further analysis.

4. Results

This section presents the results obtained after applying our evaluation strategy.

4.1 Fiducial Results

The performance evaluation of the proposed fiducial approach for the HiMotion database with 6 minutes cut produced an average equal error rate (EER) of 0.70% with a standard deviation (std) of 0.05%, and an average accuracy (Acc) of 85.27% with an std of 16.57% with results obtained in approximately 8 minutes.

The performance evaluation of the proposed fiducial approach for the HiMotion database without cut produced an average EER of 0.36% with an std of 0.13%, and an average Acc of 61.45% with an std of 35.22% with results obtained in approximately 6 hours and 17 minutes, as shown in Table 1.

Table 1 – EER of datasets with and without cut at 6 minutes

DB Version	Subjects	Approach	EER	STD
With Cut	26	Fiducial	0.70%	0.05%
Without Cut	26	Fiducial	0.36%	0.13%

Source: The authors

4.2 Non-Fiducial Results

The performance evaluation of the proposed non-fiducial approach for the HiMotion database with a cut in the 6th minute produced an average Acc of 60.49% with an std of 11.36%.

The performance evaluation of the proposed non-fiducial approach for the HiMotion database without cut produced an average Acc of 95.28% and std of 3.59%. Table 2 shows the results with and without the cut.

Table 2 – EER of datasets with and without cut at 6 minutes

DB Version	Subjects	Approach	Accuracy	STD
With Cut	26	Fiducial	85.27%	16.57%
With Cut	26	Non-Fiducial	60.49%	11.36%
Without Cut	26	Fiducial	61.45%	35.22%
Without Cut	26	Non-Fiducial	95.28%	3.59%

Source: The authors

5. Conclusions

This paper evaluated two biometric techniques based on the electrical activity of the heart (ECG). Taking a practical perspective and considering an unconstrained acquired data scenario to authenticate a human subject accurately. Our results showed that taking this approach to data treatment could improve system performance significantly. The results obtained show that the EER reduces from 0.70% achieved by Gamboa et al. (2014) to 0.36% using the whole dataset using the fiducial approach. The accuracy increases using the non-fiducial approach from 60.49%, result from Gamboa et al. (2014) to 95.28%.

Finding a tradeoff on the process of evaluating biometric data is a complicated duty. On the one hand, evaluating a bigger dataset can improve the accuracy and reduce the EER; on the other hand, it can reduce the system performance.

Future work regarding the fiducial and non-fiducial approaches could include a majority voting strategy to verify how it would impact the overall system accuracy. It could also be evaluated the limit to cut, other than in the 6th minute, the sampling of the dataset to have a better system performance.

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