Gabor Feature Based Classification Using LDA/QZ Algorithm for Face Recognition

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Abstract. This paper proposes a LDA/QZ algorithm and its combination of Gabor Filter-based features for the face recognition. The LDA/QZ algorithm follows the common "PCA+LDA" framework, but it has two significant virtues compared with previous algorithms: 1) In PCA step, LDA/QZ transforms the feature space into complete PCA space, so that all discriminatory information is preserved, and 2) In LDA step, the QZ-decomposition is applied to solve the generalized eigenvalue problem, so that LDA can be performed stably even when within-class scatter matrix is singular. Moreover, the Gabor Filter-based Features and the new LDA/QZ algorithm are combined for face recognition. We also performed comparative experimental studies of several state-of-art dimension reduction algorithms and their combinations of Gabor feature for face recognition. The evaluation is based on six experiments involving various types of face images from ORL, FERET, and AR database and experimental results show the LDA/QZ algorithm is always the best or comparable to the best in term of recognition accuracy.

1 Introduction

Due to the military, commercial, and law enforcement application, there has been much interest in automatically recognizing faces in still and video images recently. Many methods have been proposed for face recognition within the last two decades [1]. Among these methods, the linear discriminant analysis (LDA) based methods are most widely used. The LDA, also called Fisher linear discriminant (FLD), defines a projection that makes the within-class scatter small and the between-scatter large. However, it is well-known that classical LDA requires that one of the scatter matrices is nonsingular. For the face recognition application, all scatter matrices can be singular since the feature dimension, in general, exceeds the number of sample size. This is known as the singularity, undersampled, or Small Sample Size(SSS) problem [4].

Many LDA extensions were proposed to overcome the singularity problem in face recognition, such as PCA+LDA [2][17][3], Regularized LDA [8], LDA/GSVD [20], LDA/QR [19]. Among these extensions, PCA+LDA, a two-stage method, received relatively more attention. By applying first principle component analysis (PCA) for dimensionality reduction and then LDA for discriminant analysis, Belhumire *et. al.* developed an approach called Fisherfaces. Using a similar

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scheme, Swets and Weng [3] have pointed out the Eigenfaces [7] derived using PCA are only the most expressive features (MEF). The MEF are unrelated to actual recognition, and in order to derive the most discriminant features (MDF), one needs a subsequent LDA projection. More recently, Liu and Wechsler presented an enhanced Fisher discriminant model (EFM), which only selects the dominant PCs that capture most spectral energy for LDA. Jing et. al [21] proposed to select the PCs according to their "Fisher discriminability". Zheng et.al [16] developed a GA-Fisher method which uses genetic algorithm to select appropriate PCs for LDA. This type of approaches have two major limitations: 1) the optimal value of the reduced dimension for PCA is difficult to determine [19][20], and 2) the dimension reduction stage using PCA may potentially lose some useful information for discrimination [13].

This paper introduces a novel LDA/QZ algorithm to address the limitation of previous PCA+LDA approaches. Specifically, the LDA/QZ algorithm uses the QZ decomposition to circumvent non-singularity requirement of the LDA and thus can perform discriminant analysis in the complete PCA space. Thus, the LDA/QZ algorithm has two advantages compared with previous "PCA+LDA" methods: 1) no intermediate dimensionality selection procedure is required 2) no discriminatory information is lost theoretically [13]. Moreover, the Gabor Filter-based Features [9][10][11][12] and the new LDA/QZ algorithm are combined for face recognition. The feasibility of the LDA/QZ algorithm and its combination of Gabor feature have been successfully tested on six face recognition experiments using three data sets from the ORL, AR [6], and FERET [5] database. In addition, Comparative experimental studies of several state-of-art dimension reduction algorithms and their combination of Gabor feature for face recognition are given.

2 Linear Discriminant Analysis by QZ Decomposition (LDA/QZ)

2.1 PCA Plus LDA and Its Limitation

For simplicity of discussion, we will assume the training data vectors $a_1, \ldots, a_n$ form column of a matrix $A \in \mathbb{R}^{m \times n}$ and are grouped into k class as $A = [A_1, A_2, \ldots, A_k]$, where $A_i \in \mathbb{R}^{m \times n_i}$ and $\sum_{i=1}^{k} n_i = n$. Let N_i denotes the set of column indices that belong to class i. The class centroid $c^{(i)}$ is computed by taking the average of columns in the class i, i.e., $c^i = \frac{1}{n_i} \sum_{j \in N_i} a_j$, and the global centroid c is defined as $c = \frac{1}{n} \sum_{j=1}^{n} a_j$. Then the within-class and between-class, and mixture scatter matrices are defined [4] as

$$S_w = \frac{1}{n} \sum_{i=1}^{k} \sum_{j \in N_i} (a_j - c^{(i)})(a_j - c^{(i)})^T, \tag{1}$$

$$S_b = \frac{1}{n} \sum_{i=1}^{k} n_i (c^{(i)} - c)(c^{(i)} - c)^T, \text{and} \tag{2}$$