Palmprint Recognition using Fisher-Gabor Feature Extraction

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***Abstract*— This paper presents a new approach for palmprint recognition using a combined Fisher linear discriminant (FLD) and Gabor Wavelet responses. Gabor wavelets have properties of being more robust to image illuminations, small translations, limited rotations and having a superior feature representation in both spatial and frequency domains. On the other hand, FLD seeks those projections that are efficient for data discrimination and produces well separated classes in low-dimensional subspaces. The new combined method involves convolving a palmprint image with a series of Gabor wavelets at different scales and rotations before extracting features from the resulting Gabor filtered images. Linear discriminant analysis is then applied to the feature vectors for dimension reduction as well as class separability. Experiments show that the proposed method yields a high classification rate even when using a simple classifier when compared with other popular approaches reported in the literature.**

I. Introduction

A wide variety of systems require reliable personal recognition schemes to either confirm or determine the identity of an individual requesting their services. The main purpose of such schemes is to ensure that the rendered services are accessed only by a legitimate user, and not anyone else. One of the new recognition schemes is the palmprint which is provides rich personal information for automatic recognition of individuals based on the principal lines, wrinkles and ridges on the palm [1][2]. Since the patterns of an individual's palmprint are stable and unique [3], they can be used as personal signatures for human identification. However, the similarity between the principal lines from different persons [1][3] make it difficult to discriminate different palmprints with an acceptable accuracy. For this reason, we believe that palm texture will add extra discriminating power since the feature extraction is a crucial step in the recognition process especially for palmprint images with low resolution qualities (i.e., of 75dpi).

One of the most attractive tool to capture useful information to maximize the simultaneous localization of energy in both spatial and frequency domains is Gabor filter [4] [5][1]. A Gabor filter can be applied to the whole image through a filtering process in order to break down the image content into different scales, orientations or with a combination of both with the aim of obtaining an efficient feature extraction to maximize the classification. However, the resulting dimensionality of the feature vectors extracted is usually very high when a series of Gabor filters are used to convolve the image. A usual method for dimensionality reduction is to use a subspace projection. Two fundamental linear subspace transform based methods: Eigenpalms [6] and Fisherpalms [7] have had a significant influence for a considerable reduction of the feature vector dimensional reduction while still maintaining an acceptable discrimination. Eigenpalms are a set of eigenvectors obtained when applying principal component analysis (PCA) to a set of training images in the spatial domain to approximate the original data by a linear projection onto the leading eigenvectors. However, PCA computes those components that are useful for representing data and as such it does not assume that these components should be useful for discriminating between classes. In other words, PCA seeks projections that are optimal for image reconstruction from a low dimensional basis and it may not be optimal for discrimination purpose [8]. Compared with PCA, FLD is a well-known method for feature extraction and dimensionality reduction which seeks projections that are efficient for data discrimination. It is used to determine the low-dimensional space that helps to group the images of the same class and separate images of different classes. In this paper, we describe an approach that combines Gabor feature extraction and linear discriminant analysis for a high palmprint recognition. This involves extracting discriminant features from images using a series of Gabor wavelets at different scales and orientations and projecting the resulting feature vectors into a subspace before authentication can be performed. Finally, a distance measure is used to determine the similarity between a query palmprint image against images in a database in order to assess the performances achieved.

The rest of the paper is organized as follows. A review of Gabor Wavelet Transform (GWT) is described in Section II. The proposed approach is discussed in Section III while Section IV gives some experimental results. Finally, conclusions are drawn in Section V.

II. Review of Gabor Wavelet

A general 2-D Gabor function $\psi(x,y)$ is defined as:

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y}\ exp\ [-\frac{1}{2}(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}) + j2\pi Wx] \quad (1)$$

where the spatial coordinates (x, y) denote the centroid localization of an elliptical Gaussian window. The parameters σ_x and σ_y are the space constants of the Gaussian envelop along x and y axes, respectively. The Fourier transform $G(u, v)$ of the Gabor function $g(x, y)$ can be written as:

$$G(u,v) \ = \ exp\ \{-\frac{1}{2}[\frac{(u-W)^2}{\sigma_u^2} + \frac{v^2}{\sigma_v^2}]\} \quad (2)$$

where W represents the frequency of the sinusoidal plane along the horizontal axis and the frequency components in the x and y direction are denoted by the pair (u, v), while $\sigma_u = \frac{1}{2\pi\sigma_x}$ and $\sigma_v = \frac{1}{2\pi\sigma_y}$. By considering a non-orthogonal basis set formed by Gabor functions, a localized frequency description can be obtained by expanding a signal with this basis. Self-similar class functions, known as Gabor Wavelets, can be generated by dilations and rotations of the mother wavelet $\psi(x, y)$ through the generating function :

$$g_{mn}(x,y) \ = \ a^{-m} g(x', y'), \ a > 1 \quad (3)$$

by considering $m = 1, ...S$ and $n = 1, ...K$. S and K denote the total number of dilations and orientations, respectively, and:

$$\begin{aligned} x' &= a^{-m}(x\cos\theta + y\sin\theta) \quad (4) \\ y' &= a^{-m}(-x\sin\theta + y\cos\theta) \end{aligned}$$

where $\theta = \frac{n\pi}{K}$ is the angle. To ensure that the energy is independent of m, a scale factor a^{-m} is introduced. By considering the redundant information presented in the filtered images due to the non-orthogonality of the Gabor wavelets, Manjunath et al [9] designed a strategy to reduce the redundancy of the Gabor wavelet filter bank, where the half-peak magnitude of the filter responses touches each other in the frequency spectrum.

A. Gabor Filter Design

Let U_l and U_h denote the lower and the upper center frequencies of interest. Then the design strategy results in the following equations for computing the filter parameters σ_u and σ_v [9].

$$a \ = \ (\frac{U_h}{U_l})^{\frac{-1}{S-1}} \quad (5)$$

$$\sigma_u \ = \ \frac{(a-1)U_h}{(a+1)\sqrt{2ln2}} \quad (6)$$

$$\sigma_v \ = \ \tan(\frac{\pi}{2k})[U_h - 2ln(\frac{\sigma_u^2}{U_h})][2ln2 - \frac{(2ln2)^2\sigma_u^2}{U_h^2}]^{\frac{-1}{2}} \quad (7)$$

where $W = U_h$. In order to eliminate sensitivity of filter responses to absolute intensity values the real components of 2D Gabor filters are biased by adding a constant to make them zero mean since most of the useful information in a palmprint image is contained within a limited frequency band. Four scale and eight orientations appear to have achieved an acceptable performance in our experiments.

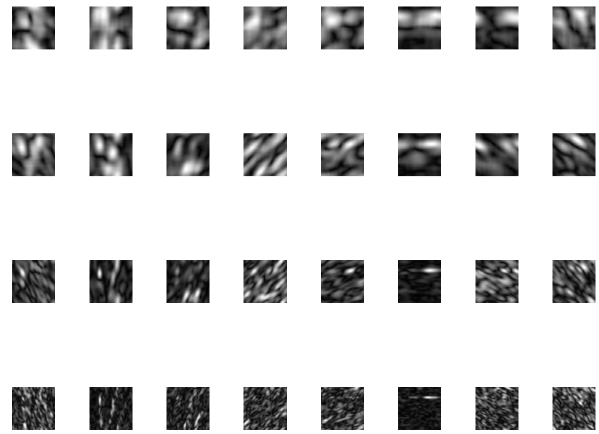

Fig. 1. Responses of Gabor wavelets (Magnitudes) for S = 4 and K = 8

B. Gabor feature representation

The Gabor representation of a palmprint image $\mathrm{x}(x, y)$ can be obtained by convolving the image with the family of Gabor filters as follows:

$$W_{m,n}(x,y) \ = \ \int\int \mathrm{x}(x,y) g^*_{mn}(x - x_0, y - y_0) dx_0 dy_0 \quad (8)$$

where $W_{m,n}(x, y)$ denotes the result corresponding to the Gabor filter at scale S and orientation K and * indicate the complex conjugate. Figure 1 shows the magnitude of the convolution result of a random palmprint image with 32 Gabor filters with $U_l = 0.05$ and $U_h = 0.4$, in which four scales and eight orientations have been used to generate a series of Gabor responses involving a trade filter bandwith against the size of the scaling factor between frequencies of the successive filters, as well obtaining a broad and uniform coverage of the spectrum. As a result, a palmprint image can be represented by a set of Gabor wavelet coefficients $(W_{m,n}(x, y), m = 0, ..., 3; n = 0, ..., 7)$. The magnitude of each coefficient $W_{m,n}(x, y)$ is normalized to zero mean, unit variance and at each scale level the coefficients are resampled by a factor of $1/2^{(s-1)}$ giving a dimensionality that is $1/4^{th}$ of the previous level. This overcomes the dimensionality explosion relating to using a filter-bank with different scales and orientations. Finally, the coefficients are converted into a vector x_{mn} by concatenating the rows. A discriminative feature vector x can be derived to represent the image $I(x, y)$ using equation (9) as follows:

$$\mathrm{x} = [\mathrm{x}_{0,0}^T \ \ \mathrm{x}_{0,1}^T \ \ ... \ \ \mathrm{x}_{3,7}^T] \quad (9)$$

The dimension of the derived feature vector still too high for an efficient classification process since it requires a large memory space and a high computational effort. The following sections introduce Fisher linear discriminant (FLD) technique to reduce the high dimensionality of the feature vector.

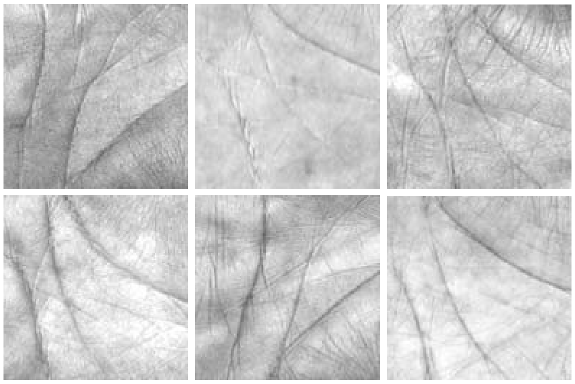

Fig. 2. Samples palmprint from the database under different light conditions

III. Discriminant Analysis

PCA and FLD have been successfully applied to palmprint recognition, PCA identifies a subspace spanned by the training images in order to decorrelate the variance pixel values. Unlike PCA, FLD aims to find a projection matrix which is optimized to separate different classes. However for palmprint image applications all scatter matrices S_W (within class) can be singular since the dimension of image vector exceeds, in general, the number of data points (known as singularity problem). To tackle this problem, the derived feature vectors $[\ \mathrm{x} \mid \mathrm{x}_1;\ \mathrm{x}_2; ...;\ \mathrm{x}_N\ ]$ are firstly projected into a lower dimensional space by PCA so that the resulting within-class scatter matrix is nonsingular. Then, a standard FLD is employed to process the projected samples. This method, which has been used efficiently in face recognition [8], is described as follows:

Let us consider a feature vector corresponding to the set of training images as a set of N samples derived by Gabor wavelet decomposition $[\ \mathrm{x} \mid \mathrm{x}_1;\ \mathrm{x}_2; ...;\ \mathrm{x}_N\ ]$ taking values in an n-dimensional Gabor space, and let us assume that each feature vector belongs to one c classes $[\ X_1, X_2, ..., X_c\ ]$.

(i) compute the transformation matrix of PCA transformation W_{pca}:

$$W_{pca} = \text{argmax}|W^T S_T W| = [\mathrm{w}_1, \mathrm{w}_2, ..., \mathrm{w}_m] \tag{10}$$

where $[\ \mathrm{w}_i \mid i = 1, 2, ..., m(m < n)\ ]$ is the set of eigenvector of S_T corresponding to the nonzero eigenvalues and S_T is the total scatter matrix defined as:

$$S_T = \sum_{k=1}^{N} (x_k - \mu)(x_k - \mu)^T \tag{11}$$

(ii) compute the transformed within-class scatter matrix $S_W^{'}$ and the transformed between-class scatter matrix $S_B^{'}$ as follows:

$$S_W^{'} = W_{pca}^T S_W W_{pca} \tag{12}$$

$$S_B^{'} = W_{pca}^T S_B W_{pca} \tag{13}$$

where (refer to [8]):

$$S_B = \sum_{i=1}^{c} N_i (\mu_i - \mu)(\mu_i - \mu)^T \tag{14}$$

and:

$$S_W = \sum_{i=1}^{c} \sum_{x_k \in X_i} (x_k - \mu_i)(x_k - \mu_i)^T \tag{15}$$

(iii) employ a standard FLD to process the projected samples:

$$W_{fld} \quad = \quad \text{argmax} \frac{|W^T W_{pca}^T S_B W_{pca} W|}{|W^T W_{pca}^T S_W W_{pca} W|} \tag{16}$$

(iv) compute the optimal projection matrix W_{opt}:

$$W_{opt} = W_{fld} * W_{pca} \tag{17}$$

The projection of x in the FLD space is given by:

$$Y = W_{opt}^T \mathrm{x} \tag{18}$$

The columns of $[W_{opt} \mid \mathrm{w}_1, \mathrm{w}_2, ...\mathrm{w}_m]$, $(m < c - 1)$ are orthonormal vectors and the space spanned by these vectors is called a Fisher-Gabor wavelet space FGWS.

In our approach the feature vectors have been projected into Fisher-Gabor wavelet space using equations (10-18) for dimensionality reduction and class separability by taking the advantages that Gabor features contain more discriminant information and are thus more robust against illumination variations and small misalignment of the palmprint images. The similarity between a training and testing image is carried out by using the City Block Distance shown in equation (19).

$$d(y_i, y_j) = \sum_{k=1}^{n} |y_i(k) - y_j(k)| \tag{19}$$

where y_i and y_j vectors are the template stored in the database and palmprint image projected into Fisher-Gabor wavelet space respectively.

IV. Experimental Results

To gauge the effectiveness of our method, the PolyU palmprint Database [10] of 600 palmprint images comprising 100 different palms captured by a CCD-based device was used. The resolution of all of the original palmprint images is 384x284 pixels, at 75dpi. Six samples from each of these palms were collected in two sessions, three samples were captured in the first session and the other three in the second session. The average interval between the first and the second collection was two months. By using the preprocessing approach [1], palmprints are orientated and the central part of the image, whose size is 128x128, is cropped to represent the whole palmprint. Some typical samples are shown in Fig.2. As can be seen from this figure, the lighting condition in different sessions is leading to variation of visual texture.

The three images of the first session are chosen as training samples and the three images of the second session are chosen in the testing process. Y is stored as the template for each palmprint class. In the recognition stage, the input palmprint

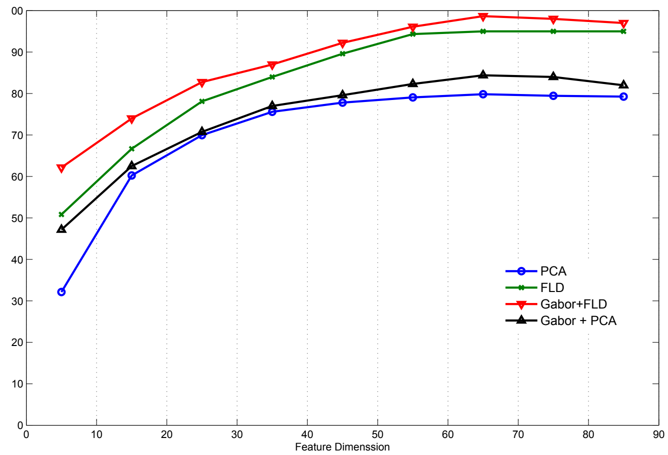

Fig. 3. Performance improvement of PCA and FLD using Gabor wavelet feature

image is projected onto the stored Fisher-Gabor wavelet space (FGWS) to compute its feature vector V and then Y is compared with the stored templates to obtain the recognition result. All of the experiments are conducted using the city block distance.

For comparison proposes, we have implemented three methods: direct PCA and direct FLD on the original palmprint images. Our proposed combined method was then implemented as described previously where a palmprint image is first transformed into a Gabor space before feature extraction and classification were carried out using PCA and FLD. In all cases, a city block distance was used. Figure.3 reports the result in terms of the standard recognition rate, which is the ratio between the number of correctly identified palmprints and the number of test palmprint images. This clearly shows that a combination of PCA and FLD with a Gabor feature improves the performance of PCA and FLD when applied directly on original images. This shows that the augmented Gabor feature vector carries more discriminating information than the original images do. The reason of the improvement is due to the robustness of Gabor wavelet in feature extraction when the images are affected by illumination variations and small image misalignments. As shown, a recognition rate of 98.67% is obtained using Gabor wavelet with FLD with a feature vector of 65 components. To further demonstrate the effectiveness of our proposed combined Gabor and FLD technique, comparison with two existing and similar methods have been carried out. The first method (Method 1) combines a wavelet decomposition and 2D PCA (2DPCA) and has been used to obtain the most discriminant information contained in the low-frequency band of a palmprint image as claimed by the authors [11]. In the second method (Method 2), a dual-tree complex wavelet transform and support vector machines are used for a reliable palmprint classification [12].

Table I depicts the results obtained where it can clearly be seen that a combined Gabor wavelet and FLD performs significantly better than earlier research results. This is due to the fact that the use of multiple filters with different scales and orientations generate more discriminating feature compared with the use of ordinary wavelet filters since palmprint texture information is random rather than uniform. This means that the local details of a palmprint image spread along different directions so that the information density in the angular direction (0-180 degree) is very important for feature extraction.

TABLE I

COMPARISON WITH OTHER METHODS

Method	Recognition Rate
Method 1	97.0%
Method 2	97.0%
Proposed method	98.67%

V. CONCLUSION

This paper proposes a new method for palmprint recognition based on a combined Gabor wavelet and Fisher linear discriminant. Due the problem of illumination variations and misalignments of palmprint images, this can be overcome by using Gabor filter responses as an input to an FLD, since FLD seeks directions that are efficient for feature discrimination and class separation. The experimental results demonstrate the effectiveness of the augmented method since by using multiple filters with different frequency responses generate more discriminating features in the distinct dominant frequencies, thus leading to a high recognition rate.

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