Improved Face Recognition Performance Using Eigen Face Algorithm

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Abstract -- **Now-a- days, computer vision field is popular and a very interesting area for research and technological development. Advancements in computers and imaging, navigation, multimedia enabled many novel computer vision applications. The aim of this paper is to effectively identify and improve face recognition performance using eigen face algorithm. In this paper, we determine minimum and maximum eigen face value for black and white or Novel color face detection.**

Keywords: Gabor filters, SVM, PCA, Neural Networks

I. INTRODUCTION

FACE recognition and significant part of the capability of human sensitivity system and is a routine charge for humans, while building a similar computational model of face recognition. Lately, confront face recognition has pulled in much consideration also its exploration has quickly stretched by not just designers anyway likewise neurosciences, since it has numerous potential applications in machine vision correspondence and programmed access control framework. Eigen face approach is one of the earliest appearance-based face recognition methods, which was developed by M. Turk and A. Pentland in 1991. This method utilizes the idea of the principal component analysis and decomposes face images into a small set of characteristic feature images called eigenfaces [1].

The recognition performance thoroughly degrades with pose and lighting variations, though the recognition performance has been improved substantially under frontal pose and optimal lighting conditions [2]. Previous the concept of eigenfaces were extended to eigen features, such as eigen eyes, eigen mouth, etc. for the detection of facial features [3].recently, fisher face space [4] and illumination subspace [5] have been proposed for face recognition under illumination condition. A previous work based on the Eigen faces approach was done by M. Turk and A. Pent land, in which, faces were first detected and then identified. In this thesis, a face recognition system based on the Eigen faces approach, similar to the one presented by M. Turk and A. Pent land, is proposed.

The scheme is based on an information theory approach that decomposes face images into a small set of characteristic feature images called Eigen faces, which may be thought of as the principal components of the initial Training set of face images [6]. Recognition is performed by projecting a new image onto the subspace spanned by the Eigen faces and then classifying the face by comparing its position in the face space with the positions of known individuals [7]. Such approaches have proven difficult to extend to multiple views and have often been quite fragile, requiring a good initial guess to quid them . Heseltine, Pears, and Austin [8] describe pre-processing techniques used to improve eigenface recognition. Tests are performed to compile data on false acceptance rates (FAR) and false rejection rates (FFR). Factors affecting face recognition include changes in intensity and direction of light, partially covered faces through sun glasses, hats, and facial hair, and changes in expressions on the face. Lanitis [9] describes an algorithm that uses the non-occluded part of the face for face recognition. The hidden part of the face is excluded from interfering with the face recognition process so that identification is improved. Gupta and Jain [10] describe a visual information n retrieval (VIR)system using recall of different type s of images from a repository, one of which has face retrieval using eigen features

II. THEOREM

In this theorem, we have Eigen values of a real symmetric matrix are all real. Contrariwise, the eigen values of a real nonsymmetric matrix may comprise real values, but may also comprise pairs of complex conjugate values with their eign values. The eigenvalues of a normal matrix with non fragment eigenvalues are complete and orthogonal, on both sides of the N- dimensional vector space.

Let the training set of face images be Γ1, Γ2, ΓM then the average of the set is defined by

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

In this face to face differs by their eign values and from the average by the vector

$$\Phi_i = \Gamma_i - \Psi . \tag{2}$$

This set of very large vectors is then subject matter to principal component analysis, which seeks a set of M orthonormal vectors, Un, which best describes the distribution of the data. The kth vector,UK, is chosen such that

$$\lambda_k = \frac{1}{M}\sum_{n=1}^{M}(u_k^T \Phi_n)^2 \tag{3}$$

is a maximum, subject to

$$u_l^T u_k = \delta_{lk} = \begin{cases} 1, & \text{if } l=k \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

The vectors UK and scalars λK are the eigenvectors and eigen values, respectively of the covariance matrix

$$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_n \Phi_n^T = AA^T. \tag{5}$$

where the matrix A=[Φ1, Φ 2, Φ M] The covariance matrix C, however is

$$N2 \times N2 \tag{6}$$

real symmetric matrix, and determining the N2 eigenvectors and eigen values is an obstinate task for typical image sizes. We need a computationally practicable method to find these eigenvectors. If the number of data points in the image space is less than the dimension of the space (M <N2), there will be only M-1, rather than N2 meaningful eigenvectors. The remaining eigenvectors will have linked eigenvalues of zero. We can solve for the N2 dimensional eigenvectors in this case by first solving the eigenvectors of an M x M matrix such as solving 16 x 16 matrix rather than a 16,384 x 16,384 matrix and then, taking suitable linear combinations of the face images Φ j.

Consider the eigenvectors v_i of A^T A such that

$$A^T A v_i = \mu_i v_i \tag{7}$$

Pre multiplying both sides by A, we have

$$AA^T A v_i = \mu_i A v_i \tag{8}$$

from which we see that Av_i are the eigenvectors of $C = AA^T$

Following these analysis, we construct the M x M matrix $L = A^T A$ where Lmn= Φ Tm Φ n and find the M eigenvectors,vi of L. These vectors determine linear combinations of the M training set face images to form the eigenfaces Ui

$$u_l = \sum_{k=1}^{M} v_{lk}\Phi_k , \quad l = 1,\dots,M \tag{9}$$

With this analysis, the calculations are greatly reduced, from the order of the number of pixels in the images (N2) to the order of the number of images in the training set (M). In practice, the training set of face images will be relatively small (M <<N2), and the calculations become quite manageable.

III. FACE BACKGROUND AND EIGENFACES

Face background in face recognition plays an eminent role in the eigenfaces approach because all information in the face image is used, without throw awaking any part of the image. Without face background, recognition performance should increase because; now the system only deals with facial information, not in the background. The results and experiment result are elaborated below; where we have received maximum and minimum value with face recognition results.

Test Input (1)

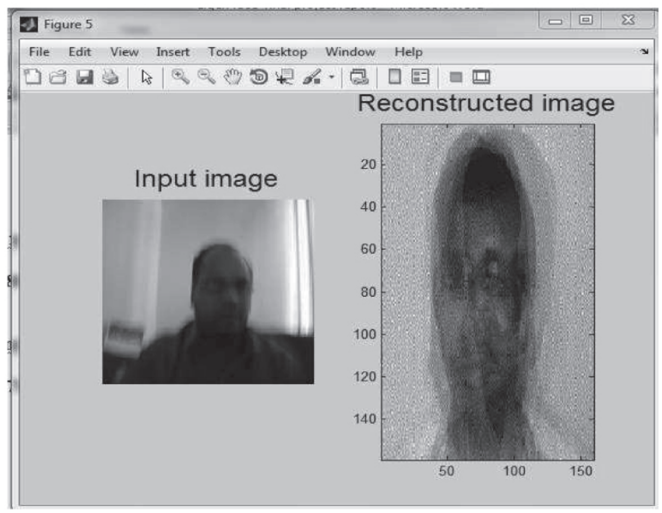

Figure 1. Test Image and Reconstructed Image.

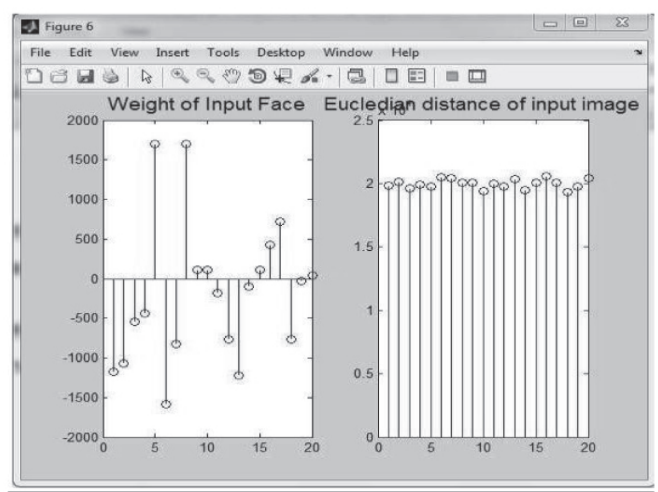

Figure 2. Weight and Euclidean Graph.

Output -

Maximum Value = 2.0542e+004
Minimum Value = 1.9312e+004

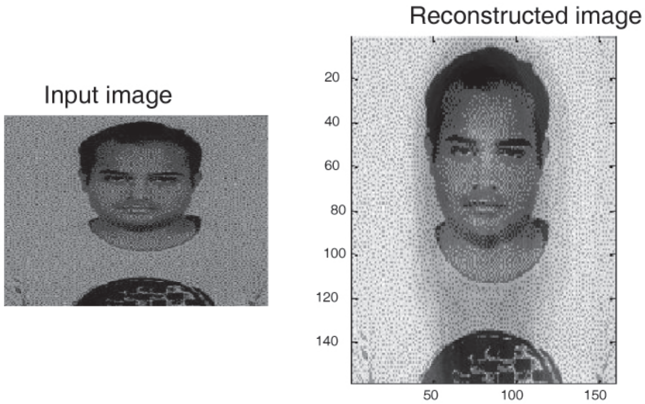

Figure. 3.

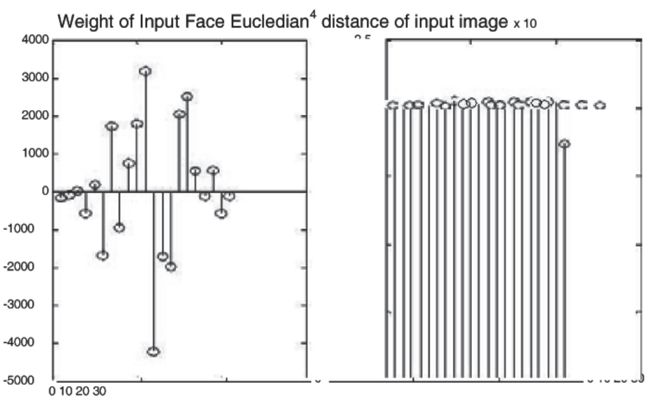

Figure 4.

Output -

MAXIMUM VALUE : 2.0486e+004
MINIMUM VALUE : 1.7330e+004

IV. CONCLUSION

An eigenfaces-based face recognition approach has been implemented in MatLab. This is to conclude that faces with different orientations, lightning, and illumination conditions have been recognized with 100% accuracy. We have received Maximum Value (2.0542e+0040 and Minimum Value (1.9312e+004) for first image and maximum value (2.0486e+004) minimum value (1.7330e+004) for second images respectively. In this paper ,we have effectively identified and improved face recognition performance using eigen face algorithm.

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