IDEA GROUP PUBLISHING ITB12299

701 E. Chocolate Avenue, Suite 200, Hershey PA 17033-1240, USA
Tel: 717/533-8845; Fax 717/533-8661; URL-http://www.idea-group.com

This paper appears in the publication, *Biometric Image Discrimination Technologies*
by David Zhang, Xiaoyuan Jing, and Jian Yang © 2006, Idea Group Inc.

Chapter IV

PCA/LDA Applications in Biometrics

ABSTRACT

In this chapter, we show some PCA/LDA applications in biometrics. Based on the introductions to both PCA and LDA mentioned in Chapters II and III, their simple descriptions are given first. Then, we indicate a significant application in face recognition. The next sections discuss palmprint identification and gait verification, respectively. For other applications, ear biometrics, speaker identification, iris recognition and signature verification are respectively described. At the end of this chapter, we point out a brief but useful summary.

INTRODUCTION

PCA is famous for its dimension-reducing ability. It uses the least number of dimensions but keeps most of the facial information. Romdhani puts forward the usage of this algorithm and shows that there exists a subspace of image space called face space (Romdhani, Gon, & Psarrou, 1999). Faces, after being transformed into this space, have the smallest least square error after we compare the image before and after it is reconstructed. We can use this characteristic for detecting face. Feraud showed the advantages and disadvantages between PCA, ANN and estimation functions (Feraud, 1997). Moghaddam uses the outputs of PCA to provide a probability matching function for face recognition (Moghaddam, Wahid, & Pentland, 1998). They used the EM algorithm to analyze the output data, and made the recognition rate more reliable.

LDA is a statistical method. It was defined by Fisher in 1937 (Fisher, 1936), and can maximize the difference between classes by using within-class scatter and between-class scatter. The distance between classes will be enlarged after a training procedure. Georphiades et al. defined a space they called fisherspace derived from LDA (Georphiades, Belhumeur, & Kriegman, n.d.). The fisherspace can not only improve the accuracy of face recognition, but also reduce the influence of the lighting problem. We describe this algorithm in the next section. Additionally, we also discuss the limitation of LDA when it does face recognition in this chapter.

FACE RECOGNITION

Previous researchers have developed numerous tools to increase the signal-to-noise ratio (Lin, 1997). To deal with complex image background, the recognizer requires a good face detector to isolate the real faces from other parts of the image. Illumination is often a major factor in the obstruction of the recognition process. To alleviate the influence of the illumination effect, people may take conventional image enhancement techniques (dynamic thresholding, histogram equalization) or train a neural network for feature extraction. Another approach to reduce the illumination effect is using the eigenface method. As will be mentioned later, the eigenface algorithm reduces the high-dimensional feature space into a low-dimensional subspace where most of the energy resides (i.e., eigenspace). According to the literature (Moghaddam, Wahid, & Pentland, 1998; Turk & Pentland, 1991a, 1991b; Lin, 1997), one or a few eigenfaces (terminology for the eigenvectors in the eigenface algorithm) could be used to represent the "illumination effect" on facial images. Therefore, putting lower weighting on those eigenfaces when doing the recognition reduces the illumination effect. Yet another remedy for illumination variation is using the fisherface algorithm. The fisherface algorithm is a refinement of the eigenface algorithm. It further reduces the eigenspace by the Fisher's linear discriminant (FLD). FLD selects the subspace in such a way that the ratio of the between-class scatter and the within-class scatter is maximized. It is reported that the fisherface algorithm outperforms the eigenface algorithm on the facial database with wide variation in lighting condition (Belhumeur, Hespanha, & Kriegman, 1997). (The detail of the fisherface algorithm will not be covered in this chapter. Interested readers please refer to Belhumeur, Hespanha, & Kriegman, 1997.)

In the following sections, we examine four pattern classification techniques for solving the face recognition problem (Belhumeur, Hespanha, & Kriegman, 1997), comparing methods that have become quite popular in the face recognition literature; that is, correlation and eigenface methods, with alternative methods developed by the authors. We approach this problem within the pattern classification paradigm, considering each of the pixel values in a sample image as a coordinate in a high-dimensional space (the image space).

Eigenface

The eigenface method is also based on linearly projecting the image space to a low-dimensional feature space (Belhumeur, Hespanha, & Kriegman, 1997; Sirovitdh & Kirby, 1987; Turk & Pentland, 1991a, 1991b). However, the eigenface method, which uses PCA