EVALUATION OF FUSION SCORE FOR FACE VERIFICATION SYSTEM

REZA ARFA

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To my beloved mother

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ABSTRACT

Given an individual face image and a claimed ID, the face verification problem is to determine whether or not he is the person he claims to be. Although this task seems to be easy for a human, this problem is one of the most challenging problems in the area of computer vision. Eigenface and fisherface are two well-known and successful face verification approaches. Despite an assumption that face verification systems based on fisherface is thought to be more accurate than eigenface system, recent studies reveal that the idea is not always true. In this research, in order to leverage on the strength of both eigenface and fisherface techniques, a fusion of these two techniques by using different fusion method is examined. Four fusion methods, namely, sum-rule, Artificial Neural Network (ANN), Linear Support Vector Machines (Linear SVM), and Gaussian Support Vector Machines (Gaussian SVM) are considered. ORL database is used to evaluate and compare different approaches. The experiments show that the Total Error Rate for individual eigenface and fisherface systems are 12.5% and 9.4% respectively. This error for the fusion based systems that use sum-rule, ANN, Linear SVM, and Gaussian SVM, as fusion techniques are 9.9%, 5.9%, 6.7%, and 6.3% respectively. The results demonstrate that fusion-based face verification system outperforms both eigenface and fisherface systems when used individually.

ABSTRAK

Diberi imej muka seorang individu beserta dengan ID yang dituntut, masalah di dalam pengesahan muka adalah untuk menentukan sama ada individu tersebut adalah identiti yang didakwanya atau tidak. Walaupun tugas ini kelihatan mudah bagi manusia, namun begitu di dalam bidang visi komputer, ia merupakan antara perkara yang amat mencabar. *Eigenface* dan *Fisherface* adalah dua teknik yang popular dan efisien. Walaupun sistem pengesahan muka berdasarkan *Fisherface* dianggap lebih tepat berbanding sistem *Eigenface*, kajian terkini mendedahkan bahawa dakwaan itu tidak selalunya benar. Bagi memanfaatkan kelebihan daripada kedua-dua teknik, satu pendekatan gabungan dengan menggunakan kaedah gabungan yang berbeza dikaji. Terdapat empat kaedah gabungan iaitu *sum-rule*, Rangkaian Neural Tiruan (*ANN*), Linear Mesin Vektor Pendukung (*Linear SVM*) dan Gaussian Mesin Vektor Pendukung (*Gaussian SVM*) dipertimbangkan. Pangkalan data ORL digunakan untuk menilai dan membanding teknik-teknik tersebut. Ujikaji menunjukkan ralat yang dikenali sebagai Jumlah Kadar Ralat bagi sistem *Eigenface* dan *Fisherface* masing-masing adalah 12.5% dan 9.4%. Ralat yang diperolehi berdasarkan sistem yang menggunakan kaedah gabungan *sum-rule*, *ANN*, *Linear SVM* dan *Gaussian SVM* masing-masing adalah 9.9%, 4.9%, 6.7% dan 6.3%. Hasil ujikaji menunjukkan bahawa sistem pengesahan muka berdasarkan gabungan mengatasi sistem *Eigenface* dan sistem *Fisherface*.

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LIST OF SYMBOLS

λ	-	Learning Rate
μ	-	Mean
θ	-	Threshold value
R^d	-	Input space
$R^{d'}$	-	Output space

LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Networks
BPNN	-	Back-propagation Neural Networks
EER	-	Equal Error Rate
FAR	-	False Acceptance Rate
FRR	-	False Rejection Rate
ID	-	Identity
ICA	-	Independent Components Analysis
K-SVM	-	Kernel Support Vector Machines
LDA	-	Linear Discriminant Analysis
L-SVM	-	Linear Support Vector Machines
MLP	-	Multi Layer Perceptrons
PC	-	Personal Computers
PCA	-	Principle Components Analysis
PDBNN	-	Probabilistic Decision Based Neural Networks
SVM	-	Support Vector Machines
SVD	-	Singular Value Decomposition

CHAPTER 1

INTRODUCTION

The face recognition problem is defined as: Given an individual face image, determine whether he is the person he claimed to be. Though this task seems to be easy for a human, as it will be explained, this problem is one of the most challenging ones in the area of computer vision. In this chapter an overview of face recognition and verification systems as well as their applications will be presented.

1.1 Background

Recognizing individuals to access to a physical or virtual domain is an important task in terms of security. Conventionally, identification process was done by a medium such as keys, passwords, tokens, PINs, and smart cards [1]. These approaches suffer from being misplaced, or stolen. The rapid progress in machine vision and image analysis research contributes to the emergence of biometric-based authentication systems. To determine an individual's identity, biometric techniques utilize human behavioral characteristics (such as signature), physical attributes (such as fingerprint, face, retina, voice, etc.) [2]. Biometric techniques provide safer, faster, and automated authentication.

Depending on the usage of different characteristic, biometric approaches vary. There has been a study conducted by *International Biometric Group* [3], which compared different types of biometric system regarding to distinctiveness, cost, effort, and intrusiveness of the system. The result is shown in figure 1-1. The ideal system is the system, which all the four parameters are furthest from the center.

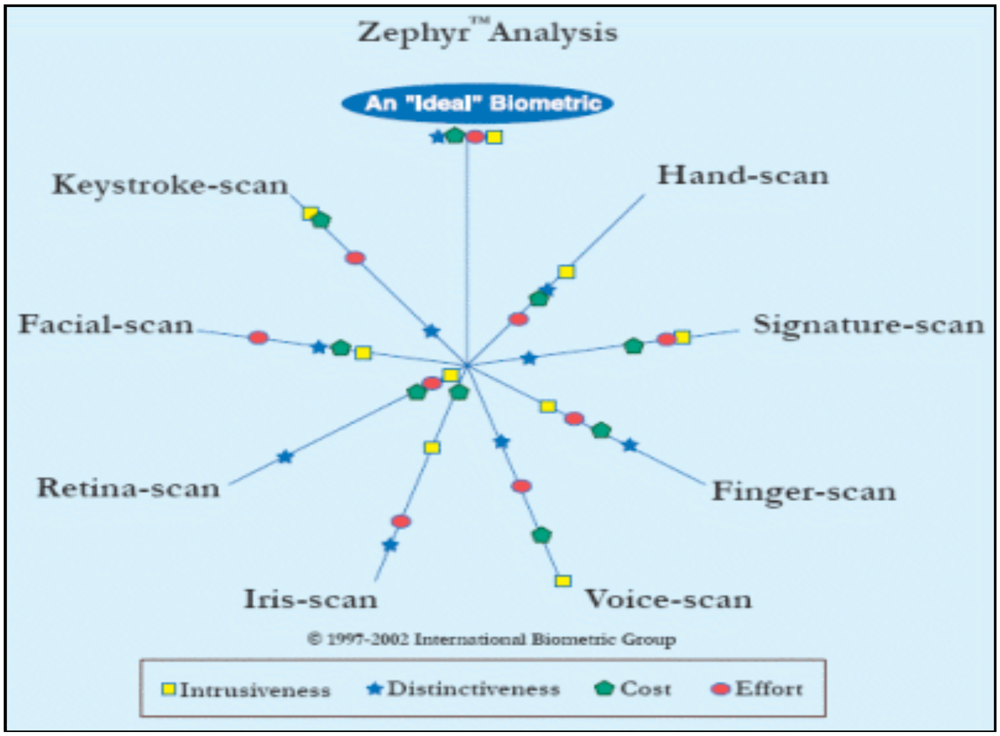


Figure 1-1 A comparison of different biometric systems (adopted from International Biometric Group [3])

The advantages of face recognition over the other biometric techniques include [2]:

- **Outstanding accuracy:** the existing face recognition system has an outstanding accuracy compares with other types of biometrics.
- **Cheap interface**: a face recognition system needs an inexpensive camera as an interface
- **None-Intrusive:** In the other types of recognition systems, users need to do an action. For example, in fingerprint-based biometric system, the user needs to place his fingers on sensor. However face recognition system is a non-intrusive biometric system.
- **Fast:** A face recognition system can recognize faces in an image with a high

speed. This advantage is very useful especially in crowded places such as shopping malls.

- **Compatible with most ID cards:** Generally speaking, the only biometric characteristic that is available in almost all ID cards and passports is an image of the holder's face.

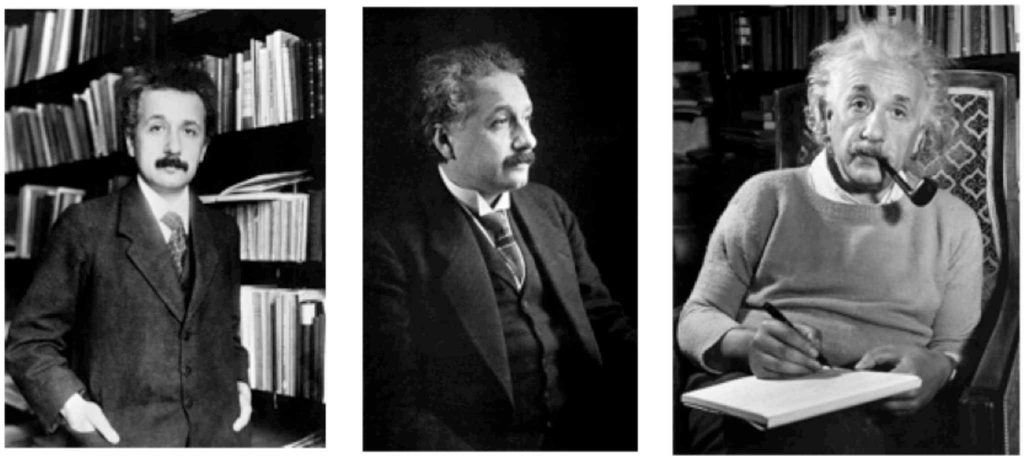
Although the task of matching a person's image with the person's face is an easy one for human being, a computerized face recognition system that can imitate human's ability has not been fully developed yet. A human brain is able to recognize familiar faces at a glance even under very different lighting condition, varying angles, scaling differently, different background, and effected by ageing. More interestingly, human can recognize familiar individual even by glancing at part of his face image. Some of the human's ability in recognizing familiar faces even with variations in the images is shown in figure 1-2. The challenge of face recognition system is to recognize faces under such variations, which has proven to be very difficult.

1.2 Automated Face Recognition System

Recognizing a face in an image consists of at least two main stages [1]: (1) face detection (2) face recognition. These two stages are shown in figure 1-3. In this subsection, an overview of each stage is presented.

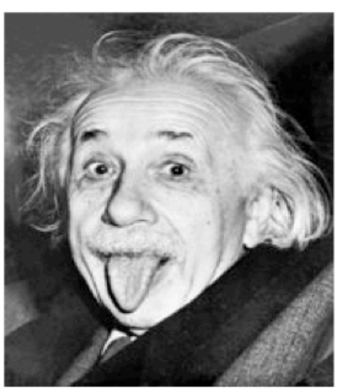
1.2.1 Face Detection

In the first stage of a face recognition system, all faces in an image are detected from non-faces or background (*Fig. 1.4*). There are two important parameters in a face detection system [4]: (1) *true positive rate* (or *detection rate*) which is the ability of a face detection system to detect faces correctly (2) *False positive rate:* the error which the system detects faces in a coordinate of an image where there is not any faces there is

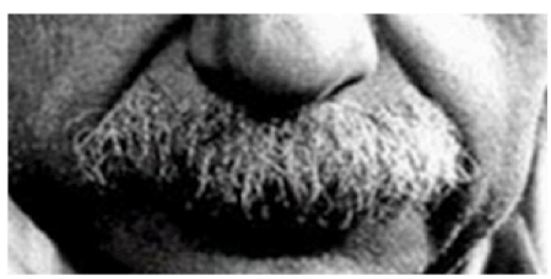


(a)

(b)



(c)



(d)

Figure 1-2 Ability of human in recognizing a familiar face under different (a) aging, (b) pose, (c) face expression, and (d) recognizing the person by seeing a part of a face

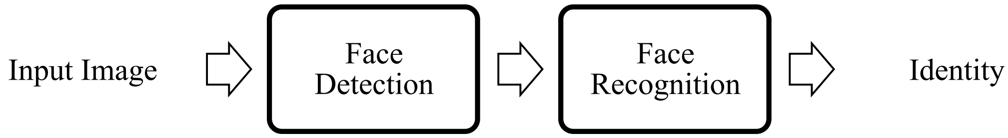


Figure 1-3 General stages of an automated face recognition system

called false positive error. An ideal face detection system has 100% detection rate, and 0% false positive error [4].

Early study on face detection focused on detecting a specific face from a background by using image-processing techniques. However, recent techniques such as Adaboost approach **[4]** can detect the faces position in an image in a few milliseconds with a high detection rate (~95% for frontal face) and relatively low false positive error (~10^-9).

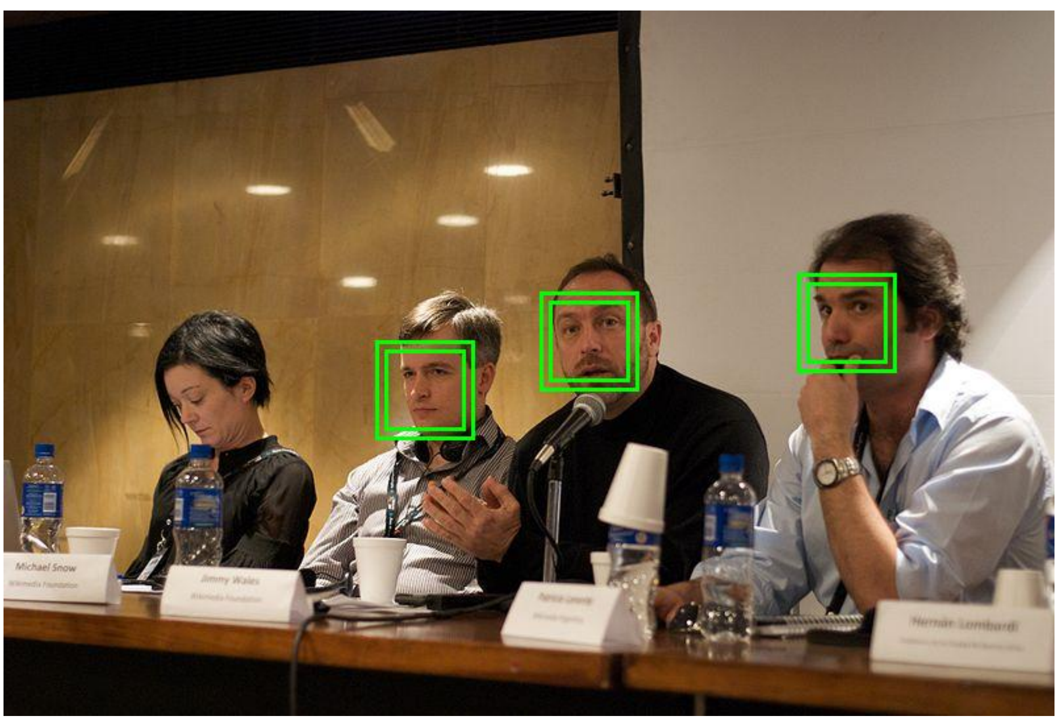


Figure 1-4 An example of a face detection system. Three faces are detected correctly, while due to pose, one face has not been detected correctly. Adopted from [5]

1.2.2 Face Recognition

After the position of the face is found, the identity of the face is recognized in the face recognition stage. Many methods have been proposed over the last few decades, which fall into three main groups (*table 1-1*):

(1) *Model (or featured) -based methods.* In these methods, distinctive facial features such as the position of lips, nose, eyes, eyebrows, etc., are extracted. The geometric relationships between them are forming the vector of features. Machine learning techniques are then utilized to match faces using this vector.

The advantages of model-based techniques include the robustness of the systems to position variation, and fast matching due to their small-size feature vector; however, these approaches suffer from the difficulty of feature detection, and low discriminative features [6].

(2) *Appearance (or holistic) -based methods.* The first stage of modeled-based approaches was based on processing the image to find facial attributes. In contrast, appearance-based methods use the global representation for identification purpose. In other words, the whole image pixels are the feature vector [1].

In appearance-based method, each image is defined in a R^N space where N is the number of pixels. Not all possible points in this space are representing a face. In fact, faces images lay on a nonlinear manifold in this N-dimensions image space. Appearance-based approaches suggest to find a proper mapping to reduce this N-dimensional space into M-dimensional space (M<N), where the faces are represented better in the new space. Two well-know appearance-based methods are Principal Component Analysis (PCA) [7], and Linear Discriminate Analysis (LDA) [8] where project the faces into subspace known as *Eigen space* and *Fisher space* respectively. In score-based face recognition systems, the projected face is then compared with the stored database via a similarity function (such as Euclidean Distance).

Since appearance-based methods use all the pixels, they do not destroy information. Indeed, since all pixels in an image assumed to be equally important, the above advantage is holistic-based methods' greatest drawback as well. However, by introducing techniques such as eigenface and fisherface, this disadvantage became less important. Generally speaking, holistic-based approaches outperform the model-based methods [9].

(3) *Hybrid methods*. In this approach, the system uses both of the above methods to make its decision.

Table 1-1: face recognition approaches [1]

Approach Categories	Examples
Appearance-Based	• Eigenface [7] • Fisherface [10] • Independent Component Analysis (ICA) [11] • Probabilistic Decision Based Neural Network (PDBNN) [12]
Model-Based	• Elastic Bunch Graph Matching [6] • Hidden Markov Model [13] • Convolutional Neural Networks [14]
Hybrid-Based	• Hybrid Local Feature Analysis [15] • Modular Eigenface [16]

1.3 Application Domains

There are two tasks which face recognition can be utilized:

- **Verification:** in this task, face recognition system is used to perform a one-to-one matching. More specifically, given an image with a claimed identity, the system should deny or accept the claimed identity

- **Identification:** despite to the first task, this task needs to perform a one-to-many matching. Given an image of a face, the system should determine the identity of the individual according to the stored database. It worth to mention that, in literature the terms *face recognition* is usually used interchangeably with the term *face identification*, although the former refers to more broad application that include both identification and verification. In the rest of this thesis, this convention is used and the term face recognition will always used instead of face identification.

Face recognition and verification have a vast number of applications range from entertainment to law-enforcement applications. Some of these applications are outlined in Table 1-2 [1]. Beside these applications, face recognition and verification techniques are used in many recently emerged applications such as expression recognition and face tracking. It is expected that in the near future, face recognition and verification will become the essential tools of all computers and smart phones.

Table 1-2: applications of face recognition **[1]**

Areas	**Application**
Entertainment	Video game, virtual reality, training programs, Human-robot-interaction, human-computer-interaction
Smart Cards	Drivers' licenses, entitlement programs, Immigration, national ID, passports, voter registration, Welfare fraud
Information Security	TV Parental control, personal device log on, desktop log on, Application security, database security, file encryption, Intranet security, internet access, medical records, Secure trading terminals
Law enforcement and surveillance	Advanced video surveillance, CCTV control, Portal control, post event analysis, Shoplifting, suspect tracking and investigation

1.4 Problem Statement

A system that can imitate the full ability of a human to verify face images has not been developed yet [1]. All the face verification algorithms suffer from robustness where they may work well under certain conditions and by changing these conditions the system's verification rate decreases rapidly [9]. This difficulty comes from the fact that from machine point of view discrimination between different face images are subtle [9]. In addition, the human's face due to aging or facial paraphernalia may vary over time. These limitations make the autonomous face verification system an active and challenging area in the field computer vision.

Researchers have proposed different face verification algorithms over the past decades [1, 9, 17]. Eigenface and fisherface are two well-known face verification techniques and among the best existing approaches [18]. Both eigenface and fisherface approaches seek to find a linear mapping matrix to project the face images into a lower dimension subspaces known as eigenspace and fisherspace respectively. The eigenface obtains the mapping matrix based on Principal Component Analysis (PCA) while the fisherface uses Linear Discriminant Analysis (LDA) to find the mapping matrix [19]. The main difference between PCA and LDA approaches is that PCA does not consider the relation of each sample to its class, while in the LDA calculations uses the class label information during the training [10].

Early studies claimed that LDA technique is more accurate than PCA approach, since the former searches for the effective direction for discrimination [10, 20]. However, recent studies show that this is not correct in general, and on different situations each of these methods outperforms the other [19].

In this research, in order to leverage on the strength of both eigenface and fisherface techniques, a fusion of these two techniques by using different fusion methods is examined. Five fusion methods, namely, sum-rule, Artificial Neural Network (ANN), Linear Support Vector Machines (Linear SVM), and Gaussian Support Vector Machines (Gaussian SVM) are considered and compared.

1.5 Objectives

The main objectives of this research are as follows:

i. To experimentally evaluate the performance of eigenface and fisherface-based face verification systems using three similarity measures, namely, Euclidean distance, Manhattan distance, and Chebysheve distance and find the most suitable similarity function for each of these approaches.
ii. To fuse eigenface and fisherface approaches in a single face verification system by using sum-rule, Linear SVM, Gaussian SVM, and ANN fusion.
iii. To compare the performance of the eigenface and fisherface systems with four fusion techniques, namely, sum-rule, ANN, Linear SVM, and Gaussian SVM.

1.6 Scope of Thesis

This thesis will cover on the following scope:

i. The research only consider on face verification system.
ii. No face detection stage is considered or preprocessing stage is considered. In other words, it is assumed that the face images are detected and preprocessed.
iii. The Olievetti Research Laboratory (ORL) database [21] is used to evaluate and compare the performance of the methods.

1.7 Thesis Organization

The thesis organized as follows:

- **Chapter 1:** describe some background information on the face recognition, including the problem statement and the objectives of the thesis.

- **Chapter 2:** consists of the literature review and explanation of the different parts of general face verification systems, the algorithm of eigenface and fisherface. Different fusion techniques are also explained in this chapter.

- **Chapter 3** explains the system setup of eigenface-, fisherface-, and fusion-based face verification system

- **Chapter 4** Presents the experiments carried out to examine the system's accuracy

- **Chapter 5** concludes about face verification system and summarizes what has been achieved in this research

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