



Chapter IX

Other Typical BID Improvements

ABSTRACT

In this chapter, we discuss some other typical BID improvements, including dual eigenspaces method (DEM) and post-processing on LDA-based method for automated face recognition. After the introduction, we describe DEM. Then, post-processing on LDA-based method is defined. Finally, we offer some brief conclusions.

INTRODUCTION

So far, there have been four BID technologies proposed in Part II, including improved UODV, CLDA, ILDA and discriminant DCT feature extraction. As other typical BID improvements, this chapter presents two effective schemes called DEM and post-processing on LDA-based method for automated face recognition.

Based on K-L transform, the dual eigenspaces are constructed by extracting algebraic features of training samples and applying them to face identification with a two-layer minimum distance classifier. Experimental results show that DEM is significantly better than the traditional eigenfaces method (TEM).

PCA- (see Chapter II) and LDA- (see Chapter III) based methods are state-of-art approaches to facial feature extraction. Recently, pre-processing approaches have been used to further improve recognition performance, but few investigations have been made into the use of post-processing techniques. Later in this chapter, we intend to explore the feasibility and effectiveness of the post-processing technique on LDA's discrimi-

nant vectors. In this chapter, we also propose a Gaussian filtering approach to post-process the discriminant vectors. The results of our experiments demonstrate that the post-processing technique can be used to improve recognition performance.

DUAL EIGENSPACES METHOD

Introduction to TEM

Automated face recognition is mainly applied to individual identification systems, such as criminal discrimination, authentication of ID cards and many security facilities (Chellappa, Wilson, & Sirohey, 1995). During the last 30 years, numerous algorithms based on geometrical features of face images have been developed. But they met great difficulty in accurately determining both positions and shapes of facial organs. Another sort of algorithms is to use algebraic features extracted by various orthogonal transforms. TEM uses principal components of an ensemble of face images and then completes the recognition procedure in an orthonormal “face space” (Turk & Pentland, 1991). However, its recognition rate is largely reduced when head posture, lighting conditions or facial expressions vary (Moghaddam & Pentland, 1994; Belhumeur, Hespanha, & Kriegman, 1997). To solve this problem, this chapter provides DEM to further analyze the features distribution in the “face space” and use coarse-to-fine matching strategy for face recognition. It is shown that this method is superior to TEM in recognition rate.

Algebraic Features Extraction

As the most optimal orthonormal expansion for image compression, K-L transform can also be used to feature extraction and pattern recognition (Oja, 1983). In TEM, the generating matrix of K-L transform is a total scatter matrix in Chapter III, and in order to achieve higher computational simplicity without loss of accuracy, a between-class scatter matrix is adopted as the generating matrix as mentioned in that chapter, too. And:

$$\mathbf{S}_b = \frac{1}{P} \mathbf{X}\mathbf{X}^T \quad (9.1)$$

where $\mathbf{X} = [(m_1 - m), \dots, (m_p - m)]$; m_i is the average image of the person's i th training samples; and P is the number of people in the training set.

It is evident that the eigenvectors of \mathbf{S}_b can span an algebraic eigenspace and provide optimal approximation for those training samples in the sense of mean-square error. Given a face image, it can be projected onto these eigenvectors and represented in terms of a weight vector regarded as its algebraic features.

However, determining the eigenvectors of the matrix, $\mathbf{S}_b \in \mathfrak{R}^{N^2 \times N^2}$, is an intractable task. It can be solved by using SVD theorem (Oja, 1983).

First, the following matrix is formalized as:

$$\mathbf{R} = \frac{1}{P} \mathbf{X}^T \mathbf{X} \in \mathfrak{R}^{P \times P} \quad (9.2)$$

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