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Human Identification Based on Electrocardiogram and Palmprint

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ABSTRACT

In this paper, a new approach in human identification is investigated. For this purpose, we fused ECG and Palmprint biometrics to achieve a multimodal biometric system. In the proposed system for fusing biometrics, we used MFCC approach in order to extract features of ECG biometric and PCA to extract features of Palm print. The features undergo a KNN classification. The performance of the algorithm is evaluated against the standard MIT-BIH and POLYU databases. Moreover, in order to achieve more realistic and reliable results, we gathered Holter ECG recordings acquired from 50 male and female subjects in age between 18 and 54. The numerical results indicated that the algorithm achieved 94.7% of the detection rate.

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1. INTRODUCTION

The increasing interest in biometry research is due to the increasing need for highly reliable security systems in sensitive facilities. From defense buildings to amusement parks, a system able to identify subjects in order to decide if they are allowed to pass or not would be very well accepted. This is because identity fraud nowadays is one of the more common criminal activities and is associated with large costs and serious security issues. Several approaches have been applied in order to prevent these problems. Traditional biometric methods, such as fingerprint and face recognition, have been employed with varying degrees of success for these applications. But other types of biometrics are being studied nowadays as well: DNN analysis, keystroke, gait, ear shape, hand geometry, iris, retina, written signature, palm print and vein pattern [1]. New types of biometrics, such as electroencephalography (EEG) and electrocardiography (ECG), are based on physiological signals, rather than more traditional biological traits.

Heartbeat information combined with traditional biometrics will reduce forgery of credentials and minimize intrusion. Basic shortcoming of single biometric modality system is that only one physiological or behavioral feature will be evaluated therefore it makes the system less accurate. The fusion of two or more biometric techniques offers the prospect of improving system performance, while also being more difficult to defeat. Multimodal systems also provide anti-spoofing measures by making it difficult for an intruder to spoof multiple biometric traits simultaneously. This paper explores the fusion of traditional Palm-print recognition techniques with a novel biometric based on the subject's electrocardiogram (ECG). Because acquisition of the ECG information requires contact sensing, this technique is best suited to verification and identification tasks for cooperative subjects. ECG and Palm-print should be independent sources of information about the subject. In principle, ECG is an inherent liveness biometric. The way the heart beats does not exist if the owner is not alive, therefore liveness testing and all the issues aurrounding liveness testing are excluded in the scenario where an inherent liveness biometric is applied for identification. Consequently, fusion of the two data sources should outperform either source alone. The remainder of the paper is structured in the following manner. Section 2 reviews the previous literature associated with ECG data for biometric identification. Section 3 describes the processing steps required to design identification system based on ECG, in Section 4, ECG and Palm print fusion is presented. The experimental results are reported in Section 5, and finally conclusion is given in Section 6.

2. ECG AS A BIOMETRIC

To date, the use of Electrocardiogram signals within a biometric system to identify individuals is sparse and preliminary. Electrocardiogram (ECG) analysis is not only a very useful diagnostic tool for clinical proposes, but also is recently studied as a potential biometric [9]. ECG [10] is a method to measure and record different electrical potentials of the heart. Willem Einthoven developed the ECG method in the early 1900s. The origin of the electrical activity measured by ECG is in the muscle fibers of different parts of the heart. Biel et al. [3] showed that it is possible to identify individuals based on a chest ECG signal. Irvine et al. [4] introduced a system to utilize heart rate variability (HRV) as a biometric for human identification. Israel et al. [5] showed the uniqueness of an individual's ECG by investigating temporal features. Israel et al.[6] presented a multimodality system that integrate Palm image and ECG signal for biometric identification. Shen et al. [7] introduced a two-step scheme for identity verification from one-lead ECG. A template matching method is first used to compute the correlation coefficient for comparison of two QRS complexes. A decision-based neural network (DBNN) approach is then applied to complete the verification from the possible candidates selected with template matching. The inputs to the DBNN are seven temporal and amplitude features extracted from QRST wave.

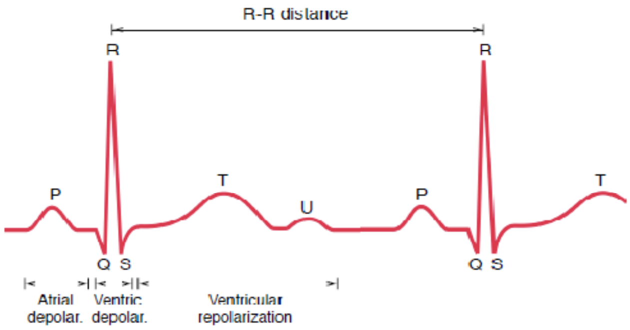


Figure 1. Basic shape of an ECG heartbeat signal

The electrocardiogram signal depicts the electrical potential of the heart over time. A typical ECG wave of a normal heartbeat consists of a P wave, a QRS complex, and a *T* wave. Figure 1 depicts the basic shape of a healthy ECG heartbeat signal. The P wave is generated when the right and left atria of the heart are depolarized and it corresponds to low frequency spectral components, 10-15 Hz [9]. The QRS complex reflects the depolarization of the right and left ventricles. It has much steeper slopes and its spectrum is concentrated in the interval of 10-40 Hz. Finally, the T wave occurs during ventricular repolarization and its position depends on the heart rate, appearing closer to the QRS complex when the rate increases [10], Atrial repolarization is less commonly observed in ECG traces and is labeled as a U wave.

3. IDENTIFICATION ALGORITHM BASED ON ECG

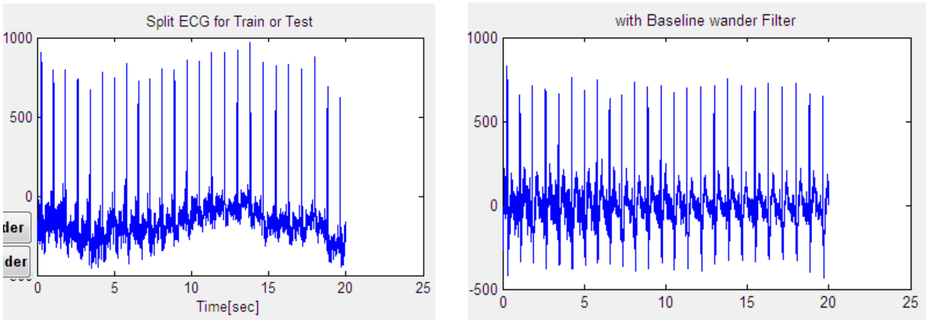
An ECG biometric system, same as other biometric systems, is essentially a pattern recognition system that operates by acquiring biometric data from an individual, extracting a feature set from the acquired data, and comparing this feature set against the template set in the database.

3.1. Preprocessing of ECG

The collected ECG data usually contain noise. Generally, the presence of noise will destroy the signal, and make the feature extraction and classification less accurate. To realize the ideal data structure

(Fig. 1), the raw ECG data must be processed to remove the non-signal artifacts. The first step is to identify the noise sources. Based upon the structure of these noise sources, a filter is designed and applied to the raw data. The filtered data is used to perform feature extraction. Broadly speaking, ECG contaminants can be classified into the following categories [11]:

- Power line interference
- Baseline wandering
- Electrode pop or contact noise
- Patient–electrode motion artifacts
- Electromyographic (EMG) noise



(a) (b)

Figure 2. (a) Raw ECG data 1000 Hz.(b) ECG waveforms with baseline wandering. The y axis is Amplitude and the x axis is time in second

Baseline wandering can be suppressed by a high-pass digital filter. Also one can use the wavelet transform to remove baseline wandering by eliminating the trend of the ECG signal. Removal of baseline wandering is necessary because without it the features cannot be extracted.
Figure 2 demonstrates the original ECG data which we acquired with Holter in 1000 HZ and the filtered signal that the baseline wandering is removed. Figure 2 demonstrates the original ECG data which we acquired with Holter in 1000 HZ and the filtered signal that the baseline wandering is removed.

3.2. Feature Extraction

After preprocessing, feature extraction is the most important module in ECG identification system. The main purpose of this module is to convert the ECG waveform to some type of parametric representation for further analysis and processing. To build an efficient human identification system, the extraction of features which can truly represent the characteristics of a subject is a real challenge. Different types of features have been studied in the past. Most of these studies use distance measures [12] or amplitude differences as features for classification. These features are usually being extracted by analyzing and localizing some fiducial points from the signal, which referred to analytic features. Another intuitive method to perform classification is to use the original data directly. However, in most cases, the dimensionality of the raw data is high, and thus not suitable for classification.

A wide range of possibilities exist for parametrically representing the ECG signal for the human recognition task, such as Wavelet Transform (WT), Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), AC/DCT [9], Linear Prediction Coding (LPC) and others. We proposed Mel-Frequency Cepstrum Coefficients (MFCC), for feature extraction in this paper. A block diagram of the structure of an MFCC processor is given in figure 3.

3.2. Classification

The classes here refer to individuals themselves. Since the classification procedure in our case is applied on the extracted features, it can be also referred to as feature matching. The state-of-the-art in feature matching techniques used in ECG recognition includes Dynamic Time Warping (DTW), Neural Network (NN) [13], Hidden Markov Modeling (HMM), and Vector Quantization. In this paper, the K-nearest neighbors approach will be used, due to its ease of implementation and high accuracy. K-nearest neighbors is a non-parametric method for classification. It assigns a class label to the new entry by examining its k nearest neighbors in the training data. The k value can be determined by using leave-one-out cross validation.

4. ECG AND PALMPRINT FUSSION

At this stage, we have the elements that could lead the system to take a decision based on each of the two modalities. However, we have observed that the application of a decision fusion increases the reliability of the final system in terms of acceptance and rejection rates. In order to achieve the maximum performance of the system, we fuse the results of the ECG and the Palm print identification systems. In the context of biometrics, three levels of information fusion schemes have been suggested [14]: Fusion at the feature extraction level, Fusion at the matching score-level, Fusion at the decision level. Figure 4 demonstrate the block diagram of proposed system.

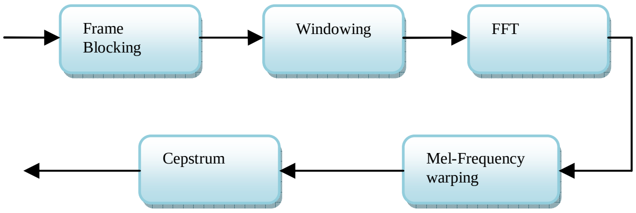


Figure 3. A block diagram of the structure of an MFCC processor

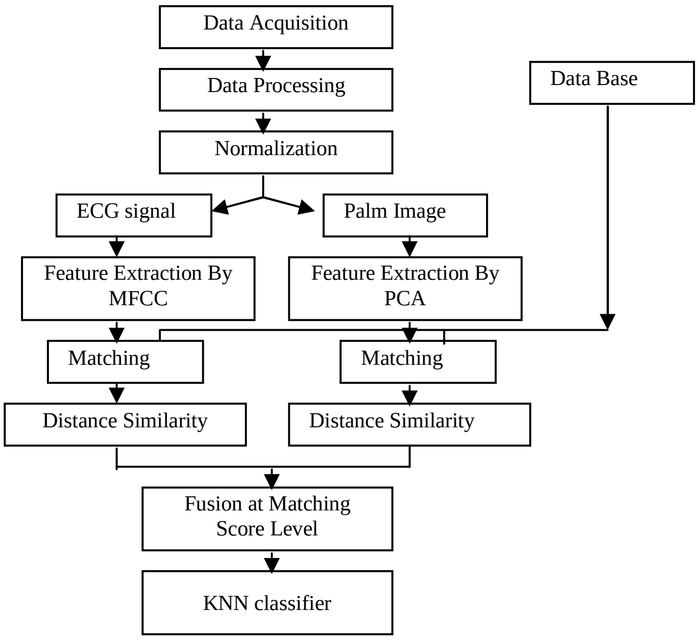


Figure 4. Fusion of two biometrics in score-level

5. EXPERIMENT

To evaluate the performance of the proposed system, we use our experiments on two sets of databases: MIT-BIH[15] for ECG database and POLYU for Palm print database. The MIT-BIH contains 89 ECG recordings from different subjects. Moreover, in order to achieve more realistic and reliable results for human identification, we gathered Holter ECG recordings acquired at 24 hours of the day from 50 male and female subjects in age between 18 and 54 by ourselves.

First of all we performed a high-pas filter in order to remove the non-signal artifacts of raw ECG data. The continuous ECG signal is blocked into frames of N samples, with adjacent frames being separated by M (M<N). After the frame blocking step, we window each individual frame so as to minimize the signal discontinuities at the beginning and end of each frame. In this step we used the Hamming window for windowing. The next processing step is the Fast Fourier Transform, which converts each frame of N samples from the time domain into frequency domain. In order to simulate the subjective spectrum, we used a filter bank, one filter for each desired mel-frequency component; the mel-spaced filter bank has a triangular band pass frequency response and is applied in the frequency domain; finally, we converted the log mel spectrum

bank to time. The result is called the mel-frequency cepstrum coefficients. Because the mel spectrum coefficients are real numbers, we can convert them to the time domain using the Discrete Cosine Transform. By applying the procedure described above, for each ECG signal a set of mel-frequency cepstrum coefficients is computed. By means of feature extraction on Palm images, we used PCA method on the subset of persons Polyu database. Images of the palm are captured at a resolution of 420*380 pixels. They are then aligned and their size is normalized. From these images, the Palm-print sub-images with a fixed size (380*380pixels) are extracted and transformed by using PCA. After extracting the features of ECG signal and Palm image as mentioned above, we measured the euclidean distance of test features and stored one in database. Then a KNN classifier is applied to make decision. The scores undergo a KNN classification with different values for K.

6. RESULTS AND DISCUSSION

In this study, we investigated two distinct security systems with only one biometric element, in order to compare them with the proposed multimodal system. The yielded results demonstrate that the performance of the multimodal system is more than single one.

In order to implement biometric systems, we used three databases, two of them for ECG biometric and one of them for Palmprint. In standard MIT-BIH database, we used one record from each subject for training and testing, the recognition rate for 50 persons was 100% (table 1), which is the same with the related works on this dataset, but the training time in the proposed method has been reduced. The ECG is variable in different times of day or in different states of the subject, so because the MIT-BIH just used one record for signal analyzing, the result was not acceptable. Therefor we tried to gather different signals of a subject, in different times and states, to have a comprehensive dataset named Dey-Hospital. In Dey-Hospital dataset we took 3 records of different times of a subject for gallery set and more than one record for testing set. we achieved the recognition rate of 89%. The performance of this method is 89% which is high enough. In comparison with the related works, this method has higher performance and is more reliable, moreover the training time is too lower. The results verified that the mel-frequency Cepstral Coefficients output can effectively identify individuals from one another. Table 2 demonstrates the results of the proposed method.

Table 1. Performance of PCA model on PALM-PRINT

Recognition rate	Number of classes				
	10	20	30	40	50
	97%	96%	88%	83%	82.1%

Table 2. Performance of MFCC model on ECG

Recognition rate	Number of classes				
	10	20	30	40	50
MIT-BIH	100%	100%	100%	100%	100 %
Dey-Hospital	98.6%	95.4%	90%	89.6%	89%

Table 3. Performance of Multimodal System

Recognition rate	Number of classes				
	10	20	30	40	50
	100%	98%	97.4%	95.9%	94.7%

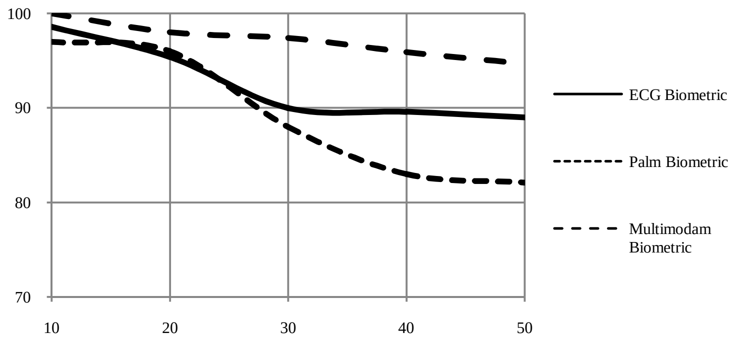


Figure 5. Comparision on ECG and palmprint system and the multimodal system

Since the MIT-BIH database has 100% performance in each number of classes, we will not achieve a realistic result in fusing with Palm print, so we prefer to use Holter ECG recordings, acquired in different times and situations of subjects in Dey-Hospital. In order to compare between unimodal and multimodal we run PCA method on Palm images and MFCC on ECG signals experiments on the subset of persons POLYU and Dey-Hospital, then we used a KNN method as classifier. Experimental results using the multimodal models obtains higher recognition rate than those obtained with unimodal models (Table 3). Figure 5 shows that the fusion technique, perform significantly better than the single modalities alone.

7. CONCLUSION

This paper presented a study on using ECG signals for individual identification. We have presented the performance results obtained by a bimodal biometric system based on physiological signal, namely ECG and Palm print. In this context we undertake fusion at the matching score level, thereby improving the overall performance of the system in terms of acceptance and rejection rates. Since frequency domain information is not too variable in ECG changes due to different states of the subjects, MFCC is suitable for extracting the constant features of the ECG. Also, we run PCA model using of KNN classifier on Palm images. In addition to, Experimental results showed using of the multimodal biometrics obtains higher recognition rate than those unimodal biometrics. In our future works, we wish to fuse multiple biometrics with ECG to improve the robustness of the system and even its performance. A further step is to extract emotions from ECG [16,17]. This would be very useful for human–computer interactions. As an example, we can think on virtual reality applications where the reactions of the computer generated avatars would take into account the emotions of the subject immersed in the virtual reality environment. Thus there is still a long way to go regarding research into this exiting possibility.

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