Stability Analysis of the 12-Lead ECG Morphology in Different Physiological Conditions Of Interest for Biometric Applications

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Abstract

The objective of this paper is to evaluate the robustness of biometric approaches based on human ECG signals. Two questions are addressed: is it required to record the ECG in supine rest as it is classically performed? Is it necessary to compare only shapes recorded in the same condition? A 12-lead ECG, from 14 normal subjects, in three experimental conditions (supine rest, standing and exercise), has been recorded. An analysis based on the computation of the Discrimination Coefficient (DC) between intra- and inter-subjects shows that comparing shapes recorded in the same condition leads to similar values of DC for the three conditions, provided that the interval length is lower than 800 ms. Merging the conditions leads to values of DC always greater than 1 provided that the interval length is lower than 600 ms. A clustering approach, based on correspondence analysis and hierarchical ascending classification, shows that, when merging the conditions, the ECG of a subject are in the same cluster in 94% of the cases.

1. Introduction

Biometric systems have for objective to perform identification of individuals using their physical and physiological characteristics. The most popular biometric systems are based on fingerprint, iris-scan or also voice and are already present in real-word applications. However, other biometrical approaches are still in investigation. Human electrocardiogram (ECG) has been recently reported as an additional tool for biometric applications [1]. The physiological and geometrical differences of the heart in different individuals display certain uniqueness in the ECG [2]. Furthermore, its major benefit, compared to other biometric modalities, leads in the fact that it is difficult to be falsified [3].

A set of studies concerning biometry based on ECG signals has been proposed in the literature. Most of them have for objective to propose systems based on the extraction of a set of temporal and amplitude features from the ECG [4, 5]. Such approaches require the detection of fiducial points, which is generally difficult. In order to overcome such difficulties, recent approaches perform pattern recognition by comparing shapes [3, 6]. As an example, in [6], three ECG leads are selected, and a distance between QRS beats is computed. All these biometric works hypothesize the stability of ECG in supine rest conditions. Only one recent work investigates the body position by comparing parameters obtained in supine rest and standing positions [7].

The objective of this paper is not to propose a new biometric system but to evaluate the robustness of biometric approaches based on ECG recordings in several experimental conditions. For this purpose, the methodology is based on shape comparison using the correlation coefficient. The stability of the ECG is evaluated over a 12-lead ECG and during three different conditions: supine rest, standing and exercise. In addition, different temporal supports are tested, from the QRS complex to the whole beat (P-QRS-T). Intra-subject case is compared to the inter-subject case and the quality of the separation is evaluated with the Discrimination Coefficient (DC) [8]. As complementary test, a clustering approach, based on correspondence analysis and hierarchical ascending classification [9, 10] has been carried out.

2. Protocol and methodology

2.1. Protocol and database

Fourteen healthy subjects have been included in the database. For each of them, the recording of a 12-lead ECG has been performed using an ECG device (Cardionics, Belgium) at the frequency of 1000 Hz. The protocol consisted in the following steps:

- 5 minutes rest (not recorded)

- 3 minutes rest
- 3 minutes standing
- 3 minutes exercise (bicycle effort)

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 disponibilities, and goes from 1 to 4. The number of ECG recordings per subject varies from 3 (recorded one time) to 12 (recorded 4 times). The number of ECG recordings in supine rest, standing and in exercise is equal to 35, 35 and 36 respectively. The total number of records is equal to 106.

2.2. Shape extraction

Each record is processed as follows (Figure 1). As preprocessing, 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 [11]. In order to perform the 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).

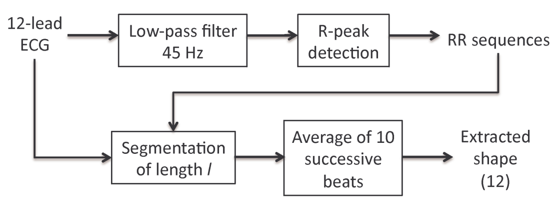

Figure 1. A shape is extracted for each ECG lead.

Figure 2 shows the shapes obtained for subject 4, over two different leads (DI and avR), with $L = 1000$. For this subject, 4 records per condition are available and superimposed. Depending on the chosen ECG lead, the electrical wave front propagation induces different types of shapes on the ECG (polarity, magnitudes). In addition, it seems that only low modifications are involved on the shape morphology from date to date in the same condition. However, we observe on the shapes obtained in exercise the presence of noise, particularly on the baseline. Furthermore, in exercise condition, we observe that when $L = 1000$, the signal contains not only the P-QRS-T segment but also the end of the precedent beat and the 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.

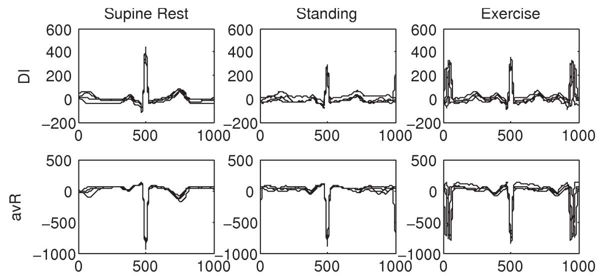

Figure 2. Extracted shapes in the example of subject 4. For each condition (supine rest, standing and exercise) 4 records have been performed and then superimposed.

A time-shift correction is applied between pairs of 12D-shapes. For this purpose, a cross-correlation is calculated between the 12 pairs of shapes in a window of length 50 ms. The delay that is kept is the value that occurs most of the time. If several values are concurrent, we keep the smallest. If all the 12 values are different the delay is put to 0.

2.3. The discrimination coefficient

The objective of this analysis is to compare pairs of ECG shapes issued from either the same subject (hypothesis H_0) either two different subjects (hypothesis H_1). The correlation coefficient is used as comparison metric, applied over the 12 leads of the ECG, providing a vector $R = [r(1), r(2), \dots\ r(12)]$, and the final correlation coefficient (or score) is the average of the vector R.

In order to quantify the separation between both hypothesis H_0 and H_1, we use the discrimination coefficient (DC) proposed by Alexander et al. in [8] and defined as:

$$DC = \frac{\mu_{H_0} - \mu_{H_1}}{\sigma_{H_0} + \sigma_{H_1}} \tag{1}$$

where μ_{H_0} is the mean of the scores when H_0 is true, μ_{H_1} is the mean of the scores when H_1 is true, σ_{H_0} is the standard deviation of the scores if H_0 is true and μ_{H_1} is the standard deviation of the scores if H_1 is true. A DC equal to 1 or below corresponds to a system with poor discrimination, if DC is between 1 and 2 the discrimination is moderate to good. Values of DC up to 2 imply very good discrimination.

3. Results

In this section, results are presented in function of the interval length L, from $L = 100$ to $L = 1000$. Two different cases are studied:

- the intra-condition case: pairs of shapes have been recorded necessarily in the same condition;

• and the inter-conditions case: pairs of shapes have been recorded necessarily in two different conditions.

3.1. Intra-condition case

Figure 3 shows the intra- and inter-subjects mean correlation coefficient for different interval lengths (from 100 to 1000 samples) in the three conditions (rest, standing and exercise), considered separately, i.e. only signals recorded in the same condition are compared. Results are averaged over all the possible combinations and provide three curves for the intra-subject case and three others for the inter-subjects case.

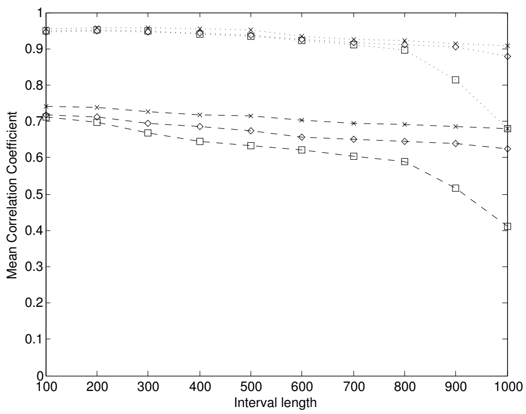

Figure 3. Intra- ($\cdots$) and inter- (- -) subjects mean correlation coefficient calculated in rest ($\times$), standing ($\diamond$) and in exercise ($\square$) for different interval lengths.

Regarding the intra-subject correlation coefficients, results presented on Figure 3 show that up to $L = 800$ intra-patient correlation coefficient is high (above 0.95), quasi-equal for the three conditions, and it is slowly decreasing when L increases. In addition, for both cases (intra- and inter-subjects), we observe that:

• The correlation coefficient is slightly higher in supine rest, than in standing, than in exercise.

• In supine rest and standing conditions, results are quasi-identical whatever the interval length, whereas in exercise, when $L \geq 900$, the correlation coefficient is breaking down.

The behavior of the discrimination coefficient, in order to verify if the separation capability between both hypotheses H_0 and H_1 is well-performed, is depicted on Figure 4. Results show that DC is always higher to 1, except in exercise where DC is breaking down when $L \geq 900$. In addition, we can observe that performance are even slightly higher in standing and exercise conditions for $300 \leq L \leq 800$ than in supine rest.

These results are really novel and important since they suggest that there is no requirement or advantage to compare only ECG shapes recorded in supine rest conditions, as it is classically done. They show that comparing ECG shapes recorded in standing condition or in exercise provides also a good discrimination coefficient, sometimes higher, which represents an obvious benefit in biometry. However, in exercise, interval length must not be greater than 800.

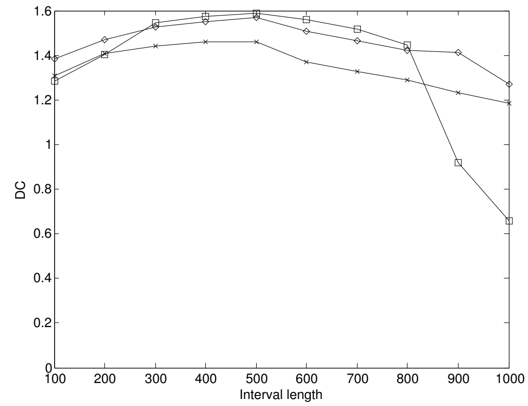

Figure 4. Values of DC calculated in rest ($\times$), standing ($\diamond$) and in exercise ($\square$) for different interval lengths.

3.2. Inter-conditions case

In this section, the inter-conditions case is studied, i.e. only shapes recorded in two different conditions are considered. The methodology is identical to the intra-condition case: intra- and inter-subjects mean correlation coefficients for different interval lengths (from 100 to 1000 samples) are calculated and then DC is computed from these values.

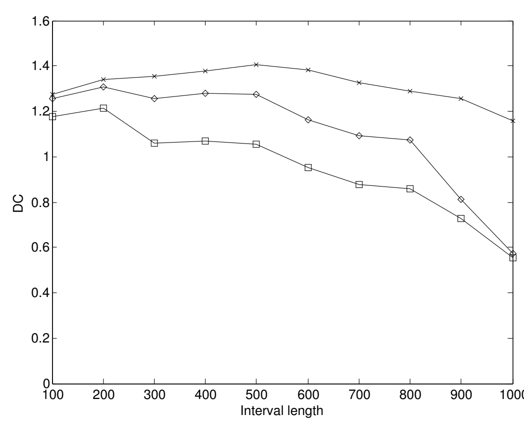

Figure 5. Values of DC calculated between rest and standing ($\times$), between standing and exercise ($\diamond$) and between rest and exercise ($\square$) for different interval lengths.

Figure 5 presents curves of DC calculated in three cases: between rest and standing, between standing and exercise and between rest and exercise. In the first case, DC is always high and similar whatever the interval length. For cases 2 and 3, DC is decreasing when L is increasing and falls below 1 when $L \geq 900$ and $L \geq 600$ respectively. In other words, merging the conditions leads to values of DC near from the values obtained in the intra-condition case, provided that the interval length is lower than 600 ms.

4. Verifications without a priori knowledge

In this section, a clustering approach, based on correspondence analysis and hierarchical ascending classification is proposed. It can be viewed as a correspondence analysis applied directly on the samples of the waveform and allows retrieving natural clusters (all the ECG of a subject in the same class) without introducing a priori knowledge. Figure 6 shows an example of clustering, with $L = 100$, for all conditions. Seven classes are obtained and only 6 ECG are not well classified (2 for D, 1 for H and 3 for F) which leads to 94% of good classification.

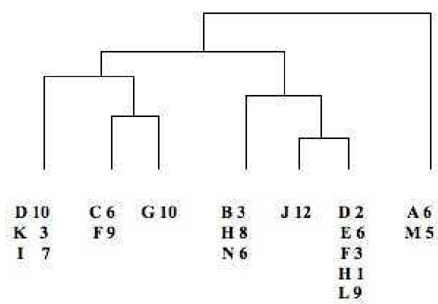

Figure 6. Example of dendogram obtained after clustering (letter: subject - number: number of ECG of the subject in the class).

Table 1 gives the results of classification when conditions are considered separately. Results show that the best clustering is obtained in standing condition and are in accordance with results reported in Figure 4 with $L = 100$.

Table 1. Percentage of good clustering.

S. Rest	Standing	Exercise
90%	94%	90%

5. Conclusion

The objective of this paper was to evaluate the robustness of biometric approaches based on human ECG signals. Results suggest that there is no requirement or advantage to restrict such studies to supine rest condition, as it is classically done. They also show that it is also possible to compare shapes recorded in different conditions. Between rest and standing conditions, performances are high even using the whole beat (P-QRS-T). When one of the two shapes has been recorded in exercise, it is preferable to restrict the interval length to lower values (QRS or P-QRS). In the last analysis, the best clustering is obtained in the standing condition with 94% of good clustering.

Acknowledgements

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