Recognition of Faces using Improved Principal Component Analysis

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***Abstract*—Face recognition has been an important issue in computer vision and pattern recognition over the last several decades. While a human can recognize faces easily, automated face recognition remains a great challenge in computer-based automated recognition research. One difficulty in face recognition is how to handle the variations in expression, pose, and illumination when only a limited number of training samples are available. In this paper, an Improved Principal Component Analysis (IPCA) is proposed for face recognition. Initially the eigenspace is created with eigenvalues and eigenvectors. From this space, the eigenfaces are constructed, and the most relevant eigenfaces have been selected using IPCA. With these eigenfaces, the input images are be classified based on Euclidian distance. The proposed method was tested on ORL face database. Experimental results on this database demonstrated the effectiveness of the proposed method for face recognition with less misclassification in comparison with previous methods.**

Keywords-face recognition, principal component analysis, eigenvectors, eigenfaces.

I. INTRODUCTION

Over the last ten years or so, face recognition has become a popular area of research in computer vision and one of the most successful applications of image analysis and understanding. Because of the nature of the problem, not only computer science researchers are interested in it, but also neuroscientists and psychologists. It is the general opinion that advances in computer vision research will provide useful insights to neuroscientists and psychologists into how human brain works, and vice versa. A general statement of the face recognition problem can be formulated as follows [1]. Given still or video images of a scene, identify or verify one or more persons in the scene using a stored database of faces. A survey of face recognition techniques has been given by Zhao et al., [1]. In general, face recognition techniques can be divided into two groups based on the face representation they use:

- Appearance-based, which uses holistic texture features and is applied to either whole-face or specific regions in a face image;
- Feature-based, which uses geometric facial features (mouth, eyes, brows, cheeks etc.) and geometric relationships between them.

Among various solutions to the problem [2] the most successful seems to be those appearance-based approaches, which generally operate directly on images or appearances of face objects and process the image as two-dimensional patterns. These methods extract features to optimally represent faces belong to a class and separate faces from different classes. Ideally, it is desirable to use only features having high separability power while ignoring the rest. Most effort in the literature have been focused mainly on developing feature extraction methods [3,4,5] and employing powerful classifiers such as probabilistic [6], Hidden Markov models (HMMs) [7] neural networks (NNs) [8,10] and support vector machine (SVM) [9].

The main trend in feature extraction has been representing the data in a lower dimensional space computed through a linear or nonlinear transformation satisfying certain properties. Statistical techniques have been widely used for face recognition and in facial analysis to extract the abstract features of the face patterns. Principal component analysis (PCA) [3,11,12] and linear discriminant analysis (LDA) [4] and discrete cosine transform (DCT) [13,14] are three main techniques used for data reduction and feature extraction in the appearance-based approaches. DCT, Eigenfaces [3] and fisherfaces [4] built based on these three techniques, have been proved to be very successful. In this paper, an Improved Principal Component Analysis (IPCA) is proposed for face recognition. The following figure illustrates the entire framework.

The rest of the paper is organized as follows: section 2 presents the improved principal component analysis. The proposed algorithm is tested and the results are presented in Section 3 and the work is concluded in Section 4.

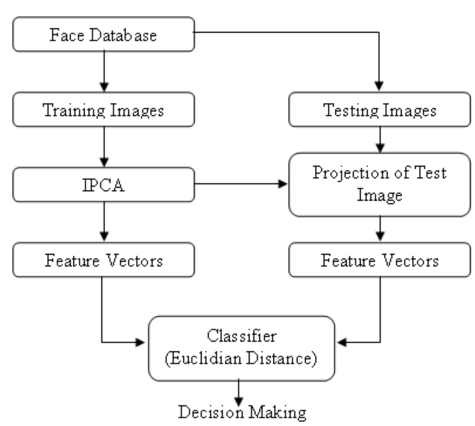

Figure 1. Overview of the Proposed System

978-0-7695-3977-5/10 $26.00 © 2010 IEEE
DOI 10.1109/ICMLC.2010.48

II. Improved Principal Component Analysis

Principal component analysis or karhunen-loeve transformation [15] is standard technique used in statistical pattern recognition and signal processing for data reduction and Feature extraction [16]. As the pattern often contains redundant information, mapping it to a feature vector can get rid of this redundancy and yet preserve most of the intrinsic information content of the pattern. These extracted features have great role in distinguishing input patterns.

A face image in 2-dimension with size N×N can also be considered as one dimensional vector of dimension N^2. For example, face image from ORL (Olivetti Research Labs) database with size 112×92 can be considered as a vector of dimension 10,304, or equivalently a point in a 10,304 dimensional space. An ensemble of images maps to a collection of points in this huge space. Images of faces, being similar in overall configuration, will not be randomly distributed in this huge image space and thus can be described by a relatively low dimensional subspace. The main idea of the principle component is to find the vectors that best account for the distribution of face images within the entire image space. These vectors define the subspace of face images, which we call "face space". Each of these vectors is of length N^2, describes an N×N image, and is a linear combination of the original face images. Because these vectors are the eigenvectors of the covariance matrix corresponding to the original face images, and because they are face-like in appearance, we refer to them as "eigenfaces". The PCA algorithm is described as follows:

First we will create the eigenspace. This step is the initialization of the system. Let the training set of M face images be $\Gamma_1, \Gamma_2, \ldots, \Gamma_M$. Some of the training images are shown in the fig 2.

The average (mean) face of the training set is defined by:

$$\Psi = \frac{1}{M}\sum_{i=1}^{M}\Gamma_i \qquad (1)$$

Figure 2. Sample Faces from the ORL Database

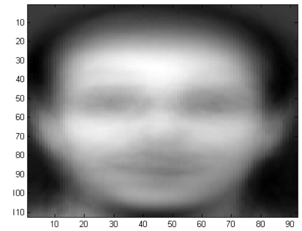

Figure 3. The average (mean) face

Fig. 3 shows an average face. Each face differs from the average face by the vector $\Phi_i = \Gamma_i - \Psi$, where i = 1,…,M. we shall rearrange these vectors in a matrix A = [$\Phi_1, \Phi_2, \ldots, \Phi_M$] of dimension N×M, which will then be subject to PCA. Matrix A has zero-mean (mean value subtracted vectors of each training face image in its columns. What we have just done is in fact a translation of the origin to the mean face.

The next goal is to find a set of M-1 orthogonal vectors, e_i, which best describes the distribution of the input data in a least-squares sense, i.e., the Euclidian projection error is minimized. We start by finding the covariance matrix:

$$C = A \,.\, A^T \qquad (2)$$

and then use eigenvector decomposition:

$$C.\, e_i = \lambda_i \,.\, e_i \qquad (3)$$

Where e_i and λ_i are the eigenvectors and eigenvalues of covariance matrix C respectively. We can do this because C is real and symmetric. λ is a diagonal matrix with eigenvalues on its main diagonal.

Once the eigenvectors of C are found, they are sorted according to their corresponding eigenvalues. Larger eigenvalue means that associated eigenvector captures more of the data variance. The efficiency of the PCA approach comes from the fact that we can eliminate all but the best k eigenvectors (with the highest k eigenvalues). Since PCA assumes the directions with the largest variances are the most principal (important), these eigenvectors will then span the M' dimensional face space and that is the new feature space for recognition. Eliminating eigenvectors associated with small eigenvalues actually eliminates the noise from the image. There are at least three proposed ways to eliminate eigenvectors.

- First is the mentioned elimination of eigenvalues with smallest eigenvalues. This can be accomplished by discarding the last 60% of total number of eigenvectors.
- The second way is to use the minimum number of eigenvectors to guarantee that energy E is greater than a threshold. A typical threshold is 0.9 (90% of total energy). If we define E_i as the energy of the i^{th} eigenvector, it is the ratio of the sum of all eigenvalues up to and including i over the sum of all the eigenvalues: where k is the total number of eigenvectors.

$$E_i = \left(\sum_{j=1}^{i}\lambda_j\right) \Big/ \left(\sum_{j=1}^{k}\lambda_j\right) \qquad (4)$$

- The third variation depends upon the stretching dimension. The stretch for the i^{th} eigenvector is the ratio of that eigenvalue over the largest eigenvalue (λ_I):

$$S_i = \lambda_i / \lambda_I \quad (5)$$

Normally, the best eigenvectors have been selected from the overall eigenspace. Here, we can't expect that the chosen vectors can best describe the faces from all the class. In our proposed method, the eigenvectors are from the same class are grouped and sorted in descending. From each group an eigenvector with maximum value is selected. In our case, we have 40 classes (subjects) in ORL face database. The eigenvectors are grouped into 40 classes and sorted. These eigenvectors are grouped together to form the principal components.

Each eigenvector has the same dimensionality as a face image and looks as a sort of a "ghost" face, so we call them eigenfaces. Transforming a point to a new space is a linear transformation so eigenvectors are merely linear combinations of the training images. The last step is to calculate the average face image for each individual and to project this image into the face space as the individual's class prototype. Ideally, two images of the same person should project to the same point in eigenspace. Any difference between the points is unwanted variation. Two images of different subjects should project to points that are as far apart as possible. This is the main idea behind the recognition in subspaces.

After creating the eigenspace we can proceed to recognition using eigenfaces. Given a new image of an individual Γ, the pixels are concatenated the same way as the training images were, the mean image Ψ is subtracted and the result is projected into the face space:

$$\omega_k = e_k^T(\Gamma - \Psi) \quad (6)$$

for k=1,..,M'. These calculated values of ω together form a vector $\Omega^T = [\omega_1, \omega_2, \ldots, \omega_{M'}]$ that describes the contribution of each eigenface in representing the input face image. In face, this is the projection of an unknown face into the face space. Ω is then used to establish which of the pre-defined face classes best describes the new face. The simplest way to determine which face class provides the best description of the input face image is to find the face class k that minimizes the Euclidian distance:

$$\varepsilon_k = \sqrt{\left\|\Omega - \Omega_k\right\|^2} \quad (7)$$

Where Ω_k is a vector describing the k^{th} face class. A face is classified as belonging to a certain class when the minimum ε_k (i.e. the maximum matching score) is below some certain threshold.

III. Experiments And Results

In order to obtain a fair empirical evaluation of face detection methods, it is important to use a standard and representative test set for experiments. To test our proposed method, the ORL Face database has been used.

The ORL face database contains a set of faces taken between April 1992 and April 1994 at the Olivetti Research Laboratory in Cambridge, UK. There are 10 different images of 40 distinct subjects. For some of the subjects, the images were taken at different times, varying lighting slightly, facial expressions (open/closed eyes, smiling/non-smiling) and facial details (glasses/no-glasses). All the images are taken against a dark homogeneous background and the subjects are in up-right, frontal position.

Initially the experiment starts with 2 training images and 8 testing images from each class. Then the same procedure is repeated by increasing the number of training images and decreasing the number of testing images. Table I shows the detection rate of our proposed method compared with the standard PCA and other existing approaches. As shown in the results, our proposed method has constant performance when compared to other methods even with the small number of training images. Fig.4 shows the performance curve of our proposed method compared with the existing approaches. Where x axis has the number of training images and the y axis has the number of testing images. The recognition accuracy is plotted on the graph. Compare to other curves, our proposed IPCA has the consistent performance.

IV. Conclusion

In this paper, a new Face recognition method is presented using Improved Principal Component Analysis (IPCA). The principal components are selected for each class independently to reduce the eigenspace. With these eigenvectors, the input images are classified based on Euclidian distance. The proposed method was tested on ORL face database. As shown in the results, the proposed IPCA method has the greater accuracy with consistency than the existing methods. The recognition rate is greater even with the small number of training images which demonstrated an improvement in comparison with previous methods.

TABLE I. Comparison of Recognition Rate

Training Images	Testing Images	PCA	PCA-NN	LDA	LDA-NN	IPCA
2	8	71	75	78	80	87
3	7	73	76	82	84	87
4	6	77	80	87	89	89
5	5	78	85	87	91	92
6	4	89	90	93	93	92
7	3	92	94	95	95	96
8	2	94	95	96	97	97

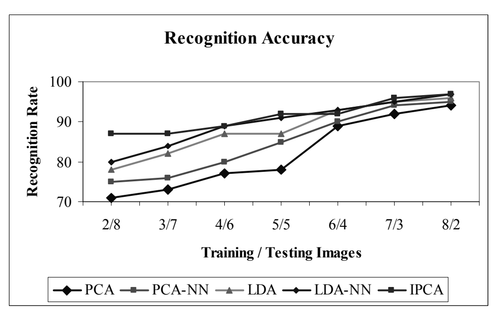

Figure 4. Performance Analysis

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