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Face Recognition Using Edge Information and DCT

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Abstract: This manuscript presents a face identification method based on the theory of Sobel Local Binary Pattern and Laplacian filters edge detectors to represent face images with enriched information. Thereafter, to refine images for less sample size, Discrete Cosine Transform is used to represent these face images in low dimension space. The proposed method of facial recognition performs well to a considerable amount under small sample problem and is also invariant to illumination changes. It shows better results as compared to previously developed face recognition methods after performing experiments on many well known databases.

Keywords: Eigenface, Discrete Cosine Transform (DCT), Laplacian Filters, Sobel Edge (SE).

1. INTRODUCTION

Over the years, facial identification has been an area of apprehension for the researchers. The authors have provided numerous facial recognition techniques to authenticate one or more persons in varying scenario using a stored database of faces (Zhao *et. al.*, 2003). In the last few decades, a number of face recognition methods have been developed to solve the issue of automatic personnel identification.

According to (Zhao *et. al.*, 2003), researchers have divided face recognition into certain categories depending on the techniques used and the recognition accuracy result obtained. So, the common types of facial recognition techniques that have been investigated over the decades are Holistic matching methods (Zhao *et. al.*,2003), Feature-based matching methods (Turk *et. al.*, 1991) and Hybrid methods (Yang *et. al.*,2002).

Holistic matching methods take the whole face as input to the recognition algorithm. Many early methods belong to this category but most popular of these are Eigenface method (Turk *et.al.*,1991), Linear Discriminant Analysis (LDA) (Yang *et. al.*, 2002) and Elastic Bunch Graph (Wiskott *et. al.*,1997).

In Feature based matching methods (Turk *et. al.*,1991), position of the local features of face are determined to construct feature vector space. These local features could be the distance between eyes, variation in nose and mouth edge information that is computed to construct the feat

2. MATERIAL AND METHODS

PCA is a linear projection method on a subspace spanned by the principal Eigenvectors of the input covariance matrix (Bmnelli *et. al.*,1993). In this method, the face images are anticipated onto characteristic space also known as Eigenspace that encodes the distinction among the known facial images. So in this way the face is transformed into a set of characteristics called Eigenfaces. The advantage of this technique is the dimensionality reduction. This reduction removes the useless information in the face, decomposes the face into Orthonormal components and represents the face as the weighted sum (Wang *et. al.*,2005).

Extension to simple PCA method is two-dimensional PCA (2DPCA) (Yang *et. al.*, 2004). This method uses clear-cut 2D image matrix to a certain extent than 1D vector for computing the covariance matrix evaluation, hence claimed to be more computationally despicable and more appropriate for small illustration size problem (Bmnelli *et. al.*,1993).

In $(PC)^2$ A, (Wu *et. al.*, 2002) presented a technique to improve the information of features space. This method is actually a preprocessing method that computes the projections along both axes of face image. These projections are then used to obtain a new derived image, also called projection image. Finally, this new consequential image is shared with the real face image to absolute the information-enriching procedure. As a result, the vital features become more significant after the preprocessing. Afterwards, the habitual Eigenface system is used for face identification (Bmnelli *et. al.*,1993).

Dimension reduction is also an area of concern. One purpose of conventional methods such as PCA and 2DPCA is to reduce the dimension of face space. (Ming *et. al.*, 2006) proposed a method based on the combination of Discrete Wavelet Transform and Discrete Cosine Transform. This combination of DWT and DCT is used to extract features of face image. The use of DCT reduces the dimension of the original face image and retains only useful information in the feature subspace. Then the Support Vector Machine (SVM) (Kim *et. al., 2001*) is used to classify these feature vectors. (Azam *et. al., 2010*) used face recognition for hexagonal images. For this purpose, they used DCT for face features extraction and neural networks for recognition. (Kailash *et. al.*, 2009) used ICA for edge information. The Eucledian and Mahalanobis distance classifiers were used for image classification. (Jianlin *et. al.*, 2010) used color and edge information for image reclamation. (Arvind *et. al.*, 2011) used DCT for Image retrieval.

3. PROPOSED WORK

Feature selection based on edges of face image is an interesting topic in research community. Sobel and Laplacian are the most widely used methods among a number of edge detection methods. So the paper uses the combination of these two methods to enhance the local features. This combination is also quite effective with illumination variations because of the fact that edges are insensitive to these variations.

Sobel operator is the basic tool for finding edge strength and direction at location (x, y) of an image. The sobel operator contains two 3x3 masks (horizontal mask M_x and vertical mask M_y) shown in **(Fig. 1)**. These masks are convolved with the original image to produce two gradient images (one in x direction and second in y direction).

-1	-2	-1
0	0	0
1	2	1

(a)

-1	0	1
-2	0	2
1	0	1

(b)

Fig.1 (a) Horizontal mask (b) Vertical mask.

Laplacian is also an edge detector and being second order derivative, it has the advantage of enhancing image features. However, it produces noisier results than gradient. The response of gradient filter to noise is lower than the Laplacian operator.

First of all, Sobel operator is applied on original face image as a result of which two images are produced using equation 1 and equation 2. Face images computed by convolving sobel masks with the original image are shown in **(Fig. 2)**. Here both images represent information in different directions.
Gradient images using sobel masks are calculated using equation 1 and equation 2.

$$g_x = \frac{\partial f}{\partial x} = M_x * \mathrm{I} \qquad (1)$$

$$g_y = \frac{\partial f}{\partial y} = M_y * \mathrm{I} \qquad (2)$$

where G_x is the gradient image in horizontal direction and G_y is the gradient image in vertical direction.

(a) (b) (c)

Fig. 2 (a) Original image, (b) Gx (c) Gy In the next step, the technique applies Laplacian operator on both (G_x and G_y) images to retrieve informative details using equation 3 and equation 4.

$$\nabla^2 \mathrm{gx} = \frac{\partial^2 gx}{\partial x^2} + \frac{\partial^2 gx}{\partial y^2} \qquad (3)$$

$$\nabla^2 \mathrm{gy} = \frac{\partial^2 gy}{\partial x^2} + \frac{\partial^2 gy}{\partial y^2} \qquad (4)$$

where $\nabla^2 gx$ is the Laplacian image of G_x and $\nabla^2 gy$ is the Laplacian image of G_y.

The output of equations 3 and 4 is shown in **(Fig. 3)**. Here only relevant information in both images is available and the useless information present in the previous step is removed.

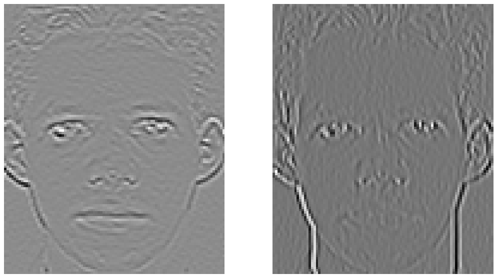

Fig. 3. Left image is ∇ 2gx and right image is ∇ 2gy.
Now the technique combines both these images to collect useful information by taking the average image using equation 5 and the result is shown in Figure 4.

$$Avg = 1/2(\nabla 2gx+\nabla 2gy) \qquad (5)$$

Fig. 4. Average image of Laplacian images

In the next step, the technique applies discrete cosine transform on both original face image and the average face image and computes the mid frequency components of both images by truncating rest of the coefficients. These retained coefficients carry enough information to recognize the face image. After calculating DCT coefficients, the paper concatenates the retained coefficients of both images. Then it supplies these retained coefficients to the Eigen face method to calculate the feature vectors by Eigenface decomposition. The flow chart of proposed system is shown **(Fig. 5)**.

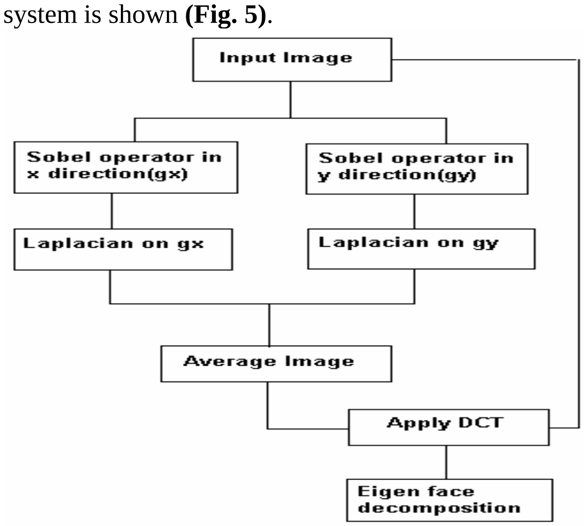

Fig. 5. Flow diagram of proposed method

4. EXPERIMENTS AND RESULTS

4.1. Performance Results on ORL Dataset

The technique evaluates the proposed method on well known ORL dataset. This dataset consists of 400 images of 40 persons with 10 images each. There are images of both males and females with different expressions, illumination and pose. This paper performs an experiment to test system on one sample problem. For this, it uses the first image of each person randomly for training purpose and remaining images for testing from which a test image is selected randomly. Now the training dataset contains 40 images and testing database consists of 360 images. Results for one image per person are shown in **(Table 1)** with varying number of Eigen vectors from 10-40. The proposed method shows superior performance with fewer Eigen vectors than other conventional methods. This corresponds to lower dimensional feature space. **(Fig. 6)** demonstrates comparison chart for one image per person with varying Eigen vectors.

Table 1. Recognition ratio on ORL database with single image and different number of Eigen vectors per person

EIGEN VECTORS	10	15	20	30	40
PCA	32%	50%	60%	61%	65%
(PC)2 A	54%	55%	56%	60%	70%
Sobel Edge & DCT (Proposed)	**60%**	**64%**	**67%**	**70%**	**73%**

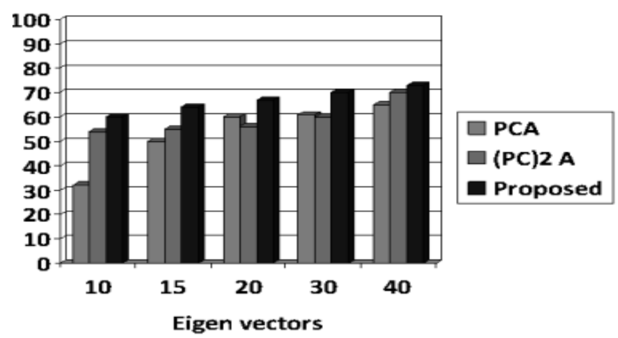

Fig.6. Comparison chart for one image per person

4.2. Performance Results on YaleFace Dataset

Table 2 demonstrates recognition accuracy on Yale face dataset composed of 165 images. The table shows the accuracy of different facial recognition methods along with the proposed sobel edge information and DCT. It also demonstrates accuracy of sobel edge information and discrete cosine transform with two dimensional principal component analysis (2DPCA) and principal component analysis (PCA) such that the prime focus of accuracy percentage is on binary 2DPCA, FR-using LBD and ILLFR(DCT) in LRD. The computed results were provided with a total of 165 images of different faces and the matched images against them along with the accuracy percentage.

Table 2. Comparison of proposed and existing work using Yale face datasets

Methods	Accuracy
PCA	71.56%
2DPCA	84.24%
Sobel Edge and DCT (Proposed)	**93.00%**
B-2DPCA	80.70%
FR-using(LBD)	87.70%
ILLFR(DCT)in LRD	88.12%
Hexagonal + DCT+MLP (Azam *et. al.*,2010)	92.77%

4.3. Performance Results on PIE Dataset

The PIE facial database comprises of 68 images and a total of 41,368 images from different angles. The images of this database were captured by synchronized cameras from 13 different directions under varying expressions, illumination and pose variation as shown in **(Fig. 7)**. This paper uses 150 images of each individual, 50 for training and 100 for testing the accuracy percentage.

Fig 7. Images of two individuals from PIE database.

Table 3. Shows the recognition percentage among kernal Fisherfaces (Yang *et. al.,* 2002), Laplacianfaces(Azam *et. al.*, 2010), Eigen faces (Zhao *et. al.,* 2003) Sobel Edge and DCT.

Table 3. The results on the PIE face datasets with comparison of Eigenfaces, Fisher faces, Laplacian faces and Proposed method SE(DCT).

Methods	Accuracy
Eigen Faces	80.66%
Fisher Faces	82.60%
Laplacian Faces	85.33%
Sobel Edge and DCT (Proposed)	**88.00%**

4.4 Performance Results on MSRA Dataset

The MSRA face image database was collected at Microsoft Research Asia composed of 12 individual images collected in two sessions with different background and illumination conditions. All the faces of this database are frontal. In the analysis process of accuracy percentage, session 1 with 60 images was used at training side and session 2 with 80 images was used at testing side in order to prove the recognition percentage. **(Fig.8)** shows 8 individual images of the MSRA database. The images in the first row were used for training and the second row images were used at testing side.

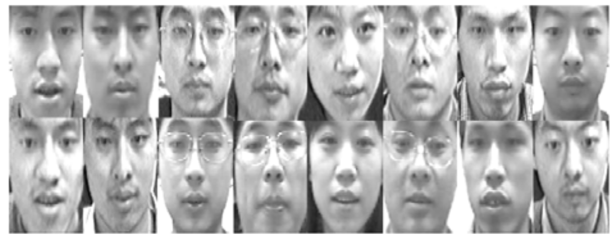

Fig 8. Images of eight individuals from MSRA database. The images in the first row are taken in first session, second row shows the images in second session.

Table 4 finally shows recognition percentage among Fisherfaces (Yang *et.al.*, 2002) Laplacianfaces (Azam *et. al.*, 2010), Eigen faces (Zhao *et. al.*,2003), 2DPCA, B-2DPCA, FR-using LBD, ILLFR(DCT)in LRD and Sobel Edge Information and DCT.

Table 4. The results on the MSRA face datasets with comparison of Eigenfaces, Fisher faces, Laplacian faces and Proposed method Sobel Edge & DCT, FR-using LBD, 2DPCA, B-2DPCA etc.

Methods	Accuracy
Eigen Faces	63.75%
Fisher Faces	75.00%
2DPCA	83.74%
B-2DPCA	88.75%
Laplacian Faces	92.50%
FR-using(LBD)	93.75%
ILLFR(DCT) in LRD	95.00%
Sobel Edge and DCT (Proposed)	**96.25%**

4.5 Performance Results on AR Dataset

The AR face data base was collected at Purdue University with a total of 4,000 images of 126 people (70 men and 56 women). **(Table 5)** provides recognition accuracy percentage of AR dataset on 1000 frontal face images out of which 100 were used at training side (60 men and 40 women) and 900 on testing side of the algorithm. Images cropped as frontal faces with variation in facial expressions, pose variation and illumination conditions.

The results of AR face datasets with comparison of Eigenfaces,Projection, B-2DPCA, ILLFR (DCT) in LRD, FR-using LBD and Proposed method Sobel Edge and DCT.

Methods	Accuracy
Eigen Faces	74.44% (670/900)
Projection $(PC)^2A$	77.78% (701/900)
B-2DPCA	86.11% (775/900)
ILLFR(DCT) in LRD	90.55% (815/900)
FR-using(LBD)	90.66% (817/900)
Sobel Edge and DCT (Proposed)	**95.55% (860/900)**

4.6 Combined Performance Results on Different Datasets

Table 6 shows the comparison of accuracy for proposed technique with different existing techniques and using different face datasets. The combined results showed the overall effectiveness of proposed work.

Table 5. The combined results using different face datasets with accuracy

Methods	Yale	PIE	MSRA	AR
PCA	71.56%	-	-	-
2DPCA	84.24%	-	83.74%	-
B-2DPCA	80.70%	-	88.75%	86.11%
FR-using(LBD)	87.70%	-	93.75%	90.66%
ILLFR(DCT)in LRD	88.12%	-	95.00%	90.55%
Eigen Faces	-	80.66%	63.75%	74.44%
Fisher Faces	-	82.60%	75.00%	-
Laplacian Faces	-	85.33%	92.50%	-
Projection $(PC)^2A$	-	-	-	77.78%
Hexagonal + DCT+MLP	92.77%			
Sobel Edge and DCT (Proposed)	**93.00%**	**88.00%**	**96.25%**	**95.55%**

7. CONCLUSION

In this paper, Sobel and Laplacian edge detectors are used to extract useful information from face image to handle one sample problem and illumination variations. DCT is used to capture only useful information and discard irrelevant details. This also reduces the dimension of image vector. For this purpose, the technique uses mid frequency components in DCT images to represent image in low dimension space.

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