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A Hybrid Approach to Face Recognition under Varying Illumination

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***Abstract*— Face recognition algorithms are mainly divided into Holistic and Feature based approaches. Principal Component Analysis (PCA) and Fisher Discriminant Analysis (FDA) are the main holistic based approaches that overcome Feature based approach. The challenging factors in face recognition are facial expressions, illumination variations and face orientations. These existing face recognition algorithms work only to a level, that too only under well controlled laboratory setups and fail under varying illuminations. Face recognition algorithms are commonly used for authentication and authorization purposes. Since they are used in computer applications for various security purposes, the importance of the whole system is necessary. To avoid the breaches in security of the existing algorithms and to outperform those algorithms computationally a need of a better algorithm exists. Hence, a hybrid approach to human face recognition is worked out to overcome these limitations. Face recognition consists of Training and Testing phases. In the Training phase the most eminent and effective features are extracted from the database images and in the Testing phase the probe test image is selected as the input and its prominent features are extracted to be compared with the database images for any matching features. The security of the algorithm purely relies on the method of extracting the feature vectors from the digital image. The proposed method of the Hybrid algorithm classifies images of individual persons into separate classes. This technique is implemented with the YALE & ORL face databases. The database images were taken at different postures, by varying the lighting and facial expressions. The performance of the Hybrid algorithm attains 96% recognition rate under varying postures and illumination conditions and it naturally outperforms the standard Holistic algorithms.**

***Keywords*— PCA (Principal Component Analysis), FDA (Fisher Discriminant Analysis), L2 norm, Hybrid approach.**

I. INTRODUCTION

Face recognition is one of the most active and widely used techniques in biometric security because of its own reliability and efficiency in the process of recognizing and authenticating a person's identity [1]. Human face plays a vital role in conveying emotion and identity. Therefore face recognition is a challenging task and a successful application of image analysis and understanding in many fields such as computer vision, pattern recognition. Today, a variety of applications require reliable identification and verification schemes to confirm the identity of the individual person based on their body characteristics [2]. Traditionally, ID cards and passwords have been used to access a secure system for access control. Later there was a security breach in these methods and a need for more secure access control technique emerged. As a result the face recognition algorithms were developed. Researchers showed keen interest because biometrics cannot be borrowed, stolen, or forgotten and therefore forging an individual is practically impossible. Face recognition system is a pattern-recognition system that recognizes a person based on a feature vector derived from the face characteristic that the person possesses [4]. Face recognition systems can operate in two modes, namely identification and verification. Identification is a process of comparing the acquired biometric information against templates corresponding to all users in the database. Verification involves comparison with only the templates that correspond to the claimed identity.

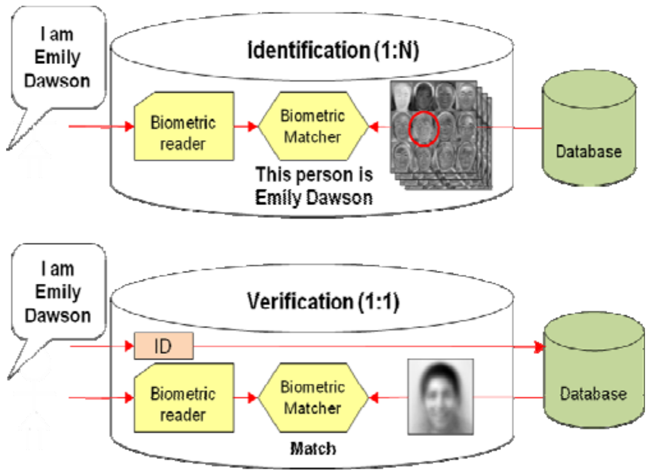

Fig. 1 Modes of Biometric system

Authentication systems are growing in all fields. Biometric authentication system uses personal features that a person possess i.e. "something that you are" rather than something you have and know. Face recognition is user friendly and non-intrusive unlike other forms of techniques such as finger print analysis and iris scans. Face recognition is one such biometric system which comes under pattern recognition. Pattern recognition here known as face recognition, is a very challenging task and works only to an extent, that too under well controlled laboratory conditions and setups. PCA is mainly used for dimensionality reduction. PCA forms the basics of all other face recognition techniques.

II. FACE RECOGNITION CHALLENGES

The following factors are really a challenge for frontal face recognition algorithms. Few of the challenges are illumination variations, pose variations, facial expressions, lighting conditions and size of the database.

III. DEFINITIONS

A. Face Detection

The process of finding a face from an image or a video frame is known as face detection. The detected face is then matched with the database images after extracting the face features.

B. Feature Extraction

Feature extraction is a process of extracting the most relevant features from a digital image. The features obtained must be most efficient to identify the subject with an acceptable error rate. Feature extraction involves dimensionality reduction and feature selection.

C. Face Classification

Face classification is the process of classifying the image after the features are extracted and selected. Several classifiers may also be combined to achieve better results. Distance and similarity measures are two examples of classifiers. Classifiers are used to improve the performance of the algorithm.

IV. HYBRID ALGORITHM

Both PCA and FDA have been widely used in facial expression recognition. PCA performs well for dimensionality reduction but PCA is not optimized for class separability and it minimizes reconstruction error under classifiers namely L2 norm. PCA doesn't reduce the between class variations and it increases the within class variations and hence resulting in low performance under different lighting conditions, facial expressions and pose variations. Rather FDA maximizes scatter of face images of between classes and minimizes scatter of within classes. But as of now there are no practical implementations of FDA because the sample space is larger than the training set. Hence we propose a Hybrid approach combining PCA and FDA for dimensionality reduction and later the face features are extracted according to our Hybrid approach where the most prominent features are calculated by the following method and stored for a match in the database.

In Hybrid approach, the optimization and dimensionality reduction process are carried out by solving the following steps and the first Eigen vector is the direction which has most variance in the data and the second vector accounts for the next largest amount of variance. Let us consider the database training images are of separate classes and each class consists of $(T_1, T_2, \ldots T_n)$ images. The training images are combined into a matrix K of size n*m, where n is the number of images and m is the total pixel value of an image. Hence each row is a single image by which the training images are represented as a vector. The mean matrix K is calculated by the following formula

$$k = (T_1, T_2, \ldots T_n)$$

$$\bar{k} = \frac{1}{m}\sum_{i=1}^{m}(T_i)$$

The mean centered data matrix, mean of the image is subtracted from the whole database training images and taking its own transpose. This is formulated as follows

$$X = (k - \bar{k})$$

The covariance matrix is calculated by taking transpose of the mean centered data matrix and its own. The covariance matrix is calculated as follows

$$\Omega = XX^t$$

The non-zero Eigen value and Eigen vectors are calculated for the covariance matrix and are calculated as follows

$$\Omega V = \lambda V$$

Where V is the Eigen vectors and λ is the Eigen values for the corresponding Eigen vector.

The data matrix X and the Eigen vectors V are multiplied to form the normalization N of the Eigen vectors. They are formulated as

$$\bar{V} = XV$$

$$N = \frac{\bar{V}}{\|\bar{V}\|}$$

The eigenspace is formulated by taking transpose of the normalized Eigen vectors and multiplying it with the data matrix.

$$T_i = N^t k_i$$

The projection matrix T_i is now divided into classes C_i for more optimization and extracting the feature vectors prominently.

$$C_i = \frac{T_i}{n_i}$$

Where n_i, is the number of images of individual persons and are divided into separate class.

The mean for the class images C_i is obtained from the projection matrix are as follows

$$m1 = \frac{1}{x_i}\sum_{i=1}^{n}(C_i)$$

The mean centered matrix for the class images is obtained as follows

$$x_i = (C_i - m1)$$

Again the mean of the centered images $\bar{x}_i$ and the sum of the class means $\bar{X}_i$ is done using the formula

$$\bar{x}_i = \sum_{i=1}^{c} x_i$$

$$\bar{X}_i = \sum \bar{x}_i$$

The luminance factor plays a major role in pose variations. The luminance factor μ and the centered luminance factor $\bar{\mu}$ for the class images is calculated as follows

$$\mu = \sum_{i=1}^{n} C_i$$

The centred luminance factor $\bar{\mu}$ for the separate class images is calculated as follows

$$\bar{\mu} = \sum_{i=1}^{n}(C_i - \mu_i)$$

The class luminance are summed up and the average of the luminance S_i of sample images is obtained by

$$S_i = \frac{1}{C_i}\left(\sum_{i=1}^{n} \bar{\mu}_i\right)$$

Therefore the luminance parameter ℓ for the entire class mean projection matrix is obtained by

$$\ell = \sum_{i=1}^{n} \left(\frac{\bar{X}_i}{(S_i)^{-1}} \right)$$

The luminance parameter ℓ is scaled by a factor to obtain the maximum scatter between the classes is by

$$\bar{\ell} = \sqrt{\ell}$$

The whitening factor for the Eigen value λ is calculated as they play a vital role in normalizing the scatter matrix and compresses the projection matrix for minimizing class seperability.

$$W = \sqrt{\lambda}$$

The scalar function of the class mean projected matrix is calculated to minimize the scatter within the class matrix and is done by multiplying the whitening factor and transpose of the luminance parameter for each class of image

$$S = \{W(\bar{\ell}^{T})\}$$

Therefore the final Eigen space is obtained after extracting the most prominent features by the above calculations and is done by taking the product of normalized Eigen vectors and the scalar function.

$$\phi = (NS)$$

Thus final Eigen space is ϕ and the training images must be projected into the final obtained Eigen space vectors. Each and every training image is projected into the Eigen space as below

$$k^{i} = (\phi^{T} X^{i})$$

Where, i is the number of training images.

The test image is again considered as a vector q and the centered test image is projected into the Eigen space of the training images.

$$X = (q - X^{i})$$

Therefore the test image q^i is projected as follows

$$q^{i} = (\phi^{T} X^{i})$$

Hence the distance measure L2 norm is applied to calculate the match for the selected test image within the database training images and is applied as follows

$$L2(k^{i}, q^{i}) = \sum_{i=1}^{n} ((k_i - q_i)^2)$$

V. Requirement Analysis

A. Hardware Requirements

1. P-4 computer system: Intel CPU @ 2.00 GHZ dual core, 2 GB DDR2 RAM, Intel 945G ATX motherboard, 80 GB HDD, keyboard and mouse.

B. Software Requirements

1. NetBeans 6.9.1, Image editor toolkit.
2. YALE & ORL dataset images.

VI. Simulations / Experimental Setup

We evaluated our algorithm using the standard ORL & YALE dataset images which are usually used for face recognition experiments and thus comparing the same with other algorithms for performance. The ORL dataset consists of 10 different images of same person with different expressions, lighting conditions and facial details from 40 different subjects to a total of 400 images. The YALE dataset consists of 11 images of each individual from 15 different subjects totalling to 165 images. Each individual's image of 5 numbers under different facial expressions is taken as the database images and the reaming images are chosen as the probe test images. An example of the sample images from the ORL & YALE database are shown in fig 2 and fig 3 respectively. The size of an individual image is 92x112 pixels with 256 grey scale levels per pixels. The faces are in upright position of frontal view, with slight left-right rotation. Therefore the dimensionality of the input image is 10304 pixel values.

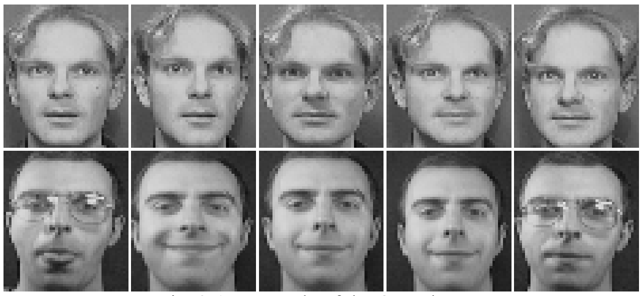

Fig. 2 An example of the ORL dataset

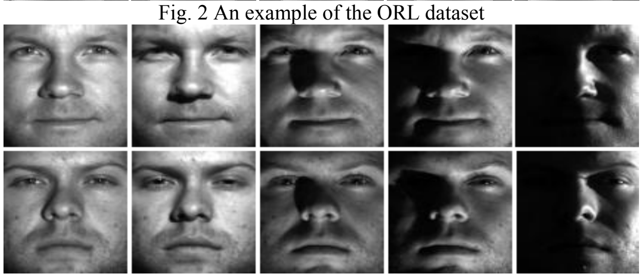

Fig. 3 An example of the YALE dataset

The above is the set of images from the ORL and YALE datasets. Five images of first subject are treated as a class and the next five images of the second subject are treated as a separate class. The above class of images are considered as the training images. The probe test image is then projected into the Eigen space of the training images and it is found that the Hybrid algorithm outperforms other conventional methods.

VII. Results

The experimental results are obtained by choosing images from the YALE database as the training images. The test image is a different image that is not present in the database. It means that the training image and the test image should not be the same. The following results in table 1 are obtained when comparing a test probe image with the training images from fig 3. The similarity and distance measure may be used to obtain a template value for each and every individual class image and based on the obtained template, during the training phase a threshold value can be set to make a decision on the selected test image. In our proposed algorithm we use the L2 norm distance measure for template calculations due to its accuracy rather than other methods. It is found that our proposed hybrid algorithm extracts the feature vectors most prominently and as a result the image to image distance measure values obtained is very satisfactory. In our algorithm we give much importance to the Eigen values for calculating the final Eigen transformation, whereas in other algorithms the Eigen values are omitted. The following table shows the results of the Eigen values obtained and there corresponding distance measure values by choosing fig 3 as the training images.

TABLE I

Class A	Eigen values	L2 norm
Image 1	429391.97	41.34
Image 2	683413.88	86.44
Image 3	1261034.63	260.02
Image 4	3309219.66	450.81
Image 5	5174352.13	887.03

The average threshold value for class A is 345.13 and during the training phase we can set a threshold around 500 to 600 in range for class A based on the L2 norm values. The following table shows the template values obtained by choosing an image from class B as the test probe image and there corresponding Eigen values and L2 norm measures are obtained.

TABLE III

Class B	Eigen values	L2 norm
Image 1	5419562.64	1615.43
Image 2	5702921.67	1618.91
Image 3	11027313.22	1625.08
Image 4	29392506.90	1639.90
Image 5	146160732.63	1774.40

The average threshold value for class B is 1654.74 and during the training phase we can set a threshold around 1500 to 1800 in range for class B based on the obtained L2 norm values. Therefore the decision is made based on the obtained average threshold value and it should be within the values that are assigned during the training phase.

The same database images are used for experimenting with the Holistic algorithms and it is found that they fail to extract the feature vectors more prominently and hence the L2 norm based template obtained for the images are very high. Hence these algorithms fail under varying lighting conditions and face illuminations when the image of the same person in the database is used as a probe test image. The L2 norm distance measure obtained is high.

TABLE IIIII

Probe image chosen	PCA method	FDA method
Image size chosen	*100*100 pixels*	*50*50 pixels*
Image 1	2358.20	1003.37
Image 2	3275.03	926.05
Image 3	886.70	992.15
Image 4	2377.06	1373.81

Hence from the above table the low performance of the Holistic algorithms in face feature extraction is concluded from the L2 norm distance measure even when the test image is that of the same subject. The FDA algorithm performs well when compared to PCA but it also fails when there is a maximum within class scatter matrix and hence the recognition rate is very low. Due to the complexity of the holistic algorithms the image size is reduced to 50*50 pixels because it takes huge time to compute the feature vectors when the size is of 100*100 pixels. The following figure corresponds to the first higher Eigen values obtained and there corresponding Eigen vectors are projected according to the Hybrid algorithm. The figure obtained shows that the most prominent features are very well extracted.

Fig. 4 Eigen faces projected with their corresponding Eigen vectors

The results obtained shows that our proposed Hybrid algorithm outperforms PCA, Asymmetric PCA, FDA and other holistic approach algorithms. A graph is plotted against the features extracted and the recognition of images by the corresponding methods. The following graph is plotted against the feature vectors vs recognition rate. In our method the recognition rate increases gradually as the extracted feature vectors increases. But in other methods namely APCA+FDA and PCA the recognition rate is very low at the end.

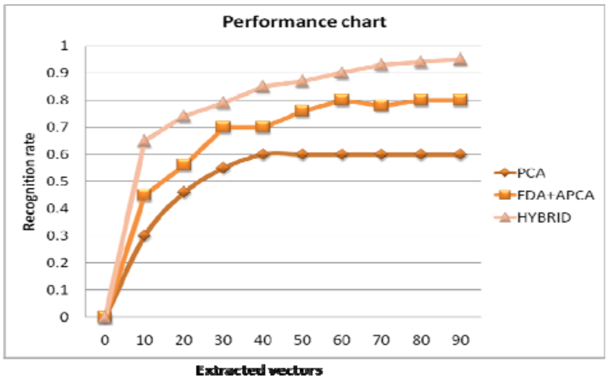

Fig. 5 Performance measure of Hybrid analysis vs holistic approaches

VIII. CONCLUSIONS

The Hybrid algorithm classifies images of individual subjects into separate classes and the obtained results shows how optimally it functions to extract the face features. The whitening factor, the luminance parameter and measuring them with a scalar value and then calculating the Eigen space is the main concept in our algorithm which extracts the face features prominently and then the probe test image is projected into the Eigen space. By these calculations it overcomes the optimization problems which are unsolved in the PCA & FDA. During the training phase the image dataset is well trained to optimize the algorithms performance. The same image datasets is implemented with the other Holistic based algorithms and the graph shows that the holistic based approach doesn't perform better than the Hybrid approach under varying lighting variations, varying illuminations and facial expressions. It is found that our proposed method attains a recognition rate of 96% during the testing phase which is much better than the other methods. We make use of the L2 norm distance measure classifier to obtain the exact facial match. The obtained results reveal that the Hybrid algorithm extracts the Eigen vectors more optimally and the accuracy of the algorithm is very high when compared to other methods. The computational speed of the Hybrid algorithm is much better when compared to other methods even when the image size is 100*100 pixels. Hence the proposed Hybrid algorithm can be combined with other evolutionary facial recognition algorithms and can attain a better strategy in extracting the Eigen vectors and other face feature vectors.

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