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Face Recognition Based On PCA Using Different Daubechies Wavelet Transforms

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Abstract— Security and authentication of a person is a crucial part of any industry, there are many techniques used for this purpose, one of them is *face recognition*. Face recognition is an effective means of authenticating a person. In this paper we present different wavelets on PCA (Principal Components Analysis) which are most popular appearance-based approaches in face recognition. PCA is recognized as an optimal method to perform face recognition, dimension reduction. Yet still, PCA has its limitations such as poor discriminatory power and large computational load. The proposed algorithm uses the concept of Daubechies to improve the performance of PCA by compression and PCA for the feature extraction and identification method. By comparing DB6 with DB8 and DB10, it concludes that DB6 having fast response on PCA performance. The Euclidean Distance Measures system is used to find the nearest matching features in the whole database.

Index Terms— Face Recognition, Principle Component Analysis (PCA), Daubechies Wavelet Transform.

1 Introduction

As one of the most successful applications of image analysis and understanding of face recognition has recently received significant attention especially during the past several years. At least two reasons are accounted for this trend. First it is widely used in real life applications and second is the availability of feasible technologies after many years of research [1]. The range of face recognition applications are very assorted such as face-based video indexing, multimedia management, biometric identity authentication, surveillance[2], image and film processing, and criminal identification[3]. Face recognition is a method of identity authentication on biometrics study [4], by comparing face recognition with another existing identification technology such as fingerprint and iris recognition. It has several characteristics that are advantageous for consumer applications such as nonintrusive, user-friendly interfaces, low-cost sensors, easy setup and active identification [5]. Face recognition method can be divided into the following categorizations such as holistic matching methods, feature-based matching methods and hybrid methods. The holistic methods used the whole face as input, Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) and Independent Component Analysis (ICA) belongs to this class of methods [6]. This paper describes PCA a recognition rate, conducted on different daubechies wavelets. PCA was selected because this method is most widely used with simple processing steps. This is beneficial to the embedded systems [4].

2 PCA Mathematical Approach

Our face recognition system consists of several steps. Each of the steps is described in detail in below:

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2.1 Initialization and Finding Principal Components

At first we take images, these images are nothing but the matrix which has pixel intensity at different rows and columns and this image could be viewed as a vector also, if an image has height h and width w, then we could formulate this image as w vectors, where each vector has h dimensions. The rows of the images are placed one after another like the below fig 1

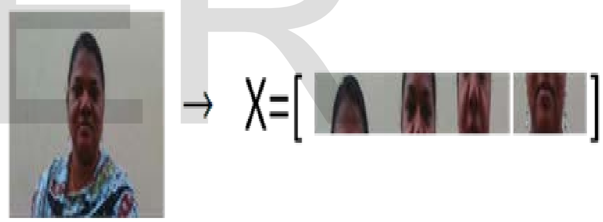

Figure 1: Formation of the face's vector from face's images

The vector which represents our image and this image has a certain space so this is called image space, if we have N images, we have image space dimension as $N \times w \times h$. In this image space all images are represented by $w \times h$ pixels, these images under same image space look like each other. They all have two eyes, a nose, a mouth etc located at the same image space. Now we will build the face space from the image space. The main task of building a face space is to describe the face images. The basis vector of this space is called principal component, the dimension of the face space will be $M \times w \times h$.
We present the mathematical formulation of Eigen faces below:
1. We obtain N training images $I1, I2, \ldots. IN$, each of these images has dimensioned $w \times h$. Convert these images into vector space by concatenation. After the concatenation a matrix is converted to a vector.

2. Represent each image I_i with its corresponding Vector λ_i:

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$$\begin{bmatrix} B_{11} & B_{12} & . & B_{1h} \\ \vdots & \vdots & \vdots & \vdots \\ B_{w1} & B_{w2} & \vdots & B_{wh} \end{bmatrix} \xrightarrow[concatenation]{} \begin{bmatrix} B_{11} \\ \vdots \\ B_{1h} \\ \vdots \\ B_{wh} \end{bmatrix} \triangleq \lambda_i$$

3. Calculate the mean face vector ω by the following equation:

$$\omega = \frac{1}{N}\sum_{i=1}^{N} \lambda_i$$

Subtract the mean face, from each face vector, λ_i to get a set of vector μ_i:
$\mu_i = \lambda_i - \varpi$

The purpose of subtracting the mean image from each image vector is to keep only the distinguishing features from each face by removing the common information. Find the covariance matrix C by the following equation:
$C = A^T A$ Where, $A = [\mu_1, \mu_2, \ldots\ldots \mu_N]$

Find the eigenvalues and eigenvectors for the covariance matrix C, Sort the eigenvectors according to the eigenvalues. Take the first M eigenvectors that have higher eigenvalues. Now each eigenvector will have N×1 dimension. Let us name those eigenvectors as η_i for i=1, 2…M.
Projection of new face to eigenfaces

When a new image is encountered, calculate the set of weights based on the new or input image and the M eigenfaces by projecting the input image onto each of the eigenfaces, the mathematical formulation is given below:

Let us consider the new image as
Find out the M eigenface components, Ψ_l, by projecting the new image :

$$: \gamma_l^T (I_{new} - \varpi) \qquad \text{for l=1,2,…M.}$$

Where,
$\gamma_l = \sum_{k=1}^{N} \eta_{lk}\, \mu_k$ For l=1, 2….M.

Create a new feature vector, for the new image by concatenating eigenface components, Ψ_1
$\Omega_{new} = [\Psi_1, \Psi_2, \ldots\ldots \Psi_N]$

2.2 Face Recognition by classification algorithms

The last step of the face recognition system is to identify the new face to be recognized or not recognized, if the face is recognized the system will tell the person's name for which the face has been recognized. In the other word, if we have N persons in the image database, we say that there are N classes where each individual person representing a class. Comparison is done by the Euclidian distance between two features Ω_{new} and Ω_i, if the distance is less than some predefined threshold t, we say that the image is recognized. The class of the new image will be one that has the least Euclidian distance with the new image, providing this distance is less than the threshold.

3 WAVELET TRANSFORM

Multiresolution methods provide powerful signal analysis tools, which are widely used in feature extraction, image compression and denoising applications. Wavelet decomposition is the most widely used multiresolution technique in image processing.

In the recent years, wavelet analysis has generated a great interest in both theoretical and applied mathematics, and the wavelet transform in particular has proven to be an effective tool for data analysis, numerical analysis, and image processing.

Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale. They have advantages over traditional Fourier methods in analyzing physical situations where the signal contains discontinuities and sharp spikes.

Wavelet Transform (WT) [7, 8] has been a very popular tool for image analysis in the past ten years. The advantages of WT, such as good time and frequency localizations, have been discussed in many research articles [9]. In the proposed system, WT is chosen to be used in image frequency analysis and image decomposition because:

- By decomposing an image using WT, the resolutions of the subband images are reduced. In turn, the computational complexity will be reduced dramatically by working on a lower resolution image.

- Wavelet decomposition provides local information in both space domain and frequency domain. Wavelet transform can be performed for every scale and translations, resulting in continuous wavelet transform (CWT), or only in multiples of scale and translation intervals, resulting in discrete wavelet transform (DWT). Since, CWT provides redundant information and requires a lot of computation; generally DWT is preferred.

A two dimensional wavelet transform is derived from two one-dimensional wavelet transform by taking tensor products. The implementation of WT is carried out by applying a one-dimensional transform to the rows of the original image data and the columns of the row transformed data respectively. In this paper, an image is decomposed into four subbands as shown in Figure 1(a).

The band LL is a coarser approximation to the original image. The bands LH and HL record the contours/edges along horizontal and vertical directions respectively. While the HH band records the diagonal edges of the image. This is the first level decomposition.

Further decomposition can be conducted on the LL subband. After applying a 3-level wavelet transform, an image is decomposed into subbands of different frequency components as shown in Figure l(b). In this paper, Daubechies wavelet is adopted for image decomposition.

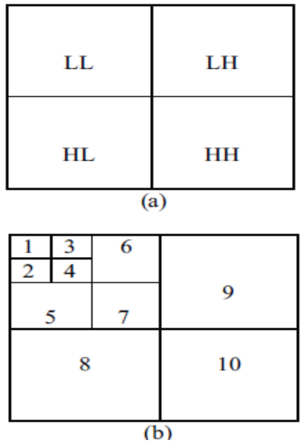

Figure 2: (a) 1-level wavelet decomposition and (b) 3-level wavelet decomposition

4 DAUBECHIES WAVELET

Named after Ingrid Daubechies, the Daubechie wavelets are a family of orthogonal wavelets defining a discrete wavelet transform and characterized by a maximal number of vanishing moments for some given support. With each wavelet type of this class, there is a scaling function which generates an orthogonal multiresolution analysis. The names of the Daubechies family wavelets are written dbN, where N is the order of the wavelet. The db1 wavelet is the same as Haar wavelet. Wavelet functions _ of the nine members of Daubechies family are

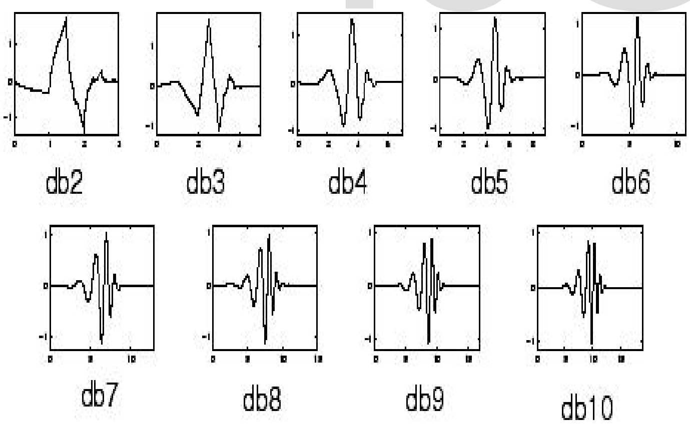

Figure 3: Wavelet functions for Daubechies family

In this paper, first we have taken self database of original faces and the original face image is decomposed by using daubechies6 wavelet transform. We have applied PCA analysis on the decomposed images to extract the features, the Euclidean Distance Measures system is used to find the nearest matching features in the whole database. The complete working of this system is given in the below flow chart:

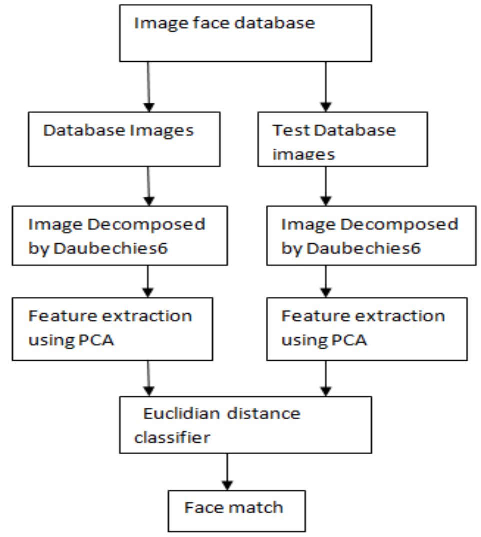

Figure 4: Flow diagram of Face Recognition

5 RESULTS & DISCUSSION

At first I take 12 images in this processing. These images are nothing but the matrix which has pixel intensity at different rows and columns. Each image has its own intensity values at different rows and columns.

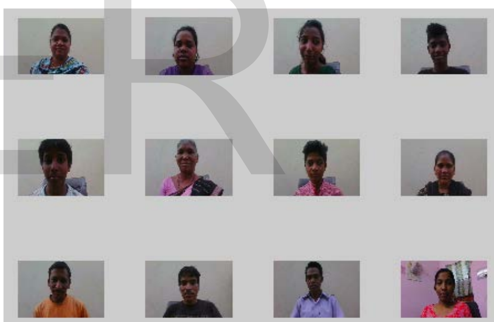

Fig5: self database of images

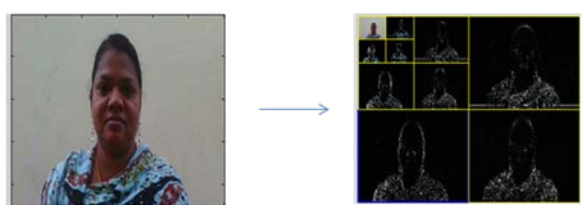

Figure6: Decomposed image

In this paper, the original facial image is decomposed [10] into three wavelet levels by using Daubechies Transform as shown in Fig 6. After extracting the data by using daubechies WT, the PCA is applied to retrieve principle component for face recognition.

This image could be viewed as a vector also. If an image has height, h and width, w, then we could formulate this image as w vectors, where each vector has h dimensions. The rows of the images are placed one after another like the Figure below:

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 $= \begin{bmatrix} a_1 \\ a_2 \\ . \\ . \\ a_N \end{bmatrix}$  $= \begin{bmatrix} b_1 \\ b_2 \\ . \\ . \\ b_N \end{bmatrix}$

 $= \begin{bmatrix} l_1 \\ l_2 \\ . \\ . \\ l_N \end{bmatrix}$

Now I calculate the mean face vector $\overline{m}$ by the following equation

$$\overline{m} = \frac{1}{M}\begin{bmatrix} a_1 + b_1 + c_1 + ...l_1 \\ a_2 + b_2 + c_2 + ...l_2 \\ . \quad . \quad . \quad . \\ . \quad . \quad . \quad . \\ a_N + b_N + c_N + ...l_N \end{bmatrix} \text{ Where M=12}$$

Subtract the mean face from each face vector, the purpose of subtracting the mean image from each image vector is to keep only the distinguishing features from each face by removing the common information.

$$\overline{a_m} = \begin{bmatrix} a_1 - m_1 \\ a_2 - m_2 \\ . \quad . \\ . \quad . \\ a_N - m_N \end{bmatrix}$$

Now I build a vector which is having order $N \times h$.

$$A = \begin{bmatrix} \overline{a_m} & \overline{b_m} & \overline{c_m} & \overline{d_m} & \overline{e_m} & \overline{f_m} & \overline{g_m} & \overline{h_m} \end{bmatrix}$$

Find the covariance matrix C by the following equation: $C = AA^T$

Find the eigenvalues and eigenvectors for the covariance matrix C. Sort the eigenvectors according to the eigenvalues. Take the first M eigenvectors that have higher eigenvalues. When a new image is encountered, calculate the set of weights based on the new or input image and the M eigenfaces by projecting the input image onto each of the eigenfaces. The last step of the face recognition system is to identify the new face to be recognized or not recognized. Comparison is done by the Euclidian distance between two features, New and Training images, if the distance is less than some predefined threshold, t, we say that the image is recognized. The class of the new image will be one that has the least Euclidian distance with the new image, providing this distance is less than the threshold.

The results of the daubechies wavelets on PCA are in the below table:

METHOD	TRAINING IMAGES	TOTAL TIME
PCA DB6	12	3.1S
PCA DB8	12	3.277S
PCA DB10	12	3.217S

Table I. Comparative Study of Access Time of Different db's

In the comparison the feature extraction process depends on time. Results have shown the less time of PCA using daubechies6 over daubechies8 and 10 based on PCA for recognition.

6 CONCLUSION

For papers accepted for publication, it is essential that the electronic version of the manuscript and artwork match the hardcopy exactly! The quality and accuracy of the content of the electronic material submitted is crucial since the content is not recreated, but rather converted into the final published version. compared the access speed of feature extraction for face recognition and the recognition rate of PCA with the DB6 based on PCA. Results have shown the superiority of PCA using daubechies6 over daubechies8 and 10 based on PCA in access speed, but Training set and test images need to be taken in good, comfortable illumination settings. Number of images in the training set is a significant factor, it impacts on defining the correct threshold value for accepting true matches and rejecting false matches. If we will take larger threshold then false recognition rate will increase.

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