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Global linear regression coefficient classifier for recognition

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ABSTRACT

In this paper, a novel classifier based on linear regression classification (LRC), called global linear regression coefficient (GLRC) classifier, is proposed for recognition. LRC classifier uses the test sample and the class subspace to calculate the distance which will be used for classification. GLRC classifier uses the test sample vector and whole train space (all the class subspaces) to calculate the global linear regression coefficient. Then GLRC computes the signed square sum of the linear regression coefficients belonging to the same class, and the result will be used for classification. A large number of experiments on Yale face database and AR face database are used to evaluate the proposed algorithm. The experimental results demonstrate that the proposed method achieves better recognition rate than LRC classifier, sparse representation based classification (SRC) classifier, Collaborative representation based classification (CRC) classifier and two phase test sample sparse representation (TPTSSR) classifier and so on.

1. Introduction

PATTERN recognition systems are critically dependent on classifiers. Nearest neighbor (NN) [1] classifier and nearest subspace (NS) [2] classifier (i.e., minimum distance to the subspace spanned all training samples from each class) are the well-known methods in pattern recognition area. NN classifies the test sample based on the best representation in terms of a single training sample, whereas NS classifies based on the best linear representation in terms of all the training samples in each class.

The number of prototype samples is usually very small, which makes the classification of NN be very difficult. So nearest feature line (NFL) [3,4] was proposed for face recognition [5–8] by Stan Z. Li et al. in 1999. NFL attempts to enhance the representational capacity of the limited sample set by using the line passing through each pair of the samples belonging to the same class. After the NFL being proposed, Chien and Wu proposed the nearest feature plane (NFP) [9] in 2002. Zheng et al. proposed the nearest neighbor line (NNL) and nearest neighbor plane (NNP) [10] in 2004, GAO et al. proposed the center-based nearest neighbor (CNN) [11] in 2007. Feng et al. proposed the nearest feature center (NFC) [8] classifier in 2012.

Samples from a specific subject class lie on a linear subspace [12–14]. Borrowing the above concept, linear regression-based classification (LRC) [15] is proposed for face identification in 2010. LRC defines the task of face recognition as a problem of linear regression. LRC classifier is the extended of NS classifier. For face recognition, the associated linear regression classification (LRC) approaches, including kernel-LRC, Improved-PCA-LRC, LDA-LRC and Unitary-LRC [16–19], have been proposed to further improve the recognition performance under different situation like variable illumination, facial expressions.

Being different to LRC using the class-model, sparse representation based classification (SRC) [20,21] uses all-class-model to classify the test sample. After the SRC classifier being proposed, some other improved methods [22–29] are presented for face recognition, such as Xu et al. propose two-phase test sample sparse representation (TPTSSR) [24], which uses a simple way to gain "sparse representation" of the test sample and obtains high accuracy. Zhang et al. propose collaborative representation based classification (CRC) [28] and so on.

Motivated by the LRC classifier, SRC classifier, CRC classifier and TPTSSR classifier, global linear regression coefficient (GLRC) classifier is proposed for recognition in this paper. LRC classifier uses the test sample and the class subspace to calculate the distance which will be used to classify the test sample. GLRC classifier uses the test sample vector and whole train space (all the class subspaces) to calculate the global linear regression coefficient. Then GLRC computes the signed square sum of the linear regression coefficients belonging to the same class, and the

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result will be used to classify the test sample. A large number of experimental on Yale face database [30] and AR face database [31] are used to evaluate the proposed algorithm. The experimental results demonstrate that the proposed method achieves better recognition rate than LRC classifier, CRC classifier, SRC classifier and TPTSSR classifier, NN classifier, NFL classifier, NFC classifier.

2. Review

Let $Y = \left\{y_i^c, c = 1, 2, \ldots, M, i = 1, 2, \ldots, N_c\right\} \subset R^D$ denote the prototype set, where y_i^c is the ith prototype belonging to cth class, M is the number of class, and N_c is the number of prototypes belonging to the cth class.

2.1. Linear regression classification (LRC)

Let each training image have $a \times b$ pixels and be represented as $y_i^c \in R^{a\times b}$, $c = 1, 2, \ldots, M$ and $i = 1, 2, \ldots, N_c$. Each image is transformed to column vector such as $y_i^c \in R^{a\times b} \to w_i^c \in R^{q\times 1}$, where $q = ab$. With the concept that patterns from the same class lie on a linear subspace, LRC constitutes a class-specific model X^c by stacking the q-dimensional image vectors

$$X^c = \left[\, w_1^c \quad w_2^c \quad \ldots. \quad w_{N_c}^c \,\right] \in R^{q\times N_c} \tag{1}$$

Let y be an unlabeled test image and our problem is to classify y as one of the classes. If y belongs to the cth class, it should be represented as a linear combination of the training images from the same class.

$$y^c = X^c \beta^c \tag{2}$$

where $\beta^c \in R^{N_c\times 1}$ is the vector of parameters, which can be calculated as follows.

$$\beta^c = (X^{cT} X_c)^{-1} X^{cT} y \tag{3}$$

where the predicted vector y^c is the projection of y onto the cth class subspace. LRC now calculates the distance measure between the predicted vector y^c and the original test vector y. $||*||$ means $L2$-norm.

$$d_c(y) = ||y - y^c|| \tag{4}$$

The rule of LRC is in favor of the class with minimum distance

$$\min_{c^*} d_c(y), \quad c = 1, 2, \ldots, M \tag{5}$$

2.2. Sparse representation based classification (SRC)

SRC [21] classifier is described as follows. Denote by $X^c \in R^{q\times N_c}$ the dataset of the cth class, and each column of X^c is a sample of class c. Suppose that we have M classes of subjects, and let

$$X = \left[\, X^1 \quad X^2 \quad \ldots. \quad X^M \,\right] \in R^{q\times MN_c} \tag{6}$$

Normalize the columns of X to have unit L2-norm.

Solve problem of the L1-norm minimization:

$$g = arg\ \min_g ||g||_1 \text{ subject to } Xg = y \tag{7}$$

Compute the regularized residuals r^c

$$r^c = ||y - X^c g^c|| \tag{8}$$

The rule of SRC is in favor of the class with minimum distance

$$\min_{c^*} r^c, \quad c = 1, 2, \ldots, M \tag{9}$$

2.3. Collaborative representation based classification (CRC)

CRC [28] classifier is described as follows. Denote by $X^c \in R^{q\times N_c}$ the dataset of the cth class, and each column of X^c is a sample of class c. Suppose that we have M classes of subjects, and let

$$X = \left[\, X^1 \quad X^2 \quad \ldots. \quad X^M \,\right] \in R^{q\times MN_c} \tag{10}$$

$\beta \in R^{MN_c\times 1}$ is the vector of parameters, which can be calculated as follows.

$$\beta = (X^T X_c)^{-1} X^T y \tag{11}$$

Compute the regularized residuals r^c

$$r^c = \frac{||y - X^c \beta^c||_2}{||\beta^c||_2} \tag{12}$$

Each column of β^c is the coefficient of the sample of class c. And rule in favor of the class with minimum distance

$$\min_{c^*} r^c, \quad c = 1, 2, \ldots, M \tag{13}$$

2.4. Two-phase test sample sparse representation (TPTSSR) classifier

TPTSSR [24] classifier is described as follows. Denote by $X^c \in R^{q\times N_c}$ the dataset of the cth class, and each column of X^c is a sample of class c. Suppose that we have M classes of subjects, and let

$$X = \left[\, X^1 \quad X^2 \quad \ldots. \quad X^M \,\right] \in R^{q\times MN_c} \tag{14}$$

$\beta \in R^{MN_c\times 1}$ is the vector of parameters, which can be calculated as follows.

$$\beta = (X^T X_c)^{-1} X^T y \tag{15}$$

Choose the max K samples according to the absolute value of β. Let each column of X is a sample of K samples.

$$\beta = (X^T X_c)^{-1} X^T y \tag{16}$$

If the all K samples from the cth class are $X_s^c \ldots X_t^c$. Let $g^c = \beta_s^c X_s^c + \ldots + \beta_t^c X_t^c$. We calculate the deviation of g^c from y by using

$$d_c(y) = ||y - g|| \tag{17}$$

The rule of TPTSSR is in favor of the class with minimum distance

$$\min_{c^*} d_c(y), \quad c = 1, 2, \ldots, M \tag{18}$$

3. Proposed methods

In this section, the proposed classifier, called global linear regression coefficient (GLRC) classifier is given.

3.1. Global linear regression coefficient classifier

Let each training image be an order $a \times b$ pixels and be represented as $y_i^c \in R^{a\times b}$, $c = 1, 2, \ldots, M$ and $i = 1, 2, \ldots, N_c$. Each gallery image is transformed to column vector such that $y_i^c \in R^{a\times b} \to w_i^c \in R^{q\times 1}$, where $q = ab$. GLRC firstly constitutes a class-specific model X^c by stacking the q-dimensional column vectors

$$X^c = \left[\, w_1^c \quad w_2^c \quad \ldots. \quad w_{N_c}^c \,\right] \in R^{q\times N_c} \tag{19}$$

Then GLRC develops the global-specific model X by stacking each class-specific model X^c.

$$X = [\, X^1 \quad X^2 \quad \ldots. \quad X^M \,] \in R^{q\times MN_c} \tag{20}$$