A NEAR REAL-TIME FACE RECOGNITION SYSTEM BASED ON EIGENFACES

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Abstract

In this paper we propose a prototype of a near real-time automatic face recognition system that is aimed for operations in a less constrained environment, using the earliest appearance-based face recognition technique called eigenfaces. The main idea of eigenfaces is to decompose face images into a small set of significant characteristic feature images called eigenvectors, which are the principal components of the original images. They do not necessarily represent facial features such as eyes, nose and mouth. These eigenvectors form a low dimension face space, which is later used in the recognition process. The system has three main modules; the image acquisition module, preparation module and recognition module. This approach is easy to implement and robust.

Key Words: Face recognition, Biometric authentication, Eigenfaces, Image processing.

1. Introduction

The biometric technology of a face recognition system is used to verify an identity of a person by matching a given face against a database of known faces. It has become a viable and an important alternative to traditional identification and authentication methods such as the use of keys, ID cards and passwords. Traditional ways are robust against theft, fraud, misplacements, forgetfulness and forgery.

Face recognition technology can be applied to a wide variety of application areas including access control for PCs, airport surveillance, private surveillance, criminal identification and as an added security for ATM transaction. In addition, face recognition system is also currently being used in growing numbers of applications as an initial step towards the next-generation smart environment where computers are designed to interact more like humans.

In recent years, considerable progress has been made in the area of face recognition with the development of many techniques. Whilst these techniques perform extremely well under constrained conditions, the problem of face recognition in uncontrolled environment remains unsolved.

Therefore, we have focused our work towards developing an automatic face recognition system, which is robust against adverse factors such as changes in lighting, orientation and scaling conditions, using eigenfaces technique. Our aim was to develop a prototype of a simple, near real- time system to operate in a less constrained environment.

Our system maintains a database of face images of known users. These face images are manually processed to normalize them in terms of its lighting, scaling and orientation. This project involves three main modules: the pre-processing module, preparation module and recognition module. The image-capturing module obtains the input image from the camera. The image captured, which is the image of an unknown person to be verified, is also known as a test image in our system. The normalization process is also performed by this module to prepare the test image for utilization in the system.

As a pre-processing step of the system, the preparation module obtains the known face images in the database to create a low dimension subspace known as face space. The unknown face captured earlier is then sent to the third module, the recognition module. This module performs the recognition process by projecting the input image into the face space created. Next, it classifies the face by comparing the input image's position in the face space with the position of known faces using the distance metric, Euclidean distance.

2. Background & Related Work

Modern research on face recognition can be divided into few categories; face detection, facial features extraction, face normalization and face identification. Face detection is often considered the pre-processing step, although it is not necessarily simple. Different specific approaches were proposed for the face detection. Among those are graph matching [1], model-based approach [2], motion-based approach [3], elastic matching [4] and probability densities [5].

The facial feature location are used either for the normalization step or identification process itself. Techniques such as Gabor filter [6], heuristic algorithm [7], Hough transform [8], eigenfeatures [9] and symmetry operators [10] can be used to locate the facial features of interest.

Face normalization is a crucial phase as the robustness behaviour of a face recognition system greatly depends on it. By performing explicit normalization such as lighting, expression, rotation and scaling normalization on the input image, robustness of the face recogniser is increased. The lighting normalization is described in detail in [11]. A traditional way of performing lighting normalization is histogram equalization [12]. For extreme illumination changes, illumination subspace [13] can be used. An affine transformation [14] is employed to perform the expression normalization. Having the facial features location, scaling and orientation can be normalized using template matching approach as described in [15].

The face identification is the actual recognition process. It is the representation of faces where comparison is performed on the input face with the database of known faces. There are various approaches in this phase. They are mainly feature-based [16], template-based [17], neural network [18], elastic graph [19] and eigenfaces [20].

Feature-based is a geometrical approach and needs the facial features location to be known in advance. Having the location, spatial configuration of facial features are captured and used to form feature vectors. Comparison is then made with the input image's feature vector with the database of the image's vector. This method requires only minimal memory and higher speed. However, it relies heavily on feature location algorithm. It is also unable to perform well under varying imaging condition.

The template-based on the other hand, is a pictorial approach. The image vector is formed by ordering the gray-scale image of the unknown face. The face image can be represented by its original gray levels, gradient magnitude or gradient vectors. The image vector is then compared to the database by calculating correlation. The image with the largest correlation is chosen to be the closest match. Although this method provides easy implementation, it is highly sensitive to scaling, noise and lighting.

The neural network has been a popular approach in face recognition and there are many variations. The most popular is the back-propagation neural network. The disadvantages of this approach are its sensitivity to lighting variation, difficulties in implementation, complex and arduous training. Even a small size image needs a large number of neurons input for processing. The fundamental problem of neural network is due to its method not explicitly using the configuration properties of faces.

Face is represented as elastic labelled graph of local textural features in the elastic graph approach. Nodes are particular points of face such as eyes, nose and mouth. This method is suitable for faces with different views. New faces are matched to find the facial landmark and then used for comparison. The recognition rate by this method is high but it is computationally expensive.

The most prominent technique is the eigenfaces approach. The scaling or normalization of facial features according to their relative importance in face recognition is the basic premise behind the eigenfaces technique. This technique does not depend upon having full three-dimensional models or detailed geometry. Unlike other techniques, eigenfaces are robust against noise, poor lighting conditions and partial occlusion. Eigenfaces are relatively insensitive to small variations in scale, rotation and expression. Eigenfaces have been shown to produce 96% accurate classification under varying lighting condition [21]. Coupled with their robustness against variations in scale and rotation, it is clearly superior over techniques based on distance between facial features. Eigenfaces requires no training and so it is not subjected to the problems associated with neural networks. Eigenfaces have also been shown to maintain accuracy even with large-scale database [9].

3. Eigenfaces in Detail

This approach was first proposed by Sirovich and Kirby [22] as an application of the principal component analysis for representation of face images. From considering face portion containing eyes and nose only, they extended their approach to full face [23]. Turk and Pentland [20] later refined this method by adding pre-processing and expanding database. They have also discovered that only a relatively small number of eigenfaces are required for the recognition process. This was a remarkable finding because it significantly reduced the computational time.

The eigenface representation method for face recognition is based on the principal component analysis. The main idea is to decompose the face images into a small set of characteristic feature images called eigenfaces, which may be thought of as the principal component of the original images. Eigenfaces are like ghostly faces formed by the eigenvectors. Some of the faces studied in our earlier coarse implementation [24], are illustrated in Figure 1.

The eigenfaces technique catches the total variation in a set of facial images and explains this variation by as few variables as possible. This is important because it allows us to explain an observation with fewer variables. This not only decreases the computational complexity of face recognition, but also scales each variable according to its relative importance in explaining the observation.

This method attempts to capture the variation between facial images in an orthogonal basis set of vectors referred to as eigenvector. The eigenvectors are thus the image vectors, which map the most significant variation between faces. Under the assumption that faces form a simply connected region in image-space (the space contains all possible images, facial and non-facial), we can represent any face as a linear combination of eigenvectors. Each face can thus be represented by a weight vector, which contains the proportions of each eigenvector needed to construct that face. By comparing the weight vector of an unknown face to the weight vectors of a database of known faces, a match can then be determined.

In our system, this approach falls in the first and third module; preparation and recognition module. Under the preparation module, two operations take place; face space creation and face space projection. Section 4.1 and 4.3 will detail the implementation of this eigenfaces approach. Figure 2 shows the screen shot of the system.

4. System Descriptions

4.1 Preparation Module

This is the initial step where the system is prepared before capturing input and recognition process. It is executed only once during the system start-up or when adding a new face image to the database.

4.1.1 Face space creation

Consider a black and white image of size $N \times N$. The notation $I(x,y)$ is simply a matrix of 8 bit values with each elements representing the intensity at that particular pixel. $I(x,y)$ may also be considered as a vector of length N^2 or a single point in a N^2 dimensional space.

In this system, our database contains images of 10 persons with each person having 6 different images. As our system excludes out-plane orientation normalization and expression normalization, variations of these are included in the database. Each person has frontal-view neutral expression, frontal-view smiling expression, 15° left-view with neutral expression, 15° left-view with smiling expression, 15° right-view with neutral expression and 15° right-view with smiling expression.

The size of each image measures 320×240 pixels. So a 320×240 pixel image can be represented as a point in a 76800 dimensional space. Facial images in general will occupy only a small sub-region of this high dimensional image space and thus not optimally represented in this coordinate system. Each face images is represented by a vector, V of dimension 76800 as shown below:

$$\begin{bmatrix} P_1 \ P_2 \ P_3 \ P_4 \ldots\ldots P_{320} \\ \ldots\ldots\ldots\ldots\ldots\ldots \\ \ldots\ldots\ldots\ldots\ldots\ldots \\ \ldots\ldots\ldots\ldots\ldots\ldots \\ \ldots\ldots\ldots\ldots\ldots P_{76800} \end{bmatrix} \quad \text{Image}$$

$$\big\downarrow$$

$$\begin{bmatrix} P_1 \ P_2 \ P_3 \ P_4 \ldots\ldots P_{76800} \end{bmatrix} \quad \text{Vector, V}$$

So, if there is M images in the database, then the training set will be $\{V_i \mid i = 1, \ldots, M\}$.

The average face of the these M images is calculated and given by

$$\Psi = \frac{1}{M} \sum_{i=1}^{M} V_i$$

Then each face V_i differs from the average face, Ψ by Φ_i

$$\Phi_i = V_i - \Psi \ ; \ i = 1, \ldots, M$$

A covariance matrix of the training images can be constructed as follows:

$$C = A A^T$$

where,

A^T = transpose of A

and,

$$A = [\Phi_1, \Phi_2, \ldots, \Phi_M]$$

The basis vector of the face space, i.e. the eigenfaces, are the orthogonal eigenvectors of the covariance matrix C. However, finding the eigenvectors of the 320×240 matrix C is an intractable task for typical image sizes. So, a simplified way of calculation has to be adopted. Since the number of training images is usually less than the number of pixels in an image, there will be only $M - 1$ meaningful eigenvectors. Therefore, the eigenfaces are computed by first finding the eigenvectors, T_l $\{l = 1,\ldots,M\}$ of the matrix M x M, matrix $L = A^TA$. The eigenvectors, U_l $\{l = 1,\ldots,M\}$, of matrix C are then expressed by a linear combination of difference face images, Φ_i $\{i = 1,\ldots,M\}$, weighted by T_l $\{l = 1,\ldots,M\}$:

$$[U_1 \ldots\ldots U_M] = [\Phi_1 \ldots\ldots \Phi_M]\,[T_1 \ldots\ldots T_M] = A \,.\, T$$

In practice, a smaller set of M' (M' < M) eigenfaces is sufficient for face identification. Hence, only M' significant eigenvector, k of L matrix, corresponding to the largest M' eigenvalues, λ are selected for eigenfaces computation, thus resulting in a further data compression. Largest eigenvalues are determined by the ratio below:

$$\frac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{N} \lambda_i} \approx 0.95 - 0.99$$

4.1.2 Face space projection

The face of each known individual, V_k projected into the face space and M' dimensional vector, Ω_k is obtained:

$$\Omega_k = U^T (V_k - \Psi) \ ; \ k = 1,\ldots,N_C \,,$$

where N_c is the number of face classes, i.e number of person in the database.

4.2 Image Acquisition Module

A person is seated in front of the camera on a chair with adjustable height. The background is a white board to ease the process of background elimination. The person's face image is then captured using a Charged

Couple Device (CCD) camera. The camera provides a resolution of 640 × 480. As a small image is preferred over a large image, we have reduced the resolution to 320 × 240. This preference is due to the reason that the computation complexity of system increases when the size of the image increases.

After the raw image is captured, it has to be pre-processed to minimize the variation caused by lighting and camera image digitization. For this, we have used histogram equalization. This technique pulls the intensity range of an image dynamically so that the image looks brighter, consequently produces an increase in image contrast, which helps in edge detection. The effect of performing histogram equalization is shown in Figure 3. Figure 3(a) is the original image and Figure 3(b) shows after transformation.

Having an input image, face detection must be performed to check whether the input image contains a face. Having the average face Ψ, eigenvectors U, and difference of face images Φ, as the outputs of preparation module, the distance, ε between the original image, V and its reconstructed image from the eigenfaces space, F is computed:

$$\varepsilon^2 = \| V - F \|^2$$

where, $F = U. \Omega + \Psi$

If the distance ε is more than the threshold θ_C, then the input image captured is not a face image, therefore, subsequent processes are aborted. However, if the distance ε, is less than the threshold, then the input image is a face image.

It is known that the head size in the input image must be close to the eigenfaces for the system to provide a good accuracy level. Adopting the head locating technique in [20], the head is detected and the face image is rescaled to the eigenfaces size.

After the left and right eyes are detected, the next task will be to adjust for in-plane rotation. Let θ be the angle subtended between left-right-eye-line and the horizontal axis. By rotating the acquired facial image θ clockwise, this angle will become zero, effectively removing any in-plane rotation.

The input image is now ready for the recognition process.

4.3 Recognition Module

A distance threshold, θ_C, that defines the maximum allowable distance from a face class as well as from the face space, is set up by computing half the largest distance between any two face classes:

$$\theta_C = \frac{1}{2} \max \{ \| \Omega_j - \Omega_k \| \}; \quad j, k = 1,\ldots, N_c$$

A new image, V is projected into a face space to obtain a vector, Ω:

$$\Omega = U^T V - \Psi$$

The distance of Ω to each face class is determined using the Euclidean distance algorithm. This algorithm recognizes faces by geometrically comparing them to faces in the database. The distance of Ω to each face class is defined by:

$$\varepsilon_k^2 = \| \Omega - \Omega_k \|^2 ; \quad k = 1,\ldots, N_c$$

These distance are computed with the threshold given in θ_C and the input image is classified by the following rules:

- $\forall k$, $\varepsilon_k \geq \theta_C$ THEN input image contains an unknown face
- $\varepsilon_{k*} = \min_k\{ \varepsilon_k \} < \theta_C$ THEN input image contains the face of individual k*

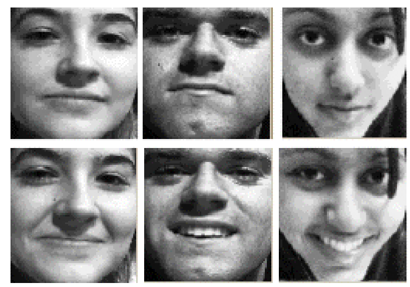

Figure 1: Some of the face images studied in previous work

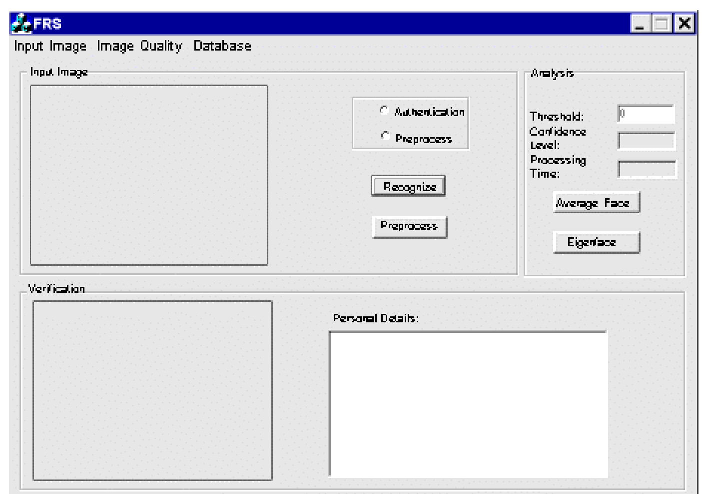

Figure 2: Screen shot of the proposed face recognition system

(a) (b)

Figure 3: Effect of histogram equalization

5. Conclusion

We are working on building this prototype of a near real-time face recognition system using the eigenfaces approach. This approach provides a good practical solution for face recognition problems. It is simple and it works well in a less constrained environment.

References

[1] T. Leung, M. Burl, and P. Perona, Finding faces in cluttered scenes using labeled random graph matching, *Proc. 5th Int. Conf. On Comp. Vision 1995,* 637–644, MIT, Boston.

[2] G. Yang and T.S. Huang, Human face detection in a complex background, *Pattern Recognition 1994*, 27 (1) : 53 – 63.

[3] T. I. P. Trew, R. D. Gallery, D. Thanassas, and R. Badique, Automatic face location to enhance videophone picture quality, *Proc. 4th British Machine Vision Conf. 1993,* 488 – 497. Springer – Verlag.

[4] M. Lades, J. Vorbruggen, J. Buhmanb, J. Lange, C. V. D. Malsburg and R. Wurtz, Distortion invariant object recognition in the dynamic link architecture, *IEEE Trans. Comput., vol 42*, 300-311, 1993.

[5] B. Moghaddam and A. Pentland, Probabilistic Visual Learning for Object Detection, *IEEE Proc. of the 5th International Conf. on Computer Vision*, Cambridge, USA, June 1995.

[6] E. Hjelmas, Feature-Based Face Recognition, *Proc of Norwegian Image Processing and Pattern Recognition Conference*, 2000.

[7] N. Poh and J. Korczak, *Biometric Authentication System* (Masters Thesis, USM, Penang, Malaysia, 2001).

[8] A. Nikolaidis and I. Pitas, Facial feature extraction and pose determination, *Pattern Recognition, Elsevier, vol. 33*, no. 11, 1783-1791, November 2000.

[9] A. Pentland, B. Moghaddam and T. Starner, View-Based and Modular Eigenspaces for Face Recognition, *IEEE Conf. on Computer Vision & Pattern Recognition*, 1994.

[10] D. Reisfeld, H. Wolfson and Y. Yeshurun, Detection of Interests Points Using Symmetry", *ICCV '90*, Osaka, Japan, Dec 1990.

[11] Y. Adini, Y. Moses and S. Ullman, Face Recognition: the Problem of Compensating for Changes in Illumination Direction", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, July 1997.

[12] R. C. Gonzales and R. E. Woods, *Digital Image Processing* (Addison Wesley, 1993).

[13] A. S. Georghiades, D. J. Kriegman and P. N. Belhumeur, Illumination cones for recognition under variable lighting: Faces, *Proc IEEE Conf on Computer Vision and Pattern Recognition*, 52-59, 1998.

[14] D. Reisfeld, N. Arad and Y. Yeshurun, Normalization of face image using few achors, *International Conf. on Pattern Recognition*, volume 1, 761-763, 1994.

[15] D. J. Beymer, Face Recognition Under Varying Pose, *Proc. IEEE Conf. On Computer Vision and Pattern Recognition*, 756-761, 1994.

[16] R. Brunelli, T. Poggio, Face Recognition through Geometrical Features, *European Conference on Computer Vision*, 792-800. Springer-Verlag, 1992.

[17] R. J. Baron, Mechanism of human facial recognition, *International Journal of Man Machine Studies*, 15:137-178, 1981.

[18] G. W. Cottrel and M. Fleming, Face recognition using unsupervised feature extraction, *Proc. Int. Neurak Network Conf*, Paris, France, July 1990, 332-325.

[19] L. Wiskott, J. Fellous, N. Kruger and C. Larsbnurg, *Trans. on Pattern Analysis and Machine Intelligence*, Vol.19, pp.775-779 , 1997.

[20] M. Turk and A. Pentland, Eigenfaces for Recognition, *Journal of Cognitive Neuroscience*, vol. 3, no. 1, pp. 71-- 86, 1991.

[21] M. A. Turk, A.P. Pentland, Face Recognition Using Eigenfaces *11th International Conference on Pattern Recognition*, pages 586--591, 1991.

[22] L. Sirovich and M. Kirby, Low dimensional procedure for the characterization of human face image, *Journal of Optical Society of America*, vol. 4, 519-524, 1987.

[23] M. Kirby and L. Sirovich, Application of the Karhunen-Loeve procedure for the characterization of human faces, *IEEE Trans., Pattern Analysis and Machine Intelligence, Vol.*, 12, No. 1, Jan 1990

[24] Jayaletchumy, K. Kalaiarasi and R.K. Subramanian, A Face Recognition System Based On Eigenfaces Technique, *MMU International Symposium on Information and Communications Technologies 2001*, Petaling Jaya, Malaysia.