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People Recognition by RGB and NIR Analysis from Digital Image Database Using Cross-Correlation and Wavelets

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Abstract

This document presents a framework for recognizing people by palm vein distribution analysis using cross-correlation based signatures to obtain descriptors. Haar wavelets are useful in reducing the number of features while maintaining high recognition rates. This experiment achieved 97.5% of individuals classified correctly with two levels of Haar wavelets. This study used twelve-version of RGB and NIR (near infrared) wavelength images per individual. One hundred people were studied; therefore 4,800 instances compose the complete database. A Multilayer Perceptron (MLP) was trained to improve the recognition rate in a k-fold cross-validation test with k = 10. Classification results using MLP neural network were obtained using Weka (open source machine learning software).

Keywords

Palm Vein Recognition, Cross-Correlation, Haar Wavelets, Multilayer Perceptron

1. Introduction

Biometric recognition of individuals is a problem that has had a growing interest in recent years due to its great need [1]-[8]. For example, when opening a bank account, registering the entry of workers in a company or institution, taking a plane trip, certifying the owner of a bank account by voice over the phone, among other cases, all of them are performing biometric analysis of individuals.

Within the field of biometrics, it could be considered a simple but general classification that encompasses all classes. Arguably there is mainly static and dynamic biometrics. In dynamic biometrics, we can observe voice recognition, signature analysis, heartbeat measurements, blood pressure, among many others. On the other hand, static biometry can be considered from body measurements such as height, weight, fingerprint analysis, distribution of veins in the palm of the hands, back or fingers, and iris analysis, among others.

Some authors focus their research efforts on multimodal biometric systems because they are more robust [9]; however, they tend to be more expensive systems. On the other hand, an advantage of vein pattern recognition systems is their ability to be relatively impossible to fake [10].

This work presents an analysis of veins distribution of palms of the hands for recognition of individuals using two-dimensional autocorrelation techniques, Haar wavelets and Neural Networks. All experimentation tests are based on cross-validation so that results can be valid. The PolyU multispectral palmprint Database was used in this research, due to its multispectral characteristics, RGB and infrared images (NIR) within a suitable Region of Interest (ROI) [11]-[15].

2. Digital Signal Processing

There are basically two procedures on which the proposal of this work is mainly based. The first is a discrete spatial cross-correlation operation that could be defined as [16] [17]:

$$c_{x,y} = \sum_{i}^{M}\sum_{j}^{N} f_{i,j}\, g_{x+i,y+j} \tag{1}$$

where f and g where f and g are images in which cross-correlation is to be operated, and c is cross-correlation of f and g.

Despite operations based on cross-correlation being representative for vein patterns, it is necessary to reduce data amount to reduce computational costs. To achieve a small but representative features set a Haar Wavelet Transform was performed on the values computed by cross-correlation.

The Haar Wavelet Transform reduces a discrete set of values into two subsets of half of its size [18] [19]. One subset called "trend" or "average" can be computed as:

$$a_m = \frac{f_{2m-1} + f_{2m}}{\sqrt{2}} \tag{2}$$

The other subset called "fluctuation" can be computed as:

$$d_m = \frac{f_{2m-1} - f_{2m}}{\sqrt{2}} \tag{3}$$

3. Proposed System

Firstly, it was observed that the most suitable images to work for the recognition of people in the PolyU database are RGB and NIRs, because the images of the blue, green and red channels enhance information such as skin folds, and NIR's contain veins patterns, this phenomenon can be observed in **Figure 1**.

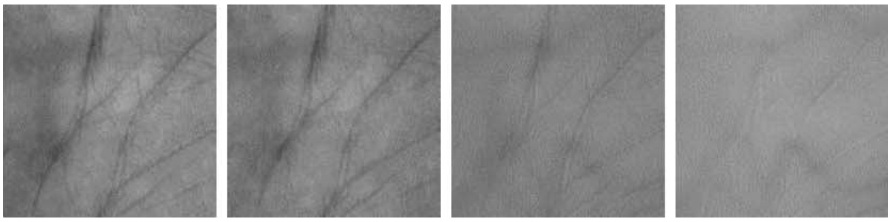

Figure 1. Shows the images of a sample captured in the blue, green, red and NIR channels.

Observing **Figure 1**, the skin folds are more visible in the blue channel, all information of these four channels can be combined by the following expression:

$$RGBI = \frac{B+G}{10} - \left(R+I\right)^{3} \tag{4}$$

Expression (4) was obtained by experimental analysis, **Figure 2** shows the application of expression (4) in the samples of **Figure 1**, skin folds and vein patterns are enhanced, this information allows to compute people recognition using 4 channels (RGB and NIR).

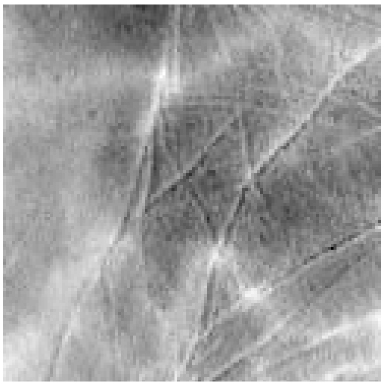

Figure 2. RGBI Image computed using RGB and NIR wave lengths using expression (4).

The most important contribution of this research is to generate a signal that represents two pairs of cross-correlations based signatures; the first pair ($s1$ and $s2$) is generated from the path at 90 and 0˚ as shown in **Figure 3** and was computed as

$$s1_x = \sum_{u=0}^{x}\sum_{j=0}^{N} f_{u,j}\, f_{M-x+u,j} \tag{5}$$

and,

$$s2_x = \sum_{v=j}^{N}\sum_{i}^{M} f_{i,v}\, f_{i,v-j} \quad j \in 1,2,\cdots,N \tag{6}$$

where f represents the RGBI image obtained from expression (4).

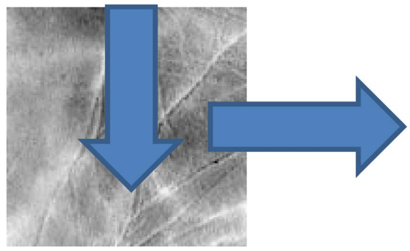

Figure 3. Representation of autocorrelation signature of the first pair of paths.

Subsequently, the other half of the signal is generated from the second pair of cross-correlations based signatures ($s3$ and $s4$) using a path of 135 and 45˚ respectively, as can be seen in Figure 4 and were computed as

$$s3_x = \sum_{u=0}^{x} \sum_{j=0}^{x} f_{u,j} f_{M-x+u,N-x+j} \tag{6}$$

and,

$$s4_x = \sum_{v=0}^{M-j} \sum_{j=0}^{N-j} f_{u,j} f_{M-u,N-j} \tag{7}$$

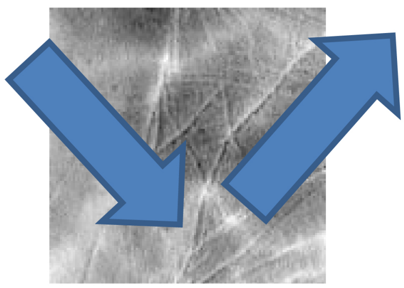

Figure 4. Representation of the autocorrelation path of second pair of paths.

At the end of the described process of two autocorrelation pairs, the four signals are concatenated to form a single one, as can be seen in Figure 5.

It should be noted that the length of the signature shown in Figure 5 is 512 elements, although these 512 are significantly less than the total number of elements that the image contains (16,380), they are still too many to be able to train properly in terms of computational costs to a Multilayer Perceptron, which leads to solving this problem, experimentally it was found that applying wavelet techniques, particularly Haar, produced the expected result, that is, reducing the number of descriptors but highly representative of the original signal, in Figure 6 it can appreciate the result of this exercise.

Figure 6 shows how the signal of the original signature composed of 512 elements (red graph) is greatly reduced and results in a smaller signal composed of 64 descriptors but equally representative of the original data (blue graph).

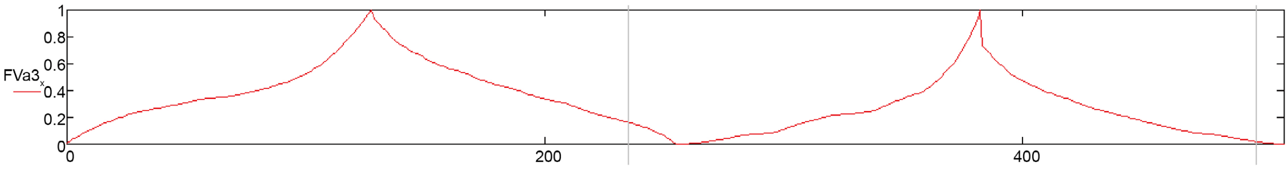

Figure 5. Cross-correlation based signatures of the paths at 90, 0, 135 and 45˚ respectively concatenated.

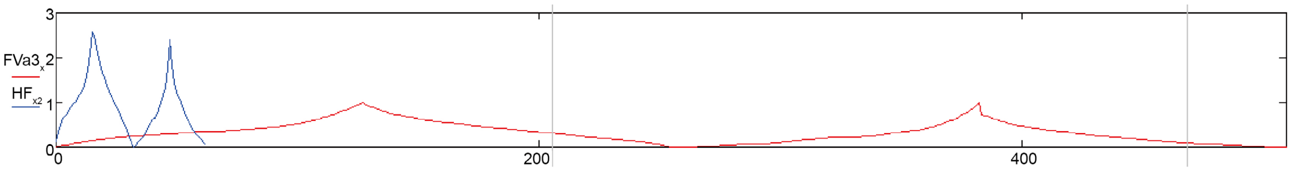

Figure 6. Redline represents cross-correlation based signatures of 90, 0, 135, and 45˚. Blueline represents signal of Haar wavelet of 3 levels.

These 64 data obtained from the Haar wavelet transformation are presented as input to the MLP (Multilayer Perceptron) so that the 100 individuals with their respective 12 versions of each can be processed with a low computational cost.

With this scheme, a 97.5% correct recognition rate was achieved using a "k-fold cross-validation" protocol with k = 10, using the Weka package.

4. Conclusions

With results achieved, it can be shown that with two pairs of cross-correlation based signatures, it is enough to generate a representative signal of each image to get a high classification performance, *i.e.*, that this signal remains stable between the different versions but representative with changes in the dynamics between individuals.

On the other hand, equally important is the consideration of the computational cost that is solved with a Haar wavelet transformation using 3 transformation levels, thus going from 512 to 64 data which are entered in the MLP for its training and operation.

With this proposed experimentation, it is possible to achieve a 97.5% correct recognition with a cross-validation scheme that supports the percentage achieved as a reliable and real result, that is, this method is robust with the system proposed using RGB and NIR images.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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