Face Recognition System Simultaneous Using PCA & LDA Method with 3d Morphable Model

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Abstract: This paper proposes a face recognition technique that effectively combines principle components analysis(PCA) and Fisherface algorithm(LDA). PCA use as dimension reduction and Fisherface algorithm as a class specific method is robust about variations such as lighting and different angle Condition. We use 3D morphable model to convert 2D image into 3D image & we can derive multiple image by different lighting and can be rotated to generate multiple images in different poses, the PCA method reduces dimensionality& LDA for the classification. In comparison with a conventional method the proposed approach could obtain satisfactory results in the perspectives of recognition rates and speeds. Especially, we could get maximum recognition rate of 99.9%for trained image & for non trained image it is upto 61.07%.

INTRODUCTION

Face recognition is a rapidly growing research area due to increasing demands for security in commercial and law enforcement applications. Face recognition using 3D images is another active area of face recognition, which provides robust face recognition with changes in pose.Fisherface is extended for face recognition from one example image per person. Fisherface is one of the most successful face recognition methods. However,

Relevant Theory
System Overview: - The overall system design is as follow: [1]

Construction of 3D face using 3D Morphable Model: Kumaravel *et al* [2], 3D face reconstruction based on morphable model is composed of two components. On is the model construction. The other is the model matching to given facial images. To construct the morphable model, prototypic 3D faces are acquired by Cyberware Scanner [1-7]. After constructing dense point-to-point correspondence of prototypes in 3D space, each prototypic faces can be represented as shape and texture vectors as follows:
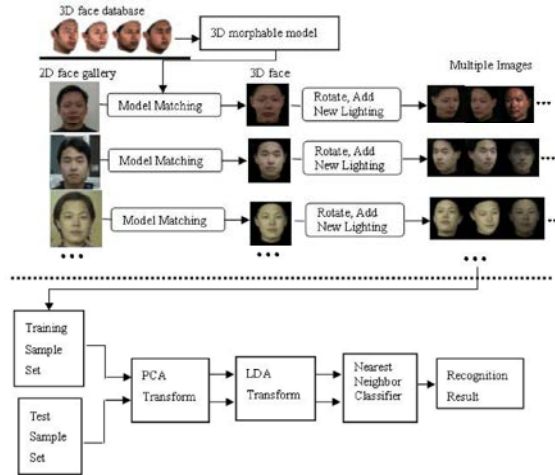

Fig. 1: System Overview

$$S_i = (X_{i1}, Y_{i1}, Z_{i1}, X_{i2}, Y_{i2}, Z_{i2}, ..., X_{in}, Y_{in}, Z_{in},)^T \in R^{3n} \quad (1)$$

$$T_i = (R_{i1}, G_{i1}, B_{i1}, R_{i2}, G_{i2}, B_{i2}, ..., R_{in}, G_{in}, B_{in},)^T \in R^{3n} \quad (2)$$

Where i= 1,2….N *N is the number of prototypic faces. n is the vertex number of 3D face model. (R, G_i, B_i) is the color value of vertex (X_i, Y_i, Z_i). PCA is utilized to give the final morphable model format as follows:
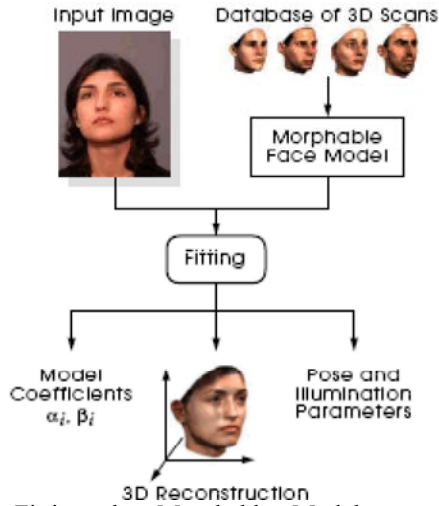

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Fig. 2: Fitting the Morphable Model to an Image produces not only a 3D reconstruction, but also model coefficients αi, βi and an estimate of head orientation, position and illumination.

Fig. 3: Reconstructed 3D face

$$S_{\text{model}} = \bar{S} + \sum_{i=1}^{m} \alpha_i S_i \qquad T_{\text{model}} = \bar{T} + \sum_{i=1}^{m} \beta_i t_i \qquad (3)$$

Where $\bar{S} + \dfrac{1}{N}\sum_{i=1}^{N} S_i$ and $\bar{T} + \dfrac{1}{N}\sum_{i=1}^{N} T_i$ are average shape and texture vectors., S_i and T_i are eigenvectors respectively. $\bar{\alpha} = (\alpha_1, \alpha_2, ..., \alpha_m)$ *and* $\vec{\beta} = (\beta_1, \beta_2, ..., \beta_m)$ are combination coefficients [5].

The matching of 3D face model to facial image is face reconstruction procedure. By model matching combination coefficients of the morphable model is determined and reconstructed 3D face is obtained by combination operation. Aim of m odel matching is to find a 3D face having the closest projective image to the input facial image. The error is defined as follows:

$$E = \sum_{(x,y)} [I_{input}(x,y) - I_{\text{model}}(x,y)]^2 \qquad (4)$$

Where (x,y) is pixel coordinate in face images.

Given an input face image, through model matching process, 3D face model of specific person can be reconstructed based on the morphable model. Left picture is the input image. Right three pictures are reconstructed 3D faces in different views.

Matching a Morphable Model to Images: A crucial element of our framework is an algorithm for automatically matching the morphable face model to one or more images Providing an estimate of the face's 3D structure it closes the gap between the specific manipulations is described and the type of data available in typical applications. Kumaravel *et al.* [8] Coefficients of the 3D model are optimized along with a set of rendering parameters such that they produce an image as close as possible to the input image.

Deriving Multiple Images from a Single Image: Having constructed the morphable model, 3D face of a specific person can be derived from a single image through model matching process. And reconstructed 3D face can be rotated to generate multiple images in different poses. New illumination model can be applied to the reconstructed 3D face to generate multiple images under different lighting conditions. Multiple images can be derived from a single image by rotating the reconstructed 3D face and adding new lighting conditions to it.

Training & Testing Set: Having constructed the morphable model, 3D face of a specific person can be derived from a single image through model matching process. And reconstructed 3D face can be rotated to generate multiple images in different poses. New illumination model can be applied to the reconstructed 3D face to generate multiple images under different lighting conditions. Multiple images can be derived from a single image by rotating the reconstructed 3D face and adding new lighting conditions to it [8].

PCA Transform: As other methods are computationally expensive and require great amounts of storage, it is natural to pursue dimensionality reduction schemes. A technique now commonly used for dimensionality reduction in computer vision particularly in face recognition is principal components analysis (PCA). PCA techniques, also known as Karhunen-Loeve
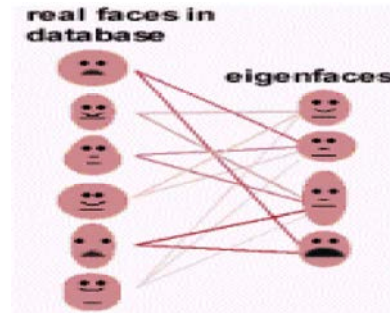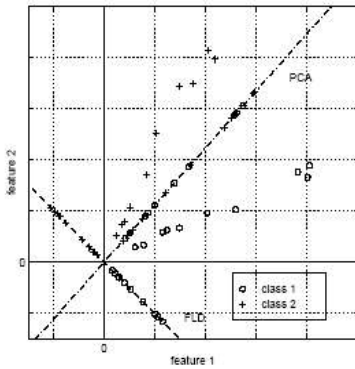
Fig. 6: Faces are Linear Combinations of eigenfaces

methods, choose a dimensionality reducing linear projection that maximizes the scatter of all projected samples. Eigenfaces are generated [1-4].

Principle Component Analysis: Starting with a collection of original face images, PCA aims to determine a set of orthogonal vectors that optimally represent the distribution of the data. Any face images can then be theoretically reconstructed by projections onto the new coordinate system. In search of a technique that extracts the most relevant information in a face image to form the basis vectors, Turk and Pentland proposed the eigenface approach, which effectively captures the variations within an ensemble of face images.

Mathematically, Kumaravel *et al.* [9] the eigenface approach uses PCA to calculate the principal components and vectors that best account for the distribution of a set of faces within the entire image space. Considering an image as being a point in a very high dimensional space, these principal components are essentially the eigenvectors of the covariance matrix of this set of face images, which Turk and Pentland termed the eigenface. Each individual face can then be represented exactly by a linear combination of eigenfaces, or approximately, by a subset of "best" eigenfaces – those that account for the most variance within the face database characterised by its eigenvalues, as depicted in Figure 6.

Consider an N-by-N face image I(x, y) as a vector of dimension N2, so that the Image can be thought of as a point in N2-dimensional space.

A database of M images can therefore map to a collection of points in this high dimensional "face space" $\Gamma 1, \Gamma 2, \Gamma 3, \ldots, \Gamma M$. as With the average face of the image set defined as

$$\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n \tag{5}$$

each face can be mean normalized and be represented as deviations from the average face by $\Phi i = \Gamma i - \Psi$. The covariance matrix, defined as the expected value of can $\Phi\Phi^T$ be calculated by the equation

$$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_n\Phi_n^T \tag{6}$$

It is reasonable to assume that each face image is independent, that is, each image is taken differently. If we further assume that all the input images into the face recognition module have been perfectly normalised, we can conclude that the variances of each Φi lie correspondingly, thus resulting in a set of time-aligned images. The significance of these assumptions is because together with the consideration that covariance is a zero-mean process, we can conclude that each Φi is independent and that cross multiplication between different Φi is possible due to their time-aligned characteristics, with the multiplication resulting in an expected value of zero [3] that by selecting the eigenvectors with the largest corresponding eigenvalues as the basis vector, the set of dominant vectors that express the greatest variance are being selected. Recall however, that an N-by-N face image treated as a vector of dimension N2 is under consideration. the resultant covariance matrix **C** will be of dimensions N2 by N2. A typical image of size 256 by 256 would consequently yield a vector of dimension 65,536, which makes the task of determining N2 eigenvectors and eigenvalues intractable and computationally unfeasible.

LDA Transform
Fisherface Method: Fisherface algorithm considers the ratio between the variation of one person and that of another person. It maximizes the determinant of between-class scatter matrix simultaneously, minimizing the determinant of within-class scatter matrix.

For a C-class problem, the between-class scatter matrix is defined as follows:

$$S_b = \sum_{i=1}^{e} \Pr(\Omega_i)(\mu_i - \mu)(\mu_i - \mu)^T \qquad (7)$$

where
$\Pr(\Omega_i)$ is the prior class probability, μ_i is the mean sample of class Ω_i and μ is the mean sample of all classes.

The within-class scatter matrix is defined as follows:

$$S_w = \sum_{i=1}^{c} \Pr(\Omega_i)\Sigma_i$$

where

$$\Sigma_i = \frac{1}{N_i} \sum_{x_k \in \Omega_i}^{c} (x_k - \mu_i)(x_k - \mu_i)^T \qquad (8)$$

is covariance matrix of within-class sample. N_i is the number of samples in class Ω_i. Fisher criteria function is defined as follows:

$$J(W) = \frac{|W^T S_b W|}{|W^T S_w W|} \qquad (9)$$

Then the projective matrix W_{fld} can be chosen as follows:

$$W_{fld} = \underset{W}{\operatorname{argmax}} \frac{|W^T S_b W|}{|W^T S_w W|} \qquad (10)$$

W_{fld} can be calculated by solving the generalized eigenvalue problem:

$$S_b W = S_w W \Lambda \qquad (11)$$

In face recognition applications, because rank of S_w $\epsilon\ R^{nxn}$ is at most N-c, where N is the number of images in training set and typically much smaller than n, number of pixels in each image, the within-class scatter matrix S_w is always singular. Kumaravel *et al* [10], to overcome this problem, PCA is first utilized to reduce the dimension of the images from N to N-c, then recalculated S_w will be non-singular and FLD can be utilized to find the projective matrix W_{fld}, which is referred to as Fisherfaces.

LDA is a Fisherface algorithm. Fisherface algorithm considers the ratio between the variation of one person and that of another person. It maximizes the determinant of between-class scatter matrix simultaneously, minimizing the determinant of within-class scatter matrix [2-6].
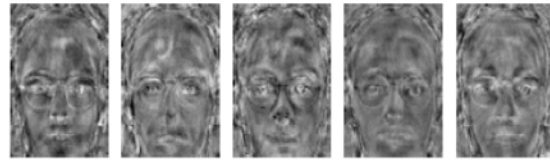

Fig. 7: The first five fisherfaces, defining a face space with no image pre-processing

Nearest neighbor Classification & Recognition Result: Recognition is performed by comparing the weights of the test face with the known weights of the database. Mathematically, a score is found by calculating the norm of the differences between the test and known set of weights, such that a minimum difference between any pair would symbolise the closest match. Then these recognition results are displayed in the suitable form.

RESULT

We have done a huge performance testing to improve our software quality. The database is trained for 13 images per person. We have given such 10 persons for our testing out of which 9 are men & 1 woman. This training is done for both PCA & LDA. Then system is tested for all database images. Then we took real time images & testing is carried out on those faces. As it is very difficult to take more real time images, we constructed new 2D faces which are not in database & testing is carried out on those faces. Our developed test tool helped us a lot in finding threshold & to analyze our system performance.

Applications: Face Recognition becomes more pressing in recent years as applications such as Biometric, Law enforcement & surveillance develop. Looking towards the need of authentication & increasing cases of breaching security or fake identities, the software can be used or extended as a powerful remedy for it & thus serve the society.

Future Scope
Issues of Implementation: We plan to speed up our matching algorithm by implementing a simplified Newton-method for minimizing the cost function. Instead of the time consuming computation of derivatives for each iteration step, a global mapping of the matching error into parameter space can be used. Data reduction applied to shape and texture data will reduce redundancy of our representation, saving additional computation time.

Table 1: Testing Results of PCA For Database & Real Time Images

Name	Number Of Training Images	Number Of Testing Images	Correctly Recognized	Success Rate (in%)
Amit	13	18	13	72.22
Shripad	13	18	15	83.33
Vikas	13	18	15	83.33

Performance for All Images=78.87% Database Images=100%
Real Time Images=20.06%

Table 2: Testing Results Of LDA For Database & Real Time Images

Name	Number Of Training Images	Number Of Testing Images	Correctly Recognized	Success Rate (in%)
Amit	13	18	13	72.22
Shripad	13	18	13	72.22
Vikas	13	18	14	77.78

Performance for: All Images=80.28% Database Images=100%
Real Time Images=26.32%

Table 3: Testing Results Of LDA For Database & Created Images

Number Of Training Images	Number Of Testing Images	Correctly Recognized	Success Rate (in%)
130	280	169	60.35

Performance for: All Images=60.35 Database Images=100%
Derived Multiple Images =26%

Extending the Database: We also plan to incorporate additional 3D face examples representing the time course of facial expressions and face variations during speech.

Extending the Face Model: Our current morphable model is restricted to the face area, because a sufficient 3D model of hair cannot be obtained with our laser scanner. For animation, the missing part of the head can be automatically replaced by a standard hair style or a hat, or by hair that is modeled using interactive manner.

CONCLUSION

Face recognition is a both challenging and important recognition technique. Among all the biometric techniques, face recognition approach possesses advantage, as its user-friendliness and non-intrusiveness.3D morphable model is utilized to derive multiple images from a single example image to form the training set which reduces training overhead while testing under some expressions, illumination and slight pose variations can be done. The overall system performance is mainly depending on the constructed 3D face. Slight variations in the feature point position creates much difference in 3D face & hence the weights. Always there is a good race between these algorithms but LDA outperform PCA whenever different lighting conditions are considered [14-16].

Created test tool helped us for deciding the threshold & finding system performance. For real time images performance of LDA (80.28%) is superior than PCA (78.87%).This is happened as PCA is more sensitive than LDA for pose & lighting conditions. PCA is simple for understanding as well as implementation whereas LDA is more complex for understanding & implementation. For images which are already trained system performance for both PCA & LDA is 100%. For images constructed by system (trained & not trained) performance of PCA (61.07) & LDA (60.35) is nearly same.

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