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Biometric verification by cross-correlation analysis of 12-lead ECG patterns: Ranking of the most reliable peripheral and chest leads

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Abstract

Background: Electrocardiogram (ECG)-based biometrics relies on the most stable and unique beat patterns, i.e. those with maximal intra-subject and minimal inter-subject waveform differences seen from different leads. We investigated methodology to evaluate those differences, aiming to rank the most prominent single and multi-lead ECG sets for biometric verification across a large population.
Methods: A clinical standard 12-lead resting ECG database, including 460 pairs of remote recordings (distanced 1 year apart) was used. Inter-subject beat waveform differences were studied by cross-correlation and amplitude relations of average PQRST (500 ms) and QRS (100 ms) patterns, using 8 features/lead in 12-leads. Biometric verification models based on stepwise linear discriminant classifier were trained on the first half of records. True verification rate (TVR) on the remaining test data was further reported as a common mean of the correctly verified equal subjects (true acceptance rate) and correctly rejected different subjects (true rejection rate).
Results and conclusions: In single-lead ECG human identity applications, we found maximal TVR (87–89%) for the frontal plane leads (I, −aVR, II) within (0–60°) sector. Other leads were ranked: inferior (85%), lateral to septal (82–81%), with intermittent V3 drop (77.6%), suggesting anatomical landmark displacements. ECG pattern view from multi-lead sets improved TVR: chest (91.3%), limb (94.6%), 12-leads (96.3%).
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Keywords: ECG biometrics; Human identity recognition; Cross-correlation analysis; QRS, PQRST patterns; Linear discriminant analysis; True verification rate

Introduction

In the last decade the electrocardiogram (ECG) based biometrics is a field of active research, focused on numerous applications in remote healthcare monitoring [1] with biosensors integrated into mobile devices [2,3], wearable smart watch-type devices [4], secure wireless body area sensor networks [5,6], and continuous authentication applications with adaptive strategies to follow individual beat variations in 24 h ECG recordings [7]. Other applications utilize the unique beat behavioral in short duration ECG recordings over 15–120 s in one-lead configuration for finger-based ECG biometrics [8–10] and merely 10s in 12-lead configuration for patient validation support and error screening of digital 'in-hospital' ECG databases [11]. The ECG, being continuously available, low-cost and routine acceptable physiological measurement, is considered to exhibit personalized beat patterns of electrical activity in respect of timing and geometry that could be, however, affected by a number of physiological factors, including age, body weight, stress, activity and cardiac abnormalities [1,12,13]. State-of-the-art research reveals the validity of single and multi-lead ECG for human biometrics in both verification [2,4,6–15] and identification [3,10,13,14,16–19] scenarios when persons with known and unknown identity are recognized, respectively.

The ECG biometric features are either morphological or waveform based. The former include temporal, amplitude, area and angle features of fiducial points over the PQRST pattern [2,10], whose correct measurement could be ensured by certified commercial ECG analysis software [11] and device [16]. Waveform-based features are calculated over the whole PQRST pattern by Euclidean distance [15], autocorrelation [9], cross-correlation [4,12,13,18,19], wavelet decomposition [3], short-time Fourier transform and log-likelihood ratio [8], or are fully independent from the fiducial point detection, using an autocorrelation over long parts of the signal, followed by a

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discrete cosine transform [14] and linear discriminant analysis (LDA) [17] for dimensionality reduction and feature extraction.

ECG biometric studies use the most common lead configurations employed in clinical practice, i.e. one to three limb leads [2–4,8–10,12,13,15], or 12-lead ECG [11,16–19]. The former focus attention at general purpose practical applications, which use only limb lead analysis, while the latter aim at effective channel combination schemes. The benefit of multi-lead ECG biometric scenario is contradictory, considering the study of Porée et al. [19] whose performances are highly correlated with the number of leads, and decrease abruptly when only one lead is used, while Biel et al. [16] reported equal identification accuracy when using all 12 leads, only limb, only chest and only lead I.

A limitation in the field for person authentication via ECG is the lack of standardized public multi-lead ECG databases, containing at least two recordings per subject with sufficient temporal separation between recording sessions. Therefore, the majority of the cited methods has been designed with small-sized ECG databases [4–6,8,10,12,14,16–19] and limited time interval between intra-subject ECGs [12,16] that might bias the reported identification accuracy from the real case scenario.

This study aims to contribute to the limited data and knowledge available about the potential of 12-lead ECG for human biometrics, relying on the person's most stable and unique beat patterns (i.e. those with minimal intra-subject and maximal inter-subject waveform differences seen from different leads). We investigated methodology to evaluate those differences based on cross-correlation and amplitude relations, aiming to rank the most prominent single and multi-lead sets for biometric verification across a large population, pondering physiologically related long-term ECG changes and recording conditions between two different sessions.

Material and methods

ECG database

This retrospective study considers a proprietary clinical ECG database (Schiller AG, Switzerland) provided for the purpose of human biometrics on a large population observed over time. Two 10 second sessions of standard resting 12-lead ECG's were recorded at two different time-points (reference point T1 and remote point T2 > T1 + 1 year) from 460 patients that do not suffer from cardiac disease (235/225 male/female, 18–106 years old), admitted in the emergency department of the University Hospital Basel in the period (2004–2009). A commercial ECG device (SCHILLER AT-110) was used for digital 12-lead ECG recordings (500 Hz, 2.5 μV/LSB) in a bandwidth (0.05–150 Hz).

Signal processing

The implemented measurement scheme is shown in Fig. 1. The feature extraction used average beat pattern on standard 12-lead ECG with duration of 500 ms, further named PQRST pattern (500 ms), calculated by the commercial ECG measurement and interpretation module (ETM, Schiller AG). Inter-subject standardization of 12-lead PQRST patterns was applied by:

- Synchronization of the cardiac depolarization process by time-alignment of the subject's PQRST pattern to a reference pattern by maximal cross-correlation in lead I. The reference pattern has been initialized at the beginning of the study as a 'normally' behaving average beat in lead I (with positive P-QRS-T waves), belonging to a subject from the population.
- Extraction of 12-lead QRS pattern (100 ms) in a window of 30 ms before and 70 ms after the fiducial point, aligned to the R-peak of the reference pattern.
- Calculation of a heart rate corrected ST-T interval (Bazett's formula).

Lead-by-lead comparison of average beat patterns in sessions T1 vs. T2 was conducted to calculate the specific waveform differences in each of 12 leads by two methods:

1) Cross-correlation analysis of QRS and PQRST patterns (COR-QRS and COR-PQRST), based on the cross-correlation function:

$$r_{\mathrm{T1,T2}}(lag) = \frac{\sum_{i=1}^{PD} Pattern_{\mathrm{T1}}(i)\,Pattern_{\mathrm{T2}}(i+lag)}{\sqrt{\sum_{i=1}^{PD} Pattern_{\mathrm{T1}}(i)^2 \sum_{i=1}^{PD} Pattern_{\mathrm{T2}}(i)^2}}, \quad (1)$$

where *Pattern* denotes QRS or PQRST with pattern duration *PD* = 100 ms or 500 ms, respectively; The *lag* value was changed in the range [−PD to PD].

Three correlation features were calculated:

- *Maximum correlation*: $r\max = \max_{lag\in[-PD,PD]} r_{\mathrm{T1,T2}}(lag) \in [0;1]$, represents the best matching of the waveforms and might be reduced by inter-subject differences of the anatomical (spatial) path followed by the heart vector during the cardiac cycle.
- *Zero-lag correlation*: $r(lag0) = r_{\mathrm{T1,T2}}(lag=0) \in [0;1]$, represents the non-synchronized similarity between the ECG patterns and might be reduced by inter-subject spatiotemporal differences of the heart vector propagation during the cardiac cycle.
- *Lag value for maximum correlation*: $lag(r\max) = abs\left(\arg\max_{lag\in[-PD,PD]} r_{\mathrm{T1,T2}}(lag)\right) \in [0; PD]$, represents the synchronization of the ECG patterns in respect of the time delay of the cardiac depolarization (QRS) plus repolarization (PQRST) process between subjects.

2) Amplitude measurements of the QRS pattern range (AMP-QRS)
   - *Minimal QRS amplitude*: $\min QRS_{p-p}(\mathrm{T1,T2})$, represents the minimal peak-to-peak amplitude of the QRS pattern in the studied lead, comparing T1 and T2 recordings. Besides being a biometric feature, this might be an indicator for unreliable lead quality or invalid measurements in case of low amplitude lead.

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