FEASIBILITY STUDY OF PHOTOPLETHYSMOGRAPHIC SIGNALS FOR BIOMETRIC IDENTIFICATION

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ABSTRACT

The utilization of photoplethysmographic (PPG) signals for biometric identification represents a novel approach in the area of secure authentication. PPG signals can be easily obtained with low cost and have great potential to serve as biometric identification mechanism. This paper explores the feasibility, along with the relevant signal processing methods, of using PPG signals of an individual as a biometric trait. PPG signals from two biometric datasets are examined. PPG signals were obtained from the fingertips of 29 healthy subjects. The experimental results demonstrate that PPG signals can be used as bio-measures for identification purposes given that PPG signals are collected under controlled environment and with accurate sensors.

***Index Terms*—** Biometrics, Photoplethysmography, Identification

1. INTRODUCTION

In the modern automated world, access to a reliable authentication system becomes essential and crucial. Traditional authentication methods are based on the user's knowledge, such as personal identification number (PIN) and passwords, or something belonging to someone, such as smart cards and cardkey. These methods can hardly meet the reliability requirements of an automated authentication system because identification cards can be lost or misplaced and passwords may be forgotten.

Compared to traditional methods, biometrics can provide enhanced security and convenience. As biometric recognition systems are increasingly deployed for many security applications, biometrics and its applications have attracted considerable interests. Recently, biometrics has emerged as one of the most reliable technologies for future human identification and verification.

Various biometric measures have been investigated for authentication purposes, including face complexion [1, 2], iris recognition [3] and ECG [4]. These approaches present different level of system complexity, cost and accuracy.

In this paper, we examine the use of photoplethysmographic (PPG) signals for human identification. Compared to other biometric approaches , PPG technique 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, ear lobe,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 [5].

The feasibility of applying PPG signals as a biological discriminant has been preliminary studied [6, 7]. These studies applied an approach to represent the pulse using four quantities: the peak number, the upward slope, the downward slope, and the time interval from the bottom to the peak. However, this approach ignores higher-order derivative information contained in the pulse and therefore, doesn't take full advantage of the pulse to improve identification accuracy and reliability. In [8] the 1st- and 2nd- order derivatives of a pulse signal are examined. The specific aim of this work is to investigate the feasibility of PPG signals as a biometric identifier in an automated way.

The rest of this paper is organized as follows: In Section 2 the methodology that was followed is described. Experimental results are presented in Section 3 followed by the discussion in Section 4. Conclusion is in Section 5.

2. METHODOLOGY

In this section, the methodology and the procedure that was followed are described. For each dataset (which will be discussed in detail in Section 3), the first half was used for training, where signals were pre-processed and Linear Discriminant Analysis was applied to yield a set of LDA weights. The rest of dataset was used for testing, where signals were pre-processed and projected to LDA space following by classification with a nearest neighbor classifier.

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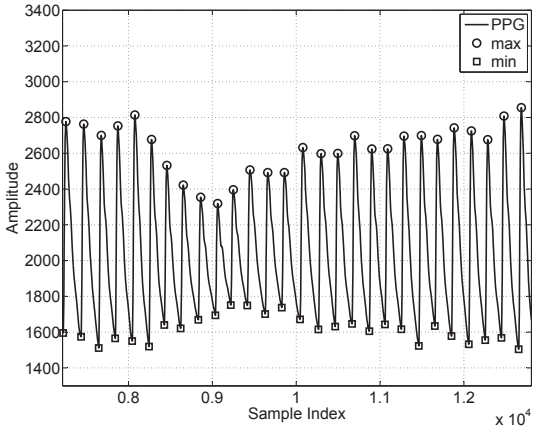

Fig. 1. PPG signal with the maximum and minimum values.

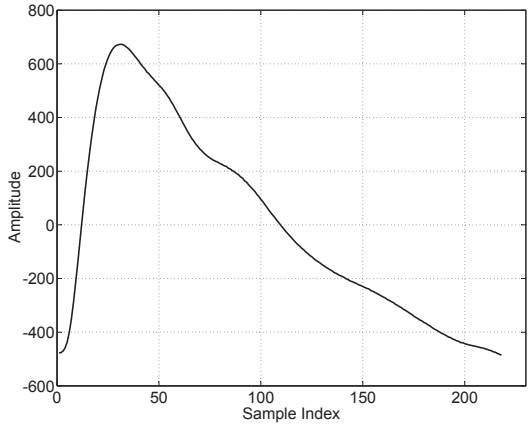

Fig. 2. PPG segment before scaling.

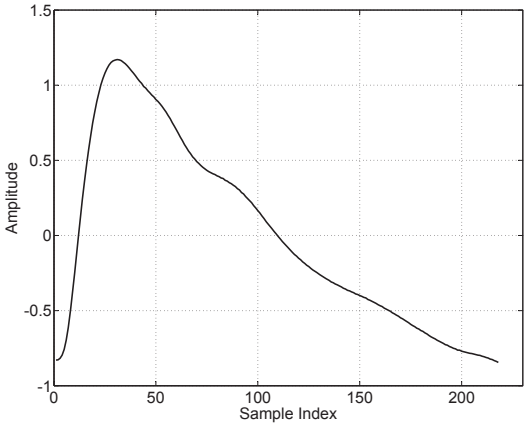

Fig. 3. PPG segment after normalization.

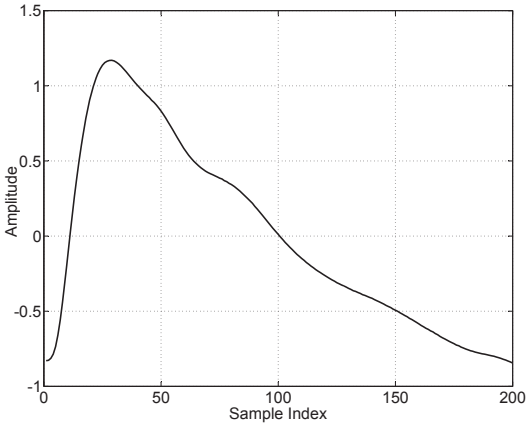

Fig. 4. PPG segment after scaling.

2.1. Pre-processing

PPG pre-processing consists of the following steps:

Step 1:*Peak detection*

To avoid being affected by high frequency noise and imperfection of the signal, instead of using the zero crossing of the first order derivative, we employ here the method proposed and implemented by E. Billauer [9]. A point is considered a maximum peak if it has the local maximal value, and is preceded (to the left) by another peak with their amplitude difference larger than a preset threshold. The threshold is manually set to be half of the average peak to peak amplitude in the dataset. Figure 1 shows the result.

Step 2:*Segmentation*

After determining the maximum and minimum points through peak detection, we define one PPG cycle as shown in Figure 2.

Step 3:*Normalization*

According to our observation from all subjects' PPG recording, PPG amplitude can change a lot even in a short period of time. Since it's the PPG morphology that's most related to one's identity, amplitude is normalized with respect to the current cycle's maximum. Figure 3 shows a PPG signal after normalization.

Step 4:*Time Domain Scaling*

Since the duration of a PPG cycle is related to one's heart rate and can potentially increase intra-subject variability, the duration is scaled to 200 samples to compensate for this factor. Figure 4 shows a PPG segment after scaling.

2.2. Linear Discriminant Analysis

Linear Discriminant Analysis(LDA) was employed as feature extraction tool. Linear Discriminant Analysis is a widely used and efficient supervised learning method for dimensionality reduction and feature extraction. Given a training set $\mathcal{Z} = \{\mathcal{Z}_i\}_{i=1}^{U}$, containing U classes with each class $\mathcal{Z}_i = \{\mathbf{z}_{ij}\}_{j=1}^{U_i}$ containing a number of windows $\mathbf{z_{ij}}$ a set of K feature basis

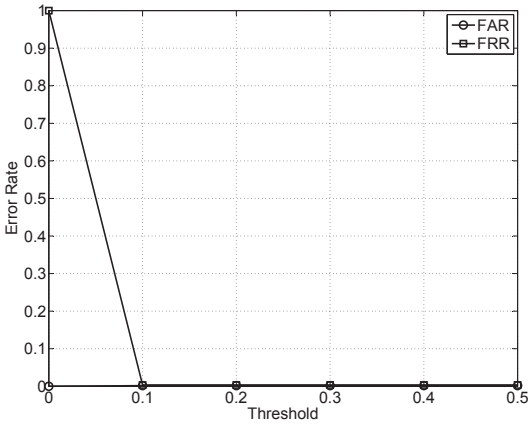

Fig. 5. Experimental Results for OpenSignal dataset.

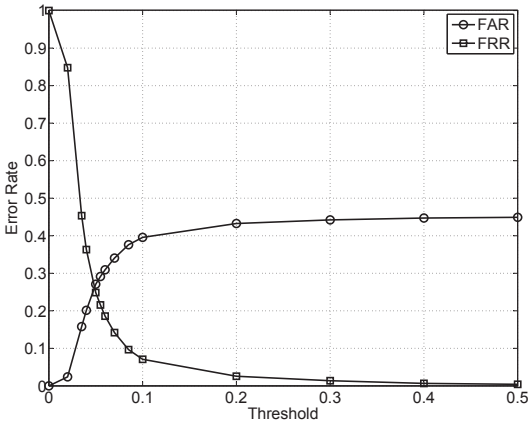

Fig. 6. Experimental Results for BioSec dataset.

vectors $\{\psi_m\}_{m=1}^{K}$ is estimated by maximizing Fisher's ratio. This ratio is defined as the between-class to within class scatter matrix. The maximization is equivalent to the solution of the following eigenvalue problem:

$$\psi = \arg\max_{\psi} \frac{|\psi^T \mathbf{S}_b \psi|}{|\psi^T \mathbf{S}_w \psi|} \tag{1}$$

where $\psi = [\psi_{\mathbf{1}}, ..., \psi_{\mathbf{K}}]$, and $\mathbf{S_b}$ and $\mathbf{S_w}$ are the between and within class scatter matrices respectively defined as:

$$\mathbf{S}_b = \frac{1}{N} \sum_{i=1}^{U} U_i (\mathbf{z}_i - \overline{\mathbf{z}})(\mathbf{z}_i - \overline{\mathbf{z}})^T \tag{2}$$

$$\mathbf{S}_w = \frac{1}{N} \sum_{i=1}^{U} \sum_{j=1}^{U_i} (\mathbf{z}_{ij} - \overline{\mathbf{z}}_i)(\mathbf{z}_{ij} - \overline{\mathbf{z}}_i)^T \tag{3}$$

where $\overline{\mathbf{z}}_i = \frac{1}{U_i} \sum_{j=1}^{U_i} \mathbf{z}_{ij}$ is the mean of class $\mathcal{Z}_i$ and *N* is the total number of training windows and $N = \sum_{i=1}^{U} U_i$.

Linear Discriminant Analysis finds ψ as the *K* most significant eigenvectors of $(\mathbf{S}_W)^{-1}\mathbf{S}_b$ that correspond to the first *K* largest eigenvalues. Having obtained the basis vectors, any test input window $\mathbf{z}$ is subjected to the linear projection $\mathbf{y} = \psi^T \mathbf{z}$.

2.3. Classification

After processing, for each subject in the dataset, the first half of the recording was used to perform LDA training (training set), while the second half was used for testing (testing set). During testing, every five consecutive PPG segments are to be projected into LDA space and compared with all the templates in galleries. *Nearest neighbor* and *majority voting* was applied to determine if there is a match for the input signal. Moreover, a threshold is applied to accept or reject the input as the identified subject.

3. EXPERIMENTAL RESULTS

In order to evaluate the performance of the proposed approach, PPG signals from two datasets were used. Experiments were carried out with identical procedure and parameter settings.

- **OpenSignal PPG Dataset:** OpenSignal is a cooperative repository of physiologic signals [10]. The dataset we used, is composed of 14 healthy volunteers. Each subject was instrumented with a finger blood volume pulse (BVP) sensor on the 4th finger of the left hand. bvpPLUX system [11] was used.

- **BioSec PPG Dataset:** BioSec is the Biometrics Security Laboratory at the University of Toronto. [12]. The dataset we used, is composed of 15 healthy volunteers. Each subject was instrumented with a finger blood volume pulse sensor on the 2nd finger of the left hand. NONIN pulse oximeter [13] was used.

Figure 5 and Figure 6 shows *false acceptance rate* and *false rejection rate* versus threshold for OpenSignal and BioSec dataset, respectively. Results for OpenSignal dataset are better than that of Biosec dataset, as the FAR and FRR reach 0.5% when the threshold is set properly. On the other hand, for Biosec dataset, an Equal Error Rate of 25% is achievable, and the threshold can be set differently to get lower FRR with an increasing in FAR, which is applicable in low security systems or multi-modal biometric systems.

4. DISCUSSION

Although identical algorithm and parameters were used for simulation in both datasets, there is a significant difference in the performance. In order to examine the inter-class and intra-class variance, all PPG segments in the testing set are

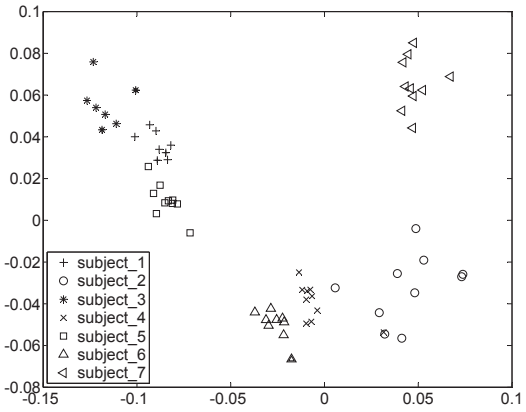

Fig. 7. Data cluster for OpenSignal dataset

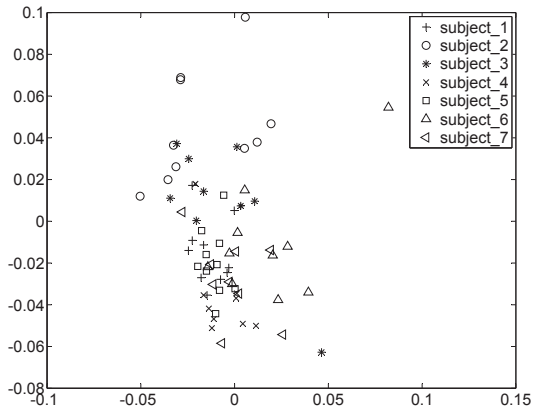

Fig. 8. Data cluster for BioSec dataset

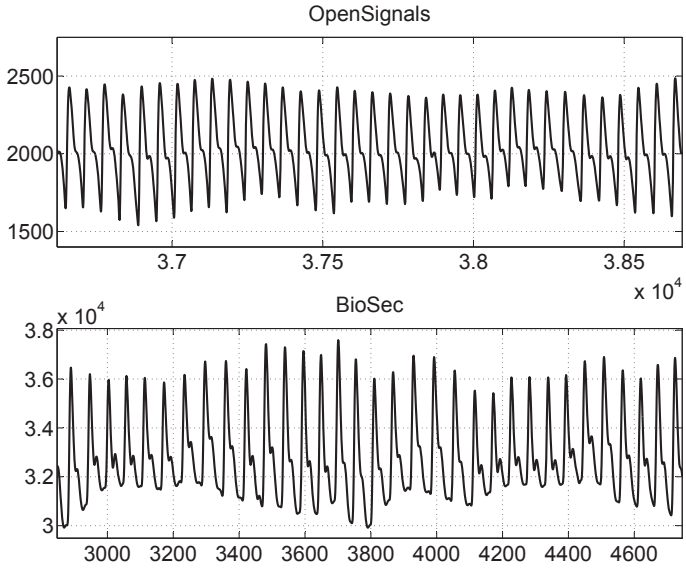

Fig. 9. Comparison of sample signals from both datasets

projected to LDA space which reduce the dimensionality to 14 for OpenSignal dataset and 15 for BioSec dataset. Furthermore, in order to visualize in two dimensional plot, Principle Component Analysis (PCA) was applied to each testing set and the first two coefficients were used to plot the corresponding data point in a two dimensional space. Data clusters for OpenSignal dataset and BioSec dataset are shown in Figure 7 and Figure 8, respectively. To make a clear demonstration, only 7 subjects are shown on the plots, with 10 sample data points randomly drawn from the testing set for each subject.

As shown on the cluster plots, samples from BioSec dataset exhibits less intra-class similarity and inter-class variance, which made the classification task difficult. We also observed this difference in time domain, where signals from Biosec dataset are relatively unstable in signal morphology, as shown in Figure 9. Possible sources of the difference may come from the device, sensor and recording conditions. Moreover, according to the experimental results with the subjects from the two datasets, it is better to obtain PPG signals in a controlled environment. In the case that PPG signals are not stable, they should be combined with another biometric signal. For instance, ECG could be recorded simultaneously with PPG and provide multi-modal biometric identification system.

5. CONCLUSION

This paper examines the feasibility of PPG signals for biometric identification mechanisms. Experiments point out that these signals are vulnerable since the equipment that is used and the recording environment are crucial, and have great impact on the biometric authentication system performance. However, it is possible to identify a person by information extracted from PPG signals given that signals were collected under controlled environment and with accurate sensors.

6. ACKNOWLEDGMENT

This work was supported in part by a Natural Sciences and Engineering Research Council of Canada (NSERC) Strategic Project Grant entitled Biometrics User-Centric Secure Networks (BUSNet).

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