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Full Length Research Paper

Face recognition using multiple eigenface subspaces

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Face recognition is grabbing more attention in the area of network information access. Areas such as network security and content retrieval benefit from face recognition technology. In the proposed method, multiple face eigensubspaces are created, with each one corresponding to one known subject privately, rather than all individuals sharing one universal subspace as in the traditional eigenface method. Compared with the traditional single subspace face representation, the proposed method captures the extra personal difference to the most possible extent, which is crucial to distinguish between individuals, and on the other hand, it throws away the most intrapersonal difference and noise in the input. Our experiments strongly support the proposed idea, in which 20% improvement of performance over the traditional "eigenface" has been observed when tested on the same face base.

Key words: Face recognition, eigenspace, subspaces.

INTRODUCTION

Face recognition (FR) has emerged as one of the most extensively studied research topics that spans multiple disciplines such as pattern recognition, signal processing and computer vision. This is due to its numerous important applications in identity authentication, security access control, intelligent human-computer interaction, and automatic indexing of image and video databases. Feature extraction algorithms mainly fall into two categories: geometrical features extraction and, statistical (algebraic) features extraction. The geometric approach, represent the face in terms of structural measurements and distinctive facial features that include distances and angles between the most characteristic face components such as eyes, nose, mouth or facial templates such as nose length and width, mouth position, and chin type. These features are used to recognize an unknown face by matching it to the nearest neighbor in the stored database. Statistical features extraction is usually driven by algebraic methods such as principal component analysis (PCA), and independent component analysis (ICA).These methods find a mapping between the original feature spaces to a lower dimensional feature space.

In this paper, the method proposed is derived from the traditional Eigenface but differs from it in essence. In Eigenface, each face image is represented as a point in a low-dimensional face subspace shared by all faces; however, the experiments conducted show one of the demerits of such a strategy: it fails to accurately represent the most discriminating features of a specific face. Therefore, we propose to model each face with one individual face subspace, named face-specific subspace. Distance from the face-specific subspace, that is, the reconstruction error, is then exploited as the similarity measurement for identification.

The rest of this paper is thus organized. An overview of feature extraction techniques like eigenface method is presented. We also explained the thresholds for face recognition and the proposed multiple eigenface subspace algorithm. Finally, the experimental results and conclusion are attained.

FEATURE EXTRACTION

The first step in any face recognition system is the extraction of the feature matrix. A typical feature extraction algorithm (Costen et al., 1996) tends to build a computational model through some linear or nonlinear transform of the data (Reisfeld and Yeshurun, 1998) so that

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the extracted feature is as representative as possible. In this paper eigenface method is used for feature extraction.

EIGENFACES

Eigenfaces are a set of eigenvectors used in the computer vision problem of human face recognition. These eigenvectors are derived from the covariance matrix of the probability distribution of the high-dimensional vector space of possible faces of human beings. The image of the eigenface may look very little like a face.

The eigenface technique uses a strong combination of linear algebra and statistical analysis to generate a set of basis faces, the eigenfaces against which inputs are tested (Jeng et al)

Before finding the eigenfaces, we first need to collect a set of face images. These face images become our database of known faces. We will later determine whether or not an unknown face matches any of these known faces. All face images must be the same size (in pixels), and for our purposes, they must be grayscale, with values ranging from 0 to 255.

Each face image is converted into a vector Tn of length N (N= imagewidth*imageheight). The most useful face sets have multiple images per person. This sharply increases accuracy, due to the increased information available on each known individual. We will call our collection of faces as face space. This space is of dimension N.

To create a set of eigenfaces, we should do the following:

1) Collect set of face images. The pictures constituting the training set should have been taken under the same lighting conditions, and must be normalized to have the eyes and mouths aligned across all images. They must also be all resampled to the same pixel resolution. Each image is treated as one vector, simply by concatenating the rows of pixels in the original image, resulting in a single row with r × c elements. For this implementation, it is assumed that all images of the training set are stored in a single matrix T, where each row of the matrix contains the 'n' value of the image.
2) Calculate the average face in face space. We then compute each face difference from the average. These differences are used to compute a covariance matrix(C) of our data set. The eigenfaces that we are looking for are simply the eigenvectors of C.
3) Calculate the eigenvectors and eigenvalues of the covariance matrix C. Each eigenvector has the same dimensionality (number of components) as the original images, and thus can itself be seen as an image. The eigenvectors of this covariance matrix are therefore called eigenfaces. They are the directions in which the images differ from the mean image.
4) Based on a statistical technique known as principal component analysis (PCA), we can reduce the number of eigenvectors for our covariance matrix from N (the number of pixels in our image) to M (the number of images in our dataset. Choose the principal components. The D × D covariance matrix will result in D eigenvectors, each representing a direction in the r × c-dimensional image space. The eigenvectors (eigenfaces) with largest associated eigenvalues are kept.

Eigenfaces represent the principal components of the face set. These principal components are very useful in simplifying the recognition process of a set of data. First take all the mean subtracted images in the database and project them onto the face space. An incoming image can similarly be projected onto the face space. Logically, faces of the same person will map fairly closely to one another in this face space. Recognition is simply a problem of finding the closest database image, or mathematically finding the minimum Euclidean distance between a test point and a database point (Figure 1).

THRESHOLD FOR EIGENFACE RECOGNITION

When a new image comes into the system, there are three special cases for recognition (Lizama et al., 1998).
a) Image is a known face in the database;
b) Image is a face, but of an unknown person;
c) Image is not a face at all. May be a coke can, a door, or an animal.

Let us define the face space as an M-dimensional sphere encompassing all weight vectors in the entire database. A fairly approximate radius of this face space will be half the diameter of this sphere, or mathematically, half the distance between the furthest points in the sphere (Figure 2).

To judge whether a new image falls within this radius, let us calculate the reconstruction error between the image and its reconstruction using M eigenfaces. If the image projects fairly well onto the face space (image follows a face distribution), then the error will be small. However a non face image will almost always lie outside the radius of the face space (Figure 2).

If the resulting reconstruction error is greater than the threshold, then the tested image probably is not a face image. Similar thresholds can be calculated for images of like faces. If an image passes the initial face test, it can be compared to the threshold values of faces in the database. A similar match process can be used as mentioned earlier.

MULTIPLE EIGENFACE SUBSPACES

Much of the previous work on eigenspace methods usually built only one eigenface space with eigenfaces of different persons, utilizing only one or very limited faces of an individual. The information of one facial image is very limited, so traditional methods have difficulty coping with differences of facial images caused by the changes of age, emotion, illumination, and hairdress.

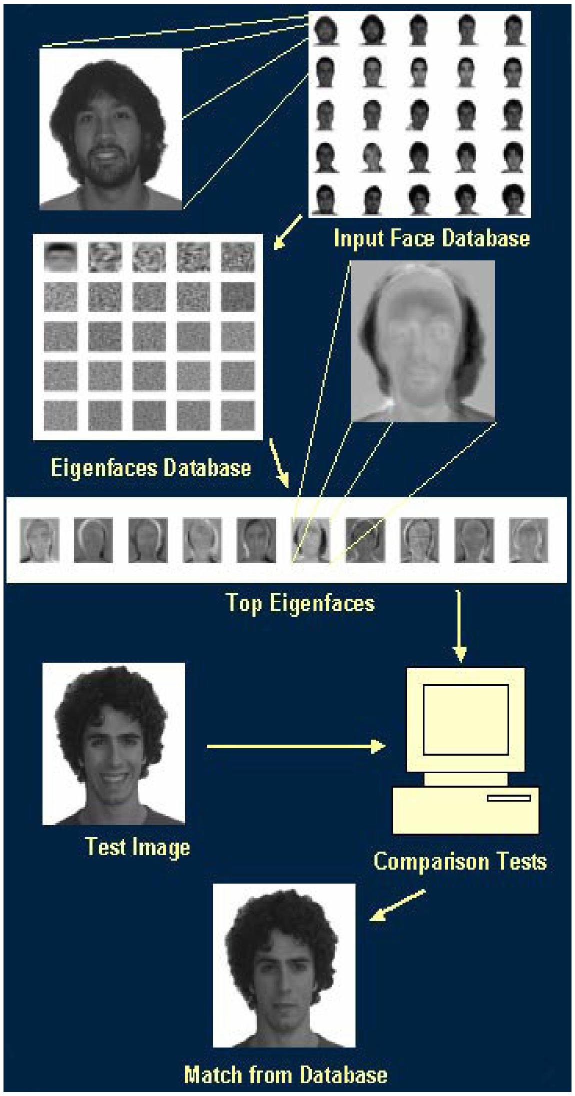

Figure 1. Robust detection system.

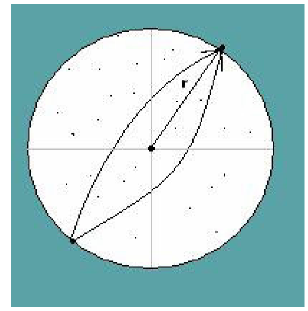

Figure 2. Threshold for eigenface recognition.

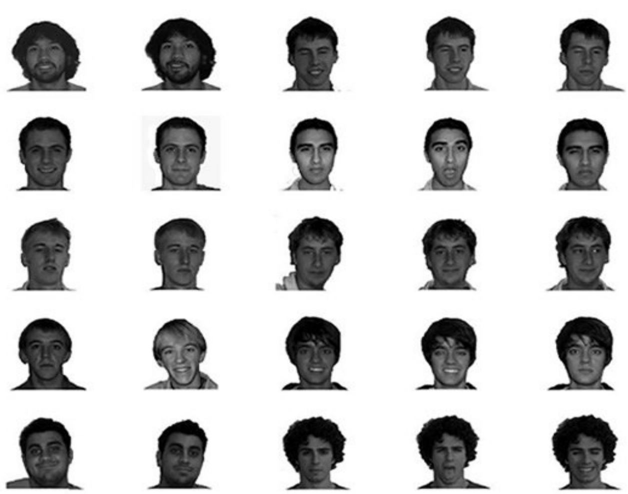

Figure 3. Example of images from RICE database.

We took advantage of facial images of the same person obtained at different ages, under different conditions, and with different emotion. For every individual we constructed an eigenface subspace separately, namely multiple eigenface spaces were constructed for a face database.

We take a set of M training images and compute the eigenvectors of their covariance matrix, and then select the M` eigenvectors (eigenfaces) with the highest eigenvalues to define an image subspace (face space). By projecting a face-image into face space we obtain a 'face-key' vector of M` dimensions. We define the 'likeness' of any two face-images as the Euclidean distance between their respective 'face-key' vectors. Using this method, we perform many comparisons between different images of the same face and images of different faces. By applying a range of threshold values to the distance measurements of these comparisons, we obtain false acceptance rates (FAR) and false rejection rates (FRR). The equal error rate (EER) is used as a single measure of the effectiveness of the system and is attained at a specific threshold value.

These may include such factors as lighting direction, intensity and colour, head orientation, image quality and facial expression. For example, suppose some images in the training data were taken with bright sunlight shining on one side of the face, the feature of having one side of the face lighter than the other may be identified as a principal component and hence used to distinguish between different people.

We conduct experiments using a database of 960 bitmap images of 120 individuals (60 male, 60 female), extracted from the RICE database (Figure 3). We separate the database into two disjoint sets: i) The training set, containing 60 images of different people of various gender, race and age taken under natural lighting conditions with neutral expression; ii) the test set containing 900 images (15 images of 60 people of various gender, race and age).

We assume that different images of the same face map to nearby points in image space and images of different faces map to far apart points. Ideally, we wish to extract the region of image space that contains faces, reduce the dimensionality to a practical value, and yet maximize the spread of different faces within the image subspace. Here we apply principal component analysis to define a space with the properties mentioned above.

1. Take a set of 'M' training images
2. Compute the average image
3. Find the difference of each image from average image
4. Construct the covariance matrix
5. Eigenvectors are sorted according to the eigenvalues

The effect is that we have reduced the dimensionality of the space to M`, yet maintained a high level of variance between face images throughout the image subspace.

Figure 4. Average face from RICE database.

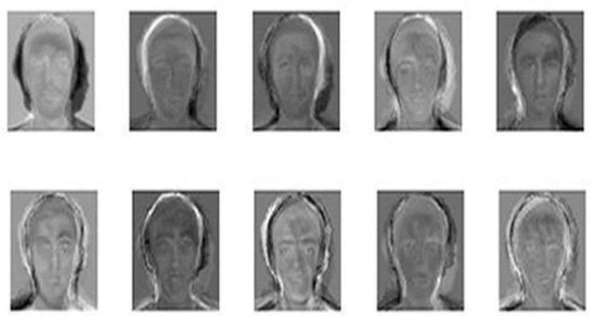

Figure 5. Top 10 eigenfaces from RICE database.

Once face space has been defined, we can project any image into face space by a simple matrix multiplication (Figure 4).

We compare any two 'facekeys' by a simple Euclidean distance measure (Barrett W 1998). An acceptance (the two face images match) or rejection (the two images do not match) is determined by applying a threshold. Any comparison producing a distance below the threshold is a match. To gather results for the false rejection rate, each of the 15 images for a single person, is compared with every other image of their face. No image is compared with itself and each pair is only compared once (the relationship is symmetric), giving 6300 comparisons to test false rejection. Using these images, every person is compared with every other person. This gives four comparisons per pair of people, with no person compared to himself and each pair only compared once (Black et al.). For each threshold value we produce a FAR and a FRR (Figure 5).

RESULTS OF EIGENFACE DETECTION TESTS

The best average recognition rate of 94.8% is achieved using multiple face Eigen subspace technique. In this instance, the selection algorithm reduces the size of the original feature vector by nearly 50% (Figure 6). In general the performance in terms of recognition rates are same with general eigenface technique but the number of selected features is smaller when using the multiple face eigen subspace algorithm. In terms of computational time, this method takes less training time than the generalized algorithm in all tested instances.

CONCLUSIONS FOR EIGENFACE DETECTION

Analysis of the eigenface recognition technique using multiple face eigenspace method gives evidence that the methods prove, at best, 90% accurate. This indicates that in any implementation of such a recognition system, there does not exist a meaningful advantage to using more eigenfaces than first providing the desired level of accuracy.

In this way it becomes evident that if higher success rates are to be assured in most reasonable conditions then refinements to the eigenface concept must be made.

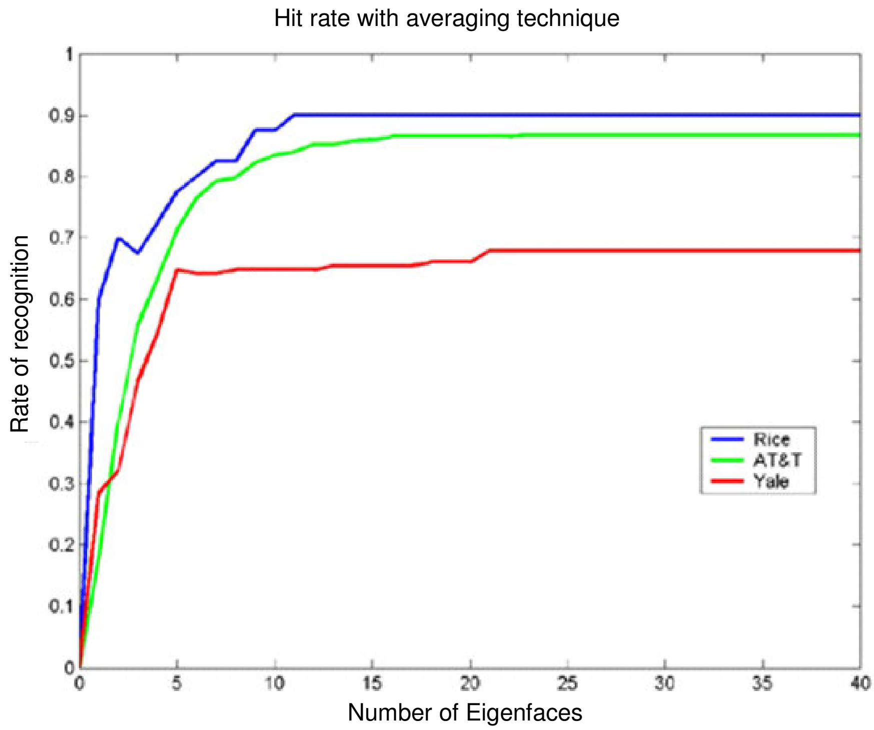

Figure 6. Rate of identification of correct individual by averaging technique.

Clearly the eigenface algorithm promise much for the field of facial image recognition but not before some technical refinement.

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