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Query Based Face Retrieval From Automatic Reconstructed Images based on 3D Frontal View - Using EICA

By Y. Vijaya Lata, Dr. A. Govardhan

Abstract- Face recognition systems have been playing a vital role from several decades. Thus, various algorithms for face recognition are developed for various applications like 'person identification', 'human computer interaction', 'security systems'. A framework for face recognition with different poses through face reconstruction is being proposed in this paper. In the present work, the system is trained with only a single frontal face with normal illumination and expression. Instead of capturing the image of a person in different poses using camera or video, different views of the 3D face are reconstructed with the help of a 3D face shape model. This automatically increases the size of the training set. This approach outperforms the present 2D techniques with higher recognition rate. This paper refers to the face detection and recognition approach, which primarily focuses on Enhanced Independent Component Analysis(EICA) for the Query Based Face Retrieval and the implementation is done in Scilab. This method detects the static face(cropped photo as input) and also faces from group picture, and these faces are reconstructed using 3D face shape model. Image preprocessing is used inorder to reduce the error rate when there are illuminated images. Scilab's SIVP toolbox is used for image analysis.

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GJCST Classification: *I.4.6, I.5.1*

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Y. Vijaya Lata[α], Dr. A. Govardhan[Ω]

Abstract-- Face recognition systems have been playing a vital role from several decades. Thus, various algorithms for face recognition are developed for various applications like 'person identification', 'human computer interaction', 'security systems'. A framework for face recognition with different poses through face reconstruction is being proposed in this paper. In the present work, the system is trained with only a single frontal face with normal illumination and expression. Instead of capturing the image of a person in different poses using camera or video, different views of the 3D face are reconstructed with the help of a 3D face shape model. This automatically increases the size of the training set. This approach outperforms the present 2D techniques with higher recognition rate. This paper refers to the face detection and recognition approach, which primarily focuses on Enhanced Independent Component Analysis(EICA) for the Query Based Face Retrieval and the implementation is done in Scilab. This method detects the static face(cropped photo as input) and also faces from group picture, and these faces are reconstructed using 3D face shape model. Image preprocessing is used inorder to reduce the error rate when there are illuminated images. Scilab's SIVP toolbox is used for image analysis.

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I. Introduction

Face recognition systems are ubiquitous and has received substantial attention from researchers in biometrics and computer vision communities ever since security has become critically important in this commercial world. Many approaches have been proposed for face recognition systems for a captured digital photograph or a video clipping. These approaches have been prevailing since a few decades in two-dimensional space. Many algorithms are being introduced and improved then and then for the increase of the efficiencies in the recognition rates for the face recognition systems. The conventional algorithms are able to produce better results over the previous algorithms. But these conventional approaches are unable to achieve the success rates in a dramatic way due to some constraints[11]. These problems include the representation of the faces in a two-dimensional space, which is in a three-dimensional space. Thus, here a three-dimensional approach is being proposed to improve the efficiency of face recognition sy tems.

This paper aims at presenting a three-dimensional approach, a new approach, towards the face recognition systems. In this approach only a single two-dimensional face is given as an input along with the three-dimensional face shape model. Here, it is made sure that the features of the two-dimensional input face and that of the three-dimensional face model are at the same positions. Thus in this process only the essential features of a face which represent the face are been taken into consideration. The features such as hair, ears and neck parts are cropped which do not account for face recognition. Thus, even the reconstructed images also do not contain these parts to the maximum possible extent.

As the features are aligned properly, the texture of the three-dimensional face model will also be the same as on the two-dimensional input face[11][12]. Then, the face model is being rotated upon the required angle to obtain a new view of the face. In this process, some of the points are missed, overlapped and neglected, which requires the smoothing of those missing points in the face by using the concept of the nearest neighbours. Thus, the missing texture is retrieved by using this concept.

Finally, the newly obtained views of the input face are been projected onto the two-dimensional space. Thus, here a 3D(regenerated 3D face) to 2D(regenerated 2D face) projection is applied after the 2D(frontal input face) to 3D(face model) projection.

(a) (b) (c) (d)

About[α]- Professor, Department of Computer Science and Engineering, Gokaraju Rangaraju Institute of Engineering and Technology Hyderabad- 500090, A.P.,India.
E-mail- vijaya_lata@yahoo.com
About[Ω]- Professor & Principal Department of Computer Science and Engineering JNTUH College of Engineering Jagityala, Karimnagar(Dist.), A.P.,India.
E-mail- govardhan_cse@yahoo.co.in

(a) 3D face model
(b) 3D face model after smoothing
(c) face with texture
(d) a new view with PIE

Figure1: Reconstruction of a new face with PIE[1]

The newly constructed images are being used for training the face recognition system to improve the efficiencies over the 2D approaches for face recognition. The proposed work has the following advantages: 1) Input to this proposed system is only a single frontal face with normal pose, illumination and expression(PIE). 2) Different views of a face are generated instead of capturing the images of a person in different poses using cameras or videos. 3) Automatic increase of the training set. 4) Outperforming the present 2D approaches with higher recognition rates.

Frontal Faces *Recostructed Faces*

Figure 2: Reconstructed faces for Own Database

Query based face retrieval is one of the applications of content-based image reterieval (CBIR). It requires a robust feature extraction method that is capable of deriving low-dimensional features effective for preserving class separability. Such low dimensional features are also important when one considers the computational efficiency[1] . The present paper focuses on query based face image retrieval using EICA and PCA which works on static as well as group images . In the EICA method enhanced retrieval performance is achieved by means of generalization analysis, in the reduced PCA space. EICA method has better performance than the popular face recognition methods. The present system is trained with the database shown in Figure (2), where the frontal images are taken and other images are reconstructed using 3D face shape model.The analysis have been carried out on two-dimensional face database using PCA and EICA, and also on reconstructed 3D faces.

II. THREE-DIMENSIONAL APPROACH

In this section, the three-dimensional face reconstruction is being described in detail. Firstly, the three-dimensional face model is introduced and then the rotation of the face model is presented in a detailed manner to get the different views of the input face.

a) *Three-Dimensional Face Shape Model*

Here, the three-dimensional face shape model is represented as two-dimensional matrix which contains the height of the features of the face. The three-dimensional face model used in this paper is shown in Figure (3). This has been extracted from the GAVAB database[11][12] consisting of various face shape models. But, only one among them is selected here which was appropriate for the input images used in this paper. For the ease in computation, the height matrix of the face model is resized to 64 x 64 i.e. 64 rows and 64 columns without leading to any misinterpretation of the data.

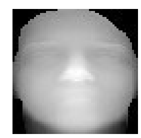


Figure 3: 3D face shape model

Let h be the height matrix representing the face model. The original face model is been cropped till the necessary features required to represent the face and then resized. Thus, the value at h(i,j) gives the height of the feature point at the i^{th} row and j^{th} column of the face.

b) *Rotation in a Plane for Different Poses*

Rotation of the points is done by applying the rotation matrix on the points. To make them rotate in an appropriate manner without losing any data, rotation of the points is done by keeping one of the axes as fixed to minimise the burden of filling the missing areas which would be described later.

Let the rotation matrix be represented by m which is defined as follows.

$$m_x = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\alpha & -\sin\alpha \\ 0 & \sin\alpha & \cos\alpha \end{bmatrix}$$ where α is the angle measured in degre

$$H(i,j) = [i \; j \; h(i,j)] \cdot m_x$$

Thus, new points have been derived. So, the H matrix consists of the new position of the point in the 3D space. While deriving these new points, it has been observed that some points have been overlapped and so the values for some of the pixels have been missed. The following steps are taken to overcome this problem.

1) Firstly, if two or more points are intended of having the same position, then the point with the maximum height is considered and the rest of them are neglected. This is done for each pixel.

2) The missing values have been filled by the nearest neighbourhood pixels by smoothing them.

In this process no data has been misinterpreted to the possible extent.

c) *Texture Mapping*

After rotating the points, the texture is mapped according to the input face image. As each newly derived position after rotation of the points is stored in the previous position of the fontal face model, the texture of each pixel is mapped to the new position easily.

As described earlier, the missing points have been smoothened to the value of the nearest neighbour, there is a possibility of increasing and decreasing of the number of pixels for the particular texture than that of the 2D face image. For the ease in smoothening, the points are rotated in the plane by keeping one of the axes, say x-axes, as constant because determination of the value to be substituted for the missing values would be a cumbersome task.

Figure 4(a): Left pose

Figure 4(b): Right pose

If the angle is positive, then a left side view is generated for the face model and a right side view of the face model is generated as shown in figure (a) and (b) respectively. Thus, the left and right side views are generated by keeping the x-axis as constant.

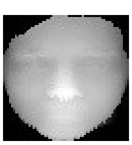


Fig 5(a) Down view

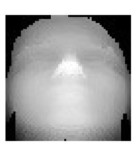


Fig 5(b) Top view

Similarly, the top and down views are generated by keeping the y-axis as the constant. The positive angle rotation gives the down view and the negative angle rotation gives the top view.

III. Face Reconition Using PCA Algorithm

The recognition system consists of a training set and then the testing of the images is been carried out to recognise the testing images with those present in the training set. The training set consists of the images where the images are been trained onto the neural network. The neural network is designed with the help of the eigenvectors generated representing the training set which will be described clearly in the subsequent sections.

a) *Representation of Images*

Face images are represented by intensity values of each pixel. Let the dimensionality of each image be m x n. This means that each image consists of grid of pixels with m rows and n columns. Let I(x,y) represents intensity values for all pixels. So total number of pixels of each image will be m x n, let this value be denoted as N.

Now this image can also be considered as a vector of dimension N. So for example, say here, the images have the dimension of 64 x 64 pixels, then the dimension of the image vector will be 4096. So he--re N = 4096. Normally for all images, since dimensiona--lity of image is large, the value of N, dimension of image vector is also large.

b) *Principle Component Analysis*

Let there be n number of images used for testing. Each two-dimensional image is represented as a single dimensional data, as described in the above section, which are aligned together to form the data of the training set. Then its mean data is calculated by subtracting each image data with the average of the training set.

$$D_i = I_i - (1/n)\Sigma I_i$$

Here D forms the data set and I_i is data of i^{th} image. Then the covariance matrix, L, is obtained by the correlation of the dataset by multiplying the dataset with its transpose.

$$L = D \cdot D^T \text{------------------- (1)}$$

$$L = D^T \cdot D \text{------------------- (2)}$$

In equ.(1) the size of the resultant covariance matrix is N×N, which is high in dimension and is reduced to n×n in equ.(2). The eigen vectors (V) and eigen values (λ) of this covariance matrix are calculated which form the solutions to the given problem space i.e. training dataset.

$$L \cdot V = \lambda V$$

These eigen vectors are sorted in decreasing order of their corresponding eigen values. Thus, n eigen vectors are formed which are able to classify the distinct features of the images in the training set. Generally, all the eigenvectors are not necessary for the classification of the images. The eigen vectors with the negative eigen values are discarded. Further reduction of the eigen vectors to some extent does not affect the recognition process and thus unnecessary computation is avoided. The m sorted and reduced eigen vectors (Vm) are projected on to the training set to get the eigen vectors of the training set.

$$EV = V_m \cdot D$$

Then the weights of the training set are been computed by projecting the data of each training image onto the eigen vectors of the training set which form the trained neural network.

$$O_i = EV \cdot D_i$$

Testing a new image(T) involves the steps performed on the data of individual training image by forming its one-dimensional data and subtracting the mean data of training set from it. This is then projected onto the eigen vectors to compute the weights of the testing image.

$$O_{new} = EV \cdot (T - (1/n)\sum I_i)$$

$$e_i = O_i - O_{new}$$

$$k = i \text{ , where } \min(e) = e_i$$

Then the training weights and testing weights are compared by any distance measuring criteria such as the Euclidean distance. The training image having the least difference based upon the Euclidean distance with the testing image is given as the nearest (k^{th}) matching image.

IV. Face Recognition Using EICA

This method is the enhanced form of ICA because of its enhanced retrieval performance for face recognition. Enhanced retrieval performance is achieved by means of generalization analysis and it operates in the reduced PCA space.

a) *Training Data*

Step 1: The not well illuminated images are preprocessed by using intensity normalization method, in which the lightening source increases by the factor, each RGB component of each pixel in the image is scaled by the same factor. The effect of this intensity factor is removed by dividing by the sum of the three color components. Since the pixels of the resulting image have equal intensity, summing the three color channels would result in a blank image. Therefore, to create an image with single scalar values for each pixel (as required by our Eigen face system) either consider a single color channel, or sum just the red and green components (the chromaticities).

Step 2: For the preprocessed training data calculate the image matrix X. Here the preprocessed image is resized to a 64×64 matrix will be converted to 4096×n,where n is the number of images in the data base.

Step 3: The covariance of the image matrix is to be calculated in order to find eigen values and eigen vector by applying PCA procedure.

--The covariance of image matrix is defined as

$COV = XX^T$.

--The eigen values and corresponding eigenvectors are computed for the covariance matrix.

$\Omega V = \Lambda V$

where V is the set of eigenvectors associated with the eigenvalues Λ.

Sort the eigenvectors according to their corresponding eigenvalues. Consider only the eigen vectors with non zero eigen values. This matrix of eigenvectors is the eigen space V , where each column of V is an eigenvector.

$V = [v_1|v_2 \ldots |v_p]$

Step 4: The new random vector in the reduced(50-dimensional) space is defined as

$Y = P^t X$

where P is the orthogonal eigen vector matrix of 50 dimensional.

The ICA method implemented in the appropriate reduced space is an Enhanced ICA method.

Step 5: Find the covariance of the random vector which is defined as,

$COV = YY^T$

The eigen values and corresponding eigenvectors are computed for the covariance matrix.

$\Omega V_1 = \Lambda V_1$

here V1 is the set of eigenvectors associated with the eigen values Λ.

Step 6:Calculate the basis vector which is defined as

$BV = (PV_1)^T$

Step 7:Find the basis vector for all images in training set

Z=BV x X

Train Group: Similarly the train group database is implemented using the above algorithm to calculate the basis vector for all the train group database.

b) *Testing Data*

An input image is read from the data base and it is preprocessed using intensity normalization method**.**

Step 1: Calculate the image matrix X2 for the preprocessed input image. Find the input image and is resized to 64x64 matrix which is now converted to $4096.n_1$,where n_1 is number of images in test data base.

Step 2: The testing basis vector Z2 is defined as

Z2=BV x X2.

Step 3: $E=((T-Z2)^t x (T-Z2))$,where T is defined as the Basis Vector of the complete training images. In Scilab the Euclidean distance is calculated by using min method.

[Dist,Place]=min(E)

Step 4:The minimum Euclidean distance will give output image. To retrieve the details of the output image the location is to be found in database. The location can be known by using place variable which is found while calculating Euclidean distance.

After finding position, details of student are stored in result.txt and are displayed later.

V. Implementation in Scilab & Results

The above discussed methodologies have been implemented in Scilab. The algorithm has been tested for the standard image database such as Yale's database, and also on own database.

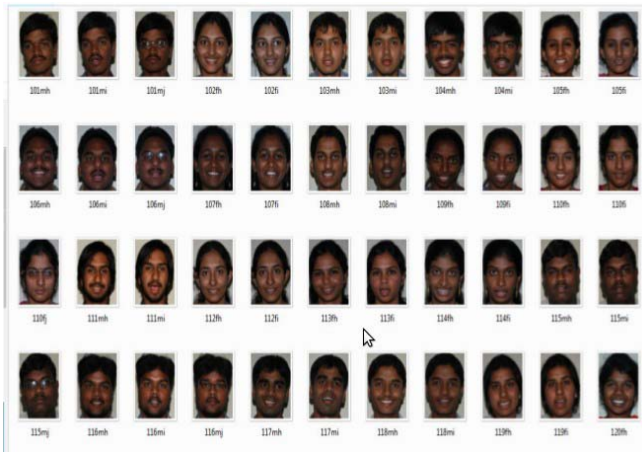


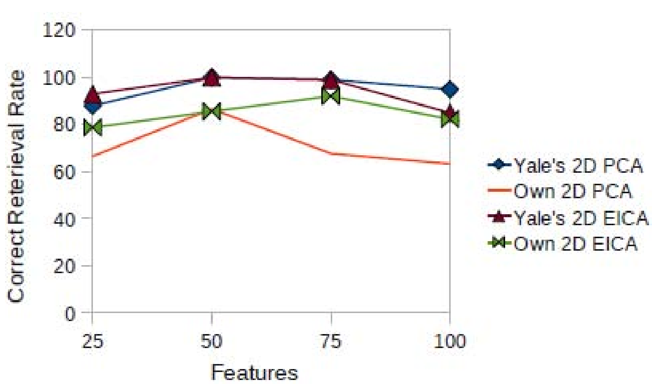
Figure 6: Own Database

PCA – Without reconstruction(2D)

	Accuracy %	Fault %
Yale's	100	0
Own	86.66	14.34

EICA - Without reconstruction(2D)

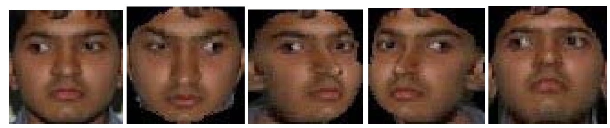
	Accuracy %	Fault %
Yale's	100	0
Own	92.13	7.87



The reconstructed 2D faces based on 3D frontal view using 3D shape face model

(a) (b) (c) (d) (e)

Figure 7: *Yale's Database – (a) original image (b)-(e) reconstructed image*



(a) (b) (c) (d) (e)

Figure 8: Own Database – *(a) original image (b)-(e) reconstructed image*

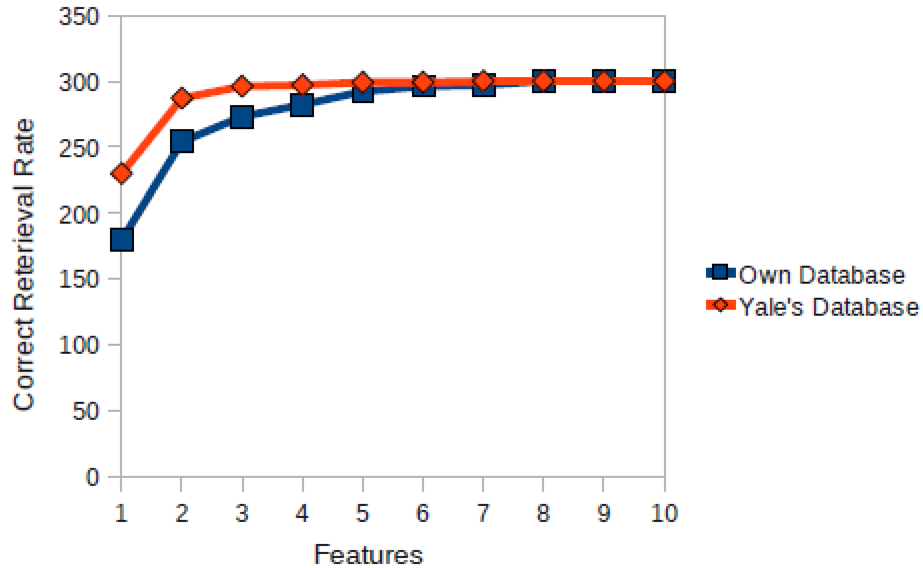
By taking single frontal image of 10 subjects each system can generate new poses of each subject in left view, right view, top view and down view. As a result 30 images per subject are generated out of which 15 images are given for training and 15 are given for testing. The images which are given for training are not included for testing.

As shown in the above figures, the faces from the single frontal face are reconstructed in different views automatically and are used for the recognition process. A testing is performed on these images by giving half of the images for the training set and the rest of the images are been tested onto the training set which are also of the normal illumination and expression as of the training images.

Here, ten subjects in each database are been selected whose features are appropriate to that of the face shape model used in this paper. Totally 300 reconstructed images (10 left view, 10 right view, 5 top view, 10 down view) have been trained along with the original frontal faces. Another 300 reconstructed images (10 left view, 10 right view, 5 top view, 5 down view) have been tested onto the training set. This is done for each of the mentioned databases. The images that are given for training are not included for testing and those given for testing are not included for training.

Database	2D approach	3D approach
Yale's Database	80 %	100 %
Own Database	65 %	99 %

Table showing the success rates of face recognition on Yale's Database and Own Database in different approaches



VI. Conclusion

The above described three-dimensional approach is outperforming the 2D approaches as higher recognition rates are been obtained. The burden of capturing the images in different views and aligning them properly in the 2D approach is not present in the 3D approach. This process is being carried out with a single frontal image as input and thus automatically increasing the training set with different poses. Using the personalised 3D face shape models will increase the clarity of the reconstructed images and thus other constraints in face recognition such as illumination and expression would be easily overcome.

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