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FACE RECOGNITION USING SEMI DISCRETE DECOMPOSITION AND FLDA FOR SINGLE TRAINING IMAGE PER PERSON

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ABSTRACT

PCA and FLDA are mainly used in face recognition and feature extraction. PCA uses eigen vector and FLDA uses within class scatter matrix and between class scatter matrix. When within class matrix becomes singular, it cannot be evaluated. A new method called semi-discrete decomposition is used in single image per person problems. The performance of this method is tested on 4-data bases, namely ORL, UMIST, Poly u-NIR, YALE. The proposed method performs better than SVD based approach and QRCP based approach in terms of recognition rate with training times in two times higher than QRCP.

Keywords*: Face recognition, Fisher Linear Discriminant Analysis, Semi Discrete Decomposition, Singular Value Decomposition***.**

1. INTRODUCTION

Face recognition is mainly used in securities, crime detection surveillance, human computer interaction. As the training sample size is limited, performance is affected. More number of training samples per each person is required for good performance. Many algorithms are there to overcome this difficulty.

SAM - Sub space analysis method [1] extracts basis vectors based as some criteria and extraction features by forming face image as a linear combination of basis vector. PCA method finds Optimal orthogonal bases with minimum mean square error. FLDA - Fisher linear discriminant analysis forms optimal projection vectors by maximizing the ratio between the determinants of between class and within class scatter matrices of training face images. Eigen face method [2] was proposed by Turk and pentland. Based on eigen face method, many PCA based algorithm have been developed. FLDA aims at findings projection vectors which separates the datas among different class. A Fisher face method for face recognition was developed. It uses PCA first to convert data into lower dimensional space and then apply FLDA for face recognition FLDA outperform PCA.

The drawback of FLDA is within class scatter matrix may become singular. Tian et al [3] proposed to use generalized inverse to avoid singular value problem. Non-singularity of within class matrix is formed by adding a small perturbation and this was proposed by Hong et al [4]. 2D FLDA was proposed by Ye et al. [5]. There is no image to vector transformation in 2D FLDA. It directly calculates within class and between class scatter matrices. In real world scenario, for example driving licence, passport identification only one training sample is available. and within class scatter matrix may be zero and FLDA fails.

To overcome this drawback, Wang et al [6] assumed that all human beings posses a similar intra-class variation, and formed within class scatter matrix by using other subjects. Wu et a1 [7] proposed (PC)2A approach that linearly combines first order images and original training samples to form the new training set. Chen et al [8] divided the test and training image into non - overlapping patterns but it is much time consuming approach.

Quan et al [9] proposed a new SVD based method based on subspace. In this approach image is separated into two parts. General appeance part and difference part. Difference

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part is used to evaluate within class scatter matrix and general appearance part is used to evaluate between class scatter matrix. The general drawback of this method is training time is more. Mehmet Koc et al [10] proposed a new method based on QRCP algorithm. Recognition rates are higher than SVD based approach. The proposed method uses semi discrete decomposition (SDD). The proposed method obtains better recognition rates compared with [8] and [9] with a compromise in training time. It is proved that the proposed method produces good results and outperforms than other approaches.

2. TWO DIMENSIONAL FISHER LINEAR DISCRIMINANT ANALYSIS (2D-FLDA)

It finds the optimal projection vectors that separate different classes as far as possible [10]. Number of classes is C. Number of selected samples from each class is N. A_j^i be the jth image from ith class. mi is average of ith class.

$$M^i = \frac{1}{N}\sum_{j=1}^{N} A_j^i \qquad j = 1,2,\dots C \tag{1}$$

The optimal projection vectors can be calculated by maximizing the J(X)

$$J(X) = \frac{X^T S_B X}{X^T S_W X} \tag{2}$$

Where

$$S_w = \sum_{i=1}^{C}\sum_{j=1}^{N}\left(A_j^i - M_i\right)^T\left(A_j^i - M_i\right)$$

i = 1,2,..C;

$$S_B = \sum_{i=1}^{C}\left(M_i - M\right)^T\left(M_i - M\right)$$

$$M = \frac{1}{C}\sum_{i=1}^{C} M^i \tag{3}$$

Optimal projection vector [x1, x2….xn] are calculated and each samples is projected into projection vectors, and test image is also projected.

$$B_j^i = A_j^i\left(x_1 : x_2 : \dots . x_d\right) \tag{4}$$

$$i = 1,2,\dots .C, \quad j = 1,2,\therefore N.$$

Test image is also projected into the projection vector

$$B_{test} = A_{test}\left[x_1; x_2; ..x_d\right] \tag{5}$$

The test image belongs to a particular class is identified based on the formula.

$$C^* = \arg\min_i \left\{\sum_{k-1}^{d}\left\| y_k^{test} - y_k^{ij}\right\|_2\right\}$$

i=1,2,…C j=1,2…. N (6)

3. SEMI DISCRETE DECOMPOSITION (SDD)

It provides more accurate approximation for less storage compared to other methods such as truncated singular value decomposition [15]. The SDD approximation of mxn matrix is

$$A_k = \left(x_1 x_2 \dots\dots x_n\right)\begin{pmatrix} d_1 & 0 & \dots\dots & 0 \\ 0 & d_2 & \dots\dots & 0 \\ \vdots & \vdots & & \\ 0 & 0 & \dots\dots & d_n \end{pmatrix}\begin{pmatrix} y_1^T \\ y_2^T \\ \vdots \\ y_k^T \end{pmatrix}$$

$$= \sum_{i=1}^{i=n} d_i x_i y_i^T \Rightarrow X_n D_n Y_n^T$$

Here each xi is m-dimensional vector and each yi is n-dimensional vector and the entries in the vectors are (1,0,-1) and d1,d2,….dn are positive scalars. The SDD doesn't reproduce A exactly, but it uses very little storage with respect to approximation. A rank K SDD requires the storage of k(m+n) values from {1,0,-1} and k scalars.

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$$A \approx X_n D_n Y_n^T$$

The column of X_n and Y_n need not be linear by independent.

ALGORITHM

1) Input: Matrix $A \in R^{m \times n}$, non-negative integer k

2. Output: k-dimensional SDD of A i.e. matrices $X_k \in \{-1,0,1\}^{m \times k}$, $Y_k \in \{-1,0,1\}^{n \times k}$ and diagonal $D_k \in K_+^{k \times k}$

3. $R_1 \leftarrow A$

4. for j = 1,2,…..k

i) Select $y_j \in \{-1,0,1\}^n$

ii) While not converged

a) Complete $x_i \in \{-1,0,1\}^m$ given y_j X R_j

b) Complete y_i given x and R_j

iii) End while.

iv) Set d_j to average of $R_j \circ x_j y_j^T$ over non-zero location of xy^T

v) Set x_j as the jth column of x_j, y_j as the jth column of Y_j and d_j is the jth column of X_j, Y_j is the j_{th} column of Y_j and d_j is the j_{th} column of D_j

vi) $R_j + 1 \leftarrow R_j \rightarrow d_j x_j y_j^T$

5. End.

6. Return X_K, Y_K, D_k.

Fig. 1.Face Image Corresponds For K=25 In ORL Database

Fig. 2.Face Image Corresponds To K=30 In ORL Database

4. EXPERIMENTS

YALE [11], UMIST [12], PolyU-NIR [13], ORL [14] face data bases are used. In all the cases one sample is used for training and the other samples are used as testing purposes. For all cases recognition rate was calculated based on projection vectors.

4.1. Experiments With Yale Data Base

Total images in the data set are 165. It belongs to 15 different persons. Each different person has 11 images. These 11 images are center-light, glasses, happy, normal, and right light, sad, without glasses, sleepy, surprised and wink. All the eye coordinates are normalized and final size of image is 120x110. Fig.3 shows the recognition rates of the proposed method and method given in [8] and in [9]. The proposed method gives better recognition rates compared with other methods with more training time.

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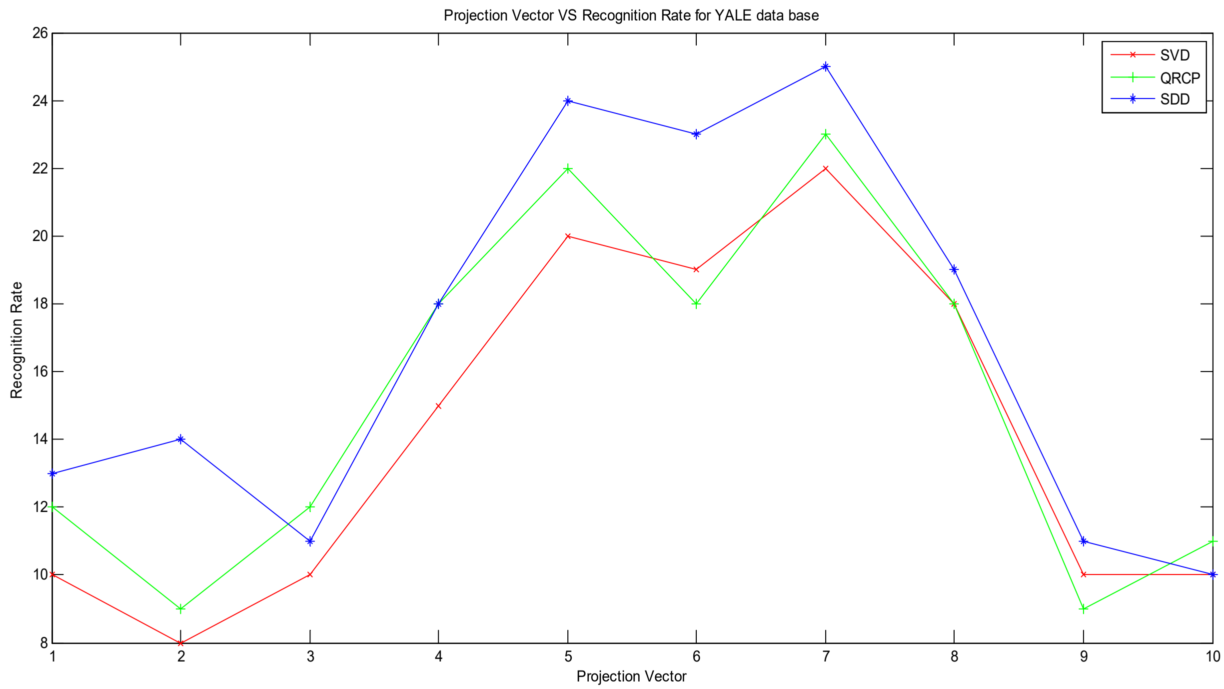

Fig. 3 Projection Vector Vs Recognition Rate For YALE Database

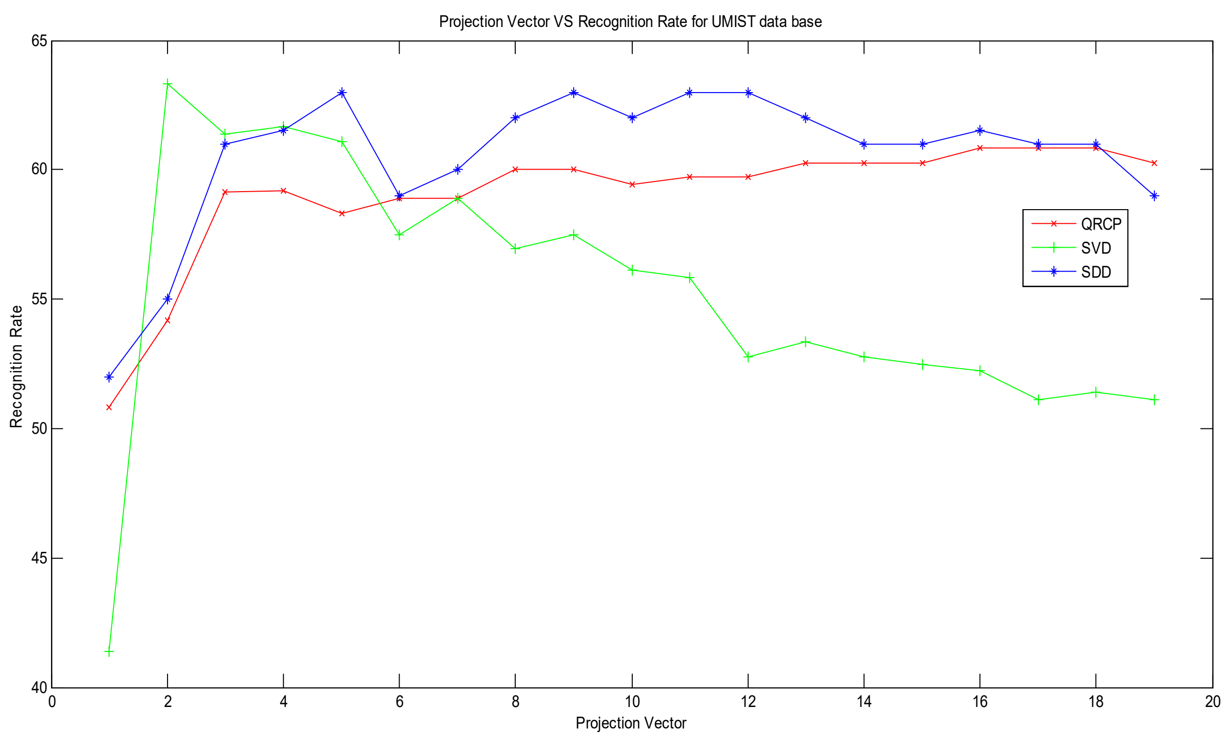

Fig. 4 Projection Vector Vs Recognition Rate For UMIST Database

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4.2. Experiments With Umist Data Base

Total images in this data base are 64. No of different subject is 20. Number of images per subject varies from 19 to 48. Size of cropped image is 112X92 with 8-bitgray scale. The recognition rates of proposed method compared to method in [8] and method in [9] are shown in Fig. 4. The proposed method gives better recognition rates when the projection vector ranges from 6 to 16 with more training time.

4.3. Experiments With Poly U-Nir Data Base

It contains different images of 350 different people. It includes scale, illumination, expression, different pose blurring, time etc., and the image is cropped to 120X90 with 8 bit gray scale from original size of 576X768. We selected 420 images from 60 subject and we selected the projection vector up to 20.

Except projection vector 7, 12 and 13 all projection vectors from 1-20 gives better recognition rates with more training time. This is shown in Fig.5.

4.4. Experiments With Orl Data Base

Total image in the ORL data base is 400. It contains 40 persons. Each person has 10 different images. These images are with facial expressions, illumination an many more facial details. Size of each image is 112X 92 pixels with 8-bit. One image is used as training and the remaining nine images are testing images. Fig. 6 shown the recognition rates of proposed method compared with SVD [8] and QRCP [9]. It performs very well for the projection vector range 1-9 and projection vectors 12 and 13. Table 1 shows the training times of different methods.

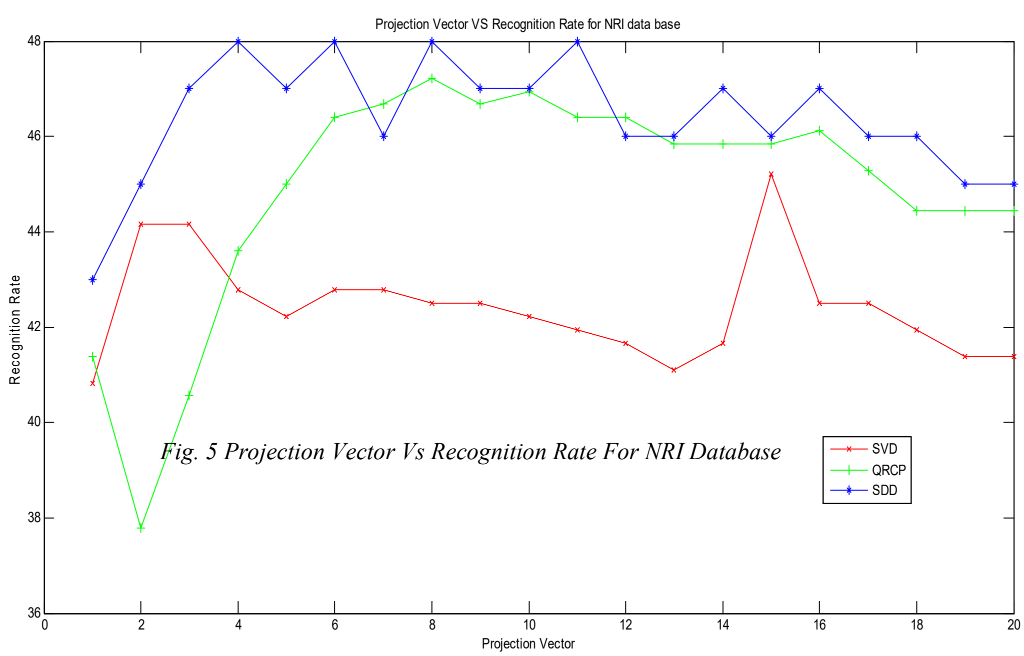

Fig. 5 Projection Vector Vs Recognition Rate For NRI Database

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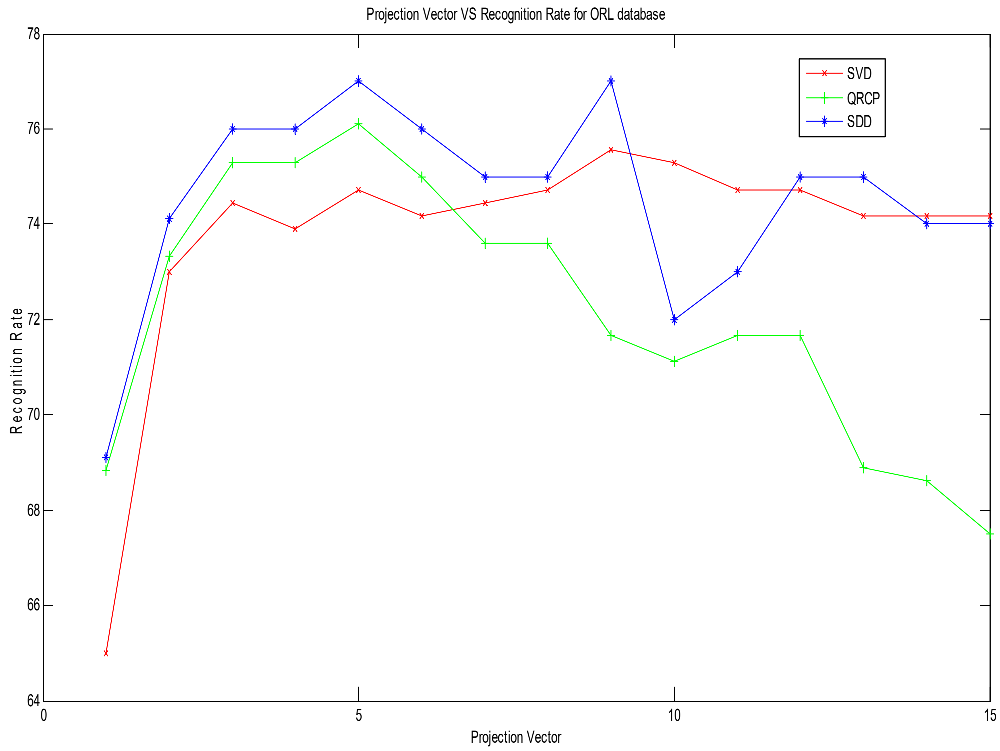

Fig. 6 Projection Vector Vs Recognition Rate For ORL Database

Table – 1 Training Times Of Different Methods

	ORL (ms)	YALE (ms)	UMIST (ms)	POLY U - NIR (ms)
SDD - based	610	301	360	800
QRCP based	339	163	200	544
SVD based	627	312	363	936

5. DISCUSSION AND CONCLUSION

In some situation only one sample is available for each subject in a data base. Some virtual images are also generated using some specified technique. Here the two virtual samples are generated using face image. The training set consists of totally three images, we tested the image with ORL, YALE, UMIST, PolyU-NIR face databases. Better recognition rates were achieved with more training time. The execution time is slightly more compared to SVD and QRCP methods. In the future we will try to reduce training time and increase recognition rate through some other method.

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