ABSTRACT

Face Recognition is a field of multidimensional applications. Face detection is an integral part of face detection. A lot of work has been done, extensively on the most of details related to face recognition. This idea of face recognition using PCA is one of them. We here implement some standard methods for face recognition and show their respective comparative performances. We implement face recognition using PCA and Eigen core method and then perform recognition using LDA and histogram equalization. At the end of the paper, we compare the accuracy of all implemented methods using Matlab. The focus here is on trying to find advantages and disadvantages with the different approaches. First we start by looking at some of the earliest approaches using simple feature based methods. Then we take a look at some more sophisticated statistical and holistic methods like PCA, Eigen faces, LDA, fisher faces and ICA.

Keywords: Eigen Core, Face Recognition, LDA, PCA, Histogram Equalization, Matching, Matlab

1. SUMMARY OF THE PAPER

This paper presents the face recognition system using a LDA, PCA, Eigen Core Methods. In the second section, we present basic geometric methods and template matching. Third and fourth sections include PCA and LDA. Fifth section gives detail of ICA. Section sixth describes Eigen faces. Section seven describes histogram method for face recognition. Section Eight gives Data base, implementation results and algorithm. Section nine include references.

2. GEOMETRIC METHODS AND TEMPLATE MATCHING

[7] developed two simple algorithms for face recognition. The first one is based on the computation of a set of geometrical features, such as nose width and length, mouth position and chin shape. One major motivation for using geometric methods is that in an image with sufficiently low resolution, it is impossible to distinguish the fine details of a face. On the other hand, it is often quite easily possible for a human to recognize the person. The remaining information in the low resolution image is almost pure geometrical and implies that these properties of face features are sufficiently enough for face detection and recognition. The configuration of the features can be described by a vector of numerical data representing the position and size of the main facial features, eyes and eyebrows, nose and mouth. This information can be supplemented by the shape of the face outline. The other algorithm proposed by [7] is based on template matching. In the simplest version of template matching, the image represented by an array of intensity values, is compared using a suitable metric (usually Euclidean distance) to a single template representing the whole face. The use of feature vectors seems very unstable and limited because the variation of the data from different pictures of the same face was in the same order of magnitude as the variation between different faces. The method is sensitive to all sorts of disturbances such as facial expressions or varying pose.

3. PRINCIPAL COMPONENT ANALYSIS (PCA)

Principal component analysis (PCA) has been called one of the most valuable results from applied linear algebra. PCA is used abundantly in all forms of analysis - from neuroscience to computer graphics - because it is a simple, non-parametric method of extracting relevant information from confusing data sets. With minimal additional effort, PCA provides a roadmap on how to reduce a complex data set to a lower dimension in order to reveal the recognition techniques. PCA, a frequently used statistical technique for optimal loss compression of data under least square sense, provides an orthogonal basis vector-space to represent original data. The first introduction of a low-dimensional characterization of faces was developed at Brown University by [8]. This was later extended to Eigen space projection for face recognition by [9] and [10].

The Eigen space is a subspace of the image space spanned up by a set of Eigen vectors of the covariance
matrix of the trained images. These Eigenvectors are also called Eigen faces because of their face-like appearance. The projection of an image into Eigenspace will transform the image into a representation of a lower dimension which aims to hold the most important features of the face and make the comparison of images easier.

Eigen values and Eigenvectors are [11] defined as If \( v \) is a nonzero vector and \( \lambda \) is a number such that

\[
Av = \lambda v \tag{Equation 1}
\]

then \( v \) (from Equation 1) is said to be an eigenvector of \( A \) with Eigen value \( \lambda \).

For example

\[
\begin{bmatrix} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} \end{bmatrix} \begin{bmatrix} 1 \\ 2 \end{bmatrix} = \frac{3}{2} \begin{bmatrix} 1 \\ 2 \end{bmatrix} \tag{Equation 2}
\]

The term

\[
A = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}, \quad \text{Eigen vector is} \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad \text{and} \quad \text{Eigen values of} \ 3
\]

The Eigen face method for human face detection is remarkably clean and simple. The basic concept behind the Eigen face method is information reduction. When one evaluates even a small image, there is an incredible amount of information present. From all the possible things that could be represented in a given image, pictures of things that look like faces clearly represent a small portion of this image space. Because of this, we seek a method to break down pictures that will be better equipped to represent face images rather than images in general. To do this, one should generate ‘base-faces’ and then represent any image being analyzed by the system as a linear combination of these base faces. Once the base faces have been chosen, we have essentially reduced the complexity of the problem from one of image analysis to a standard classification problem. Each face that we wish to classify can be projected into face-space and then analyzed as a vector. A k-nearest-neighbor approach, a neural network or even a simple Euclidian distance measure can be used for such classification. The technique can be broken down into the following major activity components:

1. Generate the Eigen faces.
2. Project training data into face-space to be used with a predetermined classification method.
3. Evaluate a projected test element by projecting it into face space and comparing to training data for face detection and recognition process.

In the appearance model each face in the database is represented as a linear combination of Eigen faces. The other recognition/detection scheme is called the discriminative model. Two datasets are obtained by computing intrapersonal differences (matching two different images of the same individual in the dataset) and extra personal differences (matching different individuals in the dataset). Two datasets of Eigen faces are generated by performing PCA on each class and a similarity score between two images is derived by calculating a Bayesian probability measure. Although the performance of the appearance model is lower than the discriminative model.

Results shows Eigen faces methods are robust over a wide range of parameters and produce good recognition/detection rates on various databases. However outside this parameter range the algorithm can break down sharply. But significant variation in scale, orientation, translation and lightning will cause it to fail.

Principal Component Analysis [1][6] is one of the most powerful techniques that have been used in image recognition or in compression. PCA is a statistical method under the broad title of factor analysis.

The functions which PCA [1][6] can perform are

1. Prediction
2. Redundancy removal
3. Feature extraction
4. Data compression, etc.

Because PCA [1][6] is a classical technique which can perform functions in the linear domain, thus the applications having linear models are much suitable, as for example,

1. Signal processing
2. Image processing
3. System and control theory
4. Communications, etc.

The field of face recognition has so many areas of applications as in security, biometric systems, banks and many more that are beyond the list. Moreover, face recognition can be partitioned into

1. face identification
2. face classification or sex determination.
3. The most useful applications contain people surveillance (in crowded areas)
4. Video content indexing
5. Personal identification (e.g. driver’s license)
6. Mug shots matching
7. Entrance security, etc.

4. LINEAR DISCRIMINANT ANALYSIS (LDA)

[12] used FLD to cluster images for the purpose of identification. Also in 1997, [13] of Yale University used FLD to identify faces, by training and testing with several faces under different lighting. Fisher Linear Discriminant (FLD) [5] analysis, also called Linear Discriminant [4] Analysis (LDA) finds the line that best separates the points. For example, consider two sets of points, colored green and blue, in two-dimensional space being projected onto a single line. Depending on the direction of the line, the points can either be mixed together or be separated. In terms of face recognition this means grouping images of the same class and separate images of different classes. Images are projected from a \( N \)-dimensional space, where \( N \) is the number of pixels in the image, to a \( M-1 \) dimensional space, where \( M \) is the number of classes of images. The LDA method, which creates an optimal projection of the dataset, maximizes the ratio of the determinant of the between-class scatter matrix of the projected samples to the
determinant of the within-class scatter matrix of the projected samples. The within-class scatter matrix, also called intra-personal, represents variations in appearance of the same individual due to different lighting and facial expression, while the between-class scatter matrix, also called the extra-personal, represents variations in appearance due to a difference in identity. In this way, fisherfaces can project away some variation in lighting and facial expression while maintaining discrimination ability. The fisher face method is very similar to the Eigen face method, but with improvement in better classification of face images by using interclass and intra-class relationships to separate them. With LDA, it is possible to classify the training set to deal with different people and different facial expressions. The fisher faces method is quite insensitive to large variations in lighting direction and facial expression. When compared to the Eigen face method, this algorithm is more complex, something which increases the computational requirements, but show lower error rates. Besides, due to the need of better classification, the dimension of the projection in face space is not as compact as in the Eigen faces approach. Another drawback comes from the fact that the fisherface method uses particular class information and therefore is recommended to have many images per class in the training process. (Figure 2)

5. INDEPENDENT COMPONENT ANALYSIS (ICA)

Independent Component Analysis (ICA) is a technique for extracting statistically independent variables from a mixture of them. The technique is quite new and has originated from the world of signal processing. ICA can be used to estimate the contribution coefficients from the two signals, which allows us to separate the two original signals from each other. According to [14], ICA in a task such as face detection, much of the important information may be contained in the high-order relationships among the image pixels. Some success has been attained using data-driven face representations based on PCA, such as Eigen faces. PCA is based on the second-order statistics of the image set, and does not address high-order statistical dependencies such as the relationships among three or more pixels. Independent component analysis (ICA) however separates the high-order moments of the input in addition to the second-order moments. ICA thus in some ways provides a more powerful data representation than PCA since its goal is to provide an independent rather than an uncorrelated image decomposition and representation.

[3] But some properties like coloring, width and length are more easily captured by PCA than ICA, since ICA basis vectors are more spatially localized than their PCA counterparts. (Figure 1)

6. EIGEN FACES

The Eigen face [2] method for human face recognition is remarkably clean and simple. The basic concept behind the Eigen face method is information reduction. When one evaluates even a small image, there is an incredible amount of information present. From all the possible things that could be represented in a given image, pictures of things that look like faces clearly represent a small portion of this image space. Because of this, we seek a method to break down pictures that will be better equipped to represent face images rather than images in general. To do this, one should generate ‘base-faces’ and then represent any image being analyzed by the system as a linear combination of these base faces. Once the base faces have been chosen we have essentially reduced the complexity of the problem from one of image analysis to a standard classification problem. Each face that we wish to classify can be projected into face-space and then analyzed as a vector. A k-nearest-neighbor approach, a neural network or even a simply Euclidian distance measure can be used for classification. The technique can be broken down into the following components:

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7. HISTOGRAM METHOD

Histogram method (figure 3) is one of the robust techniques which can be used for recognition. The property of histogram is, that it remains unaffected with change in facial expression, with change in minor illumination variations, with change in pose. These properties make histogram equalization a benchmark for face recognition. We here implement the histogram equalization for face recognition.

8. DATA BASE, IMPLEMENTATION AND RESULTS

We here use ORL database and MIT database for evaluating the performance. In all experiments the 40 individuals of the ORL database were considered. There are 200 original training images and 200 test images. Image Size is 92 x 112 The Number of unique people are 40. The Number of pictures per person are 10 in this database. In the MIT database Image Size is 480 x 640 for each image under test. Number of unique people are 154 in which 82 are Males and 72 are Female.

Number of pictures per person are 6

Different Conditions are considered in like frontal and slight tilt of the head. The algorithm for all techniques and comparative performance is as shown below.
**Algorithm: Face Recognition PCA**

**Step 1:** Data Set of Training image \{T_1, T_2, T_3, ..., T_n\}

**Step 2:** Data Set of Test image \{L_1, L_2, L_3, ..., L_n\}

**Training**

**Choice 1 (Eigen method)**

Step 3: Compute Mean of training set

Step 4: Compute eigenvector and centre image

**Testing**

Step 5: Extract PCA

Step 6: Calculate Euclidean distance

Step 7: Projection of image from eigen space vector

**Matching**

Step 7: If D(E)_test = D(E)_train set

Matched

Step 8: Else

Not-Matched

**Choice 2 FLD**

Step 9: Projecting images onto Fisher linear space

Step 10: Fisher’ * PCA’ * (Training database – mean value database)

Step 11: Repeat steps 7 to 10

**Choice 3 Histogram base method**

Step 12: Calculate H_test set

Step 13: Calculate H_train set

Step 14: H_test set = H_train set

Step 15: Do steps 7 to 10

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**Fig 1:** Recognition by Eigen space method

**Fig 2:** Recognition by FLD method
From the above (figures 4-6), it can be concluded that from accuracy point of view, the histogram technique is best suited (from table 1) for the face recognition method. However in histogram method, speed is the main issue of concern. With proper training using NN (neural network) and by reducing the size of feature vector, we can certainly improve the speed and performance of histogram method.

### References


[6] Face Recognition using Principle Component Analysis Kyungnam Kim Department of Computer Science University of Maryland, College Park MD 20742, USA O.


