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A Simple Face Recognition Algorithm using Eigeneyes and a Class-Dependent PCA Implementation

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Abstract: In this study, a face recognition system using PCA on eigenimages is proposed. This system automatically detects the eyes region from a face image using the wavelet transform. These detected eyes are separated from the face image then eigeneye decomposition is performed. A new classification based on the least squares estimate to improve recognition accuracy is also proposed. Good improvement in classification is achieved which outperforms traditional PCA on the whole face especially when taking into accoun the substantial reducation in the computational complexity of the proposed algorithm.

Key words: Face recognition, eigeneyes, class-dependent, PCA

INTRODUCTION

Face recognition is widely used in biometric systems. Although, some reliable systems of biometric identification have been developped, most of these algorithms require strict subject cooperation. To create efficient biometric systems, a good research effort has been spent on optimizing such algorithms. The main 2 factors used to compare different algorithms are: complexity and efficiency (Zhao *et al*., 2003). Unfortunately, most existing techniques require long training and recognition times. Most face recognition techniques developed use the complete face image (Turk and Pentland, 1999) while few others perform operations on local features like eyes, nose, mouth etc (Kanada, 1977; Kelly, 1970). It has been observed experimentally that good recognition rate can also be achieved using only local facial features. It was shown that techniques using the whole face are prone to errors dues the changes of face feature over time. Features like facial hair and beard can also affect face recognition accuracy. Unlike the complete face, eyes do not change significantly with time. As such, we propose here the idea of using eyes for face recognition.

In this study, we propose a novel face recognition system. This system first detects the eyes from the face image. These detected eyes are then separated from the face image to perform eigenfeature decomposition. We then use these eigenfeatures to classify test images. A best fit of the projection of unknown image onto the eigenspace is calculated using a least squares approach. Distance between this fit and the original image projection is used for classification. In this research, we have used the AT and T faces database. This database consists of 400 gray-scale images of 40 persons.

EXTRACTION OF EYES FROM FACE IMAGES

The first step of the proposed system starts by extracting the eyes image from the given face images. We applied this technique to all 400 images to create a local eyes database. This process is explained in the following flowchart (Fig. 1).

Eyes detection

Wavelet decomposition: Wavelets have been widely used in facial feature extraction. The main rationale is that wavelets provide a powerful multi-resolution analysis of the image. The wavelet decomposition of an image is usually by applying a series of filters. By applying a

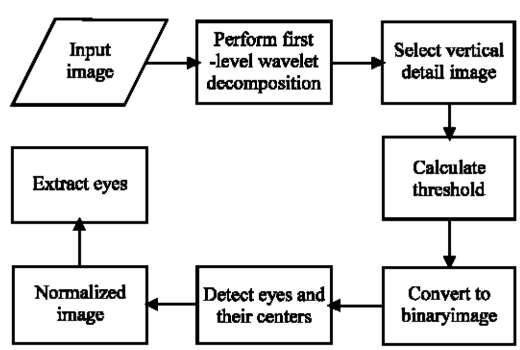

Fig. 1: Flowchart for extracting the eyes images

Fig. 2: One level wavelet decomposition

low-pass (H) and a high-pass (G) filter, we can get an approximation image and a details image to the original image.
This is performed as follows:

$$A_n = [H_x * [H_y * A_{n-1}]\downarrow x]\downarrow y$$
$$D_{n1} = [H_x * [G_y * A_{n-1}]\downarrow x]\downarrow y$$
$$D_{n2} = [G_x * [G_y * [H_y * A_{n-1}]\downarrow x]\downarrow y$$
$$D_{n3} = [G_x * [G_y * A_{n-1}]\downarrow x]\downarrow y$$

where, * is the convolution operator, ↓ x and ↓ y are subsampling along rows and columns, respectively. A n is the approximation at level n and D n are the details at level n. A 0 is the original image. The selection of these filters is an important issue and is application dependent. A lot of research efforts has been spent to develop specific filters for speicific applications. In this research, the filters we used are the filters proposed in Garcia and Tziritas (1999). These were found very efficient for our application of interest:

$$H(z) = 0.853 + 0.377(z + z^{-1}) - 0.111\,(z^2 + z^{-2}) - 0.024(z^3 + z^{-3}) + 0.038(z^4 + z^{-4}) \quad (1)$$

$$G(z) = -z^{-1} H(z^{-1}) \quad (2)$$

In our experiments, we performed a one-level decomposition to obtain an approximation and three details images (Fig. 2). Notice that the facial features (edges) are mostly in the horizontal directionrection. As such, we selected this horizontal detail image for further processing. This one level decomposition gave enough information on the prominent edges of the image.

Fig. 3: Binary image after thresholding

Thresholding to create the binary image: The detail image from the previous stage is then converted to a binary image through thresholding. We propose here to use for threshold the average of the highest and the lowest gray level of the detail image. The resulting binary image consists of only of the high-intensity points represeting the boundaries of the eyes, mouth, nose etc. Some other edges will also be visible depending upon the image. Morphological opening is then performed to remove the points at the border and some isolated points to get a clean binary image as shown in Fig. 3.

Detecting the eyes and their centroids: It is obvious that the position of the eyes can now be determined if we search for non-black points in both row and column directions. This way, we can separate both eyes and estimate the centers by calculating the centroid of these eyes regions. Once the centers of the eyes are known in the binary image we can map the centers in the original image as well. Some of our results are shown in Fig. 4.

Normalization of the image: Once we have the centers of eyes we can normalize each image such that the line between the two centers is horizontal, as shown in Fig. 5 (through rotation). Let the distance between the centers of eyes be d. After rotating the whole image we use this distance (d) to extract a useful area. Based on extensive experiments, we decided to extract an area 1.8 d wide and 0 65 high. The details are shown in Fig. 6. The figure shows that, using these distances, we are able to cover the area containing the eyes and the eyebrows.

Fig. 4: Successful detection of eyes region

Fig. 5: Normalizing the image

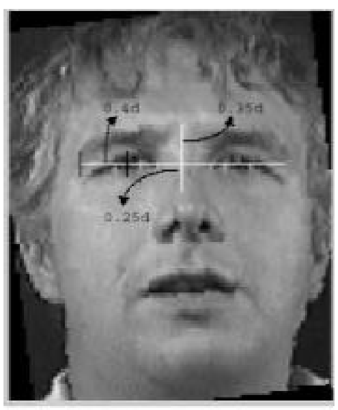

Fig. 6: Extraction of eyes area

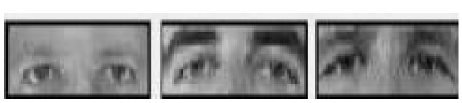

Fig. 7: Samples from the eyes database

This is done with all images in the ATT database. All eyes images are then resized to a standard of 30×75 image to create the eyes database. Some samples from the resulting database are shown in Fig. 7.

FACE RECOGNITION USING EIGENFEATURES

During the recognition stage, we propose to use Principal Component Analysis (PCA). PCA has been proven very robust to minor changes in features. Specifically, PCA is a dimension reduction technique based on the concept of finding the main directions in the data. These main directions are the eigenvectors extracted from the covariance matrix obtained from the data. From the 400 images, we selected 160 (4 per person) for training. The remaining images were used for testing.

Before training, we compute a mean image from these training images and subtract it from all the images. The mean image is shown in Fig. 8. This is done to simplify the implementation of the Before initiating the PAC decomposition, we first convert the two dimensional images into vectors by concatinating the rows. Let x_i denote the i th image in vector form of dimension N ×1, then the estimated mean image (for a database of M images), shown in Fig. 8, is calculated as:

$$m_x = \frac{1}{M}\sum_{i=1}^{M} x_i \tag{3}$$

Let ei and λ i be, respectively the eigenvectors and corresponding eigenvalues of Cx-the estimated covariance matrix given by:

$$C_x = \frac{1}{M}\left[\sum_{i=1}^{M} x_i x_i'\right] - m_x m_x' \tag{4}$$

Then a transformation matrix A, whose rows are the eigenvectors of Cx can be used to project an image into the eigenspace formed by the eigenvectors eis. This transformation is $y = A(x - m_x)$. In this transformation, dimension reduction is performed while preserving the components that contribute most of the variance. We can select an arbitrary number of significant eigenvectors for projecting an image into the eigenspace. As the number of eigenvectors is increased, a better representation of the image is obtained. Usually the number of images used for training (M) is less than the number of pixels (N) in an image. In order to simplify the expensive process of eigenvectors calculation dimensionality reduction of C_x matrix is performed. The overall recognition rate for the PCA decomposition is usually displayed as a function of the number of eigenvectors. Obviously, the recognition rate improves as we increase the number of eigenvectors to form eigenspace. Similar, to the concept of eigenfaces, we call the eigenvectors obtained from eyes images as eigeneyes.

These eigeneyes are found by applying PCA on eyes database. The process of finding the eigeneyes is the training stage of system. Once the system is trained, we test it on a number of images. Obviously, these test

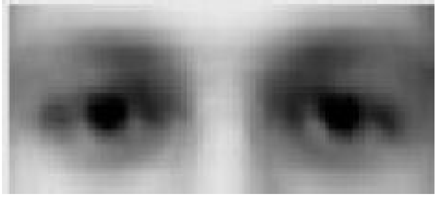

Fig. 8: Mean image

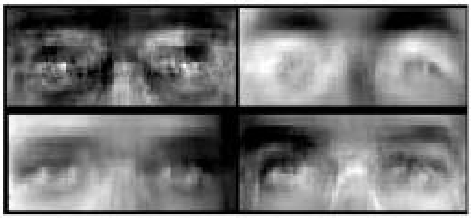

Fig. 9: The first 4 eigeneyes

images are not used in the training process. These test images (after removing mean) are projected onto the eigenspace. Similarly, all training images in the database are projected onto the eigenspace. We then compute the distance between the projection of the unknown (test) image and all the projections from the training images of the database. The class which gives the minimum distance is declared as the class of the unknown test image. Euclidean distance metric is used in this case. The first four eigeneyes can be seen in Fig. 9. In the next study, we propose a new method for improving classification using the least squares approach.

IMPROVING PCA USING LEAST SQUARES

The problem with the tradition PCA is that each of the images from the same class (person) are considered to be a class in itself. In this research, we propose to use the least squares estimate of the unknown image projection to improve classification. In this method, the process requires a model that relates the unknown image to the images in each class. This can be done with the help of one or more coefficients. The image obtained by using these coefficients is called fitted image. To avoid the complexity that occurs due to the large size of image we use the projections of the images onto the eigenspace. The difference between the projection of the unknown image (x) and the projection of the fitted image ($\hat{x}$) is defined as error ($\in$), also called residual.

$$\in = x - \hat{x} \tag{5}$$

Note that the images x and $\hat{x}$ are in vector form. The least squares method minimizes the summed square of residuals to obtain the coefficient estimates. Let us say we decide on using only three training images per class, then we need three coefficients ($\alpha 1$, $\alpha 2$, $\alpha 3$). These can be found using the following Eq:

$$\begin{aligned} x &= \alpha_1 x_1 + \alpha_2 x_2 + \alpha_3 x_3 + \in \\ x &= [x_1 x_2 x_3] \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} + \in \\ x &= X_c \alpha + \in \end{aligned} \tag{6}$$

Here, X_c is a matrix, unique for each class, formed by the projections of three images for that class and $\in$ is the error vector. The LS estimate of the coefficient vector, $\hat{\alpha}$, can be found by:

$$X_c^T X_c \hat{\alpha} = X_c^T x$$

$$\hat{\alpha} = (X_c^T X_c)^{-1} X_c^T x$$

This $\hat{\alpha}$ is used to find $\hat{x}$ given in Eq. 5 as:

$$\hat{x} = X_c \hat{\alpha} \tag{7}$$

Estimated images ($\hat{x}$) are calculated for all classes for the given test image. After that we evaluate the euclidean distance between the test image and estimated images. The class of the estimated image that gives minimum distance is said to be the class of the unknown image.

EXPERIMENTAL RESULTS

We are using the AT and T face database in our experiments. There are ten different images of each of 40 distinct subjects. The eyes database was created using this face database. The experiments for face recognition were performed for 2 different numbers of training samples. The first result of Fig. 10 compares the recognition rate when this technique was applied to faces and eyes separately.

It can be seen that the results are quite satisfactory if we do not consider the high computation time required for identifying faces (due to large size).

The results show that as we increase the number of eigeneyes used for classification the recognition rate improves. The recognition rate can also be increased if we increase the number of training samples. Figure 11 compares the results when the system was trained with four and six eyes per person. The results show that the improvement in recognition rate is very good. By using

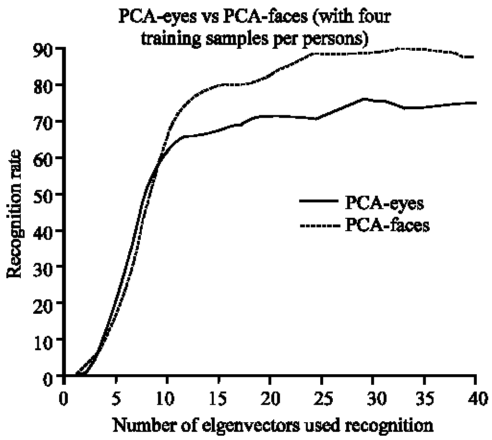

Fig. 10: Comparison of recognition rate when PCA was applied to whole face vs only eyes

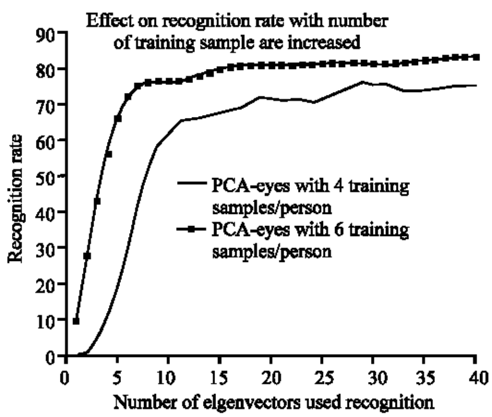

Fig. 11: Comparison of recognition rate (different number of training samples)

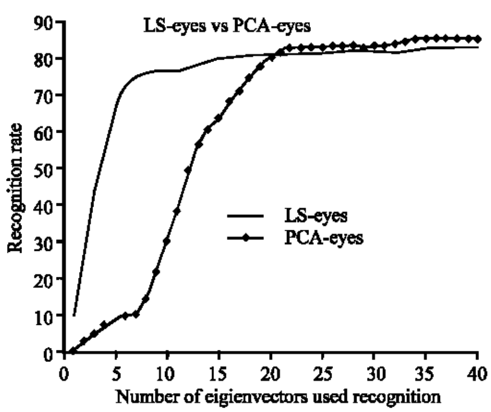

Fig. 12: Comparison of the two techniques discussed in the study

the least squares method to classify an unknown (test) image we can further improve the recognition rate for the eyes database. This is shown in Fig. 12, where we have used the least squares estimate of the unknown image.

The reseaerch in Hjelmas and Wroldsen (1999) discussed the face recognition problem using only eyes. They have used the same AT and T face database for this purpose. Both eyes of a face are extracted separately using manual location of eyes centers. Using the minimum distance classifier of city block distance they were able to achieve a recognition rate of 84.4% as compared to 86% for the least-squares method proposed in this study (without manual interference). The maximum recognition rate for this database is 96% reported by Lucas (1997). This was achieved using the whole face images.

CONCLUSION

For a database with large variations, we are able to get good result by using only the eyes. The recognition rate can be increased significantly if we use more samples for training. The least squares method proved to be more efficient and effective. The proposed technique is rotation invariant and has the huge advantage of low computational complexity given the small size images we work with.

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