Face Recognition Using Eigenface and Discrete Wavelet Transform

Muzammil Abdulrahman, Yusuf G. Dambatta, A. S. Muhammad, and Abubakar S. Muhammad

Abstract—In this paper, Eigenface and Discrete Wavelet Transform (DWT) were used in Face recognition. Recognition performance in terms of recognition rate of the proposed face recognition system was tested by conducting experiments using MATLAB on Yale database. A face database set was constructed by selecting the first 10 images of each subject as training. While the last ten dark images were used as test set making a total of 200 images. The Yale database has images with varying pose, occlusion and illumination intensity. For the Eigenface, recognition rate versus number of Eigenface was plotted and a recognition rate of 92% was obtained while a result close to 93% was also obtained when the images of the database was first decomposed by a 3-level DWT for dimensionality reduction before they are finally passed to the PCA for final dimensionality reduction.

Keywords— Discrete Wavelet Transform, Principal Component analysis

I. Introduction

FACE recognition technology has outweigh other biometrics technologies, for its potential applications in the areas such as surveillance systems, border control, security access control, e-commerce, digital libraries, human-computer interaction, military, and personal identification [1] etc. Face recognition can be described as given a face image and identify it by using a stored face database, in other words Face Recognition can be described as classifying a face either as a known or unknown, after comparing it with known individuals stored in a database.

Face recognition consists of three stages [2]:

(i) The image is captured using a camera

(ii) The image is processed using appropriate signal processing techniques to form a template

(iii) The template is compared with several other templates for identification.

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The challenge in this process is to recognize the face from a general point under different illumination conditions and facial expressions such as smile, cry sad, emotion etc. Although human being can recognize different faces and facial expressions very easily, it is not so for computers, hence very difficult for the algorithms to extract and use the information content from the face and identify it as known or unknown by comparing with the database.

Initially, the train images are utilized to create a low dimensional face space i.e. Eigenface. This is achieved by performing Principal Component Analysis (PCA) in the training image set and taking the principal components i.e. Eigenvectors with greater Eigenvalues. In this process, projected versions of all the train images are also created. After which the test images are also projected on the face space resulting in all the test images to be represented in terms of the selected principal components.

II. Literature Review

Face recognition analysis can be categorized into holistic and feature based [3]. In feature based approach, the face recognition depend upon the localization and detection of facial features such as eyes, nose, mouth and their geometrical relationships [4], while on the other hand in a holistic approach, the entire facial image is encoded into a point on high dimensional space. Images are represented as Eigen images.

Turk and Pentland [5] developed an approach for face recognition using Eigenface. The research provides the computational pattern recognition for the face. Heseltine, Pears, and Austin [6] explain preprocessing techniques for enhancing Eigenface recognition. Experiments were conducted to compile data on false acceptance rates (FAR) and false rejection rates (FFR). The Factors that affect face recognition performance include changes in intensity and direction of light, partially covered faces through sunglasses, hats, and facial hair, and changes in expressions on the face. The paper highlights the effect of light illuminating one side of the face resulting in a principal component, which provides errors in identification of faces.

Gupta and Jain [7] developed a visual information retrieval (VIR) system using recall of different types of images from a repository, one of which has face retrieval using Eigen features. Image transformations are computed for each face. The limitation is that the computations become too intense as

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the database increases, hence difficult to automate and thus requiring for human intervention along with high associated training costs. Graham and Allinson [8] states that if the image of the person in the database is different from the test image, the system should recognize the person, which is defined as pose invariant recognition. When test images have different poses, the system should still be able to recognize the individual. For a computer this task may be unlikely because computers view images in pixels. To make the computer capable of invariant recognition, features must be removed. Pose invariant recognition is based on using different images of people for training, or by creating a 3D model, which can be used to generate more images.

III. Principal Component Analysis (PCA)

The aim of the PCA is to reduce the dimensionality [3], [12] of the raw data (features) while retaining as much as possible of the variation present in the dataset i.e. it compute a linear transformation that maps data from a high dimensional space to a lower dimensional sub-space. It finds orthonormal basis for data, sorts dimensions in order of importance and discard low significance dimensions. Though dimensionality reduction implies information loss, yet enough information need to be preserved as much as possible.

IV. Discrete Wavelet Transform

Discrete Wavelet Transform DWT [9] is use in analysis of signals and images. It decomposes an image into a set of basic functions called wavelets and the decomposition is defined as the resolution of an image. DWT has been proved to be a very useful tool for image compression in the recent years [10]. It supports the multi resolution analysis of data i.e. it can be applied to different scales according to the details required, which allows progressive transmission and zooming of the image without the need of extra storage. 2D-DWT is implemented as a set of filter banks, comprising of a cascaded scheme of high-pass and low-pass filters. The final result obtained is a decomposition of the input image into four non-overlapping multi-resolution sub-bands: LL, LH, HL and HH. The sub-band LL represents the low frequency component of DWT coefficients while the HH sub-bands represent the high frequency component of DWT coefficients. In this work LL is explored for face recognition. There are a lot of wavelet filters like, Daubechies wavelets, Coiflets, biorthogonal wavelets, and Symlets. These various transforms are different in mathematical properties such as symmetry, number of vanishing moments and orthogonality. Finally some mathematical distance techniques are used to retrieve the relevant faces from the database based on minimum distance. Distance measures are based on Euclidean distance.

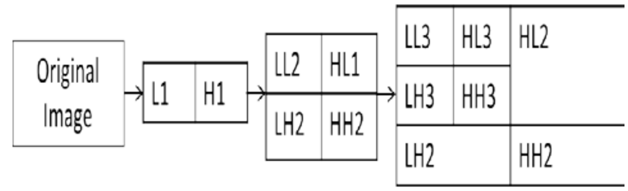

Fig. 1 The flowchart of the Wavelet Transform on the digital image

Fig. 2 The result of the 2-D Discrete Wavelet Transform from level one to level three [11]

FLOWCHART

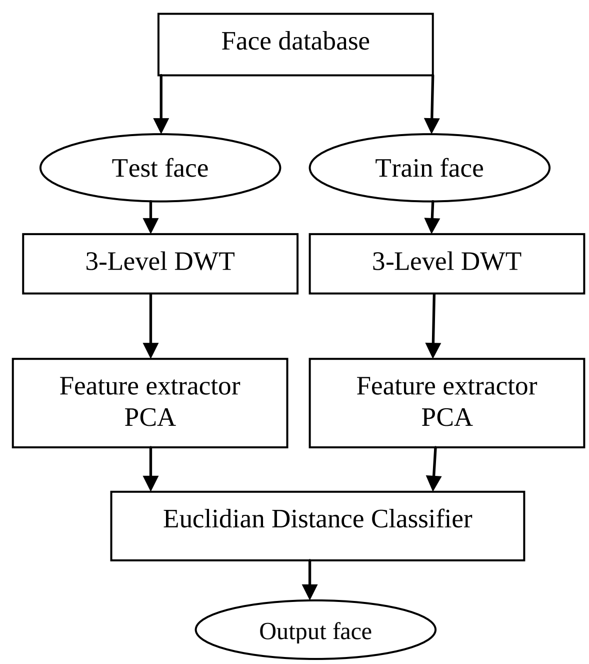

Fig. 3 Flowchart of the Proposed Algorithm

V. Result

Recognition performance in terms of recognition rate of the proposed face recognition system is tested by conducting experiments using MATLAB on Yale database. A face database set was constructed by selecting the first ten images of each subject were used for training. While the last ten dark images was used as test set making a total of 200 images. The Yale database has images with varying pose, occlusion and illumination intensity since changes in illumination affects the low frequency spectrum LL components are chosen. The Eigen faces of first 20 were shown below. The recognition rate versus number of Eigen face was plotted and a recognition rate of 92% was obtained while a result close to 93% was also obtained when the images of the database was first decomposed by a 3-level DWT for dimensionality reduction before they are finally passed to the PCA for final dimensionality reduction. In the Eigenface, the face of the test image will be reconstructed after comparing it with the Eigen face of the database by comparing it weight, the higher the number of Eigenfaces chosen the better and the closer the reconstructed image to the original. The reconstruction of Eigenface of a *non face image* also look like a face, but will be rejected because its weight will not be closer to any of the Eigenface in the database.

VI. Discussion

A 3-level LL DWT was chosen because the LL allows the low frequency of the image to pass while attenuating higher frequencies. Since the noise and edges are among the higher frequency component they will be suppressed hence reducing the dimensionality of the image before passing it to PCA. The efficiencies of using Eigenface alone and using DWT then PCA is almost the same in this case because the images in the database are not noisy and are of the same dimensions but in a noisy images the DWT-PCA will be of higher efficiency and it converge faster than the Eigenface.

It can also be seen that during image reconstruction the higher the number of Eigenfaces chosen the better and the closer the reconstructed image to the original but at the expense of computational difficulty, hence a proper choice for the number of Eigenfaces to be chosen so as to reduce computation complexity.

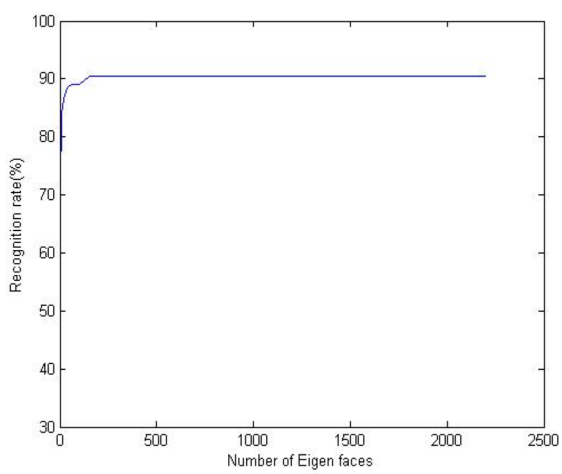

Fig. 4 PCA Recognition Rat**e**

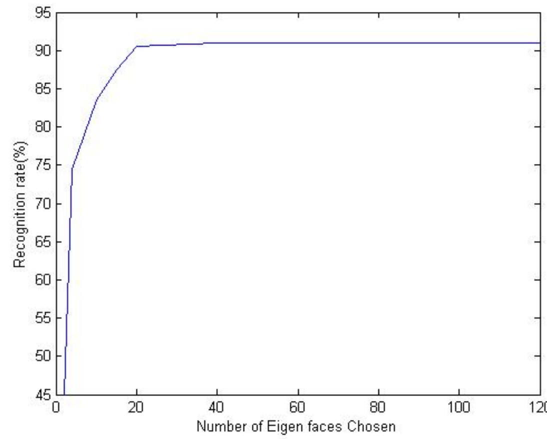

Fig. 5 Recognition Rate of PCA on 3-level DWT

VII. Conclusion

The performance of the two algorithms were compared and the performance of DWT-PCA is higher than that of Eigenface alone since it converge with relatively the same recognition rate but the former converge faster than the latter. Also the number of levels in DWT affects efficiency.

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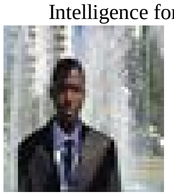

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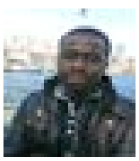

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