New Technique for DCT-PCA Based Face Recognition

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***Abstract*—Automatic face recognition is a high level computer vision research. As faces are complex natural stimuli that differ dramatically, hence developing a computational approach for accurate face recognition is very difficult indeed. In this paper a robust face recognition system is developed and tested. Here 2D Discrete Cosine Transform (DCT) is exploited for feature extraction and certain normalization techniques are invoked that increase its robustness to variation in facial geometry and illumination. The DCT coefficients of face images are truncated in Gaussian or exponential way. Then without doing inverse DCT Principal Component Analysis (PCA) is applied directly for dimensionality reduction. Lastly face recognition task is performed by K-nearest distance measurement. Only a few non-zero eigenvalues related eigenvectors are taken for this method and experimental tests on the ORL face database are performed which give outperform result with respect to existing techniques. This method achieved cent percent result when the prob image is applied from the same database.**

***Index Terms*— Discrete Cosine Transform, Principal Component Analysis, Automatic Face Recognition, K-Nearest Distance, ORL Face Database.**

I. INTRODUCTION

Face recognition plays as hot subject for research for security, surveillance and other application like data base matching, passport, commercial and low enforcement etc. It is a challenging research area, as the face of same person appears differently under varying lighting condition, expression, pose, occlusion in real life. It is also an important method as compare to other biometric recognition when probs are uncooperative or in uncontrolled environments. Though much progress has been made in developing robust algorithm still there are some unsolved problems as the facial changes make the recognition task very difficult even human beings do some recognition mistakes time to time. Research is still continued in this field for efficient universal identification methods to identify criminal and terrorism and as a tool of forensic intelligence.

The algorithms developed for face recognition problems are generally grouped into two categories [1, 2] namely feature based and holistic based. The geometrical analysis of the facial features like eyes, nose and mouth are analyzed in feature based after facial feature detection, whereas faces are analyzed as two dimensional patterns in holistic approaches. As facial features detection is difficult against rotation, scale and illumination variation, holistic approaches are generally implemented for feature vectors [3].

Statistical techniques have been widely used for face recognition and in facial analysis to extract the effective features of the face patterns. Dimensionality reduction is essential for extracting effective features and reducing computational complexity in classification stage. Principal component analysis (PCA) [4], [5], Linear discriminate analysis (LDA) [6] and Discrete cosine transform (DCT) [7] are the main techniques used for data reduction and feature extraction in the appearance based approaches. DCT, Eigen faces [4] and Fisher faces [8] have been proved to be very successful among the others. All these methods extracts features to optimally represent faces belong to a class and separate the faces. In the literature it has been found that most efforts are given mainly on developing feature extraction methods and employing powerful classifiers such as Euclidean distance Classifier, Hidden Markov Models (HMMs) [9], neural networks [10], [11] and support vector machine (SVM) [12].

This paper presents an appearance based face recognition method which is based on DCT coefficients that most effective for recognition rather restoration and are selected using frequencies analysis. The DCT coefficients are truncated in Gaussian or exponential way. In the next step we reduce the dimensionality of features using well established PCA method as it is the optimal dimensionality reduction method for Gaussian distributed data. PCA is applied without doing the inverse DCT to reduce the computational complexity as in [13] the authors have experimentally proved that the PCA can be applied on reduced DCT coefficients to achieve better recognition performance. The framework of the entire proposed technique is shown in Fig.1. At last classification has been made by K-nearest distance measurement using Euclidean distance method[15]. The experimental tests on the ORL face database are performed.

The rest of the paper is organized as follows: section II presents proposed method and the background of DCT and PCA. In section III simulation process is discussed and results are presented. Finally the work is concluded in section IV.

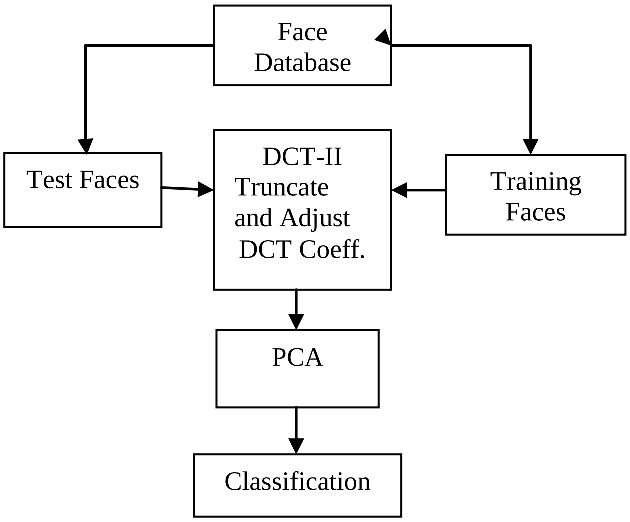


Fig.1. - Block diagram of the proposed method.

II. Proposed Method for Face Recognition

A. Discrete Cosine Transform

The Discrete Cosine Transform (DCT) is an invertible linear transform that the data points in terms of sum of cosine functions oscillate at different frequencies. DCT generates the coefficients from which it is possible to restore back the transformed signal to the original signal by applying the inverse DCT. The 2D-DCT used as the DCT-II, is shown in equations (1) and (2).

Given an input image *f(x, y)* of size *m* x *n*, the 2D $m \times n$ DCT is defined as follows:

$$C(u,v) = \alpha(u)\alpha(v)\sum_{x=0}^{m-1}\sum_{y=0}^{n-1} f(x,y)\cos\frac{\pi(2x+1)u}{2m}\cos\frac{\pi(2y+1)v}{2n} \qquad (1)$$

The variables *m* and *n* are coordinates of the space domain and *u* and *v* are the coordinates of frequency domain.

where, $\alpha(u) = \sqrt{\frac{1}{m}}$ for $u = 0$,

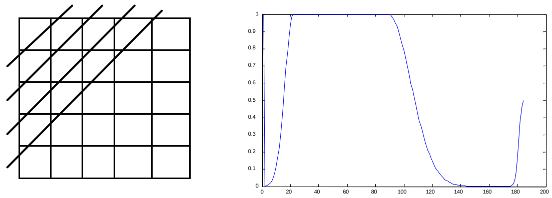
$= \sqrt{\frac{2}{m}}$ for $u = 1, 2, \ldots\ldots\ldots, m-1$

and $\alpha(v) = \sqrt{\frac{1}{n}}$ for $v = 0$,

$= \sqrt{\frac{2}{n}}$ for $v = 1, 2, \ldots\ldots\ldots\ n-1$. (2)

B. Proposed Method

In holistic feature extraction method DCT converts high-dimensional face images into low dimensional space in which more significant facial features are maintained. The DCT coefficients are generally divided into three bands as low frequencies, middle frequencies and high frequencies. Low frequencies coefficients are related to illumination variation and smooth regions (like forehead, cheeks etc) of face and high frequencies coefficients represent noise as well as small variations (like edge and details) of face image. The middle frequencies coefficients contain useful information of basic structure of the image which is more suitable candidate for recognition [14]. Hence we can't just discard the low frequency components to compensate illumination variations if the image is not so much affected by lighting conditions. Similarly we can't just truncate the high frequency coefficients to remove noise as they are responsible for details and edge of the image. In this method we consider all the aspects and accordingly design a mask. The coefficients are modified as exponential or as Gaussian way giving equal weight to the same frequency coefficients i.e. to give same weight to the coefficients of respective slant line as shown in Fig.2. Here we give emphasis to the edge and detail variations of the image but not to the smooth regions and brightness of the image as shown in Fig.3.The accurate reconstruction is not required for face recognition. In the next step PCA has been applied for feature extraction directly to the modified DCT coefficients. In [13], authors proof that as the DCT is an orthogonal transformation, PCA can be directly implemented in the DCT domain.



(a) (b)

Fig. 2. - Truncated Method (a) Slant lines (b) Mask

Fig. 3- (a) Original image (b) Reconstructed Image using above mask.

C. Principal Component Analysis

Principal component analysis for face recognition is based on the information theory approach in which the relevant information in a face image is extracted as efficiently as possible. It reduces the dimensionality of the description by projecting the points onto the principal axes, where orthonormal set of points are in the direction of maximum covariance of the data.

Let us consider the face images I_i of size *m* by *m*. Then we convert the image matrix in to a vector of size m^2. The training set of n faces can be written as $I = (I_1, I_2, \ldots\ldots\ldots, I_n)$ and the average image is found by

$$A = \frac{1}{n}\sum_{i=1}^{n} I_i \tag{3}$$

The vector $Y_i = I_i - A$ is the difference image of each face image where the face images have been centered. The covariance matrix is obtained from the difference vectors as

$$C = \frac{1}{n}\sum_{i=1}^{n} Y_i . Y_i^T \tag{4}$$

The eigenvectors of the covariance matrix are computed. And k eigenvectors corresponding to the k largest eigenvalues are selected for the matching purposes. Consider that the $V = (V_1, V_2, \ldots\ldots, V_k)$ where $k \le n$, are the eigenvectors of the covariance matrix . The eigenvectors V_i and eigenvalues $\boldsymbol{\lambda_i}$ of C are such that

$$\boldsymbol{CV_i = \lambda_i V_i} \tag{5}$$

Once the eigenvectors are found, they are sorted according to their corresponding eigenvalues; a larger eigenvalues mean that more the variance in the data is captured by the eigenvector. Then the "face space," spanned by the top k eigenvectors, is constructed as the feature space for recognition. As they appear as somewhat ghostly like as shown in Fig 4, hence they are called as "Eigen-Faces".

(a) (b) (c) (d)

Fig..4 –(a) Mean face (b) 1st Eigen face (c) 2nd Eigen face (d) 3rd Eigen face.

III. Simulation results

A. Face Database

In order to test the algorithm mentioned above we used ORL (Olivetti Research Laboratory) face database [16]. This database contains 400 images that belong to 40 people, each person in 10 different poses. The faces were photographed at different moments, with varying lighting, facial expressions (eyes closed/opened, smiling/not smiling), facial poses and facial details (with/without glasses, with/without beard), among other type of variations. The images are in grayscale, with dimension of 92x112 pixels. Some examples are shown in Fig.5.

C. Tests

First tests were conducted by leave-one-out method and in second conducted by cumulative leave-one-out approach. In leave-one-out method ten rounds of test were done. In the first round, the tenth pose from all persons is excluded and used as test face remaining nine were used as training. In the second round, ninth pose leaved as test face and remaining were used as training face and so on. In the second case some different

Fig. 5- Sample images for a subject of the ORL Database.

poses were taken as training and remaining other poses were considered as test images. These tests were performed several times with different numbers of selected eigenvectors using different geometric shape of the mask. Simulation results of first and second tests are shown in Table 1 and Table 2 respectively.

D. Classification

The test face is projected to the face space and then comparison is done using a similarity measure that resembles the test face with other training faces in the database. The simplest way to determine which face provides the best resemblance is the Euclidean distance. Euclidean distance is defined as the straight-line distance between two points.The distance between a test face T and the training vectors V *is,* $d = \sqrt{\|V - T\|}^2$. A face is classified to a certain class when the Euclidean distance(d) is minimum. To confirm we have considered K-nearest distance. The majority matching is the matched face as shown in Fig. 6. In this method we have considered 3-nearest distance for all the tests.

IV. Conclusions

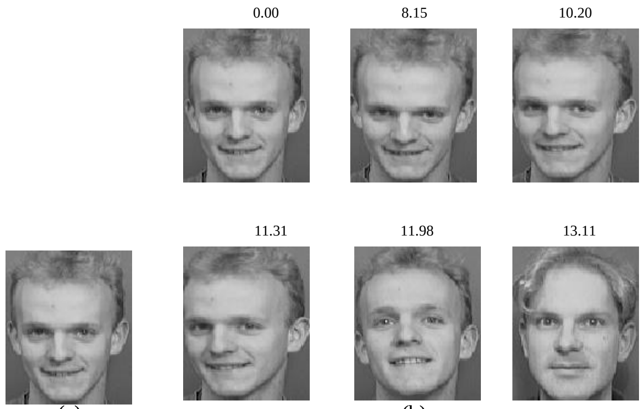
In this paper a new face recognition method is presented using truncated DCT-PCA. It is fast, relatively simple, and has been shown to work well in constrained environment The DCT coefficients are truncated in exponential or Gaussian way giving some weight to the all type of frequencies components. The principal components are selected for each class to reduce the eigenspace. With these eigenvectors the test images are classified based on Euclidean distance. As shown in the results the proposed method has greater accuracy with the other existing methods. This work can be applied to the other databases to see the result of proposed method for cross validation. One factor to look out for is the computational complexity involved here. This will be a major issue when trying to implement the system on real time system. The research will be focused to develop the computational model for face recognition that will be fast, simple and accurate in different environments.

Table 1. Results of Leave-one-out method.

Expt. No	Training Set	Test Set	% of Recognition DCT-PCA	% of Recognition Proposed Method
1	1:9	10	92.5	95
2	1:8 & 10	9	95	97.5
3	1:7 & 9:10	8	97.5	97.5
4	1:6 & 8:10	7	97.5	100
5	1:5 & 7:10	6	100	100
6	1:4 & 6:10	5	97.5	100
7	1:3 & 5:10	4	100	97.5
8	1:2 & 4:10	3	100	100
9	1 & 3:10	2	100	100
10	2:10	1	97.5	100

Table 2. Results of cumulative leave-one-out method

Expt. No	Training Set	Test Set	% of Recognition DCT-PCA	% of Recognition Proposed Method
1	1:5	10	92.5	95
2		9	95	97.5
3		8	97.5	97.5
4		7	97.5	100
5		6	100	100
6		5	97.5	100
7		4	100	97.5
8		3	100	100
9		2	100	100
10		1	97.5	100



(a) (b)

Fig. 6.-(a) Test image (b) Results of 6 nearest matching images indicating'd' on the top.

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