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Chapter VII

An Improved LDA Approach

ABSTRACT

This chapter gives an improved LDA (ILDA) approach. After a short review and comparison of major linear discrimination methods, including the eigenface method, fisherface method, DLDA and UODV, we introduce definitions and notations. Then, the approach description of ILDA is presented. Next, we show some experimental results. Finally, we summarize some useful conclusions.

INTRODUCTION

In this section, we first give a brief review of some important linear discrimination methods that we have mentioned in earlier chapters. In the field of pattern recognition, and especially in image recognition, image data are always high dimensional and require considerable computing time for classification. The LDA technique we showed in Chapter III is thus important in extracting effective discriminative features and reducing dimensionality, and costs little computing time. It has been shown in many applications of image recognition that LDA can satisfy these requirements (Swets & Weng, 1996; Loog, Duin, & Haeb-Umbach, 2001; Vailaya, Zhang, Yang, Liu, & Jain, 2002; Nishino, Sato, & Ikeuchi, 2001). So far, many linear discrimination methods have been proposed for use in image recognition. Two of the most well-known are the eigenface and fisherface methods.

Based on PCA (see Chapter II) (JainDuin & Mao, 2000), the eigenface method (see Chapter IV) (Turk & Pentland, 1991) uses the total covariance (or scatter) matrix S_t, as the production matrix to perform the KL transform. It cannot, however, make full use of pattern separability information like the Fisher criterion, and its recognition effect is not ideal when the size of the sample set is large (Martinez & Kak, 2001; Belhumeur, Hespanha, & Kriegman, 1997).

The famous fisherface method (see Chapter IV) (Belhumeur, Hespanha, & Kriegman, 1997) combines PCA and the Fisher criterion (Fisher, 1936) to extract the information that discriminates between the classes of a sample set. It is a most representative method of LDA. Nevertheless, Martinez and Kak (2001) demonstrated that when the training data set is small, the eigenface method outperforms the fisherface method. Should the latter be outperformed by the former? This provoked a variety of explanations. Liu and Wechsler (2000) thought that it might have been because the fisherface method uses all the principal components, but the components with the small eigenvalues correspond to high-frequency components and usually encode noise, leading to recognition results that are less than ideal. In line with this theory, they presented two EFMs (Liu & Wechsler, 2000) and an enhanced Fisher classifier (Liu & Wechsler, 2000) for face recognition. Their experiential explanation lacks sufficient theoretical demonstration; however, an EFM does not provide an automatic strategy for selecting the components.

Chen, Liao, Ko, Lin, and Yu (2000) proved that the null space of the within-class scatter matrix S_w contains the most discriminative information when a small sample size problem takes place. Their method is also inadequate, however, as it does not use any information outside the null space. Yu and Yang (2001) propose a DLDA approach to solve this problem. It simultaneously diagonalizes both the between-class scatter matrix S_b (or S_t) and S_w. Let $W^T S_w W = D_w$, and let $W^T S_b W = I$ or $W^T S_t W = I$. According to the theory, DLDA should discard some of the eigenvectors of D_w that correspond to the higher eigenvalues, and keep the remainders, especially those eigenvectors that correspond to the zero eigenvalues. This approach, however, has a number of limitations. First, it does not demonstrate how to select its eigenvectors. Second, the related demonstration is rather difficult. Third, in the application of DLDA, there is a contradiction between the theory and the experiment. The theory requires that the eigenvectors of D_w corresponding to the higher eigenvalues be discarded, but the experiment obtains the improved recognition results by employing all of the eigenvectors of D_w.

ODV (see Chapter V) is a special kind of LDA method that has been applied to a wide range of applications in pattern classification (Cheng, Zhuang, & Yang, 1992; Liu, Cheng, Yang, & Liu, 1992; Liu, Cheng, & Yang, 1993). It requires that every discrimination vector satisfy the Fisher criterion and the obtained Fisher discrimination vectors are necessary to satisfy the orthogonality constraint (Foley & Sammon, 1975); but as a result, its solution is more complicated than other LDA methods. Jin, Yang, Hu, and Lou (2001) proposed a UODV method (see Chapter V) that used the constraint of statistical uncorrelation. UODV produces better results than ODV on the same handwritten data, where the only difference lies in their respective constraints (Jin, Yang, Tang, & Hu, 2001). Jing, Zhang, and Jin (2003a, 2003b) subsequently presented a more rational UODV method and generalized theorem for UODV.

Many others methods have been proposed. Zhang, Peng, Zhou, and Pal (2002) presented a face recognition system based on hybrid neural and dual eigenfaces

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