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An Efficient Frequency Domain Algorithm For Face Recognition Based On Two-Dimensional Principal Component Analysis

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Abstract: - In this contribution, a fast Frequency Domain Two-Dimensional Principal Component Analysis (FD2DPCA) algorithm is proposed for facial recognition. The algorithm has attractive properties with respect to computational complexity and storage requirements. The experimental results obtained by applying the new algorithm to the ORL and Yale databases, confirmed the significant reduction in the storage and computational requirements while retaining the excellent recognition accuracy of the spatial domain 2DPCA.

Key-World: - PCA, 2DPCA, FD2DPCA, Face recognition, Feature matrix.

1 Introduction

Within the last several years, numerous algorithms have been proposed for face recognition. In 1991 Turk and Pentland [1,2] developed the Eigenfaces method based on the principal component analysis (PCA) or Karhunen-loeve expansion [3,4]. The main idea of PCA is to find the vectors that best account for the distribution of face images within the entire image space. The Eigenfaces technique yielded good performance in face recognition despite variations in the pose, illumination and face expressions. Recently Yang et al [5] proposed the two dimensional PCA (2DPCA), which has many advantages over PCA (Eigenfaces) method. It is simpler for image feature extraction, better in recognition rate and more efficient in computation. However it is not as efficient as PCA in terms of storage requirements, as it requires more coefficients for image representation. In this paper, we propose a fast frequency domain algorithm based on the 2DPCA method that minimizes the storage requirements, by reducing the number of coefficients representing the images without sacrificing the recognition rate.

This paper is organized as follows: Section 2 describes the 2DPCA method. Section 3 presents the proposed algorithm. Section 4 discusses the results obtained by testing the new algorithm on the ORL and Yale databases. Section 5 presents the conclusions.

2 Two-Dimensional Principal Component Analysis

Statistical projection methods, such as the eigenfaces method [1, 2] have been used widely. They have given good results for various face recognition databases. Recently Yang et al [5] presented the 2DPCA method that forms the covariance matrix S from N training images A_i (where $i=1$ to N). A_i has m rows and n columns. The processing is performed in 2D rather than converting each image into a one dimensional vector of size mxn as in [1].

The n x n S matrix is computed from

$$S = \frac{1}{N}\sum_{i=1}^{N}(A_i - \overline{A})^T (A_i - \overline{A}) \qquad (1)$$

Where $\overline{A}$ is the mean matrix, of all the N training images.
A set of k vectors $V = [V_1, V_2 \ldots V_k]$ of size n is obtained, so that the projection of the training images on V gives the best scatter.
It was shown [5] that the vectors V_j *(where* $j = 1$ *to* k*)* are the k largest eigenvectors of the covariance matrix S, corresponding to the largest eigenvalues.
V is used for feature extraction for every training image A_i.
The projected feature vectors $Y_1, Y_2, \ldots Y_k$, where

$$Y_{j,i} = A_i V_j \qquad j = 1,2,\ldots.k \quad , i = 1\ldots N \qquad (2)$$

are used to form a feature matrix B_i of size mxk for each training image A_i. Where

$$B_i = [Y_{1,i}, Y_{2,i}, \ldots Y_{k,i}] \qquad i = 1,2,..N \qquad (3)$$

The tested image is projected on V, and the obtained feature matrix B_t is compared with those of the training images.
The Euclidean distances between the feature matrix of the tested image and the feature matrices of the training images are computed. The minimum distance indicates the image to be recognized.

$$d(B_t, B_i) = \sum_{j=1}^{k}\left\| Y_{j,t} - Y_{j,i} \right\|_2 \qquad (4)$$

Where $\left\| Y_{j,t} - Y_{j,i} \right\|$ denotes the distance between the two principle component vectors $Y_{j,t}$ and $Y_{j,i}$.

3 The Proposed algorithm

The proposed algorithm represents the images and their covariance matrix in the frequency domain. Typically, the energy in facial images is concentrated in the low spatial frequency range. This result in considerable reduction in the coefficients required to represent the images. Consequently the computational and storage requirements, are greatly simplified as will be shown later. The algorithm is described below.

3.1 Training mode

In the training mode the features of the data base are extracted and stored as described by steps 1 through 7.

Step 1: The covariance matrix S for the N training images is calculated using (1).

Step 2: The Two-dimensional discrete cosine transform (DCT2) is applied to S, which yields T.

$$T = DCT2(S) \qquad (5)$$

Step 3: The significant coefficients of T are contained in a submatrix, S',(upper left part of T) of dimension $n' \times n'$. Fig.3 shows the ratio of energy in S' to the energy in T, as a function of n'. S' is used to replace S in our algorithm.

Step 4: A set of k' eigenvectors $V' = [V_1', V_2' \ldots V_{k'}']$ of size n' corresponding to the largest k' eigenvalues is obtained for S'. Since the dimensions of S' is much smaller than S, k' is smaller than k.

Step 5: The Two-dimensional DCT is applied to each image A_i of the N training images, yielding T_i' ($i=1$ *to* N).

Step 6: The submatrix A_i' from T_i', containing most of the energy is retained (upper left part of T_i'). This submatrix is used to represent the training image. Dimensions of A_i' is $l' \times n'$ where $l' \leq n'$.

Step 7: The feature matrices of the training images B_i' are calculated in a manner similar to (2) and (3). Thus

$$Y_{j,i}' = A_i' V_j' \qquad j = 1,2,\ldots.k' \text{ and } i = 1,2,..N \qquad (6)$$

$$B_i' = [Y_{1,i}', Y_{2,i}', \ldots Y_{k',i}'] \qquad (7)$$

Now the feature matrix representing the training image has dimensions ($l' x\ k'$) where $l' \leq n'$, n' is much smaller than n *and* m, and $k' < k$.

3.2 Testing mode

In the testing mode a facial image A_t is presented to the system to be identified. The following steps are followed

Step 1 The Two-Dimensional DCT is applied to A_t which yield T_t'.

Step 2 The sub matrix A_t' ($l' x\ n'$) is obtained from T_t'.

Step 3 The feature matrix B_t' for the testing image is calculated from

$$Y_{j,t}' = A_t' V_j' \qquad j = 1,2,\ldots.k' \qquad (8)$$

$$B_t' = [Y_{1,t}', Y_{2,t}', \ldots Y_{k',t}'] \qquad (9)$$

Step 4 The Euclidean distance between the feature matrix of the testing image B_t' and the feature matrices of the training images B_i' ($i=1$ *to* N) are computed using (4). i corresponding to the minimum distance, i_{min}, is used to identify t.

4 Experimental Results and Analysis

The proposed algorithm was applied to both the ORL database [6] and the Yale database [7]. The ORL database consists of 400 images of 40 individuals (10 images each), where pose and facial expressions are varying, Fig.1. The Yale database consists of 165 images of 15 individuals (11 images each) where illumination and face expression are varying, Fig.2. Results are compared with those obtained using the 2DPCA method.

4.1 Results for ORL database

Two experiments have been applied to the ORL data base, where all the images are grayscale with 112 x 92 pixels each.

In the first experiment, 40 images of 40 different individuals are used for training and the remaining 360 images are used for testing. The dimensions of the covariance matrix S for the 40 training images is 92x92. A two-dimensional DCT is applied to the covariance matrix S which yields T. S' is obtained for $n'=20$. The 5 largest eigenvectors of S' corresponding to the 5 largest eigenvalues are obtained, i.e, k' is chosen to be 5 (for the 2DPCA method k = 10 is used for the best recognition accuracy). T_i' (i =1 to 40) are obtained. Then A_i' of dimensions 20x20 (i =1 to 40) are determined, i.e , $l'xn'$= 20x20 in our experiment.

The feature matrices for all the training images are obtained using (6) and (7). The procedure in section 3.2 is followed for the 360 testing images. Table I gives the recognition accuracy for the proposed technique as well as 2DPCA and PCA methods.

Fig.1. Five samples for 3 individuals in the ORL database.

Fig.2. Eleven samples for one person in the Yale database .

In the second experiment 5 images per class are used for training and the remaining 200 images are used for testing. The Dimensions of *S'* and A_i*'* are the same as in the first experiment. *k'* is chosen equal to 5. For the 2DPCA method, *k* equals 10 is used for the best recognition accuracy. Results using the proposed algorithm, 2DPCA, and PCA techniques are listed in Table I,

Table I shows that the proposed algorithm yields similar recognition accuracy as the 2DPCA method. Table II illustrates the computational complexity, in terms of the number of multiplications [8], and the storage requirements, in terms of the dimensions of the feature matrix. It is seen that, for the FD2DPCA, the amount of storage is drastically reduced (by approximately 90%), while the computational complexity is lower, compared with one of the best available algorithm, 2DPCA. This is accomplished while maintaining the same level of recognition accuracy. It can be easily shown that the excellent properties of the new technique are maintained for the facial databases in section 4.1, 4.2, and others.

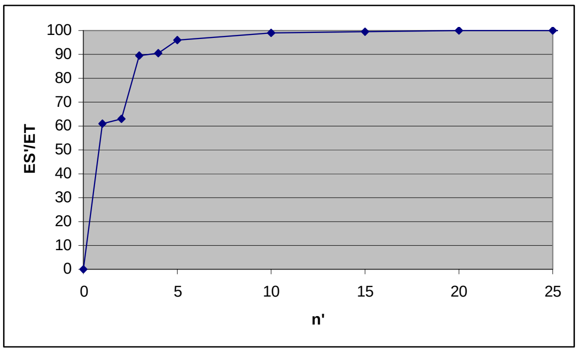

Fig.3. The ratio of energy in the FD2DPCA covariance matrix *S'* (Es') to the energy in the covariance matrix of 2DPCA (ET) as a function of number of rows and columns of *S'* (*n'*) .

Table I
Recognition accuracy for experiment I and II on ORL database using FD2DPCA, 2DPCA and PCA methods.

Method	Recognition accuracy for experiment I	Recognition accuracy for experiment II
FD2DPCA	73.61 %	92.0 %
2DPCA	72.77 %	91.0 %
PCA	62.8 %	83.5 %

Table II
Dimensions of feature matrix and number of multiplications required for N training images in ORL database, for experiment I, II.

	FD2DPCA	2DPCA
Dimensions of feature matrix per image	(20x5)	(112x10)
Storage requirements for N images	(20x5)xN	(112x10)xN
# of multiplicatn for training mode	47104+57344xN	103040xN
# of multiplicatn for testing mode	57344	103040

Table III
Recognition accuracy and dimensions of feature matrix per image for the experiment on the Yale database.

	FD2DPCA	2DPCA
Dimensions of feature matrix per image	(50 x 5)	(243 x 20)
Recognition accuracy	78.8 %	77.7 %

4.2 Results for Yale database

In this experiment the dimensions of the images used are 243x320. 5 images per class are used for training and the remaining images are used for testing. The Dimensions of *S'* is (*50x50*), and the dimension of A_i*'* is (*50x50*). *k'* is chosen equal to 5. For the 2DPCA method, *k* equals 20 is used for the best recognition accuracy. Results are listed in table III. where it shows that the proposed algorithm gives similar recognition accuracy as the 2DPCA with a feature matrix per image much more reduced in size (approximately 95%).

5 Conclusions

The Two-Dimensional principal component analysis (2DPCA) method has shown higher recognition accuracy and faster speed than eigenfaces method based on one dimensional PCA. However the 2DPCA storage requirements for feature vectors are increased by a large factor, typically greater than 10. A Frequency Domain 2DPCA algorithm is presented that significantly reduces these storage requirements and maintains the high recognition rate obtained using the 2DPCA. In addition, the proposed FD2DPCA takes advantage of existing fast implementations in the frequency domain which results in appreciable reduction in the computational complexity. Experimental results given confirm the attractive feature of the proposed technique.

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