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Proposing an Enhanced Face Recognition Technique Using Multi-Wavelet Transform

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ABSTRACT

Face recognition has been an active research for more than three decades. In general face recognition consists of feature extraction and classification. Principal Component Analysis (PCA) is one of the methods for features extraction under the appearance-based approach. However PCA came with large database, having some problems like load computation, and poor recognition accuracy. This research is an attempt to focus on large size of database problems with PCA technique. In order to make PCA work well, we suggest using Multi-Wavelet transform, which has two features. The first one is that it can decompose the image into frequency sub-band and the second feature is to reduce the resolution of the image. Moreover, in this research, the face recognition system can be classified into two phases. The first phase is training, which is of four steps. The first one is applying Multi-Wavelet transform to reduce the size of image. The second is PCA for feature extraction from images after reducing the size. The next is projection images, and finally is the library of projection images. The second phase is recognition, which is composed of three steps. The first step is similar to the training phase applied in the Multi-Wavelet transform. The second one is PCA for extraction the average from testing images, while the third is using the classification method via the Nearest Mean Classifier. Observations from the experiment results, based on Yale databases, show that the proposed method has better accuracy rate than the original PCA.

Keywords: Face Recognition, PCA, Multi-Wavelet Transform, Nearest Mean Classifier

INTRODUCTION

The research area of face recognition has been active over the last 30 years. Many studies have been conducted by scientists from different areas of psychophysical sciences and from different areas of computer sciences. Psychologists and neuroscientists basically agreed with the human perception part of the topic. In addition, engineers, who are studying machine for human face recognition, deal with the computational aspects of human face recognition. Face recognition has applications in many fields such as biometric, access control, law enforcement, security and surveillance systems, and image and film processing [1][2][3]. In addition to various applications, there are also different modes of face detection or recognition. One of them is verification, in which, through disclosing the person’s identity by presenting a verified identity card or any other means to the machine, this person under identification scrutiny such as an authorized staff, gets the verification from the system. The system verifies the presented identity by comparing and matching face features acquired from the present one with the one retrieved from the stored database under the same name. This method is known as 1-to-1 matching. The face image which has been newly acquired from the person is known as “a prop face” or “query face”. The faces that are stored in the database are called “gallery faces” or “enrolled faces”.

Another fundamental mode for face recognition is identification. In this mode, the person does not disclose any identity document or certificate to retrieve his/her own identity from the database.

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However, the newly acquired face image has to be compared with all the face images stored in the database to come to a determination whether it matches any of them or not. This method is called 1-to-N matching mode [4]. Algorithms for face recognition endeavour to solve the problems of both verification and identification. The main problems are mainly classification problems when given the still images or video of scene [1] [5] [6].

Pose, illumination, and large size database are problems associated with face recognition, which have led many researches to develop the system of face recognition. For example, the author in [7] have presented an explanation on the illumination problem, which makes the same face look different in the lighting condition. More specifically, the authors have experimentally observed with a database of 25 individual. They found out that changes induced by illumination could be larger than the differences between individuals, which cause systems, based on comparing images, to misclassify the identity of input image. To solve the problem with illumination face recognition, there are four methods. First, the heuristic method based on principal component. The second method is image comparison approach which has been evaluated by statistical methods. Next method is class-based method where multiple images of one face are under a fixed pose but in different lighting condition available. The forth method is model based approach used with 3D models which are employed by authors in [8] [9].

Another problem is that of the pose problem which is based on the face position that seems different due to changes in the view condition. Consequently, the task of face recognition in this case is difficult. Zhao [8] presented in his work a reflectance model with various albedo performed to analyze and classify various pose problems. However, with using any model, the difficulty of pose problem can be assessed and the efficacy of existing methods can be evaluated systematically. For this reason, pose problem can be divided into three categories. The first one is the small rotation angle which is a simple case with pose face problem. The second category occurs when there are a set of training image pairs (frontal and rotated images) that are the most commonly addressed case. Finally, if the training images pairs are not available and illumination variations are present, in this case, this can be classified as the most difficult case.

In addition, there are three approaches to solve the pose problem with face recognition. First, multiple images which means that multiple images per person are available. The second approach is hybrid method, which means that multiple training images are available during training. However, only one database image per person is available during recognition. Thirdly, signal image or shape methods are when no training is carried out. This approach does not seem to have received much attention [9].

On the other hand, the large size of database is joined with face recognition problems. Facial feature extraction for face recognition which is divided into feature based approach and holistic approach. To explain, feature based methods are methods that seek to robust facial variations such as rotation, scaling, and illumination. However, their accomplishments depend largely on the detection of individual facial features and characterization of geometrical relationships. Nevertheless, the next approach is holistic methods which include Principal Component Analysis (PCA), Linear Discriminate Analysis (LDA), and Independent Component Analysis (ICA), that are adopted on appearance information extracted from entire image. Feature extraction via holistic approach tries to find features with reduced dimensionality by projecting an original data onto the basis vector. With the applications of large database, we have a large set of features with different sizes, that makes it difficult to identify the required feature points [10]. To illustrate, PCA is a wide technique used with pattern recognition for feature extraction and has recently been applied on face recognition. Therefore, PCA has been proved to be the most promising approach for human face recognition. Face with PCA can be presented via weighted combination of eigenvectors which are extracted from a covariance matrix derived from a set of training faces. However, PCA with large database applications has two limitations. The first one is that the discriminative power of this method decreases when the size of the training images increases. Second, the computational load to find the eigenvector [11]. Many researchers have worked to solve the limitations with PCA, accomplishing PCA on the most transform such as WT, GWT, and DCT, to make PCA work well. The aim of the transform is decompose images into sub-band images, so that the images can be less than the size of the original image. The transform will also reduce the resolution of the image.

MATERIALS AND METHODS

Proposed Method

There are two disadvantages that PCA suffer from which are the load computation and the poor accuracy recognition [12]. To overcome these disadvantages that limit the applicability of PCA, Multi-Wavelet transform is suggested to be used with PCA to develop an original PCA. The Multi-Wavelet has two features, namely the frequency sub-band and lower resolution. Application of these features to Multi-Wavelet can fortunately solve the problems that PCA has. Nonetheless, the first disadvantages of PCA can be removed by the second feature of Multi-Wavelet and the second limitation in PCA can be removed with the first feature in Multi-Wavelet. Moreover, any system concerning face recognition requires two stages, training stage, and recognition stage. The flow chart of the proposed method is shown in Figure1.

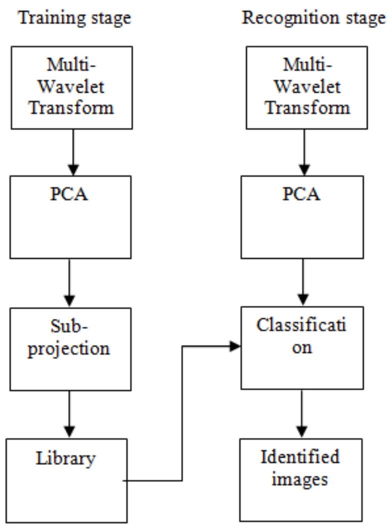


Figure1. *The Flowchart of Proposed method*

Training Stage: There are four steps in the training stage: the Multi-Wavelet transform, PCA, sub-projection, and Library step which comes after projection of the images.

Multi-Wavelet Transform

Wavelet Transform is one type of transform that may be used in image compression. A newer alternative is Multi-Wavelet transform. Multi-Wavelets are similar to wavelets but have some important differences. Wavelets may be described in the context of a multi resolution analysis with scaling function $\Phi(t)$ and wavelet function $\Psi(t)$. In fact, it is possible to have more than one scaling function and (wavelet) function this is the idea behind Multi-Wavelet, which are described in this section as a natural extension of the wavelets. Moreover, the set of scaling functions can be represented via the vector notation $\Phi(t)=[\phi_1(t),\phi_2(t),....\phi_m(t)]^T$ in this case, $\Phi(t)$ is called the multi-scaling function. Likewise, the Multi-Wavelet function is defined from the set of wavelet function as $\Psi(t)=[\psi_1(t),\psi_2(t),....\psi_m(t)]^T$. When r=1, $\Psi(t)$ is called scalar wavelet, or simply wavelet. In addition, r can be arbitrarily large, the Multi-Wavelet studied to date are primarily for r=2 [13][14]. The wavelet and scaling functions for Multi-Wavelet can be represented in equations (1) and (2).

$$\Phi(t)=\sqrt{2}\sum_{k=-\infty}^{\infty} H_k\Phi(2t-k) \tag{1}$$

$$\Psi(t)=\sqrt{2}\sum_{k=-\infty}^{\infty} G_k\Phi(2t-k) \tag{2}$$

Where H_k and G_k are low-pass and high-pass filter.

The GHM Multi-Wavelet transform is one type of Multi-Wavelet family [15] utilized in this research [16]. Figure 2 illustrated The GHM Multi-Wavelet.

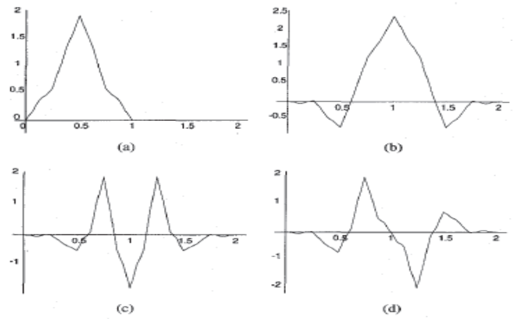


Figure2. *GHM Multi-Wavelet a and b two Scaling Functions and c, d two Wavelet Functions For GHM*

There are four scaling function H_0, H_1, H_2, H_3.Which Can be written in the following equation.

$$H_0 = \begin{bmatrix} 3/5\sqrt{2} & 4/5 \\ -1/20 & -3/10\sqrt{2} \end{bmatrix}, H_1 = \begin{bmatrix} 3/5\sqrt{2} & 0 \\ 9/20 & 1/\sqrt{2} \end{bmatrix},$$
$$H_2 = \begin{bmatrix} 0 & 0 \\ 9/20 & -3/10\sqrt{2} \end{bmatrix}, H_3 = \begin{bmatrix} 0 & 0 \\ -1/20 & 0 \end{bmatrix} \tag{3}$$

In the same way, the wavelet functions have four wavelet matrices G_0, G_1, G_2, G_3 which are illustrated in equation (4).

$$G_0 = \begin{bmatrix} -1/20 & -3/10\sqrt{2} \\ 1/10\sqrt{2} & 3/10 \end{bmatrix}, G_1 = \begin{bmatrix} 9/20 & -1/\sqrt{2} \\ -9/10\sqrt{2} & 0 \end{bmatrix},$$
$$G_2 = \begin{bmatrix} 9/20 & -1/\sqrt{2} \\ -9/10\sqrt{2} & 0 \end{bmatrix}, G_3 = \begin{bmatrix} -1/20 & 0 \\ -1/10\sqrt{2} & 0 \end{bmatrix} \tag{4}$$

According to the equation (1) and (2), the GHM have two scaling and wavelet functions satisfy the following two-scale dilation equations:

$$\begin{bmatrix} \phi_1(t) \\ \phi_2(t) \end{bmatrix} = \sqrt{2}\sum_n H_n \begin{bmatrix} \phi_1(2t-k) \\ \phi_2(2t-k) \end{bmatrix} \tag{5}$$

$$\begin{bmatrix} \psi_1(t) \\ \psi_2(t) \end{bmatrix} = \sqrt{2}\sum_n G_n \begin{bmatrix} \psi_1(2t-k) \\ \psi_2(2t-k) \end{bmatrix} \tag{6}$$

The Multi-Wavelet has 16 sub-bands, while the wavelet transform has four sub-bands. Figure 3 shows the sub-bands for each one. [17][18].

LL	LH
HL	HH

(a) Wavelet transforms

L1L1	L1L2	L1H1	L1H2
L2L1	L2L2	L2H1	L2H2
H1L1	H1L2	H1H1	H1H2
H2L1	H2L2	H2H1	H2H2

(b) Multi wavelet transforms

Figure3. (a) *The Scalar Wavelet Transform and* **(b)** *The Scalar Multi-Wavelet transform*

The next step is required to compute single–level 2D DMWT via non-separable method. The procedure is as following [19]:

- Input dimensions checking.
- Transformation matrix constructing where the transformation matrix can be rendered as equation (7) by using GHM low and high pass filters matrices as provided in (3) and (4). When GHM matrix filter coefficients value is substituted, the outcome will be a $2N \times 2N$ transformation matrix.

$$w = \begin{bmatrix} H_0 & \mathrm{H}_1 & \mathrm{H}_2 & \mathrm{H}_3 \\ H_2 & \mathrm{H}_3 & \mathrm{H}_0 & \mathrm{H}_1 \\ G_0 & \mathrm{G}_1 & \mathrm{G}_2 & \mathrm{G}_3 \\ G_2 & \mathrm{G}_3 & \mathrm{G}_0 & \mathrm{G}_1 \end{bmatrix} \quad (7)$$

- Row pre-processing.
- Pre-processing columns.
- Transformation matrix.
- To achieve the final matrix coefficients permutation can be applied to the resulting matrix.

Principal Component Analysis

PCA is standard technique on human face recognition and widely used in feature extraction. The basic idea of PCA is disintegrate a data space into linear combination of a small collection of bases, which are pair wise orthogonal and which capture the directions of maximum variance in the training set. The PCA always aspire to solve the eigenvector problem in covariance matrix. These eigenvectors are ordered with high eigenvalues called the eigenface. Egen faces with PCA lead to the reduce the dimension [20]. Figure 4 shows an example on eigenfaces.

Figure4. *Example on Eigenface*

The steps for feature extraction depending on PCA are stated below [21]:

- Creation S with M a set of face images called training images.
- $S = \Gamma_1, \Gamma_2, \Gamma_3, \ldots, \Gamma_M$ (8)
- Obtain the average images Ψ .

$$\Psi = 1/M \sum_{n=1}^{M} \Gamma_n \quad (9)$$

- Subtract each input image from average images Φ .

$$\Phi_i = \Gamma_i - \Psi \quad (10)$$

- This step look for orthogonal vectors, u_n , which best describes the distribution of the data. The

k_{th}, u_k , is chosen such that

$$\lambda_k = 1/M \sum_{n=1}^{M} (u_k^T \Phi_n)^2 \qquad (11)$$

Is maximum, subject to, $u_1^T u_k = \delta_{\lambda_k} \begin{cases} 1 & \text{if } 1{=}k \\ 0 & \text{otherwise} \end{cases}$, where u_k ,λ_k represented the eigenvalues and eigenvectors of covariance matrix C.

- Calculate the covariance matrix C has been obtained in the following equation

$$C = 1/M \sum_{n=1}^{M} \Phi_n \Phi_n^T = \mathrm{AA}^{\mathrm{T}} \qquad (12)$$

Where $\mathrm{A}= \Phi_1, \Phi_2, \Phi_3, ..., \Phi_n$

- Computation the eigenvectors of covariance matrix C is very complex task , since M far less than $N^2 \times N^2$, so reduce the size into $N \times N$ to be able to construct the matrix $L = AA^T$
- Detect the M eigenvector, v_1 of L.
- These Vector that did extraction from M eigenvector is determine the linear combinations of M training set face images this connected with eigenface.

$$u_1 = \sum_{k=1}^{M} v_{lk} \Phi_k \; l = 1, 2 \ldots \mathrm{M}$$

Sub-Projection

In this section of the research each of the original images is altered into eigenspace. This provides an array of weights that represents the contribution of each eigenface to the reconstruction of the provided image. The projection coefficients are considered as the properties that help discriminate from various individuals.

$$\omega_k = u_k^T (\Gamma - \Psi) \qquad \Omega^{\mathrm{T}} = \left[\omega_1, \omega_2, \omega_3, ..., \omega_{\mathrm{M}} \right] \qquad (13)$$

Library

Finally, when all the steps in training stage are completed, the images are then stored in the library and then sub-projection between the image in library and the images located in the recognition stage is made.

Recognition Stage

This stage plays an essential role in face recognition system. Here the recognition rate can be measured. However, recognition stage itself is subdivided into three steps: 1) Multi-Wavelet transform, it is similar the first step with training image. But, here applied on the testing images 2) PCA, to extraction the average of testing images depending on the equation (9) and 3) classification (using Euclidean Distance) to measure the matching between the images in the testing phase with the images in training phase depending on equation (14).

$$d_i = \left\| x - \mu_i \right\| = \sqrt{\sum_{k=1}^{d} (x_k - \mu_{ik})^2} \qquad (14)$$

RESULTS

Yale Database

Face recognition utilizes a database called Yale database, which consists of 11 images, 15 subjects in different conditions such as with and without glasses, illumination variation, and alterations in facial expression. Yale Database is demonstrated in Table 1shown the some properties of Yale. In addition Figure 5 shows one person as example [22][14].

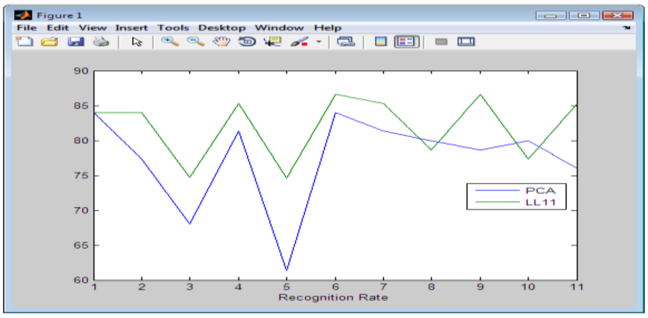
Table1. *Yale Database properties*

Number of subject	Condition	Image resolution	Number of images
15	With and without glasses Illumination Facial expression	100 by 100	165

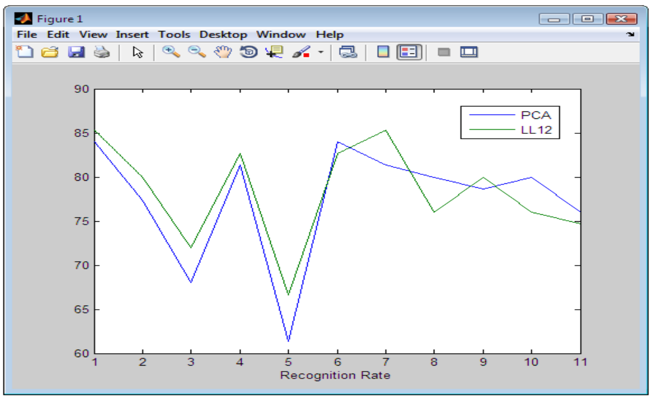
Figure5. *Yale Database for One Person with Illumination, Glasses, and Various Facial Expressions*

Experimental results

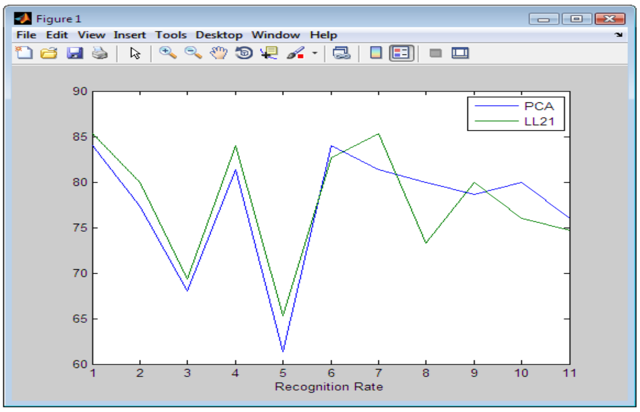
The result of proposed method was achieved on 5 images for testing and 6 images for training, depending on cross validation technique. Cross validation means it has five images into first processing for each person then, while the second processing has five images for testing for each person also, but different images not the same name of the images in the first processing and so on for 11 times. From this we have 11 cases for PCA applied on Multi-Wavelet sub-bands compared with 11 cases of PCA alone. The proposed method in many cases is better than original PCA see Figure 6. The time for proposed method is better than original PCA in all cases see as well as shown in Figure 7.



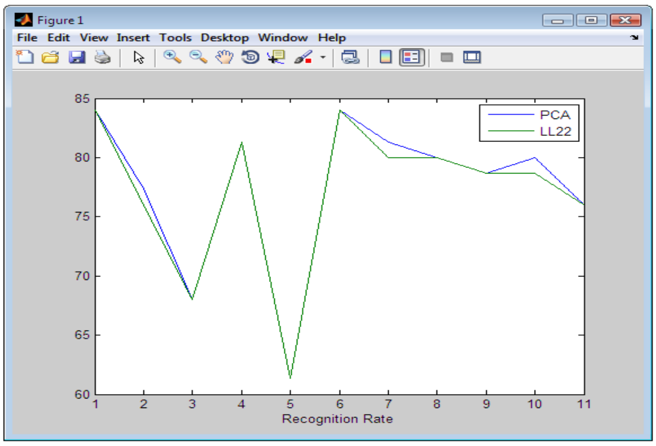
(a)



(b)

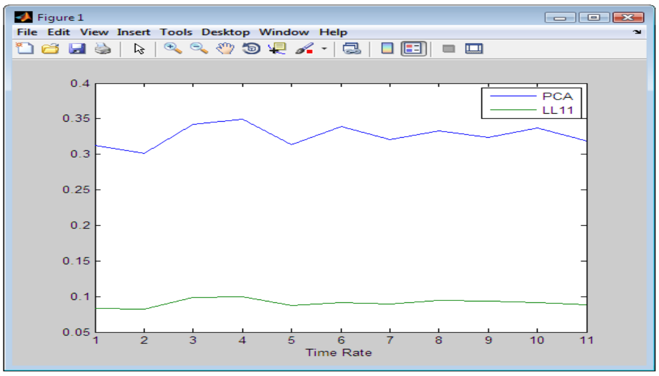


(c)

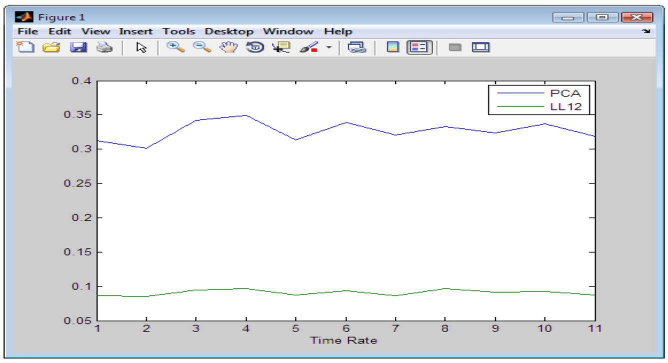


(d)

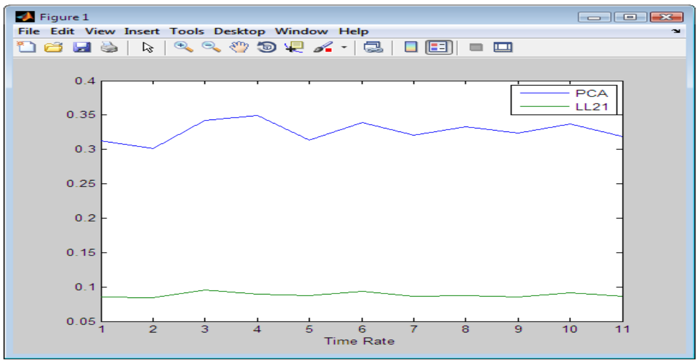
Figure6. *Recognition and times rates with five images for testing using Yale database, (a) PCA with LL11 Multi-Wavelet, (b) PCA with LL12 Multi-Wavelet, (c) PCA with LL21 Multi-Wavelet, (d) PCA with LL22 Multi-Wavelet*



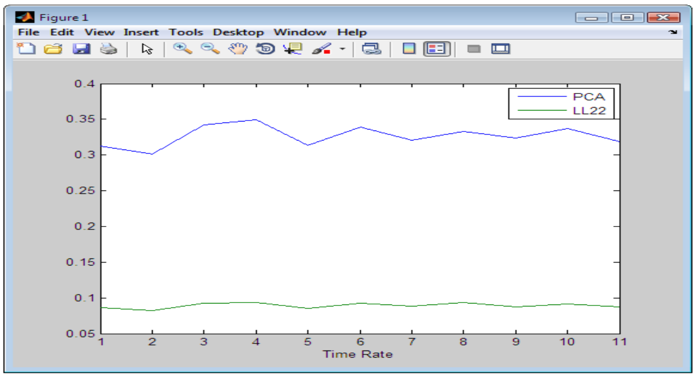
(e)



(f)



(g)



(h)

Figure7. *The time Domain database (e) PCA with LL11 Multi-Wavelet, (f) PCA with LL12 Multi-Wavelet, (g) PCA with LL21 Multi-Wavelet, (h) PCA with LL22 Multi-Wavelet.*

DISCUSSION

Feature extraction is an important issue in face recognition. PCA is one method which can represent the feature extraction in the same domain. PCA suffered with large size of database problem of two disadvantages. First, is load computation, and second, is poor accuracy matching. In order to overcome these disadvantages we suggested using Multi-Wavelet sub-bands. Multi-Wavelet Transform has 16 sub-bands LL11, LL12, LL21, LL22, LH11, LH12, LH21, LH22, HL11, HL12, HL21, HL22, HH11, HH12, HH21, and HH22. The researchers have relied on LL to reduce the size of images. PCA applied on four sub-bands (LL11, LL12, LL21, and LL22).

Figure 6 show the results between PCA applied on Multi-Wavelet sub-bands and original PCA. PCA on LL11 was achieved in Figure 6 (a), from this we see the PCA on LL11 is better than of other Multi-Wavelet sub-bands (LL12, LL21, and LL22) and PCA alone can be presented in Figure 6 (c-d). The main reason to make LL11 is well because it can be disposed of the illumination with training images. However, PCA applied on other Multi-Wavelet sub-bands such as (LL12, LL21, and LL22), has slightly less results than original PCA, the reason of this could be illumination in training images.

Figure 7 shows the time of the proposed method. The time in all cases with Multi-Wavelet sub-bands is better than original PCA. The time on Multi-Wavelet sub-bands is reducing to half using one level decomposition of Multi-Wavelet transform.

CONCLUSION

The aim of this research is to improve the PCA technique in terms of times and accuracy for feature extraction in face recognition domain depending on Multi-Wavelet Transform. In general face recognition in this research comprises of two steps. First, feature extraction using PCA, and the second is classification using Euclidean Distance. Unfortunately, PCA has two disadvantages. First, load computations, because PCA method depends on covariance matrix, this matrix deals with eigenvectors and eigenvalues. If the size of images in database is huge, the computation of eigenvectors and eigenvalues is very complex. The second disadvantage is weak in accuracy. To overcome these problems and make PCA work well the researchers adapted a Multi-Wavelet sub-bands. It has featured such as Multi-Wavelet transforms which can disintegrate the images into sub-images, and space and frequency domain which can provide local information with Multi-Wavelet transform. The proposed method provides advantages in terms of computational load and accuracy.

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