# An Efficient and Robust Face Recognition System Based on Two-Dimensional Fisher Linear Discriminant Analysis : A New Approach

Noushath S[1]* , Hemantha Kumar G[1] and Shivakumara P[2]

ABSTRACT

Eye portion of humans contains most discriminative information than any other part of the face [9]. This paper presents a new scheme of face image feature extraction. We made a successful attempt in obtaining good recognition rate by using only eye regions of a facial image. Initially, eye regions are segmented from the facial images. Segmented eye regions are then trained using two-dimensional fisher linear discriminant analysis (2DFLD) scheme. Based on experimentation it is observed that the proposed method requires fewer coefficients to represent an image and remained insensitive to noise as compared to existing methods. The proposed method has been tested on AT&T database and compared with existing methodologies. The obtained results are described qualitatively and discussed.

KEYWORDS : Eye components, Feature Extraction, Fisher's criterion, 2-Dimensional fisher linear discriminant analysis, Face recognition

## 1. INTRODUCTION

Face recognition by machines is an active area of research and spans several disciplines such as image processing, pattern recognition, computer vision and neural networks. It refers to the process of identification of individuals from images of their faces by using a stored database of faces labeled with people's identities. Humans are able to recognize others in a wide domain of circumstances, and this capability is crucial for human-human interaction.

Recently, due to military, commercial, and law enforcement applications, there has been much interest in automatically recognizing faces in still and video images. The data come from a wide variety of sources. One group of sources is the relatively controlled format images such as passports, credit cards, photo IDs, drivers' licenses, and mug shots. A more challenging class of application imagery includes real-time detection and recognition of faces in surveillance video images, which present additional constraints in terms of speed and processing requirements [1].

This task of face recognition is complex and can be decomposed into the smaller steps of detection of faces in a cluttered background, localization of these faces followed by the extraction of features from the face regions, and finally, recognition and verification [2]. It is a difficult problem as there are numerous factors such as 3D pose, facial expression, hair style, make up etc., which affects the appearance of an individual's facial features. In addition to those varying factors, lighting, background, and scale changes make this task even more challenging. Additional problematic conditions include noise, occlusion and many other possible factors.

The face recognition problem has attracted much research effort in the last years. Although it has proven to be a very difficult task even for frontal faces, certain algorithms can perform well under constrained conditions. The wide array of possible applications of

[1]Department of Studies in Computer Science, University of Mysore, Mysore-570006.

[2]Department of Computer Science, School of Computing, National University of Singapore (NUS), Singapore

Email : nawali_naushad@yahoo.co.in[1], *
hemanth_kumar@lycos.com[1],
shiva@comp.nus.edu.sg[2]

face recognition has led to a continuous search for more precise algorithms and techniques. Some authors have put emphasis on feature extraction techniques, which lead to a representation space, while others described improvements in the classification stage.

Many methods have been proposed for face recognition within the last two decades. Some methods try to model distribution of the high dimensional face space. Turk and Pentland [3] applied principal component analysis (PCA) to face detection where a set of Eigenfaces were generated.. The key idea behind this method, which uses PCA, is to find the best set of projection directions in the sample space that will maximize based on scatter matrix.

The Fisher Linear Discriminant (FLD) method is proposed in [4]. This method overcomes the limitations of the Eigenface method by applying the Fisher's Linear Discriminant criterion.

The Direct-LDA method is proposed in [5]. This method uses the simultaneous diagonalization method [7]. First, the null space of $S_B$ is removed and, then, the projection vectors that minimize the within-class scatter in the transformed space are selected from the range space of . However, removing the null space of by dimensionality reduction will also remove part of the null space of and may result in the loss of important discriminative information. Furthermore, is whitened as a part of this method. This whitening process can be shown to be redundant and, therefore, should be skipped. Jian Yang et al [11] have proposed a method called 2DLDA in which they applied IMLDA [12] technique both horizontally and vertically which makes discrimination information compact into the up-left corner of the image. Although this method used fewer coefficients to represent an image, time needed for training and feature extraction was comparatively higher than other conventional LDA methods.

The main difficulty in using the FLD and PCA schemes for face recognition is the very high-dimensional nature of the image vector. Hence computing Eigenfaces or Fisherfaces on such a high-dimensional vector will be very time consuming. An alternative way to handle the above problem of fisherface method was suggested by Huilin Xiong et al [8], called two-dimensional FLD scheme (2DFLD), which is based on a straightforward projection of the image matrix along with an alternative fisher criterion.

Similarly for the above problem of eigenface method, Yang et al [6] have shown that a "two dimensional" PCA (2DPCA) can be constructed in a straight forward manner based on the image matrix projection. The size of the scatter matrices for both 2DFLD and 2DPCA scheme is either only (m x m) or (n x n) for an image of size (m x n) instead of the size mnxmn in the classic PCA[3] and FLD[4] schemes. However, one disadvantage of both 2DPCA[6] and 2DFLD[8] schemes is that more coefficients are needed to represent an image. Hence, as size of the database increases, the computational time and storage requirement for representation and classification of the image increases drastically.

Noushath et al [13] have proposed a method based on geometrical features for automatic detection and recognition of faces. Although this method had obtained good detection and recognition rate, but remained susceptible under noisy conditions.

In this paper, an efficient method in terms of both storage requirement and execution time is proposed. Instead of training the whole face image for recognition purpose, we segment the eye region from the given face image [9] and normalize it to fixed size of 20x60. We then train these eye regions for recognition purpose using 2DFLD algorithm. We implemented the algorithm proposed by Jianxin Wu et al [9] for efficiently segmenting the eye regions from the given face image. Based on experimental results, we have found that the proposed method is more efficient in terms of recognition rate, execution time and image representation. We also observed that the proposed method is robust to noise.

The remainder of the paper is organized as follows: In section 2, the proposed method is introduced. In section 3, we describe the datasets and experimental results. In section 4, we give comparative study with some well known existing methods. Finally, we formulate our conclusions in section 5.

## 2. Proposed Methodology

In this section, we present a methodology for recognizing faces in two steps. First step is preprocessing step for segmenting eyes from the facial region. Second step is to apply 2DFLD scheme for feature extraction. Block diagram of the proposed method is shown in Fig. 1.

### 2.1 Preprocessing: Segmenting Eye Regions from Facial Image

Here we implemented the method proposed in [9] to segment the eye regions from the facial image. The motivation to segment the eyes is that the eyes regions contain most discriminative information than any other region of face viz mouth, chin, ear, nose etc [9]. In this section, we briefly describe this method for the sake of continuity.

Eyes are the most important facial features in face detection and recognition systems and also eyes are darker than other part of the face [9]. This method locates possible face patterns by combining two eye-analogue segments. At first all eye-analogue segments are found by finding regions that are roughly the same size of a real eye and are darker than their neighborhood. If locations of a pair of these segments conform to the geometrical relationship of a human face's two eyes, this method clips the corresponding image regions as eye regions and later performs face detection tasks.

Let P(x,y) be an intensity image of size $N_1 x N_2$, where $x \in [1, N_1], y \in [1, N_2], P(x, y) \in [0,1]$, in which x is the row index and y is the column index. Let $avg(P, x, y, h, w)$ be the average intensity of the image patch whose upper-left corener is (x,y) and whose size is hxw, i.e.

$$avg(P,x,y,h,w) = \frac{\sum_{i=x}^{x+h-1} \sum_{j=y}^{y+w-1} P(i,j)}{hxw}$$

Each pixel's intensity is compared to the average intensity of its eight neighborhood image patches. Let $h_e x w_e$ be the size of the eyes to be found. Eye-analogue segments are found by marking eye-analogue pixel if and only if six or more of the following constraints are satisfied:

$$P(x,y) < 0.9 * avg(P, x-[h_e/2], y, [h_e/2], 1)$$
$$P(x,y) < 0.9 * avg(P, x-[h_e/2], y+1, [h_e/2], [w_e/2])$$
$$P(x,y) < 0.9 * avg(P, x, y-[h_e/2], 1, [w_e/2])$$
$$P(x,y) < 0.9 * avg(P, x, y+1, 1, [w_e/2])$$
$$P(x,y) < 0.9 * avg(P, x-[h_e/2], y, [h_e/2], 1)$$
$$P(x,y) < 0.9 * avg(P, x+1, y-[w_e/2], [h_e/2], [w_e/2]$$
$$P(x,y) < 0.9 * avg(P, x-[h_e/2], y, [h_e/2], 1)$$
$$P(x,y) < 0.9 * avg(P, x+1, y, [h_e/2], 1)$$
$$P(x,y) < 0.9 * avg(P, x-[h_e/2], y, [h_e/2], 1)$$
$$P(x,y) < 0.9 * avg(P, x+1, y+1, [h_e/2], [w_e/2]$$
$$P(x,y) < 0.9 * avg(P, x-[h_e/2], y-[w_e/2], [h_e/2], [w_e/2])$$

Now eye analogue segments are found using eye-analogue pixels. An eye region will exist if all of the following constraints are satisfied between two eye-analogue segments.

$$d_{ij} < 2.5 w_e$$
$$d_{ij} > 1.5 w_e$$
$$|x_i - x_j| < h_e$$

in which $d_{ij}$ is the Euclidean distance between two eye-analogue segments.

In this way we initially segments eye regions from a given facial image and later we use it for training the system.

Some eye regions thus clipped from original face images using the above method are shown in Fig. 2

### 2.2 Two-Dimensional Fisher Criterion

In this section, we propose 2-dimensional fisher linear discriminant for recognizing the faces of particular database by considering eyes portion as input instead of whole face.

We project an mxn image matrix X onto m-dimensional vector space through the transformation y=Xα, where α is an n-dimensional vector, and y the m-dimensional projected vector. We need to extract optimal projection direction α so that the projected vectors in the m-dimensional space reach its maximum class separability.

The conventional Fisher criterion is not convenient for the theoretical analysis. So, in this paper we adopt the 2-dimensional Fisher criterion [8] to measure the class separability given by

$$J = \frac{tr(S_b)}{tr(S_w)} \qquad (1)$$

Where tr denotes the trace of the matrix, and $S_b$ and $S_w$, respectively denote the between-class and within-class matrices.

Suppose there are $X_j (j = 1,2,\dots,N)$ training images, which contain C pattern classes, and the ith class $C_i$ has $n_i$ samples. The images, all mxn matrices, are projected into m-dimensional vector space $y_i = X_i\alpha$. In the projection space, the measure of the class separability of the projected image is calculated by

$$J(\alpha) = \frac{tr(S_b^\alpha)}{tr(S_w^\alpha)} \qquad (2)$$

Where

$$S_b^\alpha = \frac{1}{N}\sum_{i=1}^{C} n_i(\overline{y}^i - \overline{y})(\overline{y}^i - \overline{y})^T$$

$$S_w^\alpha = \frac{1}{N}\sum\sum(y_j - \overline{y}^i)(y_j - \overline{y}^i)^T$$

in which $\overline{y}$ and $\overline{y}^i$, respectively, denote the global mean vector and the mean vector of the ith class in the projection space.

It is easy to verify that $tr(S_b^\alpha) = \alpha^T G_b \alpha$ and $tr(S_w^\alpha) = \alpha^T G_W \alpha$, where

$$G_b = \frac{1}{N}\sum_{i=1}^{C} n_i(\overline{X}^i - \overline{X})^T(\overline{X}^i - \overline{X})$$

$$G_w = \frac{1}{N}\sum_{i=1}^{C}\sum_{j\in C_i}(X_j - \overline{X}^i)^T(X_j - \overline{X}^i)$$

in which $\overline{X}$ and $\overline{X}^i$, respectively, represent the global and the ith class mean images.

$G_b$ and $G_w$ are called, image between-class scatter matrix and image within-class scatter matrix, respectively. Note that the size of the image scatter matrices is only mxm, much smaller than that of the scatter matrices whose sizes are mn x mn in the conventional FLD algorithms. Using the image scatter matrices, the two-dimensional Fisher criterion given by Eq. (1) can be expressed as

$$J(\alpha) = \frac{\alpha^T G_b \alpha}{\alpha^T G_W \alpha} \qquad (3)$$

### 2.3 Two-Dimensional FLD Feature Extraction

In this section, we describe feature extraction scheme based on 2DFLD. The objective of 2DFLD scheme is to find the optimal projection direction α in order to maximize (3). Obviously, the optimal projection direction $\alpha_{opt}$ is the eigenvector corresponding to the maximum eigenvalue of the eigenstructure:

$$G_b\alpha = \lambda G_w \alpha \qquad (4)$$

It is not difficult to handle the above eigenproblem directly, since the size of the matrix $G_b$ or $G_w$ is only mxm. In practice, one optimal projective direction is not enough to extract sufficient discriminatory features. We usually need to project the image data onto a set of orthogonal directions, namely, $\alpha_1, \alpha_2, \dots, \alpha_k$, which maximize the criterion (3). These projection directions can be selected as the k eigen-vectors corresponding to the first k largest eigenvalues of the eigenstructure (4).

The optimal projection axes of 2DFLD: $\alpha_1,\ldots,\alpha_k$ are used for feature extraction. For a given image (eye portion of a face) A, let $Y_j = A\alpha_j, j = 1,\ldots,k$. Then we have a family of projected feature vectors, $Y_1, Y_2,\ldots,Y_k$ which are called the principle component vectors of an image A. The principal component vectors obtained are used to form an m x k matrix $B = [Y_1,\ldots,Y_k]$, which is called the feature matrix or feature image of the image sample A.

### 2.4 Classification Method

After a feature matrix is obtained for each image. Then, a nearest neighbor classifier is used for classification. Here, the distance between two arbitrary feature matrices,

$B_i = \left|Y_1^{(i)}, Y_2^{(i)},\ldots,Y_d^{(i)}\right|$ and

$B_j = \left|Y_1^{(j)}, Y_2^{(j)},\ldots,Y_d^{(d)}\right|$, is defined by

$$d(B_i, B_j) = \sum_{k=1}^{d}\left\|Y_k^{(i)} - Y_k^{(j)}\right\|,$$ where

$\left\|Y_K^{(i)} - Y_k^{(j)}\right\|$ denotes the Euclidean distance between the two principal component vectors $Y_k^{(i)}$ and $Y_k^{(j)}$.

## 3. Experimental Results

In this section, we present several experiments conducted to demonstrate the utility of our method. We performed all experiments on the standard set of face images, AT & T [10], a widely used database for facial recognition tasks. We give brief introduction about the database we used in our experimentation in section 3.1 and in following section we present the experimental results obtained by the proposed method.

### 3.1 Dataset

The AT&T database contains images from 40 individuals, each providing 10 different images. For some subjects, the images were taken at different times. The facial expression (open or closed eyes, smiling or non-smiling) and facial details (glasses or no glasses) also vary. All images are grayscale and normalized to a resolution of 92x112 pixels. So, we use the AT&T database to evaluate the proposed method's performance under conditions where pose and size of samples are varied. All the ten sample images of one person from this database are shown in Fig. 3.

### 3.2 Results

In order to evaluate the efficacy of the proposed method, in this section we present the experimental results under conditions where the sample size and number of principal components are varied. Here five tests were performed with varying number of training samples $p$ (Where $p$ =2, 4, 5, 6 and 8). In each test, we varied the number of principal components k (Where k=1,2,...,20,25,30,35,40) and recognition rate was computed for all values of p and k. Table 1 presents the recognition rate achieved by proposed method, which corresponds to varying number of training samples and principal components. Fig. 4 is the graphical plot of number of principal components vs recognition rate achieved by the proposed method. Note that in all subsequent experiments of proposed method, during training process, we use only the eye regions clipped from facial image.

The main advantage of proposed method is that it needs less number of coefficients to represent an image. In our case, the image size is 20x60, so in order to represent an image with $k$ number of principal components; only 20x$k$ coefficients were used. This further reduces execution time and storage required to represent an image. From the graph drawn in Fig. 4, it is observed that despite less number of coefficients, our method is able to obtain good recognition rate.

We also tested the performance of propose method under noise conditions. For this, we randomly select one image from each class and generated 10 noisy images (with salt and pepper noise) for that class by varying noise density from 0.1,0.2,...1.0. So effectively, we created 400 noisy images corresponding to 40 different classes. We use all the images of AT&T database during training (i.e. noiseless images). So, in this experiment, the size of the training set and testing set were both 400. It can be easily ascertained from Table 2 that the proposed method obtained exceptional results under noise conditions.

Table 3 shows the execution time taken for feature extraction by the proposed method for varying number of training samples p. Here we fixed number of principal components k to be 20.

## 4. Comparative Study

In this section we give comparative study with well known existing methods such as Eigenfaces [3], 2DPCA [6], 2DFLD [8] and 2DLDA [11]. Recognition rate/accuracy, execution time and performance in the presence of noise are some factors that may be used to judge a face recognition method.

To compare the recognition rate achieved by different methods, we use first five images of each class for training and remaining five images of each class for testing. Here, again we varied number of principal components $k$ from 1,2,...,20,25,30,35,40. Table 4 presents the recognition rate achieved by different methods.

From the graph shown in Fig. 5, it is observed that the proposed method outperforms both eigenface and 2DLDA methods. It is also observed that the proposed method's performance is almost equal to 2DFLD method for all values of $k$. However, 2DFLD requires more coefficients to represent an image. Our method obtained good recognition rate with less number of coefficients. Notice in graph that from=15 onwards 2DPCA method outperforms both 2DFLD and proposed method. Again 2DPCA method requires more number of coefficients to represent a image. Trade-off is recognition rate.

Table 5 shows the recognition rate achieved by all the methods. As mentioned earlier, we use 400 noiseless images during training, and 400 noisy images during testing. It can be easily seen from the graph shown in Fig. 6 that the proposed method obtained exceptional results under different noise conditions and outperformed other methods comprehensively. This is because in our method size of the covariance matrix Q is very small (i.e. 60x60). When size of the covariance matrix reduces, effect of noise becomes irrelevant. Another convincing reason might be like this. In case of whole face image, chances of pure black or pure white pixels replaced by salt and pepper color pixels are higher. In such cases, 0 valued pixels might get changed to 255 and vice versa (since salt and pepper noise are nothing but white and black pixels). In case of proposed method we use only the eye regions. Hence drastic change in noise hit pixels will not be that much noticeable. In eye regions, probability of presence of pure black or pure white pixels is very less compared to a whole face image.

A final consideration has to be done on program execution time for feature extraction and classification. We realized all the methods (i.e., eigenface, 2DPCA, 2DFLD, 2DLDA and Proposed Method) in Matlab programming language on a Pentium-IV, 1.8 Ghz with 128MB RAM system. Table 6 compares the average execution time (s) of all the methods.

From the Table 6 it is clear that the eigenface method is computationally very expensive and time consuming than any other methods since it involves computation of covariance matrix of a very high dimension (i.e. 10304x10304, in case of AT&T database). Also, this method involves transformation of 2D face image to a single dimensional vector. Execution times of 2DFLD and 2DLDA algorithms are almost equal. Execution time of 2DPCA method is slightly better than 2DFLD and 2DLDA algorithms. From the graph (Refer Fig. 7), it is observed that execution time of proposed method is far better than these methods, since it involves computation of covariance matrix of a reduced image (i.e., eye region) and also less number of coefficients are used for representing an image.

Fig. 8(a)-(d) shows the recognition rate achieved by eigenface, 2DPCA, 2DFLD and 2DLDA methods respectively. It is observed that from the graph that 2DPCA and 2DFLD methods obtained good recognition rate even for less number of training samples and less number of principal components. But, by comparing Fig. 8(b) and Fig. (c) with Fig. 4 our method has obtained same or even better accuracy than 2DPCA and 2DFLD methods despite having less number of coefficients for representing the image.

## 5. Conclusion

In this paper, a new technique for image feature extraction and representation based on 2DFLD scheme is developed. Initially, we segment the eye portions from the facial image and train the system using only eye regions. Doing this has several advantages. Firstly, it requires very few coefficients to represent an image which leads to reduced execution time for feature extraction and storage requirements. Secondly, since eye regions of a human face have most discriminative information, the method is able to obtain good accuracy (because we train the system using only eye regions). Finally, the method remained insensitive to noise conditions. The method was tested extensively on AT&T database and compared with well-known methods. The method outperformed eigenface, 2DPCA, 2DFLD and 2DLDA methods in terms of accuracy, storage requirements, and execution time. Also the method obtained exceptional results under noise conditions when compared to other methods.

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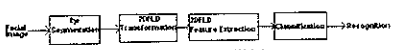



Fig. 1 Block Diagram of Proposed Method

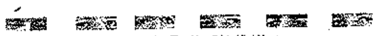


Fig. 2 Few Eye-Regions Clipped from Original Facial Image

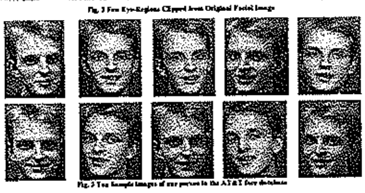


Fig. 3 Ten Sample Images of one person in the AT&T face database

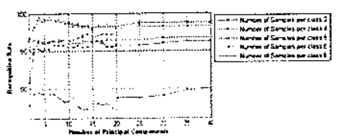


Fig. 4 Recognition rate achieved for varying number of training samples and principal components

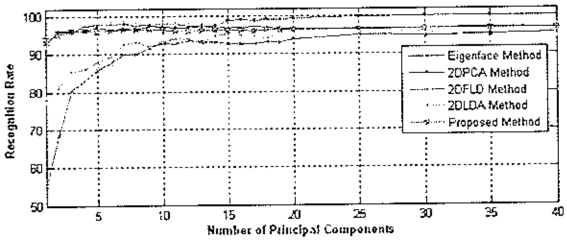



Fig. 5 Recognition rate obtained by different methods

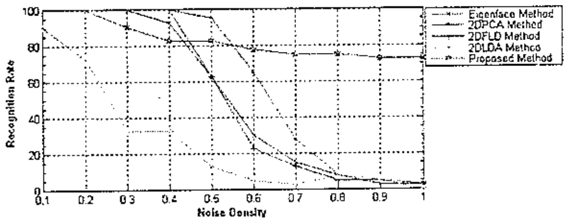



Fig. 6 Recognition rate achieved by different methods under noise conditions

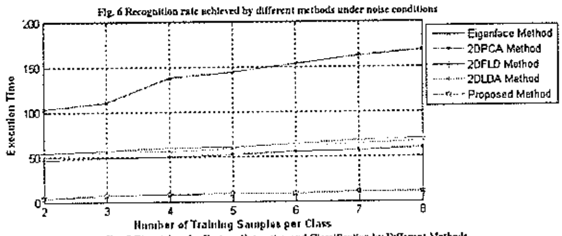
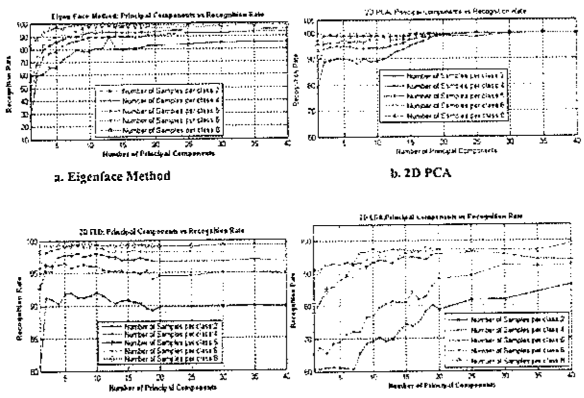



Fig. 7 Time taken for Feature Extraction and Classification by Different Methods



a. Eigenface Method

b. 2D PCA

c. 2D FLD

d. 2D LDA

Fig. 8 Performance of all the methods for varying number of samples per class

Table 1. Recognition rate achieved by the proposed method

| Principal Components (k) | Number of training samples per Class (p) | | | | | Principal Components (k) | Number of training samples per Class (p) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2 | 4 | 5 | 6 | 8 | | 2 | 4 | 5 | 6 | 8 |
| 1 | 87.75 | 90.75 | 94.00 | 95.25 | 96.50 | 13 | 87.25 | 95.50 | 96.25 | 97.00 | 98.25 |
| 2 | 89.25 | 95.25 | 95.00 | 96.50 | 98.00 | 14 | 87.25 | 95.50 | 96.25 | 97.25 | 98.25 |
| 3 | 89.50 | 95.25 | 96.25 | 96.50 | 99.25 | 15 | 88.00 | 96.25 | 96.25 | 97.00 | 98.00 |
| 4 | 89.25 | 95.00 | 96.25 | 96.00 | 99.00 | 16 | 88.00 | 96.25 | 96.25 | 97.00 | 98.25 |
| 5 | 88.75 | 95.25 | 96.00 | 96.00 | 99.00 | 17 | 87.75 | 96.25 | 96.00 | 97.25 | 98.25 |
| 6 | 89.25 | 95.25 | 96.25 | 96.25 | 99.25 | 18 | 88.00 | 95.50 | 96.50 | 97.25 | 98.25 |
| 7 | 89.25 | 95.75 | 96.50 | 96.25 | 99.00 | 19 | 87.25 | 95.50 | 96.50 | 97.25 | 98.25 |
| 8 | 88.75 | 95.75 | 96.50 | 96.25 | 99.00 | 20 | 88.75 | 95.75 | 96.50 | 98.00 | 98.25 |
| 9 | 88.25 | 95.75 | 96.50 | 96.50 | 98.75 | 25 | 88.75 | 95.75 | 96.50 | 98.25 | 98.75 |
| 10 | 88.25 | 95.50 | 96.50 | 96.50 | 98.75 | 30 | 89.00 | 96.00 | 96.75 | 98.25 | 98.75 |
| 11 | 88.75 | 95.50 | 96.00 | 96.50 | 98.50 | 35 | 89.75 | 96.25 | 96.75 | 98.25 | 98.75 |
| 12 | 87.50 | 95.75 | 96.00 | 96.75 | 98.50 | 40 | 90.00 | 96.25 | 96.75 | 98.25 | 98.75 |

Table 2. Recognition rate achieved by proposed for varying noise densities

| Noise Density | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1.0 |
|---|---|---|---|---|---|---|---|---|---|---|
| Recognition Rate | 100 | 100 | 90 | 82.5 | 82.5 | 77.5 | 75.0 | 75.0 | 72.5 | 72.5 |

Table 3. CPU Time (s) for Feature Extraction and Classification Using AT&T database

| Number of training samples (p) | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|
| Execution time | 4.17 | 6.89 | 7.36 | 8.38 | 8.91 | 10.06 | 10.86 |

Table 4. Recognition Rate Achieved by Different Methods

| Principal Components | Different Methods | | | | |
|---|---|---|---|---|---|
| | Eigenface | 2D PCA | 2D FLD | 2D LDA | Proposed |
| 1 | 55.25 | 93.00 | 92.75 | 78.00 | 94.00 |
| 2 | 68.50 | 96.00 | 96.25 | 81.25 | 95.00 |
| 3 | 80.50 | 96.25 | 96.00 | 85.50 | 96.25 |
| 4 | 83.25 | 96.25 | 97.50 | 86.00 | 96.25 |
| 5 | 85.75 | 97.25 | 97.75 | 88.00 | 96.00 |
| 6 | 87.75 | 96.50 | 97.75 | 89.25 | 96.25 |
| 7 | 90.00 | 96.75 | 98.00 | 92.75 | 96.50 |
| 8 | 90.00 | 96.50 | 97.50 | 93.25 | 96.50 |
| 9 | 91.75 | 97.50 | 97.75 | 92.00 | 96.50 |
| 10 | 93.00 | 97.25 | 98.00 | 93.25 | 96.50 |
| 11 | 92.75 | 97.00 | 97.75 | 94.00 | 96.00 |
| 12 | 93.50 | 97.00 | 97.50 | 93.75 | 96.00 |
| 13 | 93.25 | 97.50 | 97.50 | 93.00 | 96.25 |
| 14 | 93.25 | 97.50 | 97.00 | 94.75 | 96.25 |
| 15 | 92.75 | 98.75 | 97.00 | 95.25 | 96.25 |
| 16 | 92.75 | 99.00 | 97.00 | 95.00 | 96.25 |
| 17 | 92.75 | 98.75 | 97.25 | 94.75 | 96.00 |
| 18 | 93.25 | 99.00 | 97.00 | 94.00 | 96.50 |
| 19 | 93.25 | 99.00 | 96.75 | 95.75 | 96.50 |
| 20 | 93.75 | 99.25 | 96.75 | 96.00 | 96.50 |
| 25 | 95.00 | 99.75 | 96.75 | 96.40 | 96.50 |
| 30 | 94.75 | 100.00 | 96.75 | 95.75 | 96.75 |
| 35 | 95.00 | 100.00 | 97.00 | 94.25 | 96.75 |
| 40 | 95.50 | 100.00 | 96.75 | 94.00 | 96.75 |

Table 5. Performance of all Methods under Noise

| Noise Density | Performance of different approaches | | | | |
|---|---|---|---|---|---|
| | Eigenface | 2D PCA | 2D FLD | 2D LDA | Proposed |
| 0.1 | 100.00 | 100.00 | 100.00 | 90.00 | 100.00 |
| 0.2 | 100.00 | 100.00 | 100.00 | 72.50 | 100.00 |
| 0.3 | 100.00 | 100.00 | 100.00 | 32.50 | 90.00 |
| 0.4 | 92.50 | 100.00 | 100.00 | 32.50 | 82.50 |
| 0.5 | 62.50 | 95.00 | 62.50 | 12.50 | 82.50 |
| 0.6 | 30.00 | 65.00 | 22.50 | 5.00 | 77.50 |
| 0.7 | 15.00 | 27.50 | 12.50 | 2.50 | 75.00 |
| 0.8 | 7.50 | 7.50 | 5.00 | 7.50 | 75.00 |
| 0.9 | 5.00 | 2.50 | 5.00 | 5.00 | 72.50 |
| 1.0 | 2.50 | 2.50 | 2.50 | 0.00 | 72.50 |

Table 6. Average Execution Time for Feature Extraction (Dimension k=20)

| Methods | Number of training samples per class $(p)$ | | | | | | |
|---|---|---|---|---|---|---|---|
| | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Eigenface | 103.31 | 110.27 | 137.95 | 144.32 | 152.93 | 162.67 | 165.98 |
| 2D PCA | 46.39 | 48.24 | 49.87 | 52.09 | 54.65 | 57.11 | 59.96 |
| 2D FLD | 53.74 | 56.59 | 59.27 | 60.87 | 64.43 | 67.28 | 69.77 |
| 2D LDA | 49.95 | 55.32 | 55.95 | 58.44 | 61.52 | 63.80 | 65.88 |
| Proposed | 4.17 | 6.89 | 7.36 | 8.38 | 8.91 | 10.06 | 10.86 |

## Authors' Biography :

**G. Hemantha Kumar** obtained M.Sc and Ph.D in Computer Science from the University of Mysore in the year 1988 and 1998 respectively. He has published around 130 research papers in various Journals, International and National Conference proceedings. He has successfully guided four Ph.D candidates and two M.Sc Tech (by research) candidates. Currently he is guiding 4 Ph. D candidates and 4 M.Sc Tech (by research) candidates. He has delivered talk at many Universities in India and abroad. His research focuses on Pattern Recognition and Image Processing. His current area of research includes Document Analysis and Biometrics including Face and Speech recognition. He is currently working as Reader and Chairman at Department of Studies in Computer Science, University of Mysore, Mysore.

**S. Noushath** obtained M.S in Computer Systems from the University of Mysore, Mysore in the year 2004. He has published around 20 research papers in various Journals, International and National Conference proceedings. Currently he is working as a research scholar and pursuing his doctoral degree from the University of Mysore, Mysore. He is working in the field of Automatic Face Recognition System. He was previously employed in a project sponsored by AICTE in the field of Document Image Mosaicing.

**P. Shivakumara** obtained M.Sc, M.sc Tech (by research) and Ph. D in Computer Science from the University of Mysore in the year 1998, 2001 and 2005 respectively. He has published around 90 research papers in various Journals, International and National Conference proceedings. Currently he is working as a post doctoral fellow in National University of Singapore, Singapore. His research interest focuses on Pattern Recognition and Image Processing, Document Analysis and Multimedia.