Face Recognition for Biometric Security System

Ei Phyo Wai, Myint Myint Sein
University of Computer Studies, Yangon
eiphyowai27@gmail.com,chuchu0218@gmail.com

Abstract

Biometrics is used for human recognition which consists of identification and verification. In an identification application, the biometric device reads a sample and compares that sample against every record or template in the database. Identification applications are common when the goal is to identify criminals, terrorists, or other particularly through surveillance. Personal face recognition is crucial for applications such as access control, smart card verification, surveillance, human-computer interaction, etc. Also, faces are integral to human interaction. Manual facial recognition is already used in everyday authentication applications.

In this paper, a novel subspace method is proposed for face recognition. A new face recognition method DiaPCA is based on PCA (principal Component Analysis) and KNN (K^{th} nearest neighbor classifier). The recognition process consists of three stages: preprocessing, dimension reduction by using PCA, and matching of the extracted feature using KNN. Combination of DiaPCA and KNN is used for improving the capability of PCA when a few samples of images are available. In contrast to standard PCA, DiaPCA directly seeks the optimal projective vectors from diagonal face images without image-to-vector transformation. DiaPCA reserves the correlations between variations of rows and those of columns of images. DiaPCA is much more accurate than PCA. The motivation of this research is to provide the personal identification from the National Registration Card (NRC card).

1. Introduction

Human face recognition has become an active area of research over the last decade. Adaptive face recognition is needed for all biometric systems for personal identification. In this paper we first indicate that DiaPCA which is an extension to the original PCA is essentially working in images. Face recognition from images is a sub-area of the general object recognition problem and most nonintrusive modalities in biometrics. Human can recognize thousands of faces but machines cannot. Although the current face recognition systems have achieved good results for faces that are taken in a controlled environment, they perform poorly in uncontrolled situations.

Fingerprint recognition, speech recognition, vein recognition and face recognition are main themes of the biometric systems. Among all forms of biometrics, face stands out in that it can be easily and non-intrusively captured with a camera. Face Recognition has become one of the most challenging tasks in the pattern recognition field. Unlike its iris or fingerprint counterparts, face biometrics requires no extra sensors or circuitry. Face recognition can recognize criminals in public spaces (airports, shopping centers) and in stores. So face recognition occupied the essential role in every society and useful for person identification, human-computer interaction and security systems.

In between these days face recognition is used in various systems. To begin with, face authentication is a task to determine whether a person is who he/she claims to be based on his/her face. The system can be used in three scenarios including system training, registration and verification. The training process supports the system readily to be used, registration add new authorized user to the system and verification check the claimed identity of live users. The recognition of faces is also very important for many applications such as: video surveillance, retrieval of an identity from a database for criminal investigations and forensic applications. Among various solutions to the problem 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.

The main trend in feature extraction has been representing the data in a lower dimensional space computed through a linear or non-linear 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. Different methods of this approach can be broadly classified into three main categories. The first approach is based on “preprocessing and normalization”. The representative methods are histogram equalization, Gamma correction, logarithm transform, etc. for illumination normalization [4]. But these global processing techniques of image processing are found to be insufficient to overcome variations due to illumination changes.

The systems are exploiting "invariant feature extraction" method. A well established method for feature extraction is Fisher-face. This method is a statistical linear projection method in which the representativeness of the training samples controls the performance of the system. The input image contrast stretching is done by histogram equalization.

2. Overview of the System

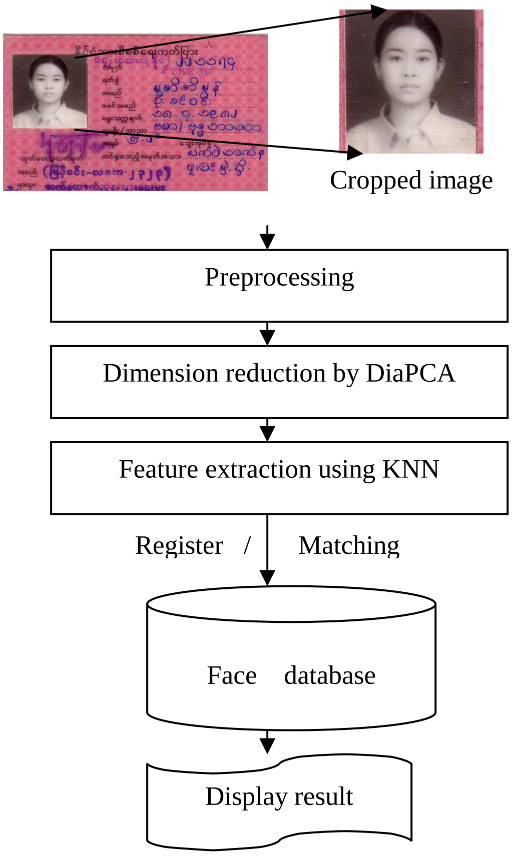

Figure 1. Overview of the proposed system

The overview of the proposed system is expressed in figure 1. Firstly, enhancing steps are performed for the cropped face image. Then, diagonal PCA method is applied to reduce the large dimensionality of the data space. Next, K^{th} nearest neighbor classifier (KNN) is used for feature extraction. Either the extract feature is stored in face database or searching the corresponding feature in face database. Finally, the complete information of the matched person is displayed.

3. Pre-processing Steps

Enhancing states include the noise filtering, gray scale converting, histogram equalization and so on. Histogram equalization maps the input image's intensity values so that the histogram of the resulting image will have an approximately uniform distribution [12-14]. The histogram of a digital image with gray levels in the range [0, L-1] is a discrete function

$$p(rk) = \frac{nk}{n}$$

where L is the total number of gray levels , rk is the kth gray level, nk is the number of pixels in the image with that gray level, n is the total number of pixels in the image, and $k = 0, 1, 2, \ldots, L - 1$. $p(rk)$ gives an estimate of the probability of occurrence of gray level rk. By histogram equalization, the local contrast of the object in the image is increased, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensity can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast without affecting the global contrast.

4. Principal Component Analysis

The Principal Component Analysis (PCA) is one of the most successful techniques that have been used in image recognition and compression. PCA is a statistical method under the broad title of *factor analysis*. The purpose of PCA is to reduce the large dimensionality of the data space to the smaller intrinsic dimensionality of feature space, which are needed to describe the data economically. This is the case when there is a strong correlation between observed variables. PCA can do prediction, redundancy removal, feature extraction, data compression, etc. Because PCA is a classical technique which can do something in the linear domain, applications having linear models are suitable, such as signal processing, image processing, system and control theory, communications, etc.

We have implemented PCA procedure in a training set of M face images. Let a face image be represented as a two dimensional N by N array of intensity values, or a vector of dimension $N2$. Then PCA tends to find a M-dimensional subspace whose basis vectors correspond to the maximum variance direction in the original image space. This new subspace is normally lower dimensional ($M << M << N2$). New basis vectors define a subspace of face images called face space. All images of known faces are projected onto the face space to find sets of weights that describe the contribution of each vector. To identify an unknown image, the image is projected onto the face space as well to obtain its set of weights. By comparing a set of weights for the unknown face to sets of weights of known faces, the face can be identified. PCA basis vectors are defined as eigenvectors of the scatter matrix S defined as:

$$S = \sum_{i=1}^{M} (xi - \mu).(xi - \mu)'$$

where μ is the mean of all images in the training set and xi is the i^{th} face image represented as a vector i. As this face space is generated using eigenvectors of scatter matrix, sometimes this is also called as eigenspace.

The eigenvectors corresponding to nonzero eigenvalues of the covariance matrix produce an orthonormal basis for the subspace within which most image data can be represented with a small amount of error. The eigenvectors are sorted from high to low according to their corresponding eigenvalues. The eigenvector associated with the largest eigenvalue is one that reflects the greatest variance in the image. That is, the smallest eigenvalue is associated with the eigenvector that finds the least variance.

A facial image can be projected onto $M'(<< M)$ dimensions by computing

$$\Omega = [v_1 v_2 \ldots v_{M'}]^T$$

The vectors are also images, so called, eigenimages, or eigenfaces .They can be viewed as images and indeed look like faces. So describes the contribution of each eigenface in representing the facial image by treating the eigenfaces as a basis set for facial images. Face space forms a cluster in image space and PCA gives suitable representation

Pattern recognition in high-dimensional spaces have pattern problems because of curse of dimensionality. Significant improvements can be achieved by first mapping the data into a lower-dimensional sub-space. The goal of PCA is to reduce the dimensionality of the data while retaining as much as possible of the variation present in the original dataset.

5. Diagonal PCA

Our motivation for developing the DiaPCA method originates from an essential observation on the PCA. PCA only reflects the information between rows, which implies some structure information (e.g. regions of a face like eyes, nose, etc.) cannot be uncovered by it. We attempt to solve that problem by transforming the original face images into corresponding diagonal face images. Because the rows (columns) in the transformed diagonal face images simultaneously integrate the information of rows and columns in original images, it can reflect both information between rows and columns. DiaPCA may find some useful block or structure information for recognition in original images. DiaPCA directly seeks the optimal projective vectors from diagonal face images without image-to-vector transformation

In the core of our system lies the Diagonal Principal Component Analysis (DiPCA) Algorithm [2], which is a tested and widely adopted for face recognition. DiaPCA can be subdivided into two components – PCA subspace training and PCA projection. During PCA subspace training, the rows of the pixels of an N1 x N2 image are concatenated into a one dimensional ‘image vector’. In practice, only a subset of the eigenfaces ($k = 1, \ldots, M'$) is retained to form a transformation matrix which is used in the PCA projection stage. Only the principal eigenfaces accounting for the most significant variations are used in the construction.

Suppose that there are M training face images, denoted by m by n matrices . For each training face image, define the corresponding diagonal face image as follows:

1)If the height m is equal to or smaller than the width n, to generate the diagonal image ***B*** for the original image ***A***.

2) If the height m is bigger than the width n, to generate the diagonal image ***B*** for the original image ***A***.

During PCA projection, a new face image vector is multiplied by the transformation matrix and projected to a point in a high dimensional PCA subspace. In this PCA subspace, the correlations among the projected images are minimized in order to facilitate easier classification [3]. The projected image is then saved as the face template of the corresponding user for future matching.

6. Nearest Neighbor Classification

Classification (similarity search) is a very crucial step in any pattern recognition application. One of the most popular non-parametric techniques is the Nearest Neighbor classification (NNC). NNC asymptotic or infinite sample size error is less than twice of the Bayes error [6]. The basic NNC rule behind these techniques is given by Cover and Hart [7]. NNC gives a trade-off between the distribution of the training data with a priori probability of the classes involved. NNC,where a high number of prototypes make the classifier more (training data) specific and a low number makes it more general [3].

7. Face Recognition

Face recognition has many applicable areas. Moreover, it can be categorized into face identification, face classification, or sex determination. The most useful applications contain crowd surveillance, video content indexing, personal identification (ex. driver's licence), entrance security, etc. The main idea of using PCA for face recognition is to express the large 1-D vector of pixels constructed from 2-D facial image into the compact principal components of the feature space. This can be called eigenspace projection. Once the eigenfaces have been computed, several types of decision can be made depending on the application. Face recognition include identification, recognition and categorization of face image.

PCA computes the basis of a space whicih is represented by its training vectors. These basis vectors, actually eigenvectors, computed by PCA are in the direction of the largest variance of the training vectors. As it has been said earlier, we call them eigenfaces. Each eigenface can be viewed a feature. When a particular face is projected onto the face space, its vector into the face space describe the importance of each of those features in the face. The face is expressed in the face space by its eigenface coefficients (or weights). We can handle a large input vector, facial image, only by taking its small weight vector in the face space. This means that we can reconstruct the original face with some error, since the dimensionality of the image space is much larger than that of face space.

Each face in the training set is transformed into the face space and its components are stored in memory. The face space has to be populated with these known faces. An input face is given to the system, and then it is projected onto the face space. The system computes its distance from all the stored faces.

The first defect is easily avoided since the first eigenface is a good face filter which can test whether each image is highly correlated with itself. The images with a low correlation can be rejected or these two issues are altogether addressed by categorizing following four regions:

- Near face space and near stored face => known faces
- Near face space but not near a known face => unknown faces
- Distant from face space and near a face class => non-faces
- Distant from face space and not near a known class => non-faces

Since a face is well represented by the face space, its reconstruction should be similar to the original and the reconstruction error will be small. Non-face images will have a large reconstruction error which is larger than some threshold. The distance determines whether the input face is near a known face. The problem of automatic face recognition is a composite task that involves detection and location of faces in a cluttered background, normalization, recognition and verification. There have been many methods proposed for face recognition. And one of the key components of any methods is a facial feature extraction. Facial feature could be a gray-scale-image.

DiaPCA is a standard technique used to approxiate the original data with lower dimensional feature vectors. The basic approach is to compute the eigen vectors of covariance matrix and approximate the original data by a linear combination of the leading eigenvectors.PCA is appropriate when the samples are from one class or group (super-class). This preprocessing stage reduces the within-class variance dramatically thus improving recognition rate. After projection, recognition is performed in the classification space based on some distance measure criterion. Therefore Principal component analysis (PCA), also known as eigenfaces is one of the state-of-the-art methods in face recognition.

KNN classifier has many advantages. This is easy to compute and very efficient. KNN is very compatable and obtain less memory storage. So it has good discriminative power. KNN is very robust to image distortions (e.g. rotation , illumination). Therefore KNN can provide the components that describe the highest variance and produce good result. So this research can produce good result by combining DiaPCA and KNN (K^{th} nearest neighbor classifier).

8. Conclusion

A novel face recognition method called diagonal principal component analysis (DiaPCA) is proposed in this paper. The essential idea of the proposed method is to generate the *diagonal face images* from the original training images, from which the optimal projective vectors are sought, therefore the correlations between variations of rows and those of columns of images can be reserved. Face Recognition System based on DiaPCA is developed in this research. The effectiveness of the proposed method can be confirmed through the experimental results.

References

[1] Adler , A . , Maclean , J : " Performance comparison of human and automatic face recognition " Biometrics Consortium Conference Sep 20-22 , Washington.

[2] D . Q . Zhang , A . F . Frangi , S . C . Chen , J . Liu , Representing image metrics: Eigenimages , Eigenvectors in proceeding of the 2nd international Symposium on Neural Networks (ISNN05) China , LNCS 3497 (2005) 659-664.

[3] J . R . Scolar , P . Navarreto , " Eigen space-based FACE recognition : a comparative study of different approaches IEEE Tran , System man and Cybemetics-part C: applications , Vol-35 , No .3,2005.

[4] J . Yang , D . Zhang , A . F . Frangi , J . Y . Yang , Two-dimensional PCA: a new approach to appearance-based face representation and recognition , IEEE Trans on Pattern Analysis and Machine Intelligences 26(1)(2004) 131-137.

[5] M . J . Er , W . Chen , S . Wu " High Speed Face Recognition based on discrete cosine transform and RBF neural network" IEEE Trans on Neural Network Vol . 16 , No . 3 , PP . 679,691.

[6] S . C . Chen , YL .Zhu , D . Q . Zhang , J . Y . Yang , Feature extraction approaches based on matrix pattern: MatPCA and matFLDA , Pattern Recognition Letters 26 (8)(2005) 1157-1167.

[7] X . Tan , S . Chen , Z . H . Zhou , F . Zhang , Robust Face recognition from a single training image per person with kernel-based SOM face , China , LNCS 3173(2004) 858-863