An Enhanced Intrinsic Biometric in Identifying People by Photopleythsmography Signal

N. S. Girish Rao Salanke, N. Maheswari and Andrews Samraj

Abstract In the area of secure authentication, the fusion of Photopleythsmography (PPG) signals for biometric identification is a novel technique. Researchers suggested the use of PPG along with other biometric components for augmenting the biometric robustness. PPG signals have great potential to serve as biometric identification appliance and can be easily obtained with low cost. Use of PPG signals for personnel identification is very appropriate during field operations in day or night. While building a large scale identification system the feature selection from PPG is a critical activity. To have the identification system more accurate, the set of features that deemed to be the most effective attributes are extracted in order to build robust identification system. Applying Kernel Principal Component analysis (KPCA) an efficient supervised learning method for dimensionality reduction and feature extraction in this experiment results in precise classification.

Keywords PPG signal · Authentication · Kernel principal component analysis (KPCA) · Mahalanobis distance

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1 Introduction

In search of robust biometrics that is not compromised, researchers started to try with unseen internal organs rather than conventional outer organs with all their varying dimension and activity. They seems to be more reliable types of biometrics in human authentication and identification systems than the simple ones used in applications like personnel security, hospital, finance, digital rights etc. conventional biometric system [1] using behavioral and physiological characteristics to allow recognition of an individual, like face recognition [2], fingerprint [3], iris and retinal patterns [4] and voice [5] are becoming very popular. The common weakness of conventional biometric system is their vulnerability and the possibility to falsity of their features. In 1977, Forsen listed the possible features of a human body that could be used for biometrics were ECG [6] and EEG [7]. The basic approach is to extract the signals from the user during the enrollment phase, the extracted signals from the user then attempts to log in, the particulars are computed, which determines the decision outcome. This is really no different than any other behavioral biometric, the novelty here is the data that are acquired. In order to acquire biological signal data, specialized hardware is required. Especially the EEG and ECG acquisition hardware is complex and tedious processes is involved. In this paper, we examine the use of Photoplethysmograph (PPG) signals, which is acquired using a very simple hardware interface for human identification [8]. PPG has distinct advantages including low development cost, easy to use without any complicated procedure and conveniently accessible to various sites of human body, such as finger, wrist or arm. Moreover, PPG signals provide a noninvasive and accurate methodology to obtain valuable physiological information such as blood oxygen saturation, heart rate and blood flow.

The blood in human body is being pumped from the heart to all parts in the body by blood vessels called arteries. Blood pressure is the force of blood pushing against the walls of the arteries. Each time the heart beats it pumps out a considerable volume of blood to the arteries. Systolic pressure which is the highest blood pressure occurs when heart is in pumping motion. Diastolic pressure is lowest blood pressure when heart is in resting [9]. Since blood pressure are an indirect measurement of heart beats and the blood pressure tend to change according to time and emotion. For instance, blood pressure will rise when a subject is awaken and excited. The unit for measurement of blood pressure is in mmHg and the notation will be systolic followed by diastolic pressure.

The Photoplethysmograph (PPG) signals reflect the change in blood volume caused by blood vessel expansion and contraction, which can be detected by photodiode if external light is illuminated into tissue. This method is based on the idea that if an externally applied pressure in the cuff is equal to the arterial pressure instantaneously, the arterial walls will be unloaded (zero transmural pressure) and the arteries will not change in size. In this condition, the blood volume will not change.

Fig. 1 Finger nail sensor to measure PPG signal

Digital Photoplethysmographic sensor used to read a PPG signal has an infrared emitter and photodiode detector. The intensity of light from infrared emitter which reaches the photodiode detector in either reflection or transmission will be measured to determine the blood volume changes. The Photoplethysmographic sensor will be placed below the tip of the finger and pressure will be applied on the proximal phalanx. Since the cuff is wrapped on the proximal phalanx of the finger rather than arm, it makes less discomfort for prolonged used. The blood volume changes on the finger will be notified by the sensor and transmitted to the system by wired or bluetooth transmitter. There will be a timer attached on the device to time the cuff pressure applied time and transmitter so that it is semi-continuous measurement. This is because to decrease the energy consumption of Bluetooth transmission and to avoid discomfort of the wearer's finger due to continuous pressure applied.

The idea of the blood pressure sensor is much like the Photoplethysmograph Fingernail Sensor for measurement of finger force which is mentioned by Stephen A. Mascaro and H. Harry Asada [10]. The finger force is measuring colouration of fingernail by using reflectance Photoplethysmography. The Fig. 1 shows the fingernail sensor used in this research.

2 Related Work

A brief survey of the related work in the area of identification using PPG signals is presented in this section. Earlier work by Y. Y Gu et al. [11, 12] on biometrics with PPG signals used to represent the pulse using four quantities; the peak number, the upward slope, the downward slope and the time interval from the bottom to peak. Jianchu Yao et al. [13] examines two important issues in applying derivatives of PPG signals as discriminants to identify and verify subjects. Andrews Samraj et al. [8] demonstrated the intra trial variability factor which enhanced the signature verification system that uses PPG Signal as one of its combination. Singular value decomposition (SVD) was used as a dimension reduction tool. In this paper, we propose a technique for human identification by applying kernel principal component analysis for dimension reduction.

3 Methodology

The methodology of this experiment is carried out in four stages as follows

(i) Experimental Setup
(ii) Preprocessing
(iii) Feature Extraction
(iv) Classification

3.1 Experimental Setup

The PPG signals were recorded using a Pulse Oximetry module (from Dolphin Medical, Inc) that was connected to a computer using a data acquisition software and captured with a sampling frequency of 37 Hz [14]. The main purpose of sampling the signal at this particular frequency is to highlight that even at this lowest frequency we were able to capture the signal. Sampling at a higher frequency is very fine and accurate and may be considered later on further progress. Four led's of Plethysmogram were fixed on each subject while recording the data. A total of 9 healthy subjects participated in this study. All the 9 subjects selected were our co- scholars at VIT University and the average age of the subjects is 34. Two PPG recordings (relaxed and stressed) were obtained from each individual with duration of 60 s. Total of 8 signals were recorded for each subject, 4 in relaxed sate and remaining 4 in the stressed state. Before recorded the stressed PPG signal the subjects were made to go up and down the staircase for a couple of times in order to increase their level of stress. There was about 30 min gap between the time of recording the relaxed and the stressed PPG signal. Figures 2, 3 shows PPG signal recorded during the relaxed and the stressed state. The aim for recording the relaxed and the stressed state signal is to detect whether there is significant fluctuation in the PPG signal features of a person in both the states. The relaxed PPG signals of all subjects shows identical waveforms but stressed PPG signals shows unidentical waveforms due to motion artifact. The same signal was used for training and the testing purpose. Both the recordings were taken separately, once when the subject was very much relaxed and the other time when he was stressed.

3.2 Preprocessing

The Preprocessing of the PPG signal consists of Peak detection, Segmentation and finally Scaling. In peak detection, we find the maximum peak of the recorded PPG

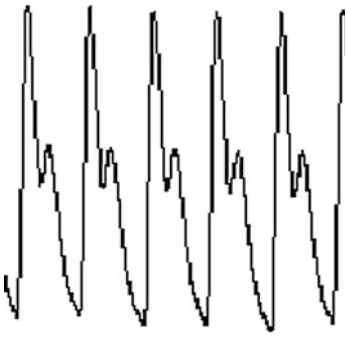

Fig. 2 Relaxed PPG
Waveform sampled at 39 Hz

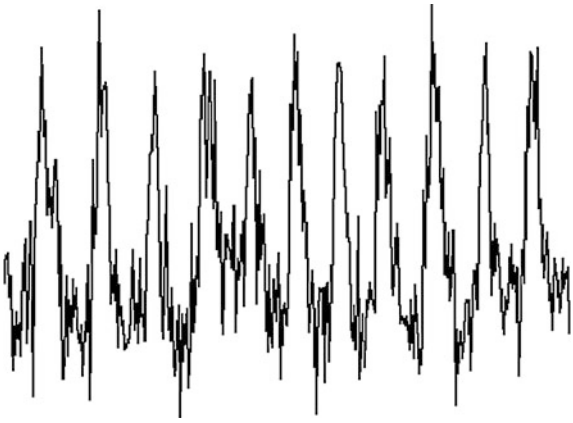

Fig. 3 Stressed PPG
Waveform sampled at 37 Hz

signal. A point is considered a maximum peak if it has the local maximal value and is preceded by another peak with their amplitude difference larger than a preset threshold. In Segmentation we define one PPG cycle with the help of the maximum and minimum points obtained through peak detection. In Scaling since one PPG cycle is nothing but a heart rate, and generally heart rate can potentially increase intra-subject variability, the time duration is scaled to 100 samples.

3.3 Feature Extraction

Kernel Principal Component Analysis (KPCA) is used as dimension reduction technique which is used for feature extraction. Kernel PCA is the reformulation of traditional linear PCA in a high-dimensional space that is constructed using a kernel function. In recent years, the reformulation of linear techniques using the 'kernel trick' has led to the proposal of successful techniques such as kernel ridge regression and Support Vector Machines. Kernel PCA computes the principal eigenvectors of the kernel matrix, rather than those of the covariance matrix. The

reformulation of PCA in kernel space is straightforward, since a kernel matrix is similar to the in product of the data points in the high-dimensional space that is constructed using the kernel function. The application of PCA in the kernel space provides Kernel PCA the property of constructing nonlinear mappings. Kernel PCA computes the kernel matrix K of the datapoints $\boldsymbol{x_i}$. The entries in the kernel matrix are defined by

$$k_{ij} = \kappa(x_i, x_j) \tag{1}$$

where $\boldsymbol{\kappa}$ is a kernel function, which may be any function that gives rise to a positive-semi definite kernel K. Subsequently, the kernel matrix K is double-centered using the following modification of the entries

$$k_{ij} = -\frac{1}{2}\left(k_{ij} - \frac{1}{n}\sum_{l} k_{il} - \frac{1}{n}\sum_{l} k_{jl} + \frac{1}{n^2}\sum_{lm} k_{lm}\right) \tag{2}$$

The centering operation corresponds to subtracting the mean of the features in traditional PCA. It subtracts the mean of the data in the feature space defined by the kernel function $\boldsymbol{\kappa}$. As a result, the data in the features space defined by the kernel function will have zero-mean. Subsequently, the principal eigenvectors $\mathbf{v_i}$, of the centered kernel matrix are computed. The eigenvectors of the covariance matrix $\mathbf{a_i}$ (in the feature space constructed by $\boldsymbol{\kappa}$) can now be computed, since they are related to the eigenvectors of the kernel matrix $\mathbf{v_i}$ and eigenvalue $\boldsymbol{\lambda_i}$ through

$$a_i = \frac{1}{\sqrt{\lambda_i}} v_i \tag{3}$$

In order to obtain the low-dimensional data representation, the data is projected onto the eigenvectors of the covariance matrix $\mathbf{a_i}$. The result of the projection (i.e., the low-dimensional data representation Y) is given by

$$y_i = \left\{ \sum_{j=1}^{n} a_1^{(j)} \kappa(x_i, x_j), \ldots, \sum_{j=1}^{n} a_d^{(j)} \kappa(x_i, x_j) \right\} \tag{4}$$

where $\mathbf{a_i^{(j)}}$ indicates the jth value in the vector, $\boldsymbol{a_I}$ and $\boldsymbol{\kappa}$ is the linear kernel function that was also used in the computation of the kernel matrix.

3.4 Classification

Mahalanobis distance based classifier is used to identify the individuals. The use of the Mahalanobis metric removes several of the limitations of the Euclidean metric like automatically accounts for the scaling of the coordinate axes, corrects for correlation between the different features and provides curved as well as linear decision boundaries. The value of r in the given below equation

Table 1 The intra subject variation in terms of Mahalanobis distance

Mahalanobis distance			
Subjects	Relaxed state	Stressed state	Intra variation
1	98.30	114.50	16.20
2	594.70	606.70	12.00
3	1119.20	1136.10	16.90
4	2116.80	2132.40	15.60
5	1009.10	1029.50	20.40
6	3110.60	3142.30	31.70
7	5099.20	5124.90	25.70
8	7130.20	7157.80	27.60
9	8094.10	8112.70	18.60

$$r^2 = (x - m_x)^I C_x^{-I} (x - m_x) \tag{5}$$

is called the **Mahalanobis distance** from the feature vector **x** to the mean vector $\mathbf{m}_x$, where C_x is the covariance matrix for **x**. It can be shown that the surfaces on which r is constant are ellipsoids that are centered about the mean $\mathbf{m}_x$. In the special case where the features are uncorrelated and the variances in all directions are the same, these surfaces are spheres, and the Mahalanobis distance becomes equivalent to the Euclidean distance.

We first generate a matching score by the selected feature compared with the stored template. For each PPG Cycle, the mahalabonis distance is calculated and is compared with the set of samples stored in the system is computed. The template resulting in the smallest distance is considered to be the match.

4 Results and Discussion

The difference in the Mahalanobis distance between the relaxed and the stressed state (Intra Subject Variation) for each subject is calculated. We observe that the mahalanobis distance of the relaxed state is less when compared to the stressed state. The table given below shows the distance for each subject for the maximum value obtained out of 30 samples extracted during the relaxed and the stressed state (Table 1).

We observed that the Intra Variation of all the subjects is very less and the average Inter Variation is 20.52. Figure 4 shows the Intra Subject Variation in Mahalanobis distance for one particular subject across 10 different samples. The Inter subject variation (calculated from the average values between the relaxed and the stressed state), the difference between the mahalanobis distance across different subjects is shown in Figs. 5, 6 reveals the wide gap between the Intra trial variability, this factor can be used as a novel method of identifying people using Photoplethysmographic signal.

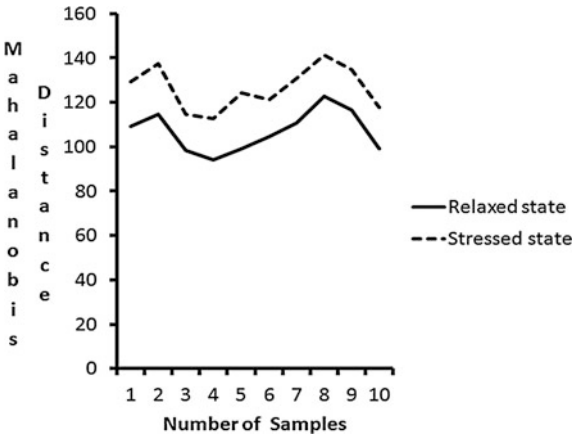

Fig. 4 Intra subject variation in terms of Mahalanobis distance

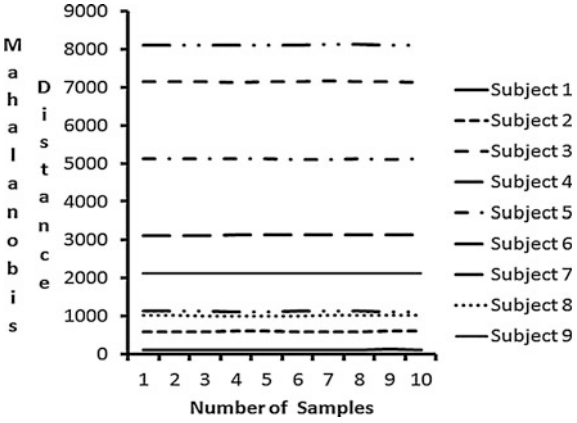

Fig. 5 Inter subject variation in terms of Mahalanobis distance

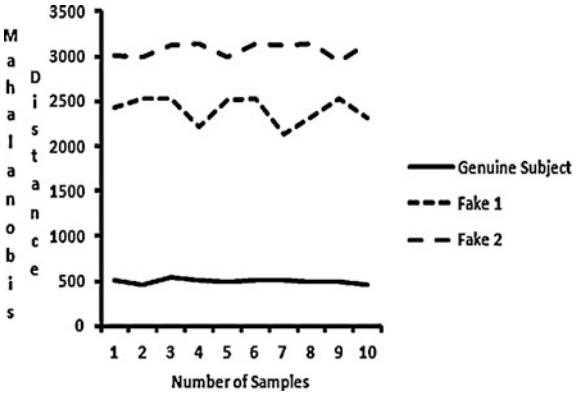

Fig. 6 Mahalanobis distance between a Genuine and Fake subject

5 Conclusion

We have presented a novel approach in this paper with the possibility of using Photoplethysmographic signal in the human identification. We observe that the stressed PPG signal from all the subjects shows distinct waveform when compared to their relaxed state that results in the difference in the mahalonobis distance, which can be used for the verification purpose. The most salient feature in using the Photoplethysmographic signal as a biometric is that it cannot be easily copied or simulated, as compared to other biometrics such as fingerprint, face or even voice.

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