Biometric Identification of Individuals based on the ECG. Which Conditions?

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Abstract

Biometric systems have for objective to perform identification, or identity verification, of individuals. Human ECG has been recently proposed as an additional tool for biometric applications. However, most of the existing studies are set in supine rest and only consider the QRS morphology after, most of the time, feature extraction from the ECG. This paper is focused on identification based on pattern recognition by comparing ECG shapes. Experiments were conducted on a database containing 11 healthy subjects, recorded in three different experimental conditions (supine rest, standing, exercise) and repeated up to four times, over 16 months. We calculate the correlation coefficient between a shape coming from an unknown individual and all the shapes of the database. We also evaluate the influence of the recording condition, the shape length and the number of leads. Best results (100% of good identification in the first rank) are obtained using the whole enrolment database, 12 leads and a shape length of 500 ms.

1. Introduction

Biometric systems have for objective to perform identification, or identity verification, of individuals. They rely on the hypothesis that there are more similarities between two recordings coming from a same individual than from two different.

Human ECG has been proposed as an additional tool for biometric applications by [1] in 2001. Then, a set of ECG-based biometric studies has occurred in the literature [2–8]. Most of them propose systems based on the extraction of a set of temporal and amplitude features from the ECG [1–3, 6–8]. Such approaches require the detection of fiducial points, which is generally a difficult task. To bypass fiducial detection, other approaches perform pattern recognition by comparing shapes of windowed ECG traces [4, 5].

All these studies are difficult to compare because they use various conditions: the number of ECG leads, the length of the window (only the QRS or more), the delays between recordings... Nevertheless, all these works have a common point, since they analyze the stability of ECG in rest conditions (supine or sitting rest). Only one recent work investigates the body position by comparing parameters obtained in supine rest and standing positions [6].

A biometric application is based on three steps: i) the enrolment, where biometric information from an individual is stored, ii) the connection steps, where an individual tries to connect to a system and biometric information is detected and compared with the information stored at the time of enrolment and iii) the decision step. Then, two contexts exist, the identity verification and the identification. In the context of identity verification [4, 8], an identity is first announced by the subject, his signal is compared to signals owning to him (one-to-one comparison) and the decision consists in accepting or rejecting the claimed identity. In the context of identification [1, 5, 7], the signal is compared to a biometric database (one-to-many comparison) and the first neighbour (or first rank identity) provides the identity of the subject.

In CinC'09 [9], we proposed a study based on pattern recognition by comparing ECG shapes, in the identity verification context. This paper is the continuation of this precedent work and is focused on identification. The objective is to evaluate the robustness of identification systems based on ECG recordings in several experimental conditions: supine rest, standing and exercise. For this purpose, we calculate the correlation coefficient between a shape coming from an unknown individual and the shapes of the database. Firstly, identification rates (percentage of good identification in the first rank) are computed as a function of the shape length (from the QRS complex to the whole beat), using 12-lead ECG, but also considering different ways to construct the enrolment database. Secondly, identification rate is evaluated as a function of the number of ECG leads for different interval lengths.

2. Protocol and methodology

2.1. Protocol and database

Protocol and database have been already reported in [9]. For this present study, we only kept subjects recorded at least two times. For each of the 11 subjects, 12-lead ECG have been recorded at the sample frequency of 1000 Hz and the protocol consisted in the following steps:

- 5 minutes supine rest (not recorded)
- 3 minutes supine rest (R)
- 3 minutes standing (S)
- 3 minutes exercise (bicycle effort) (E)

This protocol was repeated at 4 different dates: first date (reference date), 2 weeks after the first, 1 month after the second, and 15 months after the third. For each subject, the number of dates is varying in function of his availabilities, and goes from 2 to 4. The number of ECG recordings per subject varies from 6 (recorded two times) to 12 (recorded 4 times). The total number of records is equal to 93.

2.2. Shape extraction

Each ECG is then processed as depicted in Figure 1. A low-pass filter is applied to each channel with a cut-off frequency at 45 Hz. Then a beat detection procedure determines the R-peak position [10]. In order to perform the

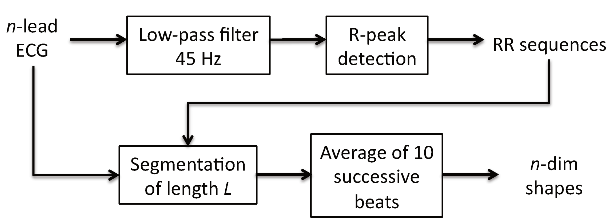

Figure 1. Shape extraction for each ECG lead.

pattern recognition task, for each record, a shape is extracted. It is based on the averaging of 10 successive beats, chosen in the second minute of the record, excluding preliminary ventricular contraction and noisy heart beats. The length L of the shapes is a varying parameter since different temporal supports have to be tested, from the QRS complex ($L = 100$ *ie* 0.1 s) to the whole beat P-QRS-T ($L = 1000$ *ie* 1 s).

Figure 2 shows the shapes extracted for three different subjects (lead DII), with $L = 1000$. For each subject, 4 records per condition are available and superimposed. We observe first that only low modifications are involved on the shape morphology from date to date in the same condition, for a given subject. However, in exercise condition, we observe that the signal contains, not only the P-QRS-T segment, but also the end of the precedent beat and the

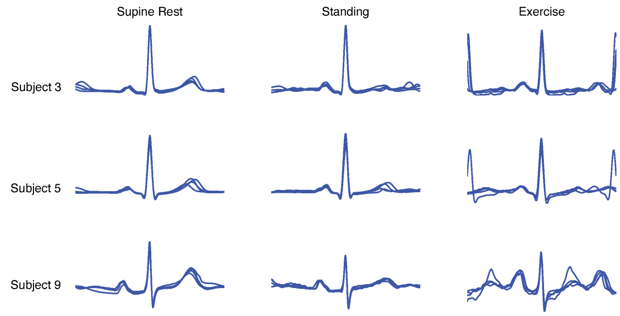

Figure 2. Extracted shapes obtained for three different subjects (lead DII). For each condition (supine rest, standing and exercise), shapes issued from four different dates are superimposed.

beginning of the following beat, due to heart rate acceleration. We can also verify the influence of the autonomic nervous system that modifies T wave position and length during exercise [11]. We also notice the presence of noise, particularly on the baseline.

By comparing signals of the three subjects, we observe that subject 5 has an ECG clearly different for the two others, contrary to subjects 3 and 5, who have much more similar ECG. These examples clearly exhibit why the identification task may be sometimes difficult.

2.3. Identification process

The objective is to calculate identification rates, in different contexts. For this purpose, each shape of the database will be successively extracted and compared to the rest of the database using the correlation coefficient (CC). The nearest neighbour, or the shape leading to the higher CC, will provide the identity of the tested individual.

For this purpose, a correlation coefficient is calculated between n-dim shapes, $n = 1, \cdots, 12$, providing a vector $R = [r(1), r(2), ... r(n)]$. If $n > 1$, the final correlation coefficient is the average of the vector R.

Different strategies will be adopted for the comparison of the shapes:

- The ”Intra-condition” case: the tested shape is compared to a database containing only shapes recorded in the same condition. As an example, if the tested shape has been recorded in standing condition (S), the enrolment database is only composed of shapes recorded in the standing condition (S). This case is denoted S - S.
- The ”Inter-conditions” case: the tested shape is compared to a database containing only shapes recorded in a different condition. If the tested shape has been recorded in standing condition, two cases will be considered: i) the case where the enrolment database is only composed of shapes recorded in supine rest (case S - R), and ii) the case

where the enrolment database is only composed of shapes recorded in exercise (case S - E).

- The "All-conditions" case: the enrolment database contains all the available shapes, *ie* at least one recording of the same subject, in each of three recording conditions.

Performances are evaluated by computing the percentage of good identification, also called the identification rate (IR).

3. Results

3.1. Results with 12 leads

In this section, performances are evaluated using 12 leads and are presented as a function of the interval length L, from $L = 100$ to $L = 1000$.

Figure 3 shows the IR calculated in the three "Intra-condition" cases in order to verify if it is possible to perform identification in other conditions than in supine rest. We first observe that for the three "Intra-conditions" cases

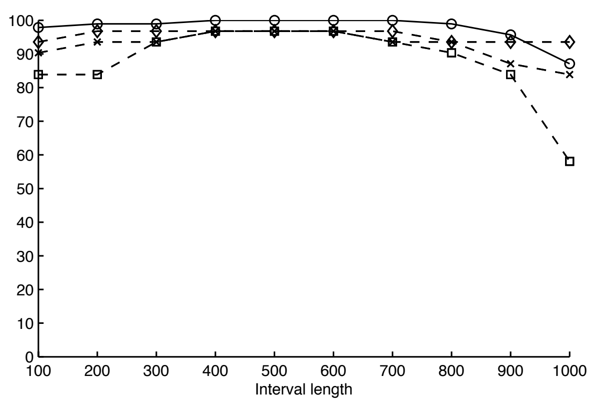

Figure 3. IR (%) calculated in the three "Intra-condition" cases: R - R (×), S - S (◇) and E - E (□), and in the "All-conditions" case (o).

(dashed-lines), performances are close and high, up to $L = 900$. Even slightly higher values of IR are obtained with the standing condition. Moreover, the optimal value of L is located between 400 and 600 and outside from these values, IR is slowly decreasing for cases R - R and S - S. In the case E - E, values of IR are the lowest and are breaking down when $L = 1000$.

Figure 4 shows the IR calculated in the three "Inter-conditions" cases in order to evaluate the loss of performance. Cases R - S and S - R have been merged in case R - S because results were close (and similarly for the two others R - E and S - E) . In this configuration, values of IR are globally decreasing when L is increasing. It is worth noticing that this decreasing is only small, between rest and standing whatever L, and between standing and exercise up to $L = 800$. However, between rest and exercise, performances are really decreasing as soon as $L \geq 600$.

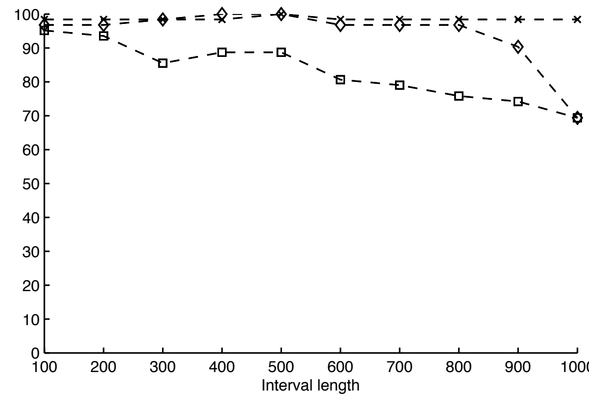

Figure 4. IR (%) calculated in the three "Inter-conditions" cases: R - S (×), S - E (◇) and R - E (□).

These results are important since they suggest that there is no requirement or advantage to limit ECG-based biometric systems to the rest conditions, as it is classically done. Indeed, high values of IR may be also obtained when comparing ECG shapes recorded in standing condition or in exercise.

They also show that good results may be obtained if the tested shape has been recorded in a condition that is not present in the enrolment database, under constraints on the interval length and avoiding the case R - E.

Finally, highest performances are obtained in the "All-conditions" case (cf. Figure 3), *ie* where the enrolment database contains the three recorded conditions, with up to 100% of good identification for several values of L. It suggests that an optimal system would consist in recording, for each individual in the enrolment database, several conditions. If it is not possible, the results obtained in both "Intra-" and "Inter-conditions" cases show that the standing position may be preferable for the testing conditions, since it is similar to the two others and allow to avoid the most difficult case R - E.

3.2. Influence of the number of leads

Because of the practical difficulty to collect 12-lead ECG, biometric systems have been evaluated with a reduced number of leads (one lead in [1–3,7,8], three leads in [4,7]). We propose here to evaluate the loss of performance if the number of leads is reduced. We performed simulations with different values of the number of leads ($n = 1, 3, 6, 12$) and the interval length ($L = 100, 500, 1000$). Results (mean ± standard deviation) are summarized in Table 1.

Results shows that performances always increase with the number of leads (higher mean and lower standard de-

Table 1. IR (%) as a function of the number of leads ($n = 1, 3, 6, 12$) and the interval length ($L = 100, 500, 1000$).

	n	All	Intra R - R	Intra S - S	Intra E - E	Inter R - S	Inter S - E	Inter R - E
$L = 100$	1	89.8 ± 3.9	75.8 ± 13.1	75.0 ± 8.1	75.5 ± 10.4	80.9 ± 7.6	75.0 ± 8.2	80.6 ± 5.3
	3	97.4 ± 2.3	86.3 ± 6.4	84.8 ± 5.0	85.0 ± 6.2	92.5 ± 4.5	93.4 ± 6.6	91.4 ± 5.4
	6	98.6 ± 1.4	89.1 ± 3.5	90.2 ± 2.3	86.9 ± 5.0	97.0 ± 2.6	97.0 ± 3.0	92.6 ± 5.1
	12	97.8	90.3	93.5	83.9	98.4	96.8	95.2
$L = 500$	1	91.4 ± 4.3	81.2 ± 11.4	76.1 ± 4.5	81.5 ± 9.2	83.1 ± 5.6	80.1 ± 7.5	57.8 ± 9.5
	3	98.2 ± 2.1	91.2 ± 4.6	90.7 ± 4.1	92.4 ± 4.7	94.0 ± 4.5	93.0 ± 5.5	76.0 ± 10.9
	6	99.4 ± 0.8	94.5 ± 3.4	95.0 ± 2.5	95.9 ± 3.3	97.6 ± 2.8	96.3 ± 3.5	83.6 ± 8.6
	12	100	96.8	96.8	96.8	100	100	88.7
$L = 1000$	1	68.4 ± 6.5	67.5 ± 10.8	65.6 ± 11.1	51.6 ± 5.4	68.4 ± 9.1	43.5 ± 6.2	41.5 ± 6.7
	3	82.3 ± 4.6	82.1 ± 7.2	82.7 ± 8.2	56.8 ± 2.3	84.9 ± 7.0	60.4 ± 8.5	57.6 ± 7.6
	6	85.9 ± 2.2	86.2 ± 2.9	89.0 ± 5.3	57.7 ± 1.0	93.1 ± 4.7	67.1 ± 6.5	64.3 ± 5.8
	12	87.1	83.9	93.5	58.1	98.4	69.4	69.4

viation). The best results are obtained with 12 leads, but there are only small differences between six and 12 leads and the gap between one and three leads is most of the time important. These results are verified for the three ”All-”, ”Intra-” and ”Inter-Conditions” cases, and whatever the interval length.

4. Conclusion

We proposed to evaluate the robustness of identification systems based on ECG. We showed, in the ”Intra-Condition” case, that there is no reason to limit them in supine rest as it is classically done, with even higher results obtained in the standing condition. The highest results were obtained with an enrolment database containing all the conditions, but if only one condition is recordable, ”Inter-Conditions” results suggest choosing the standing condition. The optimal interval length has been also studied. It is comprised into the interval [0.4, 0.6] ms in the ”Intra-condition” case. In the ”Inter-conditions” cases, L must be chosen depending on the case.

Finally, performances are highly correlated with the number of leads, and decrease abruptly when only one lead is used, which demonstrates that effort may be still done to obtain an efficient single lead system.

Acknowledgements

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