Human Authentication Implemented for Mobile Applications based on ECG-Data Acquired from Sensorized Garments

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Abstract

In recent years biometric systems gain more and more importance. Studies showed, that authentication with a clinical electrocardiogram (ECG) is principally possible and hence could be used as a biometric feature.

In this work an algorithm was implemented, which is capable of segmenting single heartbeats of a mobile recorded single-channel-ECG. Based on these heartbeats, fiducial features, features from the combination of autocorrelation and discrete cosine transform, and wavelet features were extracted and considered for the classification process. They were evaluated concerning distinctiveness and stability over time. In order to reduce the feature space, sequential forward selection was used to eliminate unstable and non-distinctive features.

A sensorized garment was used to derive ECG-signals from ten persons in order to evaluate the performance of the proposed methods. The wavelet-transform provides the best features since it is focusing on the characteristics of the QRS-complex of a human heartbeat, which provides the most stable information over time. Using the wavelet coefficients as features the developed authentication algorithm produced an equal error rate of 12.53 %.

1. Introduction

The use of biometric features for authentication becomes more and more important. Nowadays, different features like the fingerprint, a face or iris scan can be used for identity verification. Another biometric feature, which is unique for every individual, is the human heartbeat that can be measured with an electrocardiogram (ECG). Compared to other features, the human heartbeat is hard to falsify, since it naturally holds the information, whether an individual is alive. A disadvantage over other biometric features is the impeded data acquisition. Clinical ECGs use adhesive electrodes for recording the heartbeat. This kind of ECG acquisition is unhandy for everyday situations, because the electrodes always have to be mounted to the correct position on the body, before an authentication can be performed. Thus, different ways of acquiring the human heartbeat are necessary to make this kind of biometric feature usable.

There are several physiological reasons, why the heartbeat differs for every human. The first reason for these differences is the individual structure of the human heart for every person. The Purkinje system, the muscle fiber orientation and the electrical conductivity of the cardiovascular cells distinguish several individuals. Besides, the position of the heart in the human cause differences in the ECG patterns [1]. Other reasons are related to the sex, age, height and the body habitus of different subjects [2].

There are several algorithmic approaches to extract these differences. One approach of Biel et al. [3] was to determine fiducial points in a segmented heartbeat. Based on these fiducial points, differences in amplitude and time as well as angles between those points can be computed which are supposed to be unique for every individual and thus can be used as features for classification [4].

Another feature extraction method is the combination of the Autocorrelation (AC) and the Discrete Cosine Transform (DCT) [4,5]. This method does not necessarily need a segmentation of a single heartbeat. Wang et al. [4] used a segment of five second of an ECG and computed the AC of this segment. After normalizing and truncating the AC, the DCT coefficients of the AC were computed and used as features for the classification.

Other features can be obtained by computing the wavelet-transform of a segmented heartbeat [6]. This transform makes an investigation of the heartbeat in the time and frequency domain possible, because it decomposes the signal into different frequency bands.

This paper investigates, whether an ECG measured with textile electrode, which are integrated into a garment, is suitable for human authentication.

2. Material and methods

This study focused on authentication methods based on ECG-signals acquired with a mobile 1-lead-ECG system integrated in a garment. Several authentication approaches from the literature were tested on data provided by the PhysioNet databases. The three most promising methods were chosen as foundation for the development of the new authentication algorithm based on mobile recorded data - fiducial points [3,4], the combination of autocorrelation and discrete cosine transform [4,5], and wavelet-transform [6].

2.1. FitnessSHIRT

The FitnessSHIRT, developed at the Fraunhofer Institute for Integrated Circuits IIS in Erlangen, Germany, was used to acquire the mobile ECG data. A single-channel ECG can be derived via two textile electrodes integrated in a garment at lateral position approximately at the height of the 6th rib (*costae verae XI*).

The system uses a sampling rate of 256 Hz. The main module contains inter alia, the microprocessor for signal preprocessing and a microSD card for long-time data acquisition. Furthermore, the integrated Bluetooth module offers the possibility to transmit the data to mobile devices (smartphones or tablets) or to a PC for the purpose of displaying the data in a live view or further processing steps.

2.2. Test protocol and database

A total of ten healthy subjects participated in this study. All of them were males of average fitness level at the mean age of 26.3 years with an average height of 183.2 cm and weight of 78.8 kg.

All persons used the same FitnessSHIRT system to exclude the influence of different measuring systems. In order to evaluate the authentication method against stability with data over a longer period of time, three measurements of ten minutes were performed. Between each measurement a pause of at least seven days was kept. In order to improve the signal-to-noise ratio (SNR) of the signals the CV-Tronic electrode gel from the company C+V Pharma-Depot GmbH was used. The participants were in a resting position and sitting upright.

Using leave-one-out cross-validation, the data were split in training and test sets to avoid overfitting.

2.3. Classification algorithm

The main part of the proposed algorithm deals with the classification itself. This part consists of several processing steps which can be seen in Fig. 1. First, the raw signal is acquired on the hardware. In order to keep the relevant information in the ECG-Signal untouched, all frequencies up to 1 kHz pass the hardware based filter. According to the steps mentioned in the following, the signals were offline processed with the software Matlab R2012a (The MathWorks®, Natick, USA).

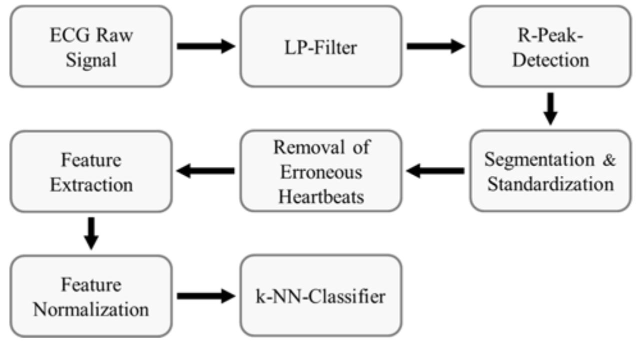

Figure 1. Classification Algorithm Overview. Based on the low-pass filtered ECG raw data, the R-peaks are detected which are used for the segmentation of the heartbeats. After filtering erroneous heartbeats the feature extraction takes place. Finally, the features are normalized and then classified using a k-NN-classifier.

Preprocessing: A finite impulse response (FIR) low-pass filter was used to reduce the noise due to e.g. the elimination of power line interferences. Using a Hamming window, the filter was realized with a cutoff frequency of 40 Hz and an empirically determined order of 50.

The detection of the R-peaks was implemented using the algorithm proposed by Pan and Tompkins [7]. As the FitnessSHIRT is using a sampling rate of 256 Hz the original filter coefficients of the algorithm had to be adopted accordingly. Furthermore, the algorithm was extended to overcome the additional noise due to the slipping of the textile electrodes.

Based on the detected R-peaks the heartbeats can be segmented. Different heart rates and the individual characteristics of a person cause a varying duration of the heartbeat and its components, especially the P- and T-wave. Considering that no waves from other segments overlap with the current segment, the duration was empirically set to 650 ms. In addition, the mean value of each segment was subtracted and the amplitude of the R-peak was normalized to 1 in order to make the segments comparable to each other.

At next erroneously detected heartbeats originated in noise or extrasystoles were removed by using an adapted method proposed by Silva et al. [8]. Such false heartbeats have to fulfill three properties in order to be detected:

- The maximum of the heartbeat is not the R-Peak.
- The minimum of the heartbeat is smaller than twice the median of the minima of all heartbeats.
- The cosine distance between the heartbeat and the average heartbeat of all segmented heartbeats is smaller than a threshold (empirically set to 0.1).

The threshold values of the second and third property were modified, because too many correct heartbeats were filtered by using the thresholds defined in [10].

Feature extraction: At this point three different approaches were used to extract the features from the preprocessed ECG-segments.

Fiducial features – For this approach, nine different fiducial points were extracted according to the work of Wang et al. [7]. The 23 time and amplitude features, which were computed after the extraction of the nine fiducial points, can be seen in Fig. 2.

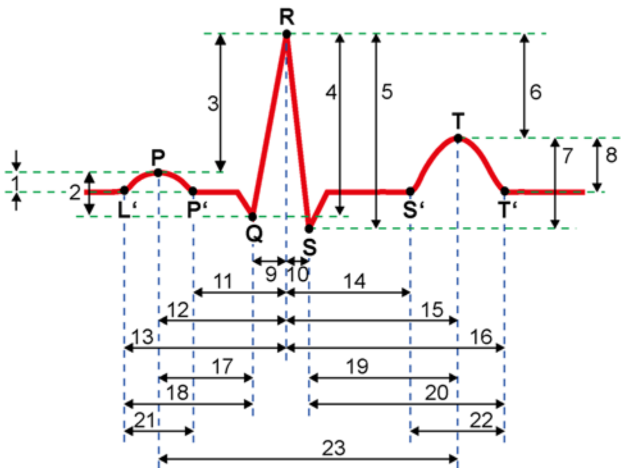

Figure 2. Fiducial Features. Visualization of the nine characteristic points, the eight amplitude features and the 15 time features.

AC/DCT features – While Plataniotis et al. [8] used a 5 s segment to compute the AC, the developed algorithm in this work only used a single heartbeat to compute the AC, because it holds the same information as a longer segment. Besides the impact of extrasystoles and the heartrate variability, which minimize the classification results, can be minimized by using only one single heartbeat. After the computation, the AC was normalized to the energy of the heartbeat, which corresponds to the maximum of the AC, and truncated to a 300 ms segment. This duration of the segment was found to yield the best classification results compared to other durations [4]. This AC segment was used to compute the DCT. The first 30 DCT coefficients were used as features for the classification, because they hold most of the information.

Wavelet features – The third feature extraction method computed the wavelet transform of a heartbeat. For this approach, the Daubechies D3 wavelet was used and 5 levels of decompositions were performed accordingly to Belgacem et al. [1]. However, in our work the heartbeat was subsampled from 256 Hz to 80 Hz. The reason for this step is that without the subsampling, the resulting coefficients of the first level of decomposition would hold no information because of the low-pass filter in the beginning of the algorithm with a cutoff frequency of 40 Hz. This approach yielded 77 features.

Normalization of Features: The next step was to reduce each feature by its mean value μ_i and to normalize it by the standard deviation σ_i:

$$x_{norm,i} = \frac{x_i - \mu_i}{\sigma_i}$$

k-Nearest Neighbors (k-NN) Classification: Using this classification algorithm the class affiliation of a sample can be determined. This classifier is often used when it comes to biometric authentication using ECG-signals. Mathematically this can be described by:

$$y = \underset{\vec{x}_i \in T}{argmin}\, D_{euc}(\vec{x}, \vec{x}_i)$$

In this study the Euclidean distance - the distance between two points in an n-dimensional space - was used to classify the samples.
Thereby, the training set *T* was used in two ways. For the identification it was used to assign a sample to a class of a known user group. For the authentication the set and a user-specific threshold was used to decide if a person is the user or not.

2.4. Feature Selection

A crucial part of the proposed method is the feature selection where the best subset of features is chosen. It is necessary because of the curse of dimensionality, which states that feature vectors in high-dimensional spaces cannot be distinguished in lower dimensions. Furthermore, the amount of data saved in the k-NN classifier is significantly reduced which has positive effects on the storage requirements. The third reason is that due to this selection the most stable features can be selected.

To reach this goal the sequential forward selection was chosen. Making use of the wrapper method redundant features can be eliminated and therefor revealed the feature set with the best classification results. This procedure was performed separately on all three feature sets and can be generally described as follows [9]:

1. Input: Set of all features Y=y_1, y_2,…y_d
   Output: Subset of features X_k = x_j | j = 1,2,…,k; $x_j \in$ Y, where k = (0,1,2,…,d).
2. Initialization: An empty set: $X_0 = \{\emptyset\}$, k = 0.
3. Inclusion: Go through the feature space and look for the feature x+ which maximizes the criterion if it is added to the feature subset (where J is the criterion function) and repeat this process until the termination criterion is reached.
4. Termination: Add features to the new feature subset X_k until either all features were considered or no improvement of the classification results could be reached.

3. Results and discussion

The accuracy (proportion of correct classified samples) of the sequential feature selection could significantly be increased by reducing the feature space (see Fig. 3). The wavelet features provided the best results (accuracy of 88.88 % with 12 features), as this method mostly selects features of the temporal stable QRS-complex. On the other side, the other two proposed extraction methods are also using instable parts of the ECG-signal which results in lower accuracy (fiducial - 71.06 % with 10 features; AC/DCT - 74.25 % with 13 features).
Furthermore, due to the decomposition of the signal with the wavelet transform, it was possible to observe the QRS-complex in a higher degree of detail.

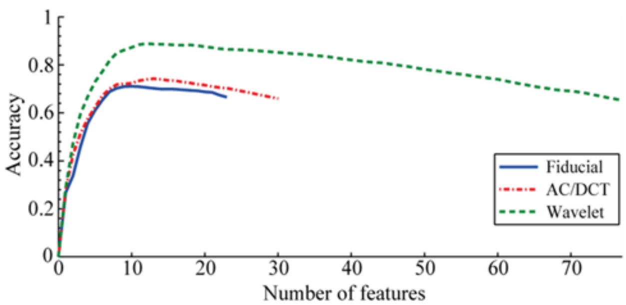

Figure 3. Feature Selection. Results of the feature selection for the three extraction methods - fiducial points with 23 (blue), AC/DCT with 30 (red) and wavelet with 77 features (green).

In this study we evaluate the equal error rate (EER), which is a common measure for biometric authentication systems. This rate is defined as the value where the false rejection rate equals the false acceptance rate.

Table 1. Authentication Results. The equal error rate (EER) for of all three proposed feature extraction methods for one session compared to three sessions.

Method	EER for one session [%]	EER for three sessions [%]
Fiducial Points	2.97	17.85
AC & DCT	1.98	15.44
Wavelet	2.32	12.53

The proposed method reached a comparable EER of around 2 % for all three approaches using data for training and testing for the classifier of one session (cf. Tab. 1). Authentication with data from three sessions used data of two sessions for the training and data of the remaining session builds up the test set. Due to the fact that the electrodes were on slightly different positions and the physiological conditions of the users differed in the various sessions, the results for the EER decreased significantly. Hereby, the wavelet-based features provided the best results of 12.53 %, as again the QRS-complex showed up as the most stable feature this feature extraction method is making use of.

4. Conclusion

We conclude that the features from the QRS-complex contain the most important information in order to perform a stable authentication. Therefore, feature extraction using the wavelet-transform provides the best results. However, stability of the classification results is limited due to the temporal differences of segments in the ECG-signal (mainly the topology of the P- and T-wave). Furthermore, the varying electrode positions in the three sessions yielded a decreased authentication rate. Further investigation of how to compensate these effects will be required.

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