Hybrid Framework for Robust Multimodal Face Recognition

M. M. Mohie El-Din[1], M.Y. El Nahas[2] and H. A. El Shenbary [1]

[1]Department of Mathematics, Faculty of Science, Al-Azhar University,Cairo. Egypt

[2] Department of Systems Engineering & Computers, Faculty of Engineering, Al-Azhar University,Cairo. Egypt

Abstract

Both two dimensional principal component analysis and fisher linear discriminant analysis are successful face recognition algorithms. Recognition rate, time complexity can be improved by combining the two algorithms with the very powerful tool discrete wavelet transform. Experiments on the ORL face database show that the proposed method outperforms PCA, LDA, DWT+LDA algorithms in terms of recognition rate and classification speed. The proposed method is very powerful and useful in solving face recognition problems.

Keywords:*2D-DWT, PCA, 2D-PCA, LDA, face recognition.*

1. Introduction

There is no doubt that face recognition has been an active research area in the last decades. There are several applications to face recognition in our life such as Credit cards, Criminal Investigations, Drivers' Licences, Security Applications, User Authentication etc. Many approaches have been used during the last two decades. In 1991, Turk M and Pentland A [1] introduced Eigenfaces method for face recognition. For recognition a new image is projected in the new subspace spanned by the eigenfaces. PCA has become one of the most successful methods for dimensionality reduction in face recognition. Many methods based on PCA were introduced. Yang J et al.[2] presented the two dimensional principle component analysis method which treat the image as 2 dimensional matrix rather than 1 dimensional vector. Luo Lin et al [3] made a modified PCA algorithm. But weakness of these methods is that they don't make full use of class information. Linear discriminant analysis is presented to solve these problems. LDA tried to find a set of projection vectors by Using within class scatter matrix and between classes scatter matrix and maximizing ratio between the determinants of these matrices of the training sample [4]. In the recent years Wavelet transform has been a very powerful tool in image analysis. Song L and Min L [5] use Discrete Wavelet Transform and 2DPCA for face recognition which give 92% recognition rate. Marasamy P and Sumathi S. [6] use DWT and LDA for increasing recognition rate. B N et al [7] integrate the Independent Component Analysis and DWT to enhance recognition rate. Wavelet transform was used to reduce dimensionality and computation time as presented in [8][9][10]. Xianwei. L et al [12] use DWT, PCA and SVM to enhance recognition rate. Yang. J et al [13] use 2DPCA for facial recognition. The extraction of image features is computationally more efficient using 2DPCA rather than PCA.

In this paper we present a framework for multimodal face recognition based on a hybrid of 2D-DWT, 2DPCA, and Fisher LDA.

The rest of this paper is organised as follows: section 2 describes the existing algorithms. Section 3 presents the proposed method in details. The proposed method is compared with existing techniques by performing tests on a well-known ORL database. Tests results of proposed method are compared with other methods in section 4. Section 5 contains conclusion and future work.

2. Face Recognition Algorithms

This section describes briefly DWT, 2DPCA, PCA and LDA literature.

2.1 Discrete Wavelet Transform

Discrete Wavelet Transform (DWT) has been used in a wide range in image analysis and it is considered as a powerful tool in face recognition, which can captures space-frequency information. The face image is analysed using two dimensional discrete wavelet transform (2D-DWT).The decomposition process of the 2D-DWT is illustrated in Figure 1.

In each level the input signal is filtered along rows and the resulted signal is filtered along column.

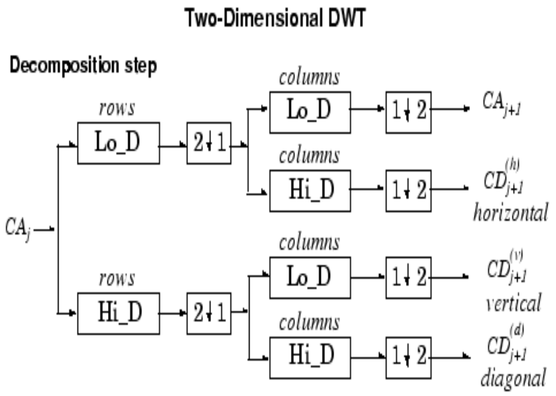

Figure 1

2.2 Principal Component Analysis

PCA is a statistical model used for face representation prior to its recognition. PCA reduces dimensionality of the data space to the smaller intrinsic dimensionality of the feature space, which are needed to describe the data economically. This reduction is realized by the linear transformation

Y=AX

Assume we have a set of N images X_1, X_2 ......X_N each image is a 2-dimentional matrix of size m by n. We convert each image to 1-dimentional column vector of size mn.

$$X_i = \begin{pmatrix} x_1 \\ x_2 \\ \cdot \\ \cdot \\ \cdot \\ x_{mn} \end{pmatrix} . \qquad (1)$$

The images set is

$$\boldsymbol{X} = [X_1 , X_2 , X_3 X_N] . \qquad (2)$$

Computethe mean image X_m

$$X_m = \frac{1}{N}\sum_{i=1}^{N} X_i \quad . \qquad (3)$$

The covariance matrix is given by the formula

$$C = \frac{1}{N}\sum_{i=1}^{N} (X_i - X_m)(X_i - X_m)^T . (4)$$

Then the eigenvalues and eigenvectors of the covariance matrix C are computed and most relevant features components are selected from them. PCA transformation matrix A can be constructed from the eigenvectors corresponding to the k largest eigenvalues of the covariance matrix C.

2.3 Two Dimensional PCA

Let X_i be an m*n image, A_k be an n dimensional unitary column, Projecting X on to A_k as shown

$$Y_k = X_i A_k , k = 1,2,3 \ldots d . (5)$$

We can get m dimensional vector Y_k which is called the feature vector of the imageX_i.

Projecting X_i onto a matrix A= (A_1, A_2 …….A_d),

We get a family of projectedfeature vectorsY= (Y_1,Y_2 …… Y_d)

The projection matrix A can be got from the training images as follows.

Assume that there are M training samples each of size m*n, the i^{th} training image X_i (i= 1, 2, 3 …. M).

The average image of all sample is $\bar{X}$.

The projection matrix A_{opt} is obtained by computing the eigenvectors A_1, A_2 …….A_d of the corresponding largest d eigenvalues of the matrix G.

$$G = \frac{1}{M}\sum_{j=1}^{M} (X_j - \bar{X})^T (X_j - \bar{X}) . \qquad (6)$$

Assume we have,

$$Y_K = X A_k , \qquad k = 1,2,3 \ldots d . \ (7)$$

Then we get m*d matrix Y= (Y_1, Y_2 …… Y_d), which is called the feature matrix or feature image of the image sampleX_i.

2.4 Linear Discriminant Analysis

Fisher's Linear Discriminant Analysis is a good example for class specific method, since the training set is labelled, it make sense to use this information to build a more reliable method to reduce the dimension of the feature space.

FLDA maximizes the ratio of the between class scatter matrix and the within class scatter matrix, Looks for a linear subspace W(c-1 component) in which the projection of the different classes are best separated.

Let $\{Y_k| \ k=1, 2 \ldots . N\}$ be a set of N samples in d dimensional space. Let l_i be class label of Y_i,

li ϵ {1,2 … c}, c is classes number, denote class i sample by N_i. Then the between class scatter matrix is

$$S_B = \sum_{i=1}^{c} N_i(\mu_i - \mu)(\mu_i - \mu)^T. \quad (8)$$

, Within class scatter matrix is defined as

$$S_W = \sum_{i=1}^{c} \sum_{k=1}^{N_i} (Y_k - \mu_i)(Y_k - \mu_i)^T. \quad (9)$$

, Total class scatter matrix is

$$S_T = \sum_{i=1}^{N} (Y_k - \mu)(Y_k - \mu)^T \quad . \quad (10)$$

, where the mean of the i-th class is

$$\mu_i = \frac{1}{N_i}\sum_{j=1}^{N_i} Y_j \quad . \quad (11)$$

, μ is the global mean of all samples.

$$\mu = \frac{1}{N}\sum_{k=1}^{N} Y_k \quad . \quad (12)$$

FLDA look for W_{opt} the optimal projection matrix which maximizing the discriminant criteria

$$W_{opt} = \frac{|W^T S_B W|}{|W^T S_W W|}.$$

If S_w is nonsingular, then W_{opt} is the matrix with the orthonormal columns which maximizes ratio of the determinant of the between class scatter matrix of the projected sample to the determinantof the within class scatter matrix of the projected sample,

$$W_{opt} = \arg\max_W \frac{|W^T S_B W|}{|W^T S_W W|}. (13)$$

$$W_{opt} = (W_1, W_2, W_3, \ldots, W_m). \quad (14)$$

, such that W_i, i=1, 2 ….m is the set of the generalized eigenvectors of the between class and within class scatter matrices corresponding to the m largest eigenvalues λ_i, i=(1, 2…. m).

$$S_B W_i = \lambda_i S_W W_i \, , i = (1,2,3 \ldots \ m). \quad (15)$$

The upper pound of m is c-1 where c is the number of classes in the training sample.

If S_w is singular, then we must use any approach like PCA to reduce dimensionality of the training sample to solve this problem.

Solving the eigenvalue problem of the total scatter matrix S_t, PCA reduce dimensionality and then use LDA to reduce dimensionality to c-1.

Assume the W_{pca},

$$W_{Pca} = \arg\max_W |W^T S_T W|. \quad (16)$$

Be the PCA transform matrix, W_{fld}

$$W_{fld} = \arg\max_W \frac{|W^T W_{Pca}^T S_B W_{Pca} W|}{|W^T W_{Pca}^T S_W W_{Pca} W|}. \quad (17)$$

Be the LDA transform matrix, then we have the optimal projection matrix $W_{opt.}$

$$W_{opt} = W_{Pca} \ W_{fld}. \ (18)$$

3. Proposed method

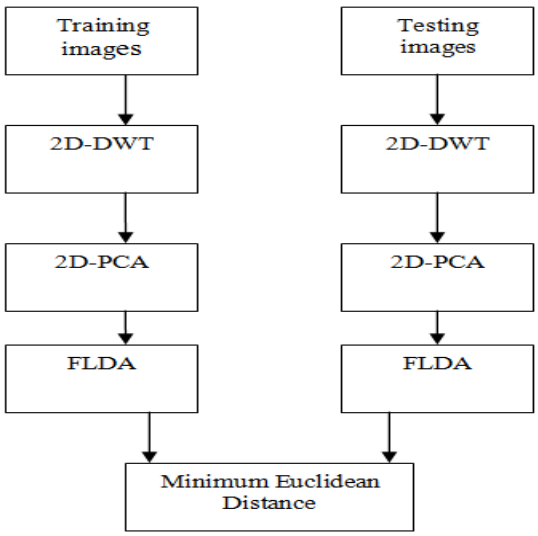

Figure 2:Block diagram of proposed method

In the proposed method we apply 2D-DWT on the given image; the face image is decomposed into 4 subband images: approximation. Horizontal, vertical, diagonal coefficients corresponding to LL, LH, HL, HH subbands.Then the approximation coefficient (LL subband) image will be decomposed into second level of the 2D-DWT. In our method we use 3 level of 2D-DWT. An example of decomposed image in 1 level 2D-DWT is shown in Figure 3.

.

Figure 3: The decomposed image in 1 level DWT

Choosing the LL subband in the 2nd level because it contains most of energy/variance of the original image, reduce dimensionality and also the LL subband is choosing in the 3rd level decomposition, example of 3 levels 2D-DWT in Figure 4.

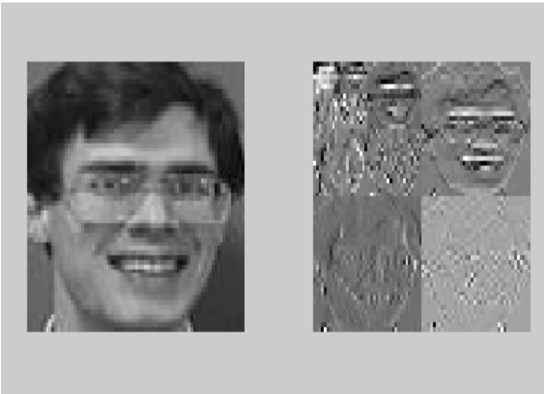

Figure 4: the Decomposed image in 3 levels DWT

Now after 3 level of 2D-DWT, we use the 2D-PCA.

The extracted features are used to classify the face image. Classification is made using fisher linear discriminant method. Finally Minimum Euclidean Distance is used to decide the class of a test face image. Block diagram of the proposed method is shown in Figure 2.

4. Experimental results

4.1. Database Description

To view the performance of the proposed method,

Experiments are performed on the well known ORL database, ORL database contain 40 different person (class), each class has 10 images in different illumination, pose, expression, facial details, such as smiling, angry, eyes open, eyes close, wearing glasses and not wearing, total of 400 images, example of some image in the ORL database inFigure 5.We select some faces image for learning and the rest for testing.

The experiments were carried out in MATLAB 7.12.0.635, on Intel(R) Core(TM) i3 CPU Processor, having 3 GB RAM. The MATLAB was installed on Windows 7.

Figure 5: sample of ORL database

4.2. Results

Experiments are performed on ORL database to compare our results with other face recognition algorithms PCA, LDA, DWT+LDA.

We select i images per class as the training data,(i=6…9) and leave the remain images for test stage. Recognition rate is shown in Table 1, and training time complexity is shown inTable 2.

InFigure 6we compare recognition rateof theproposed method and relative result in [11].

Figure 7show that the proposed method has some improvement in training time complexity.

Table 1:Recognition rates for DWT+LDA and proposed methods

# of training images	PCA [11]	LDA [11]	DWT + LDA[11]	Proposed method
6	84	85	83	93.13
7	87	89	93	95.83
8	89	91	94	96.25
9	96	97	95	97.5

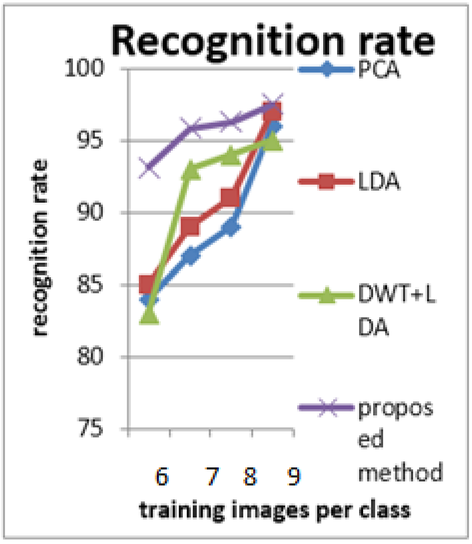

Figure 6:Comparison of recognition rates

Table 2 : Training Time complexity for DWT+LDA and proposed methods (seconds)

i	DWT+LDA	Proposed method
6	3.0352	2.8618
7	3.3183	3.1815
8	3.6012	3.4757
9	4.3766	3.6978

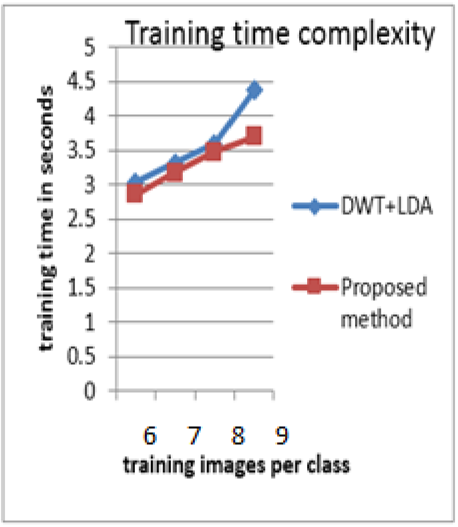

Figure 7: Comparison of training times in seconds

5. Conclusion and future work

This paper presents a new method based on

2D-DWT + 2D-PCA + FLDA for modal face recognition. The proposed system achieves a recognition rate between 93.3%, 97.5 % for increasing number of training samples. These results show also that this method outperforms the performance of known methods based on PCA, LDA, DWT+LDA, not only in recognition rate, but also in training time as shown in Figure 6, Figure 7.

Since the size of the image covariance matrix in 2DPCA is much smaller than size of covariance matrix in PCA,the extraction of image features is computationally more efficient using 2DPCA.

In the future we will test the proposed method using different databases and modify the approach to enhance recognition rate in case of small training sample size.

References

[1] M. Turk, A. Pentland, "Eigenfaces for Recognition", Journal of Cognitive Neuroscience, 3(1), pp. 71-86, 1991.

[2] J. Yang, D. Zhang, A. F. Frangi, and J. Yang, Two-dimensional PCA: A new approach to appearance-based face representation and recognition, IEEE Trans. Pattern Anal. Mach. Intell., 26(1), 2004, pp.

[3] Lin Luo, Swamy, M.N.S., Plotkin, E.l. A modifcd PCA algorithm for face recognition. Canadian Conference on Electrical and Computer Enginccring, 2003, voLl, pp. 57-60.

[4] Yu H, Yang H .A direct LDA algorithm for high dimensional data with application to face recognition. Pattern Recogn 2001,34(10):2067–2070.

[5] L. Song and L. Min, “Face Recognition Based on 2DPCA and DWT,” *IEEE*, no. 4, pp. 1459-1462, 2011.

[6] P. Marasamy and S. Sumathi, “Automatic Recognition and Analysis of Human Faces and Facial Expression by LDA Using Wavelet Transform,” *IEEE*, pp. 10-13, 2012.

[7] N. B. N. T, A. F. A, and V. Vaidehi3, “An Efficient Face Recognition System Using DWT-ICA features,” 2011.

[8] J. Yang, L. S. Oliveira, A. L. Koerich, and M. Mansano, “2D Principal Component Analysis for Face and Facial-Expression Recognition,” pp. 9-13, 2011.

[9] Y.-ting Chou, S.-ming Huang, S.-hua Wu, and J.-ferr Yang, “DWT and Sub-pattern PCA for Face Recognition Based on Fuzzy Data Fusion,” *IEEE*, pp. 296-299, 2011.

[10] A. Bansal, K. Mehta, and S. Arora, “Face Recognition Using PCA and LDA Algorithm,” *2012 Second International Conference on Advanced Computing & Communication Technologies*, pp. 251-254, Jan. 2012.

[11] P. Marasamy and S. Sumathi, “Automatic Recognition and Analysis of Human Faces and Facial Expression by LDA Using Wavelet Transform,” *IEEE*, pp. 10-13, 2012.

[12] L. Xianwei, “Face Recognition Based on PCA and SVM,” IEE no. 205074, pp. 1-4, 2012.

[13] J. Yang, L. S. Oliveira, A. L. Koerich, and M. Mansano, “2D Principal Component Analysis for Face and Facial-Expression Recognition ,” *Computing in Science & Engineering* pp. 9-13, 2011.