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Linear collaborative discriminant regression classification for face recognition ☆

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ABSTRACT

This paper proposes a novel face recognition method that improves Huang's linear discriminant regression classification (LDRC) algorithm. The original work finds a discriminant subspace by maximizing the between-class reconstruction error and minimizing the within-class reconstruction error simultaneously, where the reconstruction error is obtained using Linear Regression Classification (LRC). However, the maximization of the overall between-class reconstruction error is easily dominated by some large class-specific between-class reconstruction errors, which makes the following LRC erroneous. This paper adopts a better between-class reconstruction error measurement which is obtained using the collaborative representation instead of class-specific representation and can be regarded as the lower bound of all the class-specific between-class reconstruction errors. Therefore, the maximization of the collaborative between-class reconstruction error maximizes each class-specific between-class reconstruction and emphasizes the small class-specific between-class reconstruction errors, which is beneficial for the following LRC. Extensive experiments are conducted and the effectiveness of the proposed method is verified.

1. Introduction

As one of the most challenging topics in computer vision, automatic face recognition has received utmost attention from researchers. There are two key factors in an automatic face recognition system: (i) how to represent a face image and (ii) how to classify the face image. Most face recognition algorithms thus concentrate on face representation and classifier design.

For face representation, it is found that the high dimensional face images lie on a low dimensional subspace or sub-manifold. Therefore, many face representation methods utilize dimensionality reduction (DR) in order to project the original face image onto a proper subspace. Eigenfaces [1] based on the Principle Component Analysis (PCA) and Fisherfaces [2] based on the Linear Discriminant Analysis (LDA) are the two pivotal algorithms. PCA projects the face image onto a subspace of which maximal variances are preserved. PCA is optimal in the sense of reconstruction, however, it is not optimal for discrimination. LDA utilizes the label information of training face images to find a discriminant subspace such that the ratio of the between-class scatter over the within-class scatter is maximized. More number of DR methods were proposed later, including Independent Component Analysis (ICA) [3], Locality Preserving Projection (LPP) [4], Neighborhood Preserving Embedding (NPE) [5], Local Discriminant Embedding (LDE) [6], Semi-supervised Discriminant Analysis (SDA) [7], and so on.

Numerous classifiers have been proposed to classify the obtained face representations. Nearest neighbor classifier (NN) is widely used which classifies the testing face according to the nearest training face. Later on, NN is improved by Nearest Feature Line (NFL) [8], Nearest Feature Plane (NFP) [9], and Nearest Feature Space (NFS) [9] and these four methods are different by the constraints imposed to the training faces to represent the testing face [10]. Recently, some classifiers that significantly boost the performance of automatic face recognition have been proposed, such as Sparse Representation Classification (SRC) [11], Collaborative Representation Classification (CRC) [12] and Linear Regression Classification (LRC) [13]. SRC and CRC utilize all the training face images to linearly represent a test face image under l_1-norm and l_2-norm minimization, respectively. The representation error of each class is used to identify the true class. LRC classifies the test face images based on the assumption that face images belonging

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to the same class lie on a specific subspace. Therefore, the test face image is classified into a class that can best represent it (e.g., with the smallest reconstruction error) using linear regression. In the past few years, many improvements to SRC, CRC and LRC have been proposed [14–19].

Dimension reduction extracts efficient features before the final classification. The dimension reduced feature makes the following classification accurate and fast. However, the design of the dimension reduction and classifier is usually separated from each other which may degrade the overall performance of the face recognition system. The feature extracted by LDA does not necessarily guarantee a good performance of LRC, e.g. It is better to design dimension reduction method that best suits the classifier that will be used.

LDRC [20] extracts low dimensional features guided by the classification rule of the LRC. It learns a discriminant subspace using the Fisher criterion such that the ratio of the between-class reconstruction error (BCRE) over the within-class reconstruction error (WCRE) is maximized. The hope is that a probe face can be well represented by the training faces of the same class and is difficult to be represented by the training faces of every other class. However, some large class-specific between-class reconstruction errors (which play minor role in LRC) can dominate the BCRE and the small class-specific between-class reconstruction errors (which play important role in LRC) are neglected. As a result, the learned features tend to increase the values of those large class-specific between-class reconstruction errors, and the values of those small class-specific between-class reconstruction errors are not well increased which may be larger than the within-class reconstruction errors and cause errors in LRC.

Automatic face recognition usually does not have enough training face images which makes it a typical small-sample-size problem [12]. The reconstruction error can be large even if the probe face image is represented by the training face images of the same class which makes the classification unstable. To solve this "lack of samples problem", both SRC and CRC utilize the training faces from all classes to represent the probe face. The so-called "collaborative representation" helps to reduce the representation error. This representation is one of the key factors in the success of SRC and CRC.

The idea of collaborative representation can also be used to learn a discriminant subspace. The reconstruction error generated by the collaborative representation of many classes is usually smaller compared with the reconstruction error generated by representation of each single class. If we can find a subspace where the collaborative reconstruction error is large, then the reconstruction error of each single class will also tend to be large.

This paper proposes a novel linear collaborative discriminant regression classification (LCDRC) that uses the collaborative between-class reconstruction error (CBCRE) instead of BCRE. The collaborative between-class representation utilizes cross-class training faces to represent a probe face. The obtained CBCRE is smaller than each class-specific between-class reconstruction error (more training faces represent the probe face better). Therefore, CBCRE can be regarded as a lower bound of all the class-specific between-class reconstruction errors and it is largely determined by those small class-specific between-class reconstruction errors so that the large class-specific between-class reconstruction error domination problem can be mitigated. The maximizing of CBCRE tends to better separate the within-class reconstruction error and the small class-specific between-class reconstruction error than BCRE.

The rest of the paper is organized as follows. Section 2 introduces the LRC and LDRC. The proposed LCDRC is presented in Section 3. Section 4 conducts extensive experiments to verify the effectiveness of LCDRC. Finally, Section 5 concludes the paper.

2. Related work

2.1. Linear Regression Classification (LRC)

We denote the training face images of the ith class as $\boldsymbol{X}_i \in \mathbb{R}^{m\times n_i}$. Each column of $\boldsymbol{X}_i$ is an m dimensional face image of class i in which there are n_i training face images, and $i = 1, 2, \ldots, c$, where c is the total number of classes. All of the face images in this paper are assumed to be vectors by stacking the columns of original face images.

Assume y is a probe face image that can be represented using $\boldsymbol{X}_i$ according to

$$y = \boldsymbol{X}_i\alpha_i, \quad i = 1, 2, \ldots, c, \tag{1}$$

where $\alpha_i \in \mathbb{R}^{n_i\times 1}$ is the regression parameters; α_i can be calculated using the least-squares estimation as

$$\hat{\alpha}_i = (\boldsymbol{X}_i^T\boldsymbol{X}_i)^{-1}\boldsymbol{X}_i^T y, \quad i = 1, 2, \ldots, c. \tag{2}$$

The reconstruction of y by each class can be obtained as

$$\hat{y}_i = \boldsymbol{X}_i\hat{\alpha}_i = \boldsymbol{X}_i(\boldsymbol{X}_i^T\boldsymbol{X}_i)^{-1}\boldsymbol{X}_i^T y = \boldsymbol{H}_i y, \quad i = 1, 2, \ldots, c, \tag{3}$$

where $\boldsymbol{H}_i$ is called a *hat matrix* that maps y into $\hat{y}_i$. The reconstruction error of each class is calculated as

$$e_i = \|y - \hat{y}_i\|_2^2, \quad i = 1, 2, \ldots, c. \tag{4}$$

LRC then assigns the y to the class that has the smallest reconstruction error.

2.2. Linear discriminant regression classification (LDRC)

Assume that all the training face images form the training matrix $\boldsymbol{X} = [x_1, \ldots, x_i, \ldots, x_n] \in \mathbb{R}^{m\times n}$, where n is the number of training face images and m is the dimensionality of each training face image. The class label of each x_i is denoted as $l(x_i) \in \{1, 2, \ldots, c\}$. Assume that the subspace projection matrix is $\boldsymbol{U} \in \mathbb{R}^{m\times d}$. Each face image can be projected onto the subspace as

$$y_i = \boldsymbol{U}^T x_i, \tag{5}$$

where $y_i \in \mathbb{R}^{d\times 1}$ and $d < m$. The label of y_i is the same as that of x_i, thus implying $l(y_i) = l(x_i)$.

The subspace projection matrix $\boldsymbol{U}$ is obtained by maximizing BCRE and minimizing WCRE simultaneously, where BCRE and WCRE are calculated as

$$\begin{aligned} \mathrm{BCRE} &= \frac{1}{n(c-1)}\sum_{i=1}^{n}\sum_{j=1,\, j\neq l(x_i)}^{c}\|y_i - \hat{y}_{ij}^{inter}\|_2^2, \\ \mathrm{WCRE} &= \frac{1}{n}\sum_{i=1}^{n}\|y_i - \hat{y}_i^{intra}\|_2^2, \end{aligned} \tag{6}$$

where $\hat{y}_{ij}^{inter}$ is the reconstruction of y_i by the jth class and $l(y_i) \neq j$. $\hat{y}_i^{intra}$ is the reconstruction of y_i by the $l(y_i)$ class (y_i is excluded from the training matrix when calculating the reconstruction).

3. Proposed method

In this section, we will show how the large class-specific between-class reconstruction error domination problem can be mitigated by the collaborative representation idea.

3.1. Linear collaborative discriminant regression classification (LCDRC)

Let $\boldsymbol{X} = [\boldsymbol{X}_1, \boldsymbol{X}_2, \ldots, \boldsymbol{X}_c] \in \mathbb{R}^{m\times n}$ be the whole training face image matrix, where $\boldsymbol{X}_i = [x_{i1}, x_{i2}, \ldots, x_{in_i}] \in \mathbb{R}^{m\times n_i}$. m is the dimension of