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Face recognition using discriminative locality preserving vectors

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ABSTRACT

We proposed an effective face recognition method based on the discriminative locality preserving vectors method (DLPV). Using the analysis of eigenspectrum modeling of locality preserving projections, we selected the reliable face variation subspace of LPP to construct the locality preserving vectors to characterize the data set. The discriminative locality preserving vectors (DLPV) method is based on the discriminant analysis on the locality preserving vectors. Furthermore, the theoretical analysis showed that the DLPV is viewed as a generalized discriminative common vector, null space linear discriminant analysis and null space discriminant locality preserving projections, which gave the intuitive motivation of our method. Extensive experimental results obtained on four well-known face databases (ORL, Yale, Extended Yale B and CMU PIE) demonstrated the effectiveness of the proposed DLPV method.

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1. Introduction

Over the last ten years or so, face recognition has become a popular area of research, which has a wide range of commercial and law enforcement applications [1–4]. The problem of face recognition continues to attract researchers from disciplines such as image processing, pattern recognition, neural networks, computer vision and psychology [5–10]. One of the most successful and well-studied techniques is the appearance-based method [24]. However, appearance-based methods used in face recognition may produce the curse of dimensionality [11]. A common way to resolve the problem is to use the dimensionality reduction technique. Many linear approaches have been proposed for dimensionality reduction, such as principal component analysis (PCA) [12] and linear discriminant analysis (LDA) [13,14], which have been widely used in visualization and classification. However, PCA does not encode discriminant information which is important for a recognition task, and LDA aims to preserve global structures of samples. Furthermore, PCA and LDA fail to explore the essential structure of data with nonlinear distribution.

Based on eigenspectrum modeling of PCA, null-space LDA (NLDA) was proposed for dealing with the small sample size problem [15]. In this method, PCA is applied to remove the null space of the total scatter matrix, which contains the intersection of the null spaces of the between-class scatter matrix and the within-class scatter matrix. Then, the optimal projection vectors are found in the remaining lower dimensional space by using the null space method. Cevikalp et al. proposed a face recognition method based on the discriminative common vectors method (DCV) [16] which yields an optimal solution by maximizing the modified Fisher's linear discriminant criterion [17]. The linear methods mentioned above, however, may fail to find the underlying nonlinear structure of a data set. To remedy this deficiency, a number of nonlinear dimensionality reduction techniques have been developed in the past few years, among which two received increasing attention: kernel-based method and manifold learning based method. Kernel principal component analysis [18], generalized discriminant analysis [19], and kernel discriminative common vector [20] are the representative kernel based methods. However, the kernel based techniques are computationally intensive, and do not explicitly consider the local structure of a data set, which is important for classification.

Recently, a number of research efforts have shown that the face images possibly reside on a nonlinear sub-manifold [21–24] and many manifold learning-based approaches such as the isometric feature [25], locally linear embedding [26], and Laplacian eigenmaps [21] have been developed for analyzing high dimensional data. Manifold learning methods are straight forward in finding the inherent nonlinear structure hidden in the observation space [27]. However, none of them explicitly considers the structure of the manifold on which the face images possibly reside. Locality preserving projections (LPP) [28] is a new linear dimensionality re-

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duction algorithm. LPP transforms different samples into new representations using the same linear transform and tries to preserve the local structure of the samples. Based on LPP, some methods were further developed for face recognition, such as neighborhood preserving embedding (NPE) [29], Laplacian faces [30], orthogonal locality preserving projections (OLPP) [31], and Locality preserving indexing [32], providing encouraging performance. Although LPP is effective in many domains, it suffers from a limitation: it de-emphasizes discriminant information, which makes it unsuitable for a recognition task. In other words, for a classification problem, the locality quantity itself is not sufficient. To encode discriminant information, discriminant locality preserving projections (DLPP) has been mentioned [33]. However, similar with LDA, DLPP also suffers from the small sample size problem. Developed from the DLPP, null space discriminant locality preserving projections (NDLPP) [34] inherits the characteristics of DLPP that encodes both the geometrical and discriminant structure of the data, and addresses the small sample size problem by solving an eigenvalue problem in null space.

Inspired by LPP and DCV, we proposed a new method, termed as discriminative locality preserving vectors (DLPV), for face recognition. Based on the analysis of eigenspectrum modeling of supervised locality preserving projections (LPP) [35,36], we selected the reliable face variation subspace of supervised LPP to obtain the locality preserving vectors (LPV). The discriminative locality preserving vectors (DLPV) is based on the discriminant analysis on the LPV. Furthermore, we present a theoretical analysis of DLPV and its connections with NLDA, DCV and NDLPP.

The remainder of this article is organized as follows: the related works are described in Section 2. DLPV method and its theoretical analysis are presented in Section 3. Experimental results and analysis are presented in Section 4. Finally, conclusions are given in Section 5.

2. Related works

In this section, we will briefly review null space based linear discriminant analysis (NLDA), discriminant common vectors (DCV), locality preserving projections (LPP), and null spaced discriminant locality preserving projections (NDLPP) since our proposed DLPV stems from these methods.

2.1. Null space based linear discriminant analysis (NLDA)

Null space based linear discriminant analysis (NLDA) uses the within-class and between-class scatter matrix of the samples to obtain the projection vectors and its objective function as follows:

$$J(w_{NLDA}) = \arg \max_{|w^T S_W w|=0} \left| w^T S_B w \right| \tag{1}$$

where,

$$S_B = \sum_{i=1}^{c} n_i (m_i - \bar{m})(m_i - \bar{m})^T \tag{2}$$

$$S_W = \sum_{i=1}^{c} \left(\sum_{j=1}^{n_i} (x_j^i - m^i)(x_j^i - m^i)^T \right) \tag{3}$$

where $\bar{m}$ is the total sample mean vector, n_i is the number of samples in the ith class, m_i is the average vector of the ith class, c is the number of classes, and x_j^i is the jth sample in the ith class. We call S_W and S_B the within-class scatter matrix and the between-class scatter matrix respectively. To find the optimal projection vectors w in the null space Q of the within-class scatter matrix S_W, NLDA projects the face samples onto the null space of S_W and then obtains the projection vectors by performing PCA.

2.2. Discriminative common vectors (DCV)

DCV projects the face samples onto null space Q of S_W and then obtains the projection vectors by performing PCA. An efficient way to accomplish this task is by using the orthogonal complement of the null space of S_W, which typically is a significantly lower-dimensional space. The method can be summarized as follows:

Step 1: Choose any sample from each class and project it onto the null space Q of S_W to obtain the common vectors

$$x_{com}^i = Q Q^T x_j^i, \quad j = 1, \ldots, n_i, \; i = 1, \ldots, c$$

Step 2: Compute the eigenvectors w of $S_{com} = A_{com} A_{com}^T$, where $A_{com} = [x_{com}^1 - \bar{x}_{com} - \cdots - x_{com}^l - \bar{x}_{com}]$, and where $\bar{x}_{com}$ is the mean of all common vectors.

2.3. Locality preserving projections (LPP)

PCA and LDA aim to preserve the global structure. However, in many real-world applications, the local structure is more important. LPP seeks to preserve the intrinsic geometry of the data and local structure. The objective function of LPP is as follows [28,30]:

$$\min \sum_{ij} (y_i - y_j)^T S_{ij} \tag{4}$$

where $y_i = w^T x_i$ is the one-dimensional representation of original data vector x_i and the matrix S is a similarity matrix, which can be Gaussian weight or uniform weight of Euclidean distance using k-neighborhood or ε-neighborhood. A possible way of defining S is $S_{ij} = \exp(-\|x_i - x_j\|^2/t)$ (t is the heat kernel parameter), if x_i is among k nearest neighbors of x_j or x_j is among k nearest neighbors of x_i; otherwise, $S_{ij} = 0$. Here we assume that k is the number of neighbors. The justification for this choice of weights can be traced back to [28,30].

The minimization problem becomes

$$\begin{aligned} w &= \min \sum_{i,j} \left(w^T x_i - w^T x_j\right)^2 S_{ij} \\ &= \frac{1}{2} \operatorname{tr}\left(\sum_{ij} \left(W^T x_i - W^T x_j\right)\left(W^T x_i - W^T x_j\right)^T S_{ij} \right) \\ &= \operatorname{tr}\left(\sum_i W^T x_i D_{ii} x_i W - \sum_{ij} W^T x_i S_{ij} x_j W \right) \\ &= \operatorname{tr}\left(W^T X (D - S) X W\right) = \operatorname{tr}\left(W^T X L X^T W\right) \end{aligned} \tag{5}$$

with the constraint $w^T X D X^T w = 1$, where D is a diagonal matrix whose entries are column (or row) sums of S, $D_{ii} = \sum_j S_{ji}$, and $L = D - S$.

The optimal projection axis w is given by solving the generalized eigenvalue problem:

$$X L X^T w = \lambda X D X^T w \tag{6}$$

where λ is the eigenvalues.

The objective function of LPP considers the difference between any two face images, which may belong to the same individual or different individuals. It is obvious that LPP subspace concentrates on both the intrinsic difference and transformation difference.

2.4. Null space discriminant locality preserving projections (NDLPP)

Discriminant locality preserving projections (DLPP) encodes both the geometrical and discriminant structure of the data manifold. The objective function of DLPP is

$$J = \max \left(\frac{\sum_{i,j=1}^{c} (m_i - m_j) B_{ij} (m_i - m_j)^T}{\sum_{l=1}^{c} \sum_{i,j=1}^{n_c} (y_i^l - y_j^l) S_{ij} (y_i^l - y_j^l)^T} \right) \tag{7}$$

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