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Principal Component Analysis of Directional Images for Face Recognition

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Abstract: This study addresses new face recognition method based on Principal Component Analysis (PCA) and Directional Filter Bank (DFB) responses. Our method consists of two parts. One is the creation of directional images using DFB from the original face image. The other is transforming the directional images into eigenspace by PCA, which is able to optimally classify individual facial representations. PCA analysis is primarily used as a dimensionality reduction technique with least consideration to the recognition aspect. The basic idea of combining PCA and DFB is to provide PCA with some recognition ability. In our system recognition ability of the PCA is enhanced by providing directional images as inputs. The experiment results showed the remarkable improvement of recognition rate of 21.25% in Olivetti data set.

Key words: Principal Component Analysis (PCA), eigenvectors, eigenvalues, Directional Filter Bank (DFB)

INTRODUCTION

Face recognition is largely motivated by the need for surveillance and security, telecommunication and digital library, human-computer intelligent interaction and smart environments[1-4]. The face recognition primarily based on the understanding how people process and recognize each others face and the development of corresponding computational modal for automated face recognition.

Developing a computational modal for the recognition of natural objects such as human faces is quite difficult, because they are complex and multidimensional. The general approach is to start with a given set of features and then attempts to derive an optimal subset (under some criteria) of features leading to high recognition performance. Principal Component Analysis (PCA) is a popular technique used to derive a starting set of features for face recognition. Turk and Pentland[5] develop a well-known PCA-based face recognition method, referred to as Eigenfaces method. More recently, a principal component analysis of imagery has also been applied for robust target detection[6,7], nonlinear image interpolation[8], visual learning for object recognition[9,10] and visual servoing for robotics[11].

However, PCA analysis was used primarily as a dimensionality reduction technique and did not the recognition aspect. This is due to the fact that PCA is based on the optimal representation of the data in the sense of mean-square error. One way to improve the PCA stand-alone recognition performance, one needs to combine further this optimal representation criterion with some discrimination criterion.

One widely used discrimination criterion in the face recognition community is the Fisher Linear Discriminant (FLD, a.k.a. Linear Discriminant Analysis, or LDA)[12], which defines a projection that makes the within-class scatter small and the between-class scatter large. As a result, FLD derives compact and well-separated clusters. FLD is behind several face recognition methods[13,14]. As the original image space is high dimensional, most of these methods apply PCA first for dimensionality reduction, as it is the case with the Fisherfaces method due to Belhumeur *et al.*[14]. Subsequent FLD transformation is used then to build the Most Discriminating Features (MDF) space for classification[13]. The drawback of FLD is that it requires large training sample size for good generalization.

In contrast, one can provide a preprocessing step that outputs discriminating feature classes. Then PCA can

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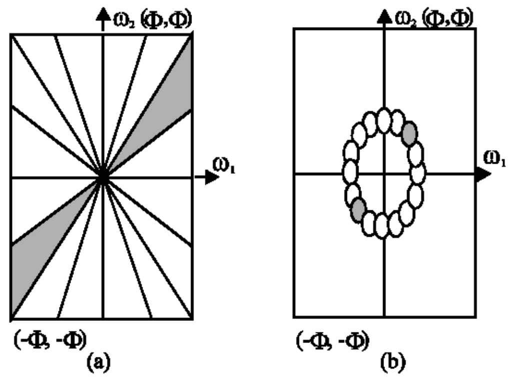

Fig. 1: Regions used by (a) the DFB (b) the Gabor filter bank-based method for feature extraction

be used with each class to reduce the dimensionality. This view is described by Ki-chung *et al.*[15], where the Gabor filter responses are used as input vectors to the PCA. It is mentioned that Gabor filter responses works well with PCA and results in a system that is less sensitive to the rotation and illumination with improved classification. However, as described by Chul-Hyun *et al.*[16], Gabor filter bank has overlapping and missing subband regions the DFB, on the other hand, is a contiguous subband representation as shown in Fig. 1. Accordingly, a DFB can represent linear patterns, as found around eyes, nose and mouth area, more effectively, than a Gabor filter bank. The positive effect, in case of Gabor filter bank, of extracting special frequency and directional feature and suppressing noise component is much offset by the negligence of useful information existing outside the specified frequency range. This study represents Directional Filter Bank (DFB) as a preprocessing step to provide directional discriminating feature spaces. DFB based directional analysis has played a major role in wavelet image denoising[17], fingerprint image enhancement[18], fingerprint image enhancement in a binary domain[19]. In this study, DFB effectively decomposes the face image into eight directional images and each directional image contains directional features associated with a particular direction. This preprocessing can be regarded as a discrimination process. Then PCA is used with each directional image in isolation. Finally, the PCA outputs based on each directional image is analyzed for recognition purpose.

Creation of directional images: It has two categories as follows:

Directional filter design: The directional analysis employed in this paper decomposes the spectral region of a given image into wedge-shaped passband regions. It is easily shown that these wedge-shaped regions correspond to directional components of an image. The filters related to wedge-shaped regions are commonly referred to as fan filters.

The schematic diagram of DFB structure is in the form of a tree with two-band splits at the end of each stage (Fig. 2) where each split increases the angular resolution by the factor of two. The first stage employs the complementary hour-glass filters. The filters for next two stages are obtained by linear transformation of the first stage hour-glass filters. For implementing linear transformation, the uni-modular matrices M and R are utilized. The rules for the selection of these matrices are presented by Park *et al.*[20]. Once the filters for each stage are implemented, they can be combined on branch by branch basis to get the required fan filters as shown at the end of third stage in Fig. 2.

$$R_1 = \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix} \quad R_2 = \begin{pmatrix} 1 & -1 \\ 0 & 1 \end{pmatrix}$$

$$M = \begin{pmatrix} 1 & 1 \\ -1 & 1 \end{pmatrix}$$

$$R_3 = \begin{pmatrix} 1 & 0 \\ 1 & 1 \end{pmatrix} \quad R_4 = \begin{pmatrix} 1 & 0 \\ -1 & 1 \end{pmatrix}$$

One important difference between present proposed structure and DFB structure presented[20], is the absence of decimator. It was pointed out that if sub-bands need to be processed for directional energy estimates, the decimation present in the conventional filter bank structure poses problem[21]. This means that two samples located at the same spatial index (n_1, n_2) in two different sub-bands I and j will not necessarily correspond to same spatial region in the original image. This problem was circumvented by employing nearest neighborhood or bilinear interpolation to make all sub-bands of the same size[21]. However, in the present structure, decimators at each stage are taken out and filters are designed by linear transformation in the frequency domain to get fan filters. Furthermore, to avoid ringing artifact in the output, ideal fan filters are avoided by employing non-ideal hour-glass filters using an FIR lowpass filter.

Directional images: Directional images are obtained by applying all directional filters constructed as above. Eight directional images were obtained (Fig. 3). These directional images can be regarded as decomposition of the original image in eight pieces based on direction. Directional images contain features associated with global directions rather than local directions. By creating directional images, noise

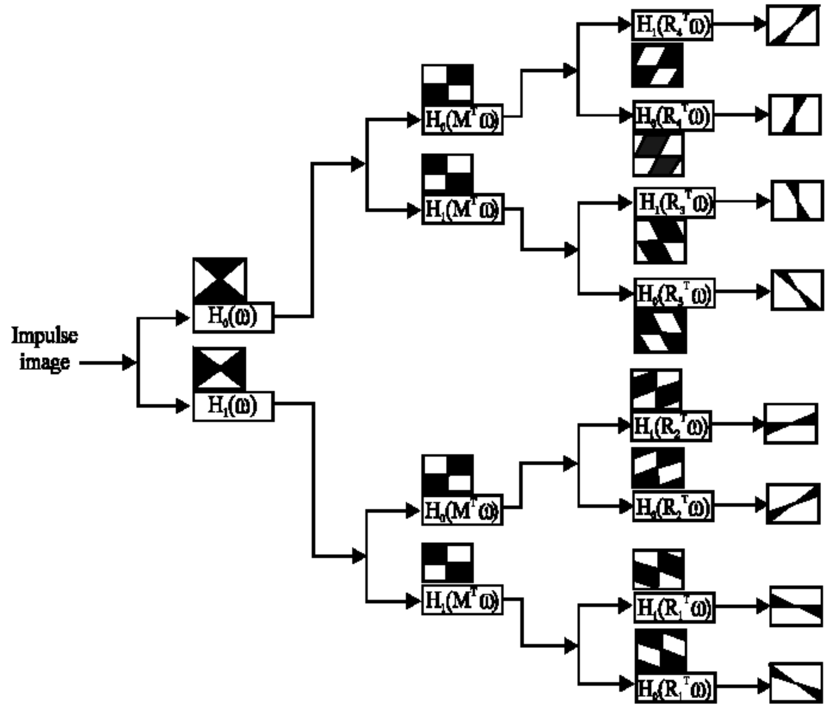

Fig. 2: Directional filter bank schematic diagram

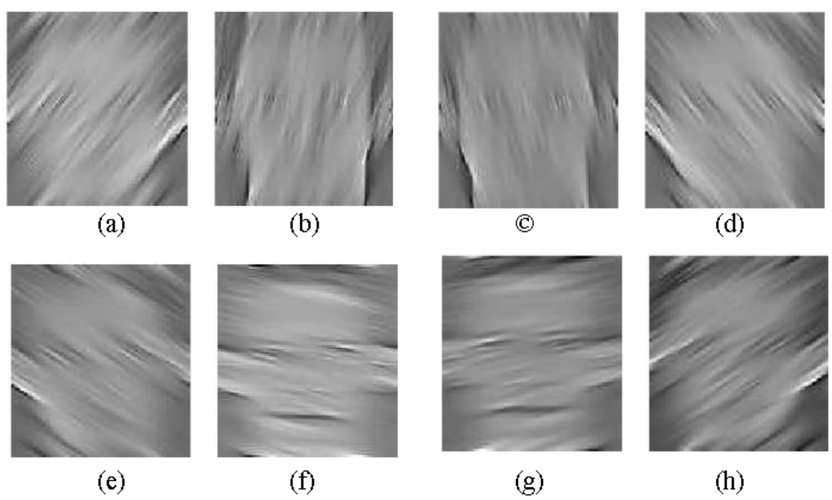

Fig. 3: Creation of directional image: a) Directional image 1, b) Directional image 2, c) Directional image 3, d) Directional image 4, e) Directional image 5, f) Directional image 6, g) Directional image 7, h) Directional image 8

of the original image was divided into eight different directions, thus reducing noise energy eight times.

Principal Component Analysis (PCA): PCA generates a set of orthonormal basis vectors, known as principal components (PCS) that maximize the scatter of all projected samples. Let X= [$X_1, X_2, \ldots, X_n$] be the sample set of the original images. After normalizing the images to unity norm and subtracting grand mean a new image set Y= [$Y_1, Y_2, \ldots, Y_n$] is derived. Where, each

$Y_i = (y_{i_1}, y_{i_2}, \ldots, y_{i_n})^t, \quad i = (1, 2, \ldots, n)$

The covariance matrix of normalized image is defined as:

$$\sum Y = \frac{1}{n} \sum_{i=1}^{n} Y_i Y_i^t = \frac{1}{n} Y Y^t \qquad (1)$$

and the eigenvector and eigenvalue matrices Φ, Λ are computed as:

$$\sum Y\Phi = \Phi\Lambda \tag{2}$$

Note that YY^t is an N×N matrix while Y^tY is an n×n matrix. If the sample size n is much smaller than the dimensionality N, then the following method saves some computation[5]:

$$(Y^t Y)\ \Psi = \Psi\ \Lambda_1 \tag{3}$$

$$\sigma = Y\Psi \tag{4}$$

where, $\Lambda_1 = \text{diag}\ (\lambda_1, \lambda_2, \ldots, \lambda_n)$ and $\sigma = [Y_1, Y_2, \ldots, Y_n]$. If one assumes that eigenvalues are sorted in decreasing order, $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_m$, then the first m leading eigenvectors define matrix P

$$P = [\Phi_1, \Phi_2 \ldots, \Phi_m] \tag{5}$$

The new feature set Z with lower dimensionality m (m << N) is then computed as

$$Z = P^tY \tag{6}$$

Proposed system: In proposed system the directional features will be used as the training set images of PCA and recognition process is performed on these images. Block diagram of proposed system is shown in Fig. 4.

The steps involved in the proposed system are as follows:

1. Obtain face images $I_1, I_2, \ldots, I_M$ of Olivetti face dataset shown in Fig. 5. This data set is composed of 400 images from 40 galleries which is constructed under various depth and plane rotations. Dataset is composed of 10 face images per a person so we have defined one as a training set and the other nine sets as testing sets in turn. We have passed whole dataset through DFB and got eight directional images for each dataset image. Then we created eight new datasets by combining same directions of all the images. After that PCA is performed on each directional dataset.
2. Constructed 10304×40 matrix where the column vector V_i was the data of training image.
3. Compute the average face vector AVG,

$$AVG = \frac{1}{M}\sum_{i=1}^{M} V_i$$

4. Subtract the mean face,

$$d_i = V_i\text{-}AVG$$

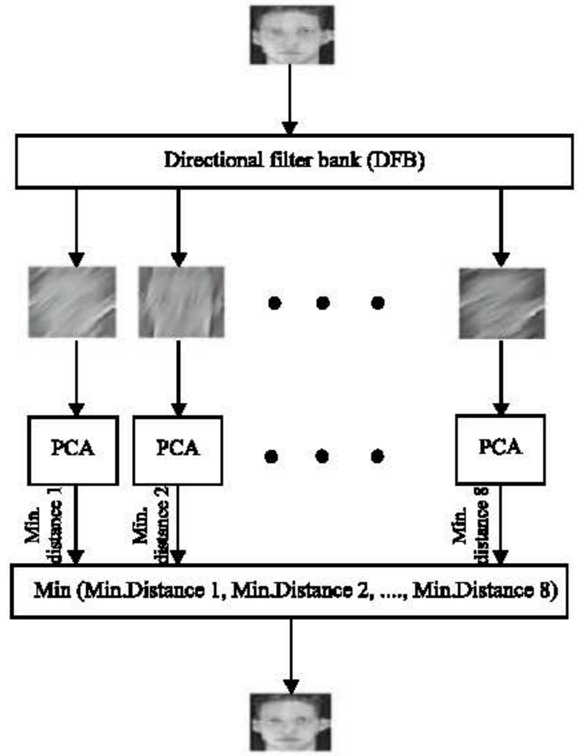

Fig. 4: Block diagram of proposed system

Fig. 5: Face images of Olivetti dataset

5. Compute the covariance matrix:

$$C = \frac{1}{M}\sum_{n=1}^{M} d_n d_n^{\ t} = A\ A^{\ t}$$

where, $A = [d_1, d_2, \ldots, d_M]$. AA^t is a very large matrix so Turk and Pentland suggested[5] a way to reduce it. They proposed that instead of AA^t, A^tA can be used.

6. Compute the M eigenvectors u_i of A^tA.
7. Keep only K eigenvectors (corresponding to the K largest eigenvalues).
8. Calculate weights of the training images by projecting mean subtracted images on the eigenvectors.

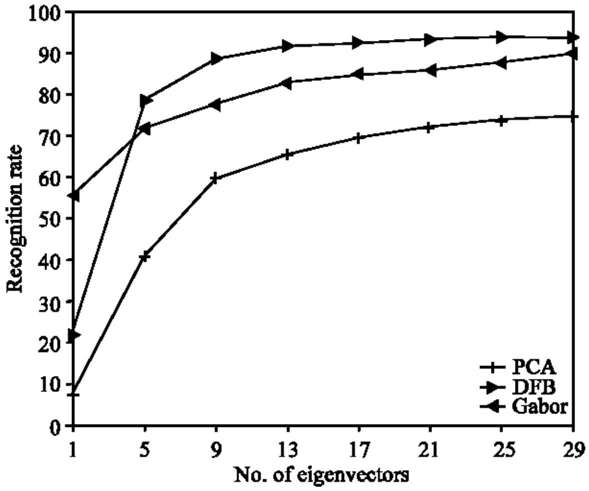

Fig. 6: Comparison of PCA, DFB-PCA and Gabor filter bank-PCA

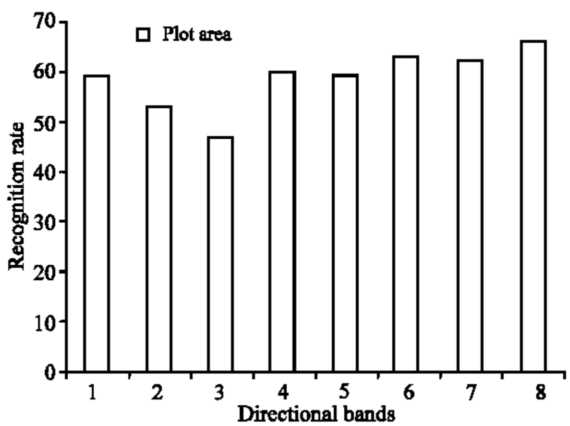

Fig. 7: Bars showing contribution of various directional images for PCA

9. For recognition of any image first calculate weights for this image and then compare it with the weights of the training image.

Simulation results: Figure 6 shows three curves comparing PCA, DFB-PCA, Gabor Filter Bank-PCA (GFB-PCA). We see that Gabor filter bank-PCA performs well when the number of eigenfaces were less than and equal to five but it is overshadowed by DFB-PCA as the number of eigenfaces are increased. We can confirm the remarkable improvement of recognition rate of 21.25% whereas Gabor filter bank-PCA gives 11% recognition rate against PCA when tested on Olivetti dataset. Further, this study investigated the question of which directional image is most effective input for PCA. The Fig. 7 shows a bar diagram of various directional images. It can be seen that direction 8 is providing 66% recognition rate. This confirms the observation that directional image 8 is providing the optimal discriminating features.

CONCLUSION

This study, presented the face recognition system that combines Directional Filter Bank (DFB) and PCA. Because face images are very sensitive to illumination and pose variation, we anticipated that the drawback could be overcome by using DFB responses as an input of PCA. The experiment results were reasonably acceptable i.e. the directional images of DFB based on principal component vectors were successful in classification and discrimination.

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