Fusion of Singular Value Decomposition (SVD) and DCT-PCA for Face Recognition

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Abstract:*In this paper, we proposed the fusion of two methods to know principal component analysis (PCA) in the domain DCT and singular value decomposition (SVD). Experimental results performed on the standard database ORL which prove that the proposed approach achieves more advantages in terms of identification and processing time.*

Keywords:*Principal component analysis (PCA), Discrete Cosines Transformation (DCT), Singular Value Decomposition (SVD), ORL database.*

1. Introduction

Biometrics methods, which have been considered a solution for the problem of person identification. The main advantages of biometrics identification methods are convenience, accuracy and security (they are more difficult to circumvent). For face based person identification systems another remarkable advantage is their ability to operate in covert mode, at a distance. More successful template matching approaches use Principal Components Analysis (PCA) or Linear Discriminant Analysis (LDA) to perform dimensionality reduction achieving good performance at a reasonable computational complexity/time. Other template matching methods use neural network classification and deformable templates, such as Elastic Graph Matching (EGM). Recently, a set of approaches that use different techniques to correct perspective distortion are being proposed. These techniques are sometimes referred to as view-tolerant. For a complete review on the topic of face recognition the reader is referred to [1]. However, there are some problems such as lightning condition, illumination, various backgrounds, aging and individual variation with feature extraction of human face. Then, how to solve variation problems in face recognition? It will be a highly challenging task if we want to solve those problems using visual images only. This paper presents the score level fusion of SVD [3] and DCT-PCA [2]. SVD-based method used in our approach considers the left and right singular vectors as a feature matrix because its recognition rate is better than SVD-based method when using singular values as the feature vectors. The

DCT-PCA is used instead of PCA in order to reduce the execution time.
The paper is organized as follows. An overview of SVD and local DCT-PCA face recognitions techniques are given in Section 2. In section 3, we present the proposed fusion scheme. The simulation results are given in Section 4, and finally the conclusion is drawn in Section 5.

2.Related Works

2.1 Discrete Cosine Transform

The DCT is a popular technique in imaging and video compression, which transforms signals in the spatial representation into a frequency representation.

The forward 2D-DCT [2, 6]of an M x N block image is defined as:

$$C(u,v) = \alpha(u)\alpha(v)\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y) * Cos(\pi(2x+1)u2M)Cos(\pi(2y+1)v2N)$$

(1)

The inverse transform is defined as:

$$f(x,y) = \sum_{u=0}^{M-1}\sum_{v=0}^{N-1} \alpha(u)\alpha(v) * Cos(\frac{\pi(2x+1)u}{2M})\, Cos(\frac{\pi(2y+1)v}{2N})$$

(2)

Where

$$\alpha(u) = \begin{cases} \sqrt{\frac{1}{M}} & if \quad u = 0 \\ \sqrt{\frac{2}{M}} & if \quad 1 \le u \le M-1 \end{cases}$$

$$\alpha(v) = \begin{cases} \sqrt{\frac{1}{N}} & if \quad v = 0 \\ \sqrt{\frac{2}{N}} & if \quad 1 \le v \le N-1 \end{cases}$$

And, x and y are spatial coordinates in the image block, and u and v are coordinates in the DCT coefficients block. Fig.1 shows the properties of the DCT coefficients in M x N blocks with the zigzag pattern used by JPEG compression to process the DCT coefficients. Although the total energy remains the same in the M x N blocks, the energy distribution changes with most energy being compacted to the low-frequency coefficients. The DC coefficient is represented by C(0,0) in the forward 2D.

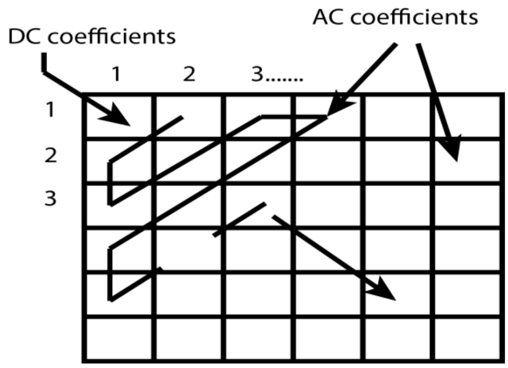

Fig. 1. Block feature of DCT coefficients and their selection in zig-zag pattern.

DCT equation. As the cosine of zero is one, the equation is simplified to:

$$C(0,0) = \frac{1}{M*N}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y) \qquad (3)$$

The DC coefficient, which is located at the upper left corner, holds most of the image energy and represents the proportional average of the M x N blocks. The remaining ((M x N) 1) coefficients denote the intensity changes among the block images and are referred to as AC coefficients. The DCT is performed on the entire image obtained after processing the input face images by histogram equalization. For that reason the researchers are investigated to add a step which could reduce the computing time. For example the local 2D DCT [6] transform has been used as a feature extraction step in face recognition (figure 2).

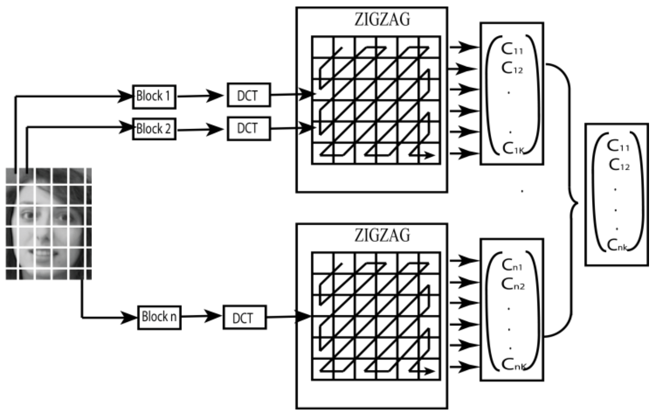

Fig. 2. Feature Extraction in DCT-LBP

2.2 face recognition algorithm based on PCA

The main idea of the PCA [4] algorithm is to express our M starting images as a basic individual orthogonal vectors (eigenvectors). This is done as follows:

- Transform each learning image column vector, and concatenate all training vectors to form a matrix X.

- Adjust learning data with respect to the average μ

$$X = X - \mu \quad (4)$$

- Calculate the covariance matrix [5].

$$G = X^T X \quad (5)$$

- Determine the matrix of eigenvectors W ordered according to the matrix of eigenvalues. Δ, itself sorted in descending order, by solving the following equation:

$$GW = \Delta W \quad (6)$$

- Projecting all training images by the matrix W as follows:

$$Y = W^T X \quad (7)$$

- Transform each image test column vector T and then used to obtain the T_P model and a similarity measure can be used to laclassification. To measure the similarity between two vectors, we used the Minkowski distance of order p:

$$L_p = \left(\sum_{i=1}^{n} |X_i - Y_i|^p\right)^{\frac{1}{p}} \quad (8)$$

such as $X = (x_1, \dots, x_n)$ and $Y = (y_1, \dots, y_n)$.
In our experiments, we used two derived distances from the Minkowski distance, the first obtained by p = 1 called the Manhattan distance (L1) and the second obtained by p = 2 and called the Euclidean distance (L2).

2.3 Process of Singular Value Decomposition (SVD)

Singular Value Decomposition (SVD) represent a significant topic in linear algebra. SVD has many practical and theoretical values? special feature of SVD is that it can be performed on any real (m, n) matrix. Let's say we have a matrix A with m rows and n columns, with rank r and $r \le n \le m$. Then the A can be factorized into three matrices:

$$A = USV^T \quad (9)$$

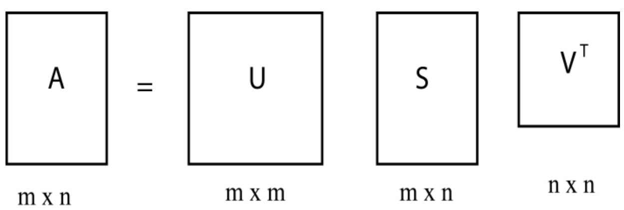

Fig. 3.Illustration of Factoring A to USV T.

Where Matrix U is an m x m orthogonal matrix

$U = (U_1, \dots, U_r, U_{r+1}, \dots U_m)$The column vectors U_i, for i = 1, 2, , m, form an orthonormal set:

$$U_i^T = \delta_{ij} = \begin{cases} 1 & if\, i = j \\ 0 & if\, i \neq j \end{cases} \quad (10)$$

And matrix V is an n x n orthogonal matrix.

$V = (V_1, \dots, V_r, V_{r+1}, \dots V_n)$The column vectors$V_i$, for i = 1, 2, , n, form an orthonormal set:

$$V_i^T = \delta_{ij} = \begin{cases} 1 & if\, i = j \\ 0 & if\, i \neq j \end{cases} \quad (11)$$

Here, S is am x n diagonal matrix with singular values (SV) on the diagonal. The matrix S can be showed in the following matrix:

$$S = \begin{bmatrix} \sigma_1 & 0 & 0 & & 0 \\ 0 & \sigma_2 & & 0 & 0 \\ 0 & & \cdots & & 0 \\ \vdots & & & & \\ 0 & & \sigma_r & 0 & 0 \\ 0 & & 0 & \sigma_{r+1} & 0 \\ \vdots & & & & \\ 0 & & 0 & 0 & \sigma_n \end{bmatrix} \quad (13)$$

For i = 1, 2, … , n, σ_i are called Singular Values (SV) of matrix A. It can be proved that:

$$\sigma_1 \ge \sigma_2 \ge \cdots \ge \sigma_r \text{ and } \sigma_{r+1} = \sigma_{r+2} = \cdots = \sigma_n = 0$$

The $V_i^{'}s$ and$U_i^{'}s$ are called right and left singular vectors of A [3].

3. THE PROPOSED APPROACH

In this section we present our methodology for fusing two appearance-based approaches for face recognition: the SVD and the DCT-LBP. Figure 5 shows the block diagram of the proposed method. It is composed of the following steps:

-Representation of the face according to the SVD and the DCT-LBP approaches;

-Computation of the distance vectors $D_{DCT-ACP}$ and D_{SVD} from all the M faces in the database;

-Normalization of these dissimilarity distance vectors;

-Combination of the two vectors according to a given fusion rule.

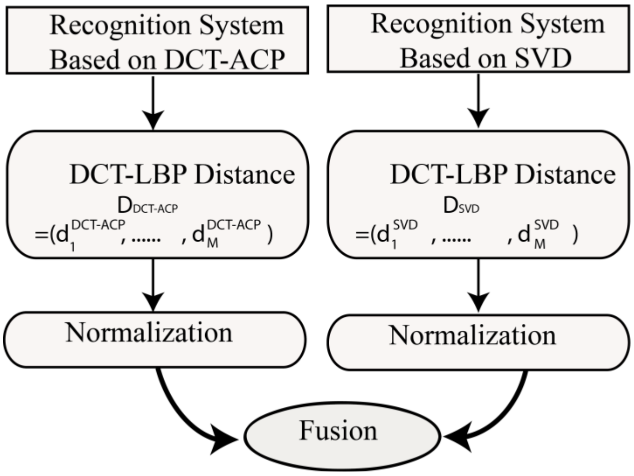

Fig. 5.Diagram of the proposed fusion.

Since the dissimilarity distance scores output of different recognition techniques are heterogeneous, score normalization is needed to transform these scores into a common domain, prior to combining them.
In this work we have used MIN-MAX and Z-score normalization techniques.
We denote a distance vector as $D = (d_1, d_2, \dots, d_M)$ and the corresponding normalized score as

$$D_n = (d_{1n}, d_{2n}, \dots, d_{Mn})$$

3.1 MIN-MAX method

This method maps the distance vector to the [0, 1] range. The quantities D_{max} and D_{min} specify the end points of the distance range [7] and D_n is given by:

$$D_n = \frac{D - D_{min}}{D_{max} - D_{min}} \quad (14)$$

Where$D_{min} = Min(d_1, \dots, d_M)$ and $D_{max} = Max(d_1, \dots, d_M)$

3.2 Z-score

This method transforms the scores to a distribution with mean of 0 and standard deviation of 1.
The operators mean() and std() denote the arithmetic mean and standard deviation operators, respectively [7]:

$$D_n = \frac{D - mean\ (D)}{std\ (D)} \quad (15)$$

4. RESULTS AND DISCUSSIONS

In order to demonstrate the effectiveness of the proposed method, we use the public database for experiments The ORL (Olivetti Research Laboratory) [7] for evaluating performance with large number of subject and complicated conditions and to analyze the accuracy on 2D face simples with extreme pose change. It contains 400 images for 40 individuals as shown in Figure 6, for each person we have 10 different images of size 112ï92½؟ pixels.
For some subjects, the images are captured at different times.\newline
The two sub-tables in table 1 represent the obtained results based on fusion of DCT-LBP layer with different parameters. Recall that P is the number of sampling points and R is the radius value, and SVD.

Fig. 4. Persons of the ORL database .

TABLE I

RECOGNITION RATES BASED ON DCT-LBP WITH DIFFERENT PARAMETERS WITH SVD IN %.

P=4	R=2	R=4	R=6	R=8
DCT-ACP	93.34	93.82	94.2	94.34
SVD	91.23	92.45	92.23	93.2
DCT-LBP and SVD	95.12	95.21	95.24	95.98
P=8	R=2	R=4	R=6	R=8
DCT-ACP	93.45	93.93	94.38	94.49
SVD	91.26	92.58	92.90	93.23
DCT-LBP and SVD	95.18	95.53	95.87	95.98
P=16	R=2	R=4	R=6	R=8

DCT-ACP	93.64	93.98	94.84	94.98
SVD	91.26	92.76	92.96	93.54
DCT-LBP and SVD	95.23	95.93	96.43	97.34

In this simulation, we have randomly selected five persons for learning, and the rest of image for testing. Thus, the total number of training image and testing is 200 for both. We calculate the learning recognition rates of SVD and DCT-ACP.

In Table II, we represent the times of learning and Identification (number of image of learning and identification is 200), times are calculated with the developed software in Matlab. We note that SVD significantly reduces the learning time and identification.

TABLE II

TRAINING AND TESTING TIME IN SECOND.

Time	Training	Testing
SVD	15.234	14.423
DCT-ACP	12.756	11.453
DCT-ACP with SVD	12.453	11.236

5. CONCLUSION

In this paper, we propose a novel fusion for face recognition. The appearance of the proposed approach compared to that of the other approaches is better. So finally we can conclude that combination of DCT-PCA with SVD it will offers higher rates of recognition. Hence. In our future work the proposed fusion can be implemented in real time object recognition system.

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