

# 2D Model Based Face Recognition/Authentication

Shuang Cui

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## 1 Introduction

Face recognition has become the most popular research area in computer vision and application in recent years. The nature of the problem has not only attracted science researchers but also fascinated neuroscientists and psychologists[8]. It is the computer vision research provides useful insights to neuroscientists and psychologists into how human brain works, and vice versa.

2D Face recognition is to identify one or more faces from still images or a video images with face stored in a scene by comparing input images with face stored in a database. Typically, human faces are similar in structure except little differences from person to person. They all belong to one class “human face”. Furthermore, when taken a picture of human face, the face space is commonly represented as principle component that embed in the high dimensional image space. In theory, by determine the number of degrees of freedom within the face space, and extract the principal modes of the component should give us the face space. In practice, due to sensor noise, the signal usually will have a non-zero component outside of the face space[2]. This introduces uncertainty into the model and requires algebraic and statistical techniques.

## 2 Overview of Face Recognition Techniques

### 2.1 Principle Component Analysis

In 1991 Kirby and Sirovich [4] proposed a face image analysis and representation using Principle Component Analysis (PCA)[3]. The first application of PCA to face recognition is developed by Turk and Pentland[7] called “Eigenfaces”. Since the basis vectors constructed by PCA had the same dimension as the input face images, there were named “Eigenfaces”[6] Figure

1 shows an example of the mean face and a few of the top Eigenfaces.



Figure 1: Eigenface[6]: average face on the left, followed by 7 top eigenfaces

After subtracting the mean face from all the face images, every face image was projected into the principal subspace; the coefficients of the PCA expansion were averaged for each subject, resulting in a single k-dimensional representation of that subject. When a test image was projected into the subspace, Euclidean distances between its coefficient vector and those representing each subject were computed[6]. Depending on the distance to the subject for which this distance would be minimized, and the PCA reconstruction error, the image was classified as belonging to one of the familiar subjects, as a new face, or as non-face.

### 2.2 Fisherfaces

Since PCA technique select a subspace which retains most of the variation, consequently the similarity in the face space is not necessarily determined by the identity. Belhumeur[10] proposed a algorithm that called “Fisherfaces” an application of Fisher’s Linear Discriminate(FLD).

The Fisherfaces algorithm first reduces the dimensionality of the data with PCA so that it can be computed, and then applies FLD to further reduce the dimensionality to  $m - 1$ . The recognition is then accomplished by a NN classifier in this final subspace. In the experiment[10] showed that fisher face algorithm outperformed the PCA algorithm on data sets containing frontal face images of 5 people with drastic lighting variations and another set with faces of 16 people with varying expressions and again drastic illumination changes.

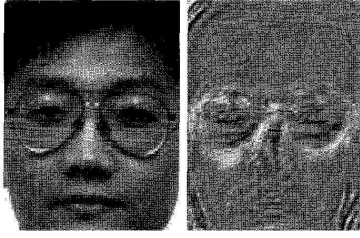


Figure 2: The left images is an image from the Yale Database of person wearing a glasses. The right image is the Fisherface used for determining if a person is wearing glasses

## 2.3 Bayesian Methods

In Bayesian formulation (1), proposed by Moghaddam [1], it casts the standard face recognition task, that is an m-ary classification problem for m individuals, into a binary pattern classification problem. It present a probabilistic similarity measure based on the Bayesian belief that the image intensity difference, denote  $\Delta = I_1 - I_2$  are characteristic of typical variations in appearance of an individual[1]. It particular define two classes of facial image variations. Intrapersonal variations  $\Omega_I$ corresponde to different facial expressions of the same individual. Extrapersonal variations  $\Omega_E$ corresponde to variations between different individuals. The densities of both classes are modeled as high-dimensional Gaussian using an PCA-based method. The maximum likelihood is used to match the face image to its class.

$$S(\Delta) = P(\Omega_I|\Delta) = \frac{P(\Delta|\Omega_I)P(\Omega_I)}{P(\Delta|\Omega_I)P(\Omega_I)+P(\Delta|\Omega_E)P(\Omega_E)}$$

Bayesian formaulation(1)

One analysis is presented in [11] evaluated PCA, LDA and Bayesian matching as “unified” under a 3 parameter subspace approach and compared in terms of performance. The experimental studies in the paper[9] and a lot of recent years papers have shown that the Bayesian matching technique out-performs LDA. However, since Bayesian formulation is probabilistic which seems making no appeal for geometry or the symmetry of the underlying data.

In a lot of recent researches, it tends to use individual face’s distinguishable landmarks, such as distance between eyes, width of nose, depth of eye sockets, cheekbones, jaw line, chin to identify a face image. The result is a little better than the method described above. However, for every algorithm there is some shortness. For example, a face image which taken from the side

do not have some of the feature that are require for recognition in some algorithms which claims work better than Eigenface.

## 2.4 Face Recognition Using Line Edge Map

Takace proposed a method which using complete approach as Yossi’s approach. It make use of edge maps to measure the similarity of face image. The faces were encoded into binary edge maps using Sobel edge detection algorithm. The similarity of the two point sets is measured using Hausdorff distance, for example, the edge maps of two faces, because the Hausdorff distance can be calculated without an explicit pairing of points on their respective data sets.

## 3 Uses of face recognition

Face recognition has been used in some areas, such as biometric authentication, law enforcement tools which use the system to capture random faces from crowds.

In January 2000[9], Tampa Bay police implemented a new technology called “faceit” during the super bowl game in America. It takes a snapshots of faces from the crowd to be compared to a database of criminal mugshots. It found 19 people with pending arrest warrants.

One of the most innovative uses of face recognition was employed by the Mexican government to remove duplicate voter registrations[5]. Officials can search through facial images in the voter database for duplicates at the time of registration. New images are compared to the records already on file to catch those who attempt to register under aliases.

In conclusion, the face recognition has been the most discussed research in recent years. Despite, a lot of algorithm has been proposed, there are no single algorithm can outperform every other algorithms in every kind test with a fast speed. The Principle component analysis and Linear Discriminant Analysis still being widely used by a lot of face recognition applications. However, improved face recognition algorithm has been developed. Some of the algorithms can recognize 3d face images as well as video face images. All current face recognition algorithms fail under the vastly varying conditions which humans need to and are able to identify other people. Next generation person recognition systems will need to

recognize people in real-time and in much less constrained situations.

## References

- [1] T. Jebara B. Moghaddam. *IEEE Computer Vision and Pattern Recognition*, 33(1771), Nov.
- [2] Baback Moghaddam Gregory Shakhnarovich. Face recognition in subspaces. *MITSUBISHI ELECTRIC RESEARCH LABORATORIES*, 1(1), May 2004.
- [3] I. T. Jollie. Principal component analysis. *Springer-Verlag*, 1(1), July 1986. New York.
- [4] M. Kirby and L. Sirovich. Application of the karhunen-loeve procedure for the characterization of human faces. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 12(1), Jan 1990. Department of Psychology, University of Stirling, UK.
- [5] ] Barry Mazor. Biometric imaging faces a reality check. *Advanced Imaging Magazine*, September 2005.
- [6] M. Turk and A. Pentland. *IEEE Computer Vision and Pattern Recognition*, (586), Dec. Maui, Hawaii.
- [7] M. Turk and A. Pentland. Eigenfaces for recognition. *Journal of Cognitive Neuroscience*, 3(1), July 1991. New York.
- [8] unknow. Face recognition. *Online*, March 2006. <http://www.face-rec.org>.
- [9] Unknow. Facial recognition system. *Wikipedia*, Jan 2007. <http://en.wikipedia.org/wiki/Facialrecognitionssystem>.
- [10] J. Hespanha V. Belhumeur and D. Kriegman. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 19(711), July.
- [11] X. Wang and X. Tang. *In Proceedings of IEEE International Conference on Computer Vision*, 33(1771), Jun. Nice, France.