Palmprint Recognition Using 2D-FLDA From a Single Image Per Person

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***Abstract*—Two dimensional Fisher linear discriminant analysis(2D-FLDA) is a very effective method for palmprint recognition. However, it cannot be used when each object has only one training sample because the within-class scatter matrices cannot be calculated. In this paper, a novel method is developed to solve this problem. Using the block segmentation, wavelet transform, and sampling methods, a new training set containing three training samples in each class can be obtained. Then the 2D-FLDA can be applied to extract the discriminant palmprint feature vectors. Finally the pattern classification can be implemented by the nearest neighbor classifier. Experimental results on the PolyU palmprint database show that the proposed method is efficient and it has better recognition performance than many existing schemes.**

***Index Terms*—single sample; Two dimensional Fisher linear discriminant analysis; block segmentation; wavelet transform; image sampling**

I. Introduction

Two dimensional Fisher linear discriminant analysis (2D-FLDA) has been successfully applied to palmprint recognition in the recent years. However, 2D-FLDA will fail when single image per person is available. Several algorithms have been proposed to solve the problem[1-4]. Chen et al.[1] divided the whole pattern into a set of non-overlapping sub-patterns to construct a new training subset and then evaluated the within-class scatter matrices and between-class matrices from these sub-patterns. Since this method needs to divide the test image into a set of non-overlapping sub-patterns, it will cost much time in classification. Yin et al.[2] proposed to obtain multiple training samples from a single image by sampling, and then Fisher linear discriminant analysis (FLDA) is applied to the set of newly produced samples. Gao et al.[3] presented a singular value decomposition (SVD) based FLDA approach to solve the single training sample. First, image was decomposed into several basis images using SVD. The basis images corresponding to the largest singular values were used to predict the general appearance of image. The original image and the predicted image were used to calculate the estimated within-class scatter. It is reported that this method outperforms many existing schemes which are proposed to overcome one sample problem[3]. In Ref.[4], a new method using QRCP-decomposition was proposed for the same one sample problem. In the proposed method, the image and its transpose were decomposed into two components using QRCP-decomposition. The image and its two approximations which were evaluated from the image and from its transpose using QRCP-decomposition were all used to obtain the training set. The image decomposition algorithm performs better than the SVD based method mentioned by Gao et al.[3] in terms of recognition rate and training time.

In this paper, we develop a new palmprint recognition using 2D-FLDA approach from a single image per person. In the developed method, three methods are used to obtain multiple training samples from a single palmprint image by the block segmentation, wavelet transform and sampling methods, and then apply 2D-FLDA to the set of newly produced samples.

The organization of this paper is as follows: In Section 2, the developed algorithm for single sample palmprint recognition based on 2D-FLDA is described in detail. Section 3 describes the feature classification. Section 4 presents the experimental results using the PolyU palmprint database. Section 5 offers our conclusions.

II. Feature Extraction Algorithms

A. Block Segmentation

The idea of block segmentation is to divide the original image $\boldsymbol{I}$ with a size of $\boldsymbol{m}\times\boldsymbol{n}$ into $\boldsymbol{p}\times\boldsymbol{q}$ blocks (similar to the matrix block in linear algebra), such that $\boldsymbol{I}$ is

$$I = \begin{bmatrix} I_{11} & I_{12} & \cdots & I_{1q} \\ I_{21} & I_{22} & \cdots & I_{2q} \\ \cdots & \cdots & \cdots & \cdots \\ I_{p1} & I_{p2} & \cdots & I_{pq} \end{bmatrix} \tag{1}$$

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where $\boldsymbol{I}_{ij}$ ($i = 1,2,\cdots, p,\ j = 1,2,\cdots, q$) is a subimage with a size of $\boldsymbol{m_1 \times n_1}$, $\boldsymbol{m=pm_1}$ and $\boldsymbol{n=qn_1}$[5]. The mean of each subimage can be calculated by

$$\mu_j = \frac{1}{m_1 n_1} \sum h(x,y) \qquad (j = 1,2,\cdots, pq) \tag{2}$$

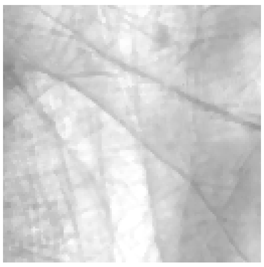
where $\boldsymbol{j}$ is the number of subimages and $\boldsymbol{h(x,y)}$ means the gray value of any point ($\boldsymbol{x, y}$) in the subimage. The characteristics of each subimage are denoted by $\boldsymbol{A_j} = [\ \mu_j\ ]$. Therefore, a low-dimensional image matrix with a size of $\boldsymbol{p \times q}$ is formed as the following:

$$A = \begin{bmatrix} \mu_{11} & \mu_{12} & \cdots & \mu_{1q} \\ \mu_{21} & \mu_{22} & \cdots & \mu_{2q} \\ \cdots & \cdots & \cdots & \cdots \\ \mu_{p1} & \mu_{p2} & \cdots & \mu_{pq} \end{bmatrix} \tag{3}$$

After preprocessing, the region of interest (ROI) with size 128×128 pixels, is extracted from the original palmprint image. Fig.1 shows the mean image result of block segmentation from the palmprint image.

B. Wavelet Transform

Wavelet transform[6] has been a very popular tool for image analysis in the past ten years. In the developed algorithm, wavelet transform is chosen to be used in increasing the number of the training sample. After preprocessing, ROI is as shown in Fig.2(a). The ROI is decomposed into four subbands as shown in Fig.2(b). The band LL is a coarser approximation to the original image. The bands LH and HL record respectively the changes of the image along horizontal and vertical directions while the HH band shows the high frequency component of the image. This is the first-level decomposition. The decomposition can be further carried out for the LL subband. After applying three-level wavelet transform, an image is decomposed into subbands of different frequency as shown in Fig.2(c). Since the size of ROI image is 128×128 pixels, the subbands 1, 2, 3 and 4 are of size 16×16 pixels, the subbands 5, 6, 7 are of size 32×32 pixels and the subbands 8, 9, 10 are of size 64×64 pixels. The low-frequency subband LL or subband 1 maintains most of the information of the original palmprint image and the values of most of points in the high-frequency subband close to 0. We can ignore the high-frequency part in the image. The low-resolution image LL or subband 1 is considered as one training sample $\boldsymbol{A}$ to increase the number of the training sample and reduce the computational complexity.

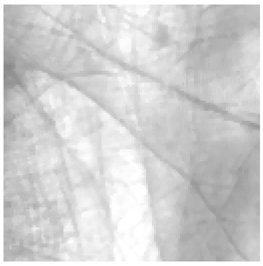


(a) ROI of the palmprint

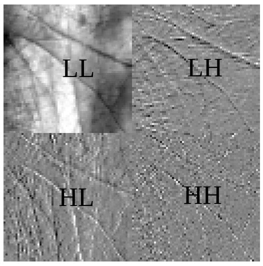
(b) The mean image of 64×64 blocks

(c) The mean image of 16×16 blocks

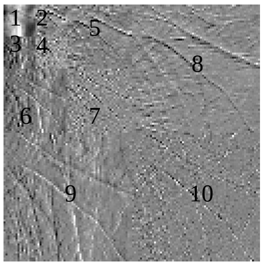
Figure 1. The mean image of block segmentation for palmprint image.



(a) ROI of the palmprint



(b) image after first-level wavelet decomposition



(c) image after three-level wavelet decomposition

Figure 2. Wavelet decomposition of a palmprint image.

C. Image Sampling

Each palmprint image in the training set is divided into smaller blocks and each block contains $P \times Q$ pixels. We can obtain sampled sub-images by taking one pixel from the same position in each block[2]. In fact, P and Q is the sampling interval in height and width respectively. If the size of the palmprint image is $M \times N$ pixels, these sampled sub-images can be represented mathematically as

$$A_{ij}(m,n) = A((m-1) \times P + 1, (n-1) \times Q + 1) \tag{4}$$

where $1 \le m \le M / P$, $1 \le n \le N / Q$. Fig.3 shows the sampling result from the palmprint image on the left using Eq. (4).

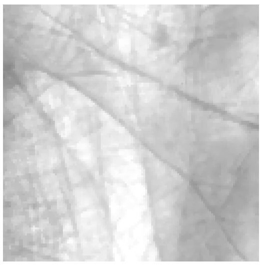
D. Two Dimensional Fisher Linear Discriminant Analysis (2D-FLDA)

Using the block segmentation, wavelet transform, and sampling methods, a new training set containing three training samples in each class can be obtained. It is obvious that 2D-FLDA can be applied to the new training set.

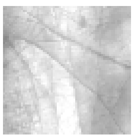
FLDA is a popular feature extraction and discriminant approach to palmprint recognition. It aims to find a set of projection vectors that separate the different classes as far as possible while compressing the same class as compact as possible. However, it is difficult to calculate accurately the generalized eigenvalues of within-class and between-class scatter matrices. Ye et al. proposed 2D-FLDA, which directly estimates the scatter matrices from 2D images and uses the fisher discriminant criterion to compute the optimal projection vectors [3].

Given N training samples $A_i \in R^{m\times n} (i = 1,2,\cdots, N)$ from C classes. The ith class C_i includes N_i samples and $\sum_{i=1}^{C} N_i = N$. Let A_i^j be the jth image from ith class. Denote by $\bar{A}$ the mean image of all samples, and by $\bar{A}_i$ the mean image of the ith class C_i and 2D-FLDA attempts to seek for a set of optimal discriminating vectors $w_j \,(j = 1,\cdots, d)$ to construct a transform matrix $W = [w_1, w_2,\cdots w_d]$ by maximizing the following criterion

$$J(W) = \frac{tr(W^{\mathrm{T}} S_b W)}{tr(W^{\mathrm{T}} S_w W)} \tag{5}$$



(a) ROI of the palmprint



(b) palmprint image sampling, where P=Q=2

(c) palmprint image sampling, where P=Q=8

Figure 3. Example of palmprint image sampling.

where superscript ‘‘T” denotes matrix transpose, tr denotes the trace of a matrix, $\boldsymbol{S_b}$ is the between-class scatter matrix

$$S_b = \sum_{i=1}^{C} (\bar{A}_i - \bar{A})^{\mathrm{T}} (\bar{A}_i - \bar{A}) \tag{6}$$

and $\boldsymbol{S_w}$ is the within-class scatter matrix

$$S_w = \sum_{i=1}^{C}\sum_{j=1}^{N_i} (A_j^i - \bar{A}_i)^{\mathrm{T}} (A_j^i - \bar{A}_i) \tag{7}$$

The maximization of Eq. (5) is equivalent to solve the generalized eigenvalue problem: $\boldsymbol{S_b W}= \boldsymbol{D S_w W}$, where $\boldsymbol{D}$ is a diagonal matrix with eigenvalues on the main diagonal. After obtaining $\boldsymbol{W}$, we can extract d discriminant features for any input image by projecting it onto $\boldsymbol{W}$. As the number of discriminating vectors, d is at most min(C-1, n). The pseudo-code for the 2D-FLDA is shown in Fig.4.

Let $\boldsymbol{A_{test}}$ be the unknown image that will be classified. The newly produced image from $\boldsymbol{A_{test}}$ is $\boldsymbol{A_t}$. Then the optimal projection vectors for the training sample $\boldsymbol{A_i}$ $(i = 1,2,\cdots, N)$ and the test sample $\boldsymbol{A_t}$ can be calculated as t_i=$\boldsymbol{A_i W}$ and t=$\boldsymbol{A_t W}$ respectively.

III. Feature Classification

The extracted feature vectors of the training images and the test image for recognition are a 1D vector. The nearest neighbor classifier is used to recognize the identity. Suppose that the extracted feature vectors of the C training images are $\{t_1, t_2, \cdots, t_C\}$, the ith person in the set has only one 1D vectors t_i for single sample palmprint recognition. The Euclidean distance between the testing image t and t_i is $d\,(t,t_i) = \sqrt{\|t\|^2 + \|t_i\|^2 - 2\,t\,t_i}$. If the distance between the t and the ith person is the shortest, i.e. $d\,(t,t_i) = \min\{d(t,t_1), d(t,t_2),\cdots; d(t,t_i),\cdots; d(t,t_c)\}$, the identity of the image t is $ID_i = \{ i / \arg\min d(t, t_i) \}$[7].

IV. Experimental Results and Analysis

A. The PolyU Palmprint Database

The PolyU palmprint database(http://www4.comp.polyu.edu.hk/~biometrics/) is one of the common largest image databases in palmprint field. The database contains 600 grayscale images corresponding to 100 different palms. Six samples from each of these palms were collected in two sessions, where 3 samples were captured in the first session and the other 3 samples in the second session. The average interval between the first and the second collection was two months. The resolution of all the original palmprint images is 284×384.

The first palmprint image of each class is chosen as training sample and the remaining five are used as testing samples. The training images have 100 samples. By using the preprocessing approach[8], palmprints are orientated and ROI with size 128×128 pixels is cropped to represent the whole palmprint. Three methods are adopted to increase the number of training samples of each class.

1) Each palmprint image in the training set is divided into $P\times Q$ subimage. The mean of each subimage is calculated, such that the palmprint image is changed into a $128/P\times128/Q$ image.
2) Following the n-level wavelet transform, we can gain an image with a size of $128/2^n\times128/2^n$.
3) Each palmprint image in the training set is divided into smaller blocks and each block contains $P\times Q$ pixels. We can obtain $128/P\times128/Q$ sampled image by taking one pixel from the same position in each block.

Using the above three methods, a new training set containing three training samples in each class can be obtained. Then 2D-FLDA is utilized to extract the feature vectors.

B. Comparison and Analysis of Recognition Results

The comparative recognition rates of three different algorithms with different subimages are shown in Table 1. The experimental results in Table 1 show that:

1) In different feature dimension, when the sub-image size is 32×32 pixels, the recognition rate of the proposed algorithm is relatively high. The larger sub-image size, the smaller is the feature vector dimension. The feature vectors lose some discriminant information, and deteriorate the recognition performance. The smaller sub-image size, the larger is the feature vector dimension. The feature vectors are redundant. When the sub-image size is moderate, the feature vectors contain most of the information to represent the palmprint image, and improve the recognition performance.
2) In the same level wavelet decomposition, with the increasing dimension of feature vectors, the recognition rate increases the top, then it decreases. The extracted feature vectors are redundant if too large dimension of feature vectors, such that the recognition performance is not good.
3) In different feature dimension and different subimages, the recognition rate of the developed method is the best among the three feature extraction algorithms. When the sub-image size is 32×32 pixels, and the feature dimension is 11, the highest recognition rate of the developed method is 74.2%. An improvement of 16.6% in recognition rate is achieved compared with the method in [3] which has the highest recognition rate of 57.6%. The proposed method also shows an improvement of 8.4% compared with the method in [2], which has the highest recognition rate of 65.8% when the sub-image size is 64×64 pixels.

V. Conclusions

This paper develops a simple but efficient method to solve the problem of single training image per person when using two dimensional Fisher linear discriminant analysis(2D-FLDA). By using the block segmentation, wavelet transform, and sampling methods, a new training set containing three training samples in each class can be obtained. It is obvious that 2D-FLDA can be applied to the new training set which cannot be directly used in the case of single training sample per person. Experimental results verify that the developed method is not only feasible but also achieves better recognition performance in single sample palmprint recognition.

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TABLE I.
THE RECOGNITION RATE(%) FOR DIFFERENT ALGORITHMS WITH DIFFERENT SUB-IMAGES

Subimages	Algorithms	Feature dimension							
		1	3	5	7	9	11	13	15
128×128	Method in [3]	37.6	51.6	56.0	57.6	57.4	57.6	57.6	57.6
64×64	Method in [2]	39.4	54.0	61.6	65.0	65.6	65.8	65.4	65.0
	Proposed method	44.0	67.6	67.6	70.2	69.2	68.8	68.8	68.4
32×32	Method in [2]	35.8	51.6	56.4	56.8	56.8	56.8	56.4	56.2
	Proposed method	45.6	64.6	72.8	74.0	73.8	74.2	74.0	73.6
16×16	Method in [2]	20.2	35.0	38.4	39.0	39.0	39.0	39.0	38.8
	Proposed method	39.2	61.4	68.8	69.0	69.4	71.0	69.8	69.8

Input: $A_1, A_2, \cdots A_N$
Output: W

Compute the mean A_i of ith class for each i as $\bar{A}_i = \frac{1}{N_i}\sum_{j=1}^{N_i} A_i^j$

Compute the global mean $\bar{A} = \frac{1}{N}\sum_{i=1}^{N} A_i$

$S_b \leftarrow 0_{n\times n}$

$S_w \leftarrow 0_{n\times n}$

for i=1:C

$S_b \leftarrow S_b + \sum_{i=1}^{C} (\bar{A}_i - \bar{A})^{\mathrm{T}} (\bar{A}_i - \bar{A})$

for j=1:N_i

$S_w \leftarrow S_w + \sum_{i=1}^{C}\sum_{j=1}^{N_i} (A_j^i - \bar{A}_i)^{\mathrm{T}} (A_j^i - \bar{A}_i)$

end

end

Computer the first d eigenvectors $W = [w_1, w_2, \cdots w_d]$ of $\boldsymbol{S_b W} = \boldsymbol{D S_w W}$

Figure 4. The pseudo-code for the 2D-FLDA. $0_{n\times n}$ denotes $n\times n$ matrix with zeros