FINGERTEC FACE RECOGNITION TECHNOLOGY WHITE PAPER

• July 2013

Scope

FingerTec presents an automatic face recognition algorithm by combining the Gabor and Linear Discriminant Analysis (LDA) methods to ensure accuracy and security when used as an authentication method. FingerTec technology is the foundation for all face recognition solutions from FingerTec and operates seamlessly with many third-party security applications, smart cards and biometric readers on the market. This article describes the principles and advantages of FingerTec technology.

Introduction

Face recognition has become one of the most important biometrics authentication technologies in the past few years. Two main reasons for extensive attention on face recognition technology are: 1. Aptness in various applications including in content-based video processing, law enforcement and security systems whereby a strong need for a robust automatic system is obvious due the widespread use of photo-IDs for personal identification and security, and 2. Although there are other reliable methods of biometrics identification available such as fingerprint and iris scans, face recognition is proven effective for its user-friendliness. The system does not require its users to do anything; it is contactless. On top of that, as one of its core components, the maturity of the digital camera technology with competitive pricing is also a contributing factor to the strong emergence of face recognition technology.

Most of the face recognition techniques have evolved in order to overcome two main challenges: illumination and pose variation. Either of these problems can cause serious performance degradation in face recognition systems. Illumination can change the appearance of an object drastically, and in most cases these differences induced by illumination are larger than the differences between individuals, what makes the recognition task more difficult. The same statement is valid for pose variation. Usually, the training data used by face recognition systems are frontal view face images of individuals. Frontal view images contain more specific information of a face than profile or other 'pose angle' images. The problem appears when the system has to recognize a rotated face using this frontal view training data. Furthermore, the appearance of a face can also change drastically if the illumination conditions vary. Therefore, pose and illumination (among other challenges) are the main causes for the degradation of 2D face recognition algorithms like Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA).

This article discusses two main algorithm families commonly used to recognize faces: Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) based recognition. Both of these two algorithms recognize faces images in different ways; 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 (observed variables) to the smaller intrinsic dimensionality of feature space (independent variables), which is needed to describe the data economically while Linear Discriminant Analysis (LDA) defines a projection that makes the within-class scatter smaller and the between-class scatter larger. It redefines the between-class scatter by adding a weight function according to the between-class distance, which helps to separate the classes as much as possible. As will be shown in this article, both algorithms have advantages and disadvantages. The continued research and development work from FingerTec has led to a more accurate and robust face recognition technology, the FingerTec Face Recognition solution.

Over the past few years, FingerTec has concentrated on developing face recognition methods within the framework of biometrics security systems and is now applying face recognition technology to other markets. FingerTec face recognition technology can be implemented as a functionally independent application or seamlessly integrated into new or existing biometrics security solutions by system integrators and solution provides.

FingerTec face recognition presents a novel and highly descriptive Gabor and LDA mixed local feature and demonstrates its performance on a challenging interclass recognition problem. With the Gabor and LDA features, the combination provides high speed, high accuracy and robustness towards illumination and expression variations for face detection and facial features extraction and has achieved a significant improvement in performance. Moreover, the combined performance deterioration is significantly lower than those employing only individual features. This algorithm is used to decrease the dimension of the eigenvector. The method of adaptive weight is used to reconstruct the within-class scatter matrix and between-class scatter, and improve the Linear Discriminant Analysis (LDA) function. The problem of accurately calculating the class mean of training samples' deviations from the centre of this class is resolved by this improved LDA discriminate function. The numerical experiments on the FERET facial database show that this method achieves better performance in face recognition than traditional methods.

PCA (Principal Component Analysis)

Principal component analysis (PCA) is one of the widely used 2D face recognition algorithm. It is based on information theory concepts, seeks a computational model that best describes a face by extracting the most relevant information contained in that face. The Eigenfaces approach is a PCA method, in which a small set of characteristic pictures are used to describe the variation between face images. The goal is to find the eigenvectors (eigenfaces) of the covariance matrix of the distribution, spanned by training a set of face images. Later, every face image is represented by a linear combination of these eigenvectors. Recognition is performed by projecting a new image onto the subspace spanned by the eigenfaces and then classifying the face by comparing its position in the face space with the positions of known individuals.

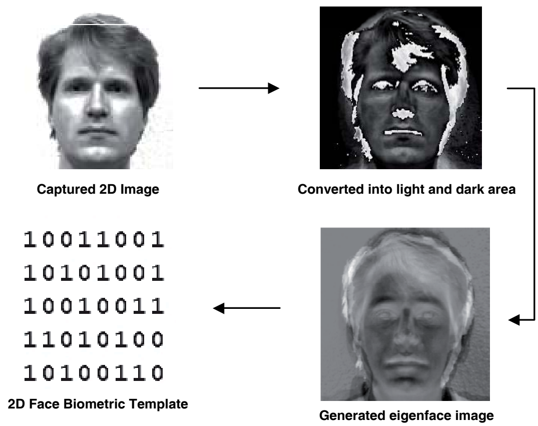


Figure 1: PCA Face Recognition Process

The PCA-eigenfaces system capture the image and change it to light and dark areas. Both the initial facial image and the facial image in question are also captured in a two-deimensional form. Then, the two images are compared according to the points of the two eigenface image. It picks out certain features and calculates the distances between them. The points are the facial features such as eyes, nose, mouth, bone curves, and other distinct features. The eigenface algorithm firstly forms overall average image. This is just the image adding all images and dividing by number of images in training set. And the eigenvectors of covariance matrix that is formed by combining all deviations of training set's images from average image is formed in order to apply eigenfaces algorithm. After finding overall average image, the order is to find eigenvectors of the covariance matrix. Visualization of eigenvectors is carried out simply applying a quantization that is if the found eigenvectors have components that are greater than 255 and smaller than 0 round them to 255, and 0 respectively.

Pros:

- Fast, needs lesser amount of memory for identification.
- Image template size small.

Cons:

- PCA face recognition algo rithm is sensitive to lighting, head orientations, facial expressions and makeup.
- PCA face image templates contain limited information.

LDA (Linear Discriminant Analysis)

LDA analysis has been one of the most popular techniques employed in face recognition. The basic idea of LDA is to calculate the fisher optimal discriminant vectors so that the ratio of the between-class scatter and the within-class scatter (Fisher Index) is maximized. Linear Discriminant Analysis or Fisherfaces method overcomes the limitations of the Eigenfaces method by applying Fisher's linear discriminant criterion. This criterion tries to maximize the ratio of the determinant of the between-class scatter matrix from the projected samples to the determinant of the within-class scatter matrix from the projected samples. Fisher discriminants will group images of the same class and separate images of different classes. Images are projected from N2-dimensional space to C dimensional space (where C is the number of classes of images). For example, consider two sets of points in a 2-dimensional space that are projected onto a single line. Depending on the direction of the line, the points can either be mixed together or separated. Fisher discriminants will find the line that best separates the points. To identify an input test image, the projected test image is compared to each projected training image, and the test image is identified as the closest training image.

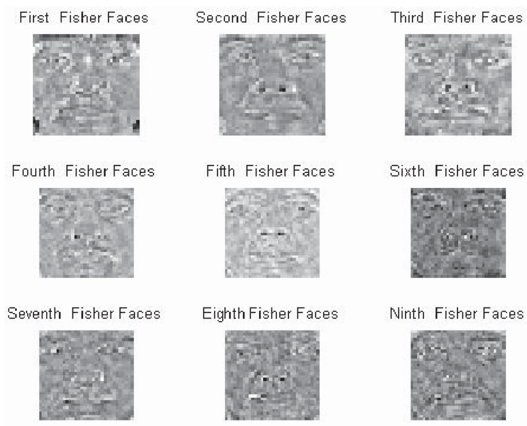
$$\hat{W} = \arg\max J(W) = \frac{|W^T S_B W|}{|W^T S_W W|}$$

The algorithm of LDA

As with Eigenspace projection, training images are projected into a subspace. The test images are projected into the same subspace and identified using a similarity measure. What differs is how the subspace is calculated. Unlike the PCA method that extracts features to best represent face images; the LDA method tries to find the subspace that best discriminates different face. The within-class scatter matrix, also called intra-personal, represents variations in appearance of the same individual due to different lighting conditions and face expressions, while the between-class scatter matrix, also called the extra-personal, represents variations in appearance due to a difference in identity. By applying this method, it is easier to find the projection directions that on one hand can maximize the distance between the face images of different classes, while on the other hand can minimize the distance between the face images of the same class. In other words, this refers to maximizing the between-class scatter matrix SB, while minimizing the within-class scatter matrix SW in the projective subspace.

Face Database

TRAINING SET



LDA Features Extraction

$$\begin{pmatrix} a_1 & +b_1 & +\cdots+h_1 \\ a_2 & +b_2 & +\cdots+h_2 \\ \vdots & \vdots & \vdots \\ a_{N^2} & +b_{N^2} & +\cdots+h_{N^2} \end{pmatrix}$$

LDA Features Vectors

Pros:

- Faster than PCA, in some cases
- Has lower error rates
- Works well even with different illumination conditions
- Works well even with different facial expressions

Cons:

- Heavy storage demands
- Can only classify a face which is "known" to the database DB
- Sensitive to self-shadowing, specularities and noise

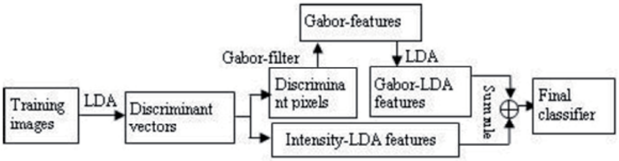
PCA vs. LDA Face Recognition

	PCA	LDA
Definition	PCA (commonly referred to as the use of Eigenfaces) is the technique pioneered by Kirby and Sirivich in 1998. With PCA, the probe and gallery images must be the same size and must first be normalized to line up the eyes and mouth of the subject within the images. The PCA approach, thus used to reduce the dimension of the data by means of basic data compression, reveals the most effective low dimensional structure of facial patterns.	Linear Discriminant Analysis (LDA) is a statistical approach for classifying samples of unknown classes based on training samples with known classes. This technique aims to maximize within-class (i.e. within user) variance. When dealing with high dimensional face data, this technique faces the small sample size problem that arises where there are a small number of available training samples compared to the dimensionality of the sample space.
How it works	The key idea behind PCA is to find the best set of projection directions in the sample space that maximizes total scatter across all images. This is accomplished by computing a set of Eigenfaces from the Eigenvectors of total scatter matrix.	The objective of LDA is to find the subspace that best discriminates different face classes by maximizing between-class scatter, while minimizing the within-class scatter. The Eigenvectors chosen by LDA provide the best separation among the class distributions, while PCA selects Eigenvectors which provide best representation of the overall sample distribution.
Template size	2 kilobytes to 6 kilobytes	2 kilobytes to 4 kilobytes
Template description	Converts each two dimensional image into a one dimensional vector. This vector is then decomposed into orthogonal (uncorrelated) principal components (known as Eigenfaces)—in other words, the technique selects the features of the image (or face) that vary the most from the rest of the image.	A standard technique in statistical pattern classification for dimensionality reduction with a minimal loss in discrimination. This is more practical, given a number of independent features that can describe the data.
Liveness testing	May be spoofed by photo or video	May be spoofed by photo or video
FAR	~0.001 (FRVT 2006 result)	~0.001 (FRVT 2006 result)
FRR	~0.010-0.017 (FRVT 2006 result)	~0.006-0.015 (FRVT 2006 result)
Accuracy	Recognition rate 83.1% based on Yale database	Recognition rate 87.7% based on Yale database
Sensitivity	Sensitive to lighting, pose or expressions	Less sensitive to lighting pose or expressions
Standard	ANSI/INCITS (M1) 385-2004	ANSI/INCITS (M1) 385-2004
Leading vendors	Neven Vision, Sagem, Toshiba, FingerTec	Cognitec, Viisage, Toshiba, FingerTec

FingerTec Face Recognition Algorithm

To overcome the negative effects in factors such as illumination, pose and expression on face recognition, FingerTec face recognition algorithm uses a combined Gabor-LDA based method. This method makes full use of discriminant vectors obtained by Linear Discriminant Analysis (LDA). Given training face images, discriminant vectors are computed using LDA. The function of the discriminant vectors is two-fold. First, discriminant vectors are used as a transform matrix, and LDA features are extracted by projecting original intensity images onto discriminant vectors. Second, discriminant vectors are used to select discriminant pixels, the number of which is much less than that of a whole image. Gabor features are extracted only on these discriminant pixels. Then, applying LDA on the Gabor features, one can obtain the Gabor-LDA features. Finally, a combined classifier is formed based on these two types of LDA features. Results from experiments on FERET face database show the effectiveness of this combined Gabor-LDA recognition method.

The diagram above illustrates the process of feature extraction and the design of the classifier. Note that discriminant vectors obtained by LDA are used to determine discriminant pixels which are related to intuitive local features. Since the number of discriminant pixels is much less than that of the whole image, the amount of computed Gabor-wavelet coefficient is decreased. Furthermore, local features and global features are combined to form the final classifier. Specifically, we describe our method as follows:



With the given training images, discriminant vectors are computed using LDA. The function of the discriminant vectors is two-fold. First, discriminant vectors are used as a transform matrix, and LDA features are extracted by projecting gray-level images onto discriminant vectors. Second, discriminant vectors are used to select discriminant pixels, the number of which is much less than that of a whole image. Gabor features are extracted only on these discriminant pixels. Then, applying LDA on the Gabor features, one can obtain reduced Gabor-LDA features. Finally, a combined classifier is formed based on these two types of LDA features.

Benefits of FingerTec Face Recognition Algorithm

SIMULTANEOUS MULTIPLE FACE PROCESSING

Performs fast and accurate detection of faces in live video streams. After face detection, a set of features is extracted from face into a template and identify with the face templates database within 1 second.

LIVE FACE DETECTION

A conventional face identification system can be tricked by placing a photo in front of the camera. FingerTec face recognition algorithm is able to prevent this kind of security breach by determining whether a face in a video stream is live or a photograph.

FACE IMAGE QUALITY DETERMINATION

A quality threshold can be used during face enrollment to ensure the quality of face templates that will be stored.

TOLERANCE TO FACE POSITION

FingerTec face recognition is more robust to different view angles and position with robust recognition up to 15 degrees. Therefore, FingerTec approach has the potential to work with higher accuracy in real work environments.

MULTIPLE SAMPLES OF THE SAME FACE

FingerTec face recognition algorithm template can contain a total of 15 face samples belonging to the same person thus allowing vast improvements in matching quality.

REDUCE FAR & FRR RATE

The FingerTec face recognition algorithm is able to process 10-12 fully capturing matching cycles per second, for extremely low False Rejection Rates (FRR) and False Acceptance Rates (FAR), which is the leader in processing and accuracy among others in the same industry.

Algorithm Performance

FingerTec has gone through many tests based on different image capturing resolutions, lighting environments, pose angles and FERET databases where more than 10,000 faces images are obtained to test the performance of the FingerTec face recognition algorithm in the past few years. Each individual has 6 frontal face images from which 4 images are selected as training images and the remained 2 images are used for testing.

Face Enrollment Results:

- 99.5% automatic enrollment
- 0.5% required manual support
- 0% failure to enroll
- Average 4-8 seconds enrollment time

Face Verification Results:

- False Acceptance Rate (FAR) <= 0.0001%
- False Rejection Rate (FRR) <= 1%
- Matching speed <= 1 second

Face recognition is one of the most active research fields as demonstrated by more than 1,000 publications that have appeared in different conferences and journals in the last few years. Feature extraction is one of the most fundamental problems in face recognition. Linear Discriminant Analysis (LDA) is a very effective way to extracting the features and reducing the dimensionality. However the classical LDA also suffers from the small sample size problem in face recognition tasks. FingerTec has presented a novel face recognition method based on Gabor wavelet and LDA. A major contribution of the method is that discriminant vectors obtained by LDA are used to determine salient local features, the positions of which are specified by discriminant pixels. Because the number of discriminant pixels is much less than that of the whole image, the amount of Gabor wavelet coefficients is decreased. Another contribution is that local features and global features are combined to form the final classifier. The Gabor-LDA based method efficiently utilizes Gabor wavelet, local features and global features, and thus results in superior performance in the experiments. FingerTec will continuously run field tests of the complete system to get statistics for continued improvement of the Gabor-LDA based recognition performance.