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Face Recognition Based on Non-Negative Factorization and FLDA for Single Training Image per Person

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Abstract: Dimensionality reduction is performed by both Principal Component Analysis (PCA) and Fisher Linear Discriminant Analysis (FLDA). Covariance matrix and Eigen vector approach is followed in PCA. FLDA finds within class and between class scatter matrices. In some situations, within class scatter matrix may become singular. Normally singular matrix does not have inverse. Two or more virtual samples are generated from the training set to avoid this problem. A new method called non-negative matrix factorization is used in single image per person problems. The proposed method performs better than SVD, QRCP and SDD method in terms of recognition rate. But training time is slightly more than QRCP and better than SVD and SDD approach.

Key words: Face recognition · Fisher linear discriminant analysis · Semi discrete decomposition · Singular value decomposition · Non-negative matrix factorization

INTRODUCTION

Today face recognition is mainly used in all walks of life such as human-computer interface, security systems, crime detection and so on [1]. Face recognition is classified based on two types: Local feature matching method and holistic matching method. Principal Component Analysis (PCA) and Independent Component Analysis (ICA) [2] is based on holistic matching. It is possible to construct a lower dimensional feature vectors from the input image. Holistic based approach is not suitable for local variation of faces. PCA and ICA performs better under well-controlled illumination and good alignment. Face recognition requires training and testing images. Performance is better if the training image per person is more than one. But in some situations only one training image per person is available. Many virtual training images per person are generated. Many algorithms are proposed to overcome this difficulty. In sub space analysis method [3] PCA method finds orthogonal basis vectors. Fisher linear Discriminant Analysis (FLDA) aims at finding optimal projection vectors by maximizing the ratio between the determinants of between class and within class scatter matrices of training images. FLDA finds projection vectors which separates the datas among different classes. The within class scatter matrix may become singular. The generalized inverse was formulated by Tian *et al*. [4] to avoid this problem. A small perturbation was proposed by Hong *et al*. [5] to avoid singular matrix problem. 2D FLDA was proposed by Ye *et al*. [6] Matrix to vector transformation is not in [6]. Within class and between class matrices are calculated directly by this method. Normally FLDA fails if the inverse of within class scatter matrix does not exist. Based on intra-class variation possessed by all human beings, Wang *et al*. [7] formulated within class scatter matrix. $(PC)^2$ approach was formulated by Wu *et al* [8] that forms the training all samples by combining first order images and original training samples. Chen *et al*. [9] divided test and training image into non-overlapping patterns. Quan *et al*. [10] developed a new SVD based method based on difference part and appearance part of image. Between class scatter matrix is evaluated using general appearance part and within class scatter matrix is

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evaluated using between class scatter matrix. The drawback of this method is more training time. Mehmet Koc *et al*. [11] formulated a new method. In this method QR-decomposition is used. Training time is reduced and recognition rate is higher than previous methods. Rajakumar *et al*. [12] proposed a new method using semi discrete decomposition. In this method two virtual images and training images are used for training purpose. This method provides higher recognition rate but running time is much higher than QRCP based method. The proposed method uses non-negative matrix factorization. This method produces high recognition rates compared with SDD based approach but training time is slightly higher than QRCP method [13-18].

Two Dimensional Fisher Linear Discriminant Analysis (2D-FLDA) [11]: It separates the different classes by finding optional projection vectors. Total number of class is C. Let N_i bet number of samples in ith class. A_j^i be jth image from ith class. M_i be mean of ith class. Let C be the total number of classes.

$$M^i = \frac{1}{Ni}\sum_{j=1}^{Ni} A_j^i \tag{1}$$

The optimal projection vectors are calculated by maximizing *J*(*X*) where X is vector

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

where S_B is between class scatter matrix and S_w is within class scatter matrix.

$$S_w = \sum_{i=1}^{c}\sum_{j=1}^{N}(A_j^i - m_i)^T (A_j^i - m_i) \quad i = 1,2,....C \tag{3}$$

$$S_B = \sum_{i=1}^{c}(M^i - M)^T (M^i - M) \tag{4}$$

Let M be the mean of all classes

$$M = \frac{1}{C}\sum_{i=1}^{i=C} M^i \tag{5}$$

Based on FLDA, projection vectors are calculated. Test images and training images are projected. Optimal projection vector for training and testing image is calculated as

$$Z_j^i = A_j^i (x_1 : x_2 : .....x_d) \tag{6}$$

and

$$= [b_1^{ij} : b_2^{ij} : ......b_d^{ij}] \quad i = 1,2,......C \quad j = 1,2,......N \text{ and} \tag{7}$$

$$Z_{test} = A_{test}(x_1 : x_2 : ....x_d) \tag{8}$$

$$= \left(b_1^{test} : b_2^{test} : ....b_d^{test}\right) \tag{9}$$

Classification of testing image is based on Euclidean distance between two vectors. The matrix used to classify the image is

$$C^* = \arg\min_i \left\{D\left(z_{test}, z_j^i\right)\right\} \quad i = 1,2,......C \tag{10}$$

$$j = 1,2,......N = \operatorname{argmin}_i \left\{\sum_{n=1}^{n=d} \left\|b_n^{test} - b_n^{ij}\right\|_2\right\} \tag{11}$$

where $\|.\|_2$ represents Euclidean distance between two vectors.

Non-negative Matrix Factorization (NNMF): Non-negative matrix factorization is originally known as non-negative rank factorization or positive matrix factorization. NMF has been analyzed for more than 25 years [17]. Many algorithms are available to calculate NNMF. They are based on optimization-based methods [18] and geometry based methods [19].

NMF is approximately the given matrix S into product of two matrices W and H. S = WH. The size of S is IXJ and size of W is IXK and size of H is KXJ and the restriction on K is K<min(I,J). NNMF is generally not unique. NNMF is a non-supervised decomposition technique that can be used for feature learning. Z squared Euclidean distance or quadratic factor are normally used cost-function to quantity the approximation error.

$$D_E(S, WH) = \frac{1}{2}\sum_i\sum_j \left(X_{ij} - (WH)_{ij}\right)^2 \tag{12}$$

The matlab inbuilt function for NNMF is nnmf. The face image of a person in UMIST database [13] is shown in Fig. 1.

The image in Fig. 1 has rank 92 and the size of the image is 112X92. Two images are generated using matlab inbuilt function for K=20 and 30 where K represent the rank of generated images. This is show in Fig. 2 and Fig. 3.

Fig. 1:

Fig. 2:

Fig. 3:

The above three images are as used as training images for a single class and LDA technique is applied to all the training images.

Experiments: The databases used for testing the face images are OMIST [13], ORL[14], YALE [15] and PolyU-NIR[16]. System flow chart is shown in Fig. 4

Experiments with ORL Face Database: Total subjects in the ORL data base are 40. Each subject has 10 images. This includes different timings, illuminations and facial expressions. Gray levels in the images are 256. The size of the image is 112X92. Nine samples are used for testing and one sample is used for training. The comparison is done based on projection vectors and recognition

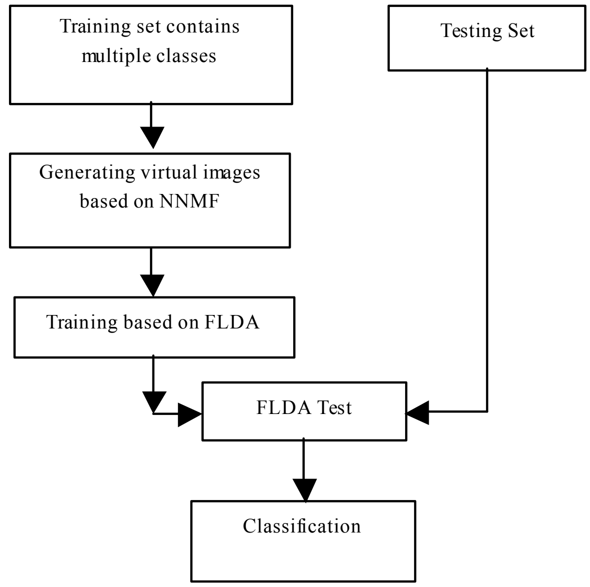

Fig. 4:

rate. The number of projection vector ranges from 1 to 15. Fig. 5 shows the recognition rates of the methods [10-12] and our proposed method.

Experiment with YALE Face Database: This database contains 15 subjects. Each subject has 11 images with illuminations, center-light, with glasses, without glass, happy, sad and wink. All the images are preprocessed. Preprocessing means all the images are cropped based on eye coordinates and the size of cropped image is 120X110. One sample is used for training and the remaining 14 samples are used for testing. The number of projection vector is maximum of 15 to minimum of 1. Fig. 6 shows the recognition rates of methods [10-12] and our proposed method.

Experiments with Poly U-NIR Face Data Base: This database contains 350 subjects. The original size of each subject is 576X768. We selected images from each subject images are normalized such that distances between the eyes are same. The size of the cropped image is 120X90. The recognition rates are 48% in SDD method and 47.2% in QRCP method and 44.1% in SVD-based method. The performance of the four methods based on projection vectors are shown in Fig.7. The range of projection vectors is one to twenty.

Experiments with UMIST Database: Total images in this database are 564. Number of subjects in the database is 20. Cropped image size is 112X92 with 256 bit gray-scale.

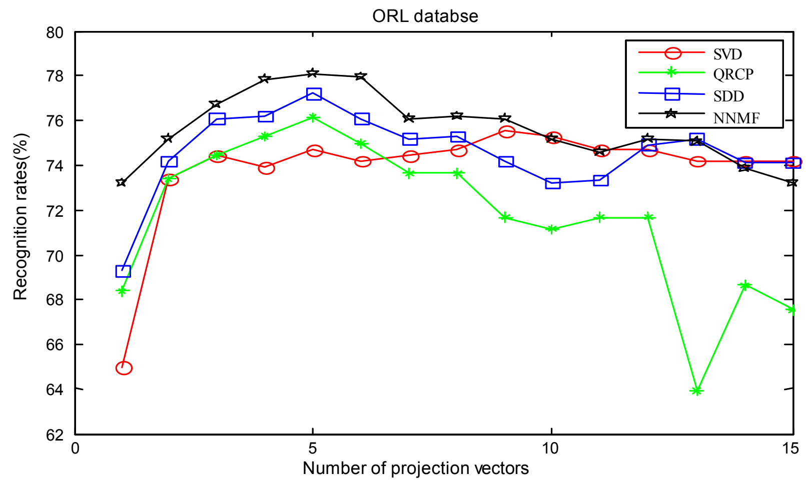

Fig. 5:

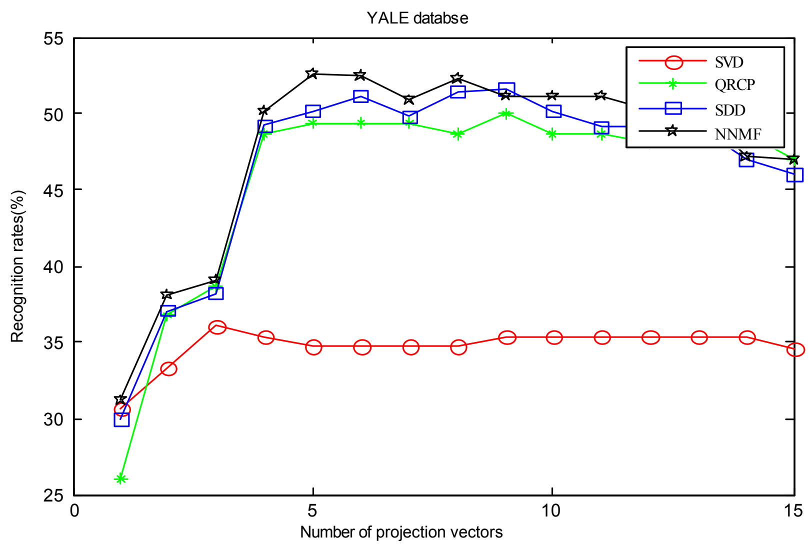

Fig. 6:

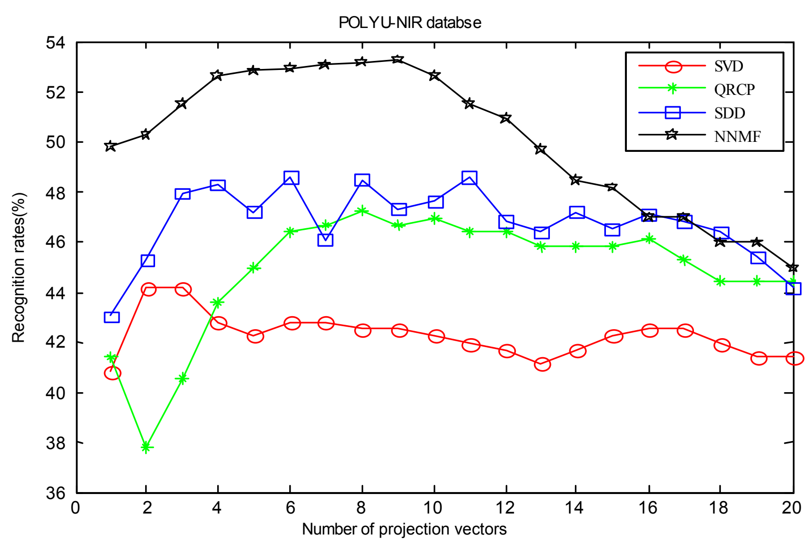

Fig. 7:

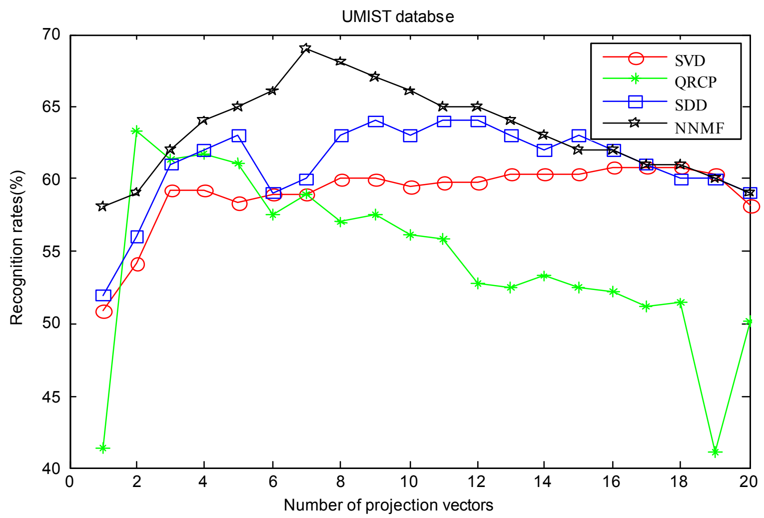

Fig. 8:

Table I: Training time (ms) of SVD, QRCP, SDD and NNMF methods

METHOD	UMIST	ORL	YALE	Poly-NIR
SVD	363	627	312	936
QRCP	200	339	163	546
SDD	360	610	301	800
NNMF	225	352	183	602

The recognition rates of the proposed method are compared to the methods [10-12]. The proposed method provides better recognition rate for the projection vectors 6-16. But training time is less than methods [11]. Fig. 8 shows the recognition rates of methods [10-12] and our proposed method.

RESULT

All the methods are implemented in MALAB. Training times of each method (SVD, QRCP, SDD, NNMF) are calculated and compared and is shown in Table I.

DISCUSSION AND CONCLUSION

One sample per class is always a problem in FLDA. Within class scatter matrix may become singular. Two or more virtual images are generated to avoid this problem. Two images are generated in addition to original image by NNMF. FLDA is applied is applied to find the recognition rates our proposed method using NNMF performs better than methods [10,11,12] in terms of recognition rates. But training time is slightly more than QRCP method [11] and less than SVD and SDD methods [10, 12]. One sample per class is a challenging problem in face recognition area. Although the proposed method provides recognition rates, training time is a problem. Our future work is based on reducing the training time with various algorithms [13-16].

CONCLUSION

Normally singular matrix does not have inverse. Two or more virtual samples are generated from the training set to avoid this problem. A new method called non-negative matrix factorization is used in single image per person problems. The proposed method performs better than SVD, QRCP and SDD method in terms of recognition rate. But training time is slightly more than QRCP and better than SVD and SDD approach.

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