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A Novel Algorithm for Finger Vein Recognition

Shalini Bhaskar Bajaj
Amity School of Engineering and Technology
Amity University Haryana
shalinivimal@gmail.com

Abstract: In image recognition, 2-D PCA (two-dimensional Principal Component Analysis) is an effective method for feature extraction. For classification of images, 2-D LDA (two dimensional Linear Discriminate) is an efficient classification method. The present paper exploits the characteristic features of these two algorithms on finger-vein database by integrating these algorithms with wavelet transforms for image recognition and classification. Comparative analysis on recognition of images with each individual methods and with the proposed integrated method has been done and is found that the integrated method not only improves the recognition rate but also reduces the time taken for recognition of the images.

Keywords: Feature extraction Wavelet transforms, 2-D PCA, 2-D LDA

1. INTRODUCTION

Physiological characteristics of a person include hand, palm, fingerprints, hand geometry, iris, DNA, retina and hand veins, etc whereas behavioural characteristics include gait, voice, signature, typing rhythm, etc. Different persons have different pattern of finger veins and hence finger vein pattern can be used as biometric technology for recognition purposes. This technology originated from the research done by Hitachi's Advanced Research Group for treatment of human brain functional activity where the near infrared was used for detection of finger vein image. Finger vein recognition system has advantages that makes it highly secure, non-contact individual identification system as compared to other biometric technologies. Finger vein technology thus becomes promising future biometric technology [1] that can be used in building access control, banking, vehicle login systems, PC login, ATM machines, etc. It can be used in designing vein based personal identification system [3, 9].

Some proposed approaches uses the concept of radon spaces suing Radon transformation [10] which detects the valley like structures using the curvature in Radon spaces whereas some uses adaptive curve transformations [11]. Another algorithm based on discriminative binary codes (DBC) learning method is proposed for finger vein recognition based on relation graph wherein binary templates are transformed to describe vein characteristics of the subjects [12]. Finger vein biometric systems are also vulnerable to presentation attacks. To control this a new method for detecting forged finger vein images was proposed in 2018 using the concept of total variation decomposition [13].

Classical linear feature extraction algorithms such as PCA and FLD are widely used in machine vision and pattern recognition. With PCA and FLD, under normal conditions, 2-D matrix is converted into a row/column vector. For higher dimensional images converting to 1-D vector is not only time consuming but at the same time estimating the accurate covariance matrix is also difficult.

To overcome these issues 2-D PCA [2] and 2-D LDA models came to existence. Both these algorithms take into account the correlation matrix but requires more number of coefficients to express image information. As 2-D PCA and 2-D LDA uses more number of coefficients an improvement over them were proposed as 2DPCA - 2DLDA algorithm [4] and bi-weighted (2D)2PCA algorithm [5] that are used in face recognition and finger vein recognition respectively. Other algorithm proposed for face recognition was proposed on wavelet transform and 2D PCA [6]. Fusion of 2DDCT, 2DPCA and 2DLDA was also proposed for face recognition technology [7].

The proposed algorithm is a fusion algorithm of wavelet transform, 2DPCA and 2DLDA to identify finger vein. The proposed algorithm has higher recognition rate and takes less time to identify finger vein pattern.

2. THEORY

A. Wavelet Transform

A mathematical tool based on decomposition of multilevel functions is called Wavelet transform [8]. A wavelet transform can be represented by coefficients called wavelet coefficients. Wavelet transforms are widely used in pattern recognition, signal processing and image processing, etc.

To obtain the relationship between the frequency and time domains, signal analysis is done. Difference between Fourier transform, and wavelet transform is that the wavelet transform works on the time domain and Fourier transform works on the frequency domain for the input signal. Advantage of wavelet transform over Fourier transform is that by translating the mother wavelet and by scaling the width of the wavelet the frequency characteristics of the signal can be obtained. Figure 1 shows HAAR wavelet decomposed 2-D image produced 2 sub-band diagram, the lowest frequency sub-bands is similar to the original image and has most of the energy of the original image thus helps in restoring the image quality. The rest of the high frequency sub-bands of wavelet coefficients are mostly very small.

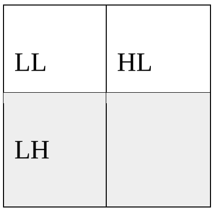


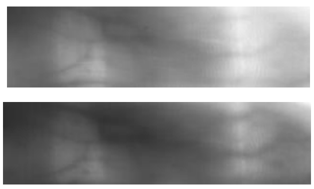
Figure 1. Wavelet decomposition sub-band map

B. 2DPCA algorithm description

Let Z denotes p x q image and Y is a q-dimensional column vector. Z projected onto Y by the following linear transformation W= ZY . Thus we get p-dimensional projected vector W called the feature vector of the image Z. Suppose there are A known pattern classes in the training set and B denotes the size of the training set. The i-th training image is denoted by a p x q matrix Zj (j = 1,2, …., B) and the mean image of all training samples is denoted by Z. Image covariance matrix is determined by maximizing the criterion whose physical sense is to find an optimal projection axes W. After projecting on W direction, the image matrix eigenvectors is decentralized to maximum extent. The optimal projection matrix is thus made up of the first h largest eigenvalues of the training matrix corresponding to the eigenvectors.

C. 2DLDA algorithm description

The principle that governs FLD is to develop a projection matrix for the training sample such that it has maximum scatter between different classes and minimum scatter between the same class after projection transformation. The objective of this algorithm is to have best separability after projection. By converting p x q-dimensional image matrix Z is projected onto the m-dimensional feature space Y, we get q-dimensional projection vector W. The objective is to have samples having the best separability after projecting. Let the training samples are composed by A classes with each class having samples. To make the p x q matrix, the i-th class and the j-th image is taken.



Optimal projection direction cannot extract discriminant information. Image data is usually projected onto a set of discriminate vectors for effective classification.

3. MODELLING AND DESIGN

The proposed algorithm for Finger-vein recognition system is as given below:

Proposed Model:

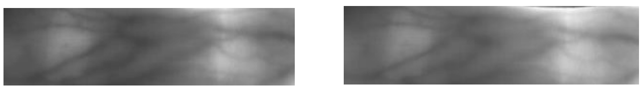
a) Enter the training samples and the test samples
b) Apply Haar wavelet transform on both training and test samples
c) Extracting low frequency sub-graphs from both training and test samples
d) Apply 2DPCA column transformation on both training and test samples
e) Apply 2DLDA column transformation on both training and test samples
f) Prepare Feature database from training samples
g) Classification of test samples on the basis of the Feature database collected from the training samples.
h) Recognition of the results

Prepare an image library using Haar wavelet transform function and extracting the low frequency sub-band images. This not only decreases the dimensions of the original image but also eliminates the redundant information of high frequency sub-bands. This further facilitates the subsequent classification of images. 2DPCA and 2DLDA column transformation are applied to obtain projection matrix. Projecting low frequency sub-band images provides feature database. Further classification can be done using nearest neighbor method.

4. EXPERIMENTAL RESULTS

The images of the fingers have been taken from the online database of fingers. The VERA Finger vein Database [14, 15] for finger-vein recognition consists of 440 images from 110 clients. Sample below shows the image of the first and second trail of the left index finger (Figure 1) and right index finger (Figure 2). All finger-vein samples have been recorded using the open finger vein sensor described in [BT12]. A total of 110 subjects presented their 2 indexes to the sensor in a single session and recorded 2 samples per finger with 5 minutes separation between the 2 trials. The database, therefore, contains a total of 440 samples and 220 unique fingers. Recordings were performed for collection of images at two different locations. From first location data was collected from 78 subjects and from second location data was collected from 32 subjects. The male and female ratio in the dataset is 7:4. The age of the subjects vary from 18 to 60 years with an average age of 33 years.

Figure 1: Image corresponding to the first and second trial for the left index finger and Figure 2: Image



corresponding to the first and second trial for the left index finger

The experiments were conducted by integrating wavelet transform and 2DPCA-2DLDA algorithm on the database and comparing the results with 2DPCA, 2DLDA and 2DPCA-2DLDA algorithms. In this paper two images were selected per person for training sample and two images for testing samples. Table 1 records the results for highest recognition rate and average recognition time for all the four algorithms. Table 2 compiles the results of the recognition accuracy obtained under different number of samples. Table 3 gives details on the recognition time obtained under different number of feature vectors.

Table 1 Highest Recognition Rate and the Average Recognition time for four Algorithms

Algorithm	1	3	5	7	9	11
2DPCA	1.12	1.22	0.99	1.03	1.01	1.10
2DLDA	1.11	1.23	1.30	1.19	1.20	1.19
2DPCA-2DLDA	0.67	0.66	0.65	0.63	0.62	0.61
WT-2DPCA-2DLDA	0.0061	0.0063	0.0064	0.0063	0.0065	0.0066

Table 2 Recognition Accuracy under Different Number of Training Samples for four Algorithms

Algorithm	Best feature vector number	Number of training images per person	Highest recognition rate (in%)	Average recognition time (in Sec)
2DPCA	7	2	93.2	1.24
2DLDA	5	2	94.5	1.35
2DPCA-2DLDA	P= 10, Q = 5	2	97.8	0.57
WT-2DPCA-2DLDA	P= 10, Q = 10	2	98.5	0.006

Algorithm	1	2
2DPCA	88.5	90.6
2DLDA	90.4	91.7
2DPCA-2DLDA	92.6	93.7
WT-2DPCA-2DLDA	98.1	98.8

Table 3 Recognition Time under Different Number of Feature Vector for four algorithms

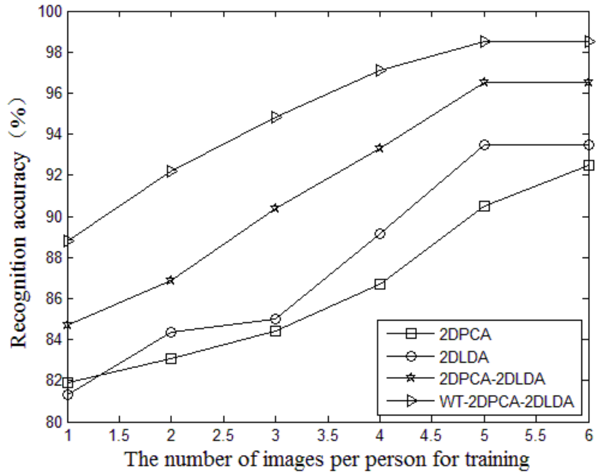


Figure 3. Recognition Accuracy of the given four algorithms on training samples

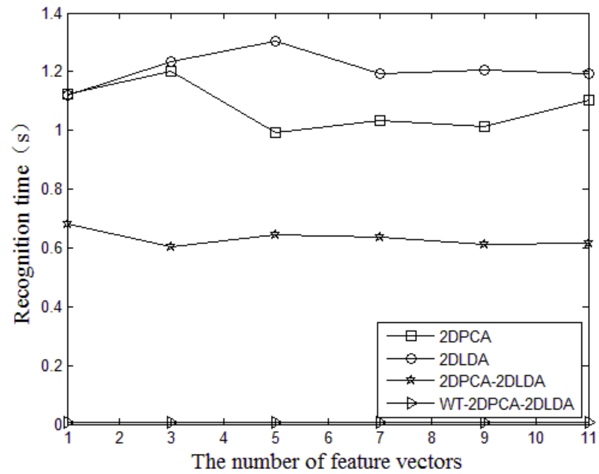


Figure 4. Recognition Time of the given four algorithms under different feature vector

5. CONCLUSION

It can be concluded from the experimental results that 2DLDA algorithm outperforms 2DPCA algorithm since the 2DPCA algorithm extracts the characteristics of the overall scatter matrix. Recognition rate of 2DPCA-2DLDA is higher than its constituent algorithms i.e. 2DPCA and 2DLDA as 2DPCA-2DLDA uses advantages of both the algorithms. 2DPCA algorithm is an example of the demonstration of diversity of data distribution whereas 2DLDA algorithm is an example of the demonstration of data classification to improve the recognition rate.

The recognition accuracy and the recognition time are best when wavelet transform is applied to 2DPCA-2DLDA algorithm. This is because noise is reduced and at the same time dimensionality reduction also takes place due to the use of wavelet transform. Thus, the feature extraction and classification time is reduced and this improves the recognition accuracy and recognition time.

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