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Face Recognition Based on SRC Combined with Sparse Embedding Dimensionality Reduction

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Abstract. Sparse representation-based classification (SRC) method has achieved good recognition results and shown strong robustness for face recognition, especially when the face image is affected by illumination variations, expression changes and occlusion. SRC method simply uses the training set as a dictionary to encode test samples. However, the high-dimensional training face data usually contain a large amount of redundant information, which will increase the complexity of this method. Therefore, the image dimensionality reduction procedure is separately performed by most of the existing methods before SRC is launched, but this may not be able to make full use of the discriminative information of the training samples. In this paper, based on the efficient SRC method, a sparse embedding dimensionality reduction strategy is combined with to achieve a face recognition method. For the proposed method, a projection matrix is used to project high-dimensional data into a low-dimensional space. At the same time, a discriminative coefficient constraint term in the objective function is introduced to reduce the classification residual of the sample through the distance relationship between all coefficients. Then the label information of the sample is used to iteratively update the projection matrix and coefficient representation. Finally, the test samples are projected into the low-dimensional space for classification. A large number of experimental results on three widely used face datasets show that the proposed method improves the discrimination of face images in low-dimensional space and can achieve better face recognition results.

Keywords: face recognition, sparse representation, dimensionality reduction, projection

1 Introduction

Face recognition (FR) is an active research area in computer vision, and has been widely used in many fields [1-2]. At the end of last century, researchers proposed to use dimensionality reduction method for feature extraction in face recognition task, such as Eigenfaces [3] based on principal component analysis (PCA), Fisherfaces [4] based on linear discriminate analysis (LDA). Although PCA and LDA can describe the global features of face image, they are not specific enough to describe the details. The local preserving projection (LPP) [5] takes into account the local structure of the data, and its essence is a linear approximation to the Laplacian feature map. Considering the importance of both local and global features, Yang et al. proposed [6] unsupervised discriminant projection (UDP). The UDP finds a projection direction to make the local scatter as small as possible and the non-local scatter as large as possible. He et al. [7] proposed neighborhood preserving embedding (NPE), which enables neighborhood structure to be preserved in the reduced dimensionality space. Inspired by the theory of compressed sensing [8], face recognition method based on sparse representation has attracted much attention and is still developing [9-12]. Wright et al. [13] developed a sparse representation-based classification (SRC), which can obtain impressive face recognition results. SRC uses the whole training sample set as a dictionary to encode the test samples, and then classify the test samples by evaluating the minimal class-specific residuals. In facial recognition system, the dimensionality of raw face image is generally higher, and the dictionary size will increase when the number of training sample increase, which will lead to the high computing cost of SRC method.

Face images are usually on low-dimensional manifolds, so it is necessary to find the most discriminative features in low-dimensional subspaces and suppress useless information to facilitate sample classification. In recent years, many methods have tried to combine dimensionality reduction (DR) with sparse representation for recognition task, and have achieved impressive results. Yang and Chu [14] proposed the SRC steered discriminative projection (SRC-DP), which uses an iterative method to find the optimal projection direction for SRC. Gu et al. [15] considered the structural information of the dictionary and proposed a dimensionality reduction method based on structured sparse representation for face recognition. This method can still achieve better performance even when the dimensionality of the dictionary is relatively small. Lu and Huang [16] proposed optimized projection for

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sparse representation-based classification (OP-SRC). OP-SRC try to find the low dimensional features which are optimal for SRC. Lu et al. proposed [17] a simultaneous feature and dictionary learning method for face recognition, which jointly learned the feature projection matrix and the structured dictionary. Oriented the unsupervised dimensionality reduction method, Zhang et al. proposed [18] a sparse representation-based classifier (DR-SRC) which has better performance than Eigenfaces and random faces under the same dimensionality. Zhang et al. [19] designed a supervised dimensionality reduction method (SDR-SRC) and applied it to face recognition. The SDR-SRC method utilizes a variant LDA to improve the separability between object class and other classes in the stage of updating the projection matrix, which is different from the DR-SRC method. Similarly, the dictionaries of the DR-SRC and SDR-SRC methods are composed of part of the original training samples, including two stages of updating the representation coefficient and the projection matrix. In practice, to improve the discriminability of the representation coefficient and the projection matrix is the most concerned part of this type of method. When the DR-SRC and SDR-SRC methods update the representation coefficients, the objective function is transformed into a standard SRC problem, and some convex optimization methods can be used to solve the representation coefficients. Unfortunately, they ignore the available information of the representation coefficients. This paper improved the SDR-SRC method and proposed a sparse embedding dimensionality reduction method under the framework of SRC for face recognition. In our method, the discriminative coefficient constraint term is introduced into the objective function, and the projection matrix and coefficient representation are updated simultaneously by using the label information of the sample, these can help SRC to achieve the best performance in the low dimensional space after projection. A large number of experimental results on ORL, Georgia Tech and FERET face database show that our method achieved better performance.

In the rest of this paper, we mainly give a brief review to SRC and DR-SRC in section 2. In section 3, we present the details of the proposed method. In the meanwhile, we conduct the experiments on three databases, discussed and analyzed the experimental results in section 4. Section 5 concludes the paper.

2 Related Works

2.1 Review of SRC

Wright et al. [13] proposed the sparse representation-based classification (SRC) method for the robust face recognition tasks. Suppose that there are training images from c classes. Let $D = [X_1, X_2, ..., X_C]$ is the matrix constructed by all training sample, here $X_i = [x_{i1}, x_{i2}, ..., x_{ik}] \in R^{h\times k}$, $i = 1,2,...,c$, and h represents the dimensions of the samples. What need to be explained is that X_i is composed by the training samples of the i-th class, each column of which is come from one sample image that is reshaped as column vector, and each class has k images. Given a testing sample $y \in R^{h\times 1}$, the procedures of SRC are as follows.

1). Normalize each column of D by using l2-norm.

2). Solve the l1-minimization problem:

$$\hat{\beta}_1 = \underset{\beta}{\operatorname{argmin}} \|\beta\|_1 \; s.t. D\beta = y \; . \tag{1}$$

3). Compute the residuals

$$r_i(y) = \left\| y - D\delta_i\left(\hat{\beta}_1\right) \right\|_2 \; for \; i = 1, \cdots, c \; . \tag{2}$$

where $\delta_i\left(\hat{\beta}_1\right)$ is the coefficient vector associated with the i-th class.

4). Then the class $C(y)$ which the test sample y belongs to is determined by

$$C(y) = \arg\min_i r_i(y) \; . \tag{3}$$

2.2 Review of DR-SRC

In [18], Zhang et al. designed an unsupervised projection matrix optimization method under SRC framework. The details of DR-SRC are described below.

Denote the k-th training sample of X as $x_k \in R^{h\times 1}$, and $X = [x_1, ..., x_k, ..., x_N] \in R^{h\times N}$. $D_k = [x_1, ..., x_{k-1}, x_{k+1}, ..., x_N] \in R^{h\times (N-1)}$ is constructed by a set of training samples without x_k. The objective function of DR-SRC method is defined as:

$$J_{P,\beta_k} = \arg\min\left\{\sum_{k=1}^{N}\left\|Px_k - PD_k\beta_k\right\|_F^2 + \lambda_1\left\|\beta_k\right\|_1 + \lambda_2\left\|X - P^TPX\right\|_F^2\right\} s.t. PP^T = I\ . \tag{4}$$

where β_k is the coefficient vector of x_k over D_k. P is a projection matrix. The first item on the right side of Equation (4) is approximation constraint, $\left\|\beta_k\right\|_1$ is sparse constraint, λ_1 and λ_2 are scalar parameters, and the last item holds that the training sample set X can be well reconstructed from the projected subspace by P. The solution of Equation (4) is a joint optimization of projection P and coefficient vector β_k.

3 Proposed Method

The number of the classes is still defined as c, and each class has ni training samples. The total number of all training samples is $N = c\times ni$. Each sample matrix is reshaped as column vectors. Denote by $x_k \in R^{m\times 1}$ the k-th training sample of training sample matrix X, and the dictionary corresponding to x_k is defined as $D_k = [x_1, ..., x_{k-1}, x_{k+1}, ..., x_N]$. The objective function in this paper is defined as

$$J(P,X,D,B) = \arg\min\left\{\sum_{k=1}^{N}\left\|Px_k - PD_k\beta_k\right\|_F^2 + \gamma\left\|\beta_k\right\|_1 + \lambda_1 h(P,X,D,B) + \lambda_2\left\|X - P^TPX\right\|_F^2 + \lambda_3 g(B)\right\} s.t. PP^T = I\ . \tag{5}$$

where the constants λ_1, λ_2 and λ_3 control the relative contribution of the corresponding terms. The first term is the reconstruction error of sample, $\left\|\beta_k\right\|_1$ is the regularization term for sparsity, the third term is discriminative reconstruction constraint, $\left\|X - P^TPX\right\|_F^2$ is to ensure that the projection matrix P can preserve the energy of each X as much as possible, and $g(B)$ is the constraint term of the discriminative coefficient. $g(B)$ is defined as

$$g(B) = \sum_{i=1}^{N}\sum_{j=1}^{N}\left(\left\|\beta_i - \beta_j\right\|_2^2 M_{ij} + \eta\left\|B\right\|_F^2\right)\ . \tag{6}$$

where η is scalar parameter, and the elements of matrix M has different forms depending on the combination of β_i with β_j. Introducing Equation (6) to the objective function can ensure the minimal difference of the coefficients of two face samples when they come from the same class, and the maximal difference of the coefficients of two face samples when they come from different class. M_{ij} is defined as

$$M_{ij} = \begin{cases} \dfrac{1}{ni}, & if\left(\beta_i,\beta_j\right)\in O \\ -\dfrac{1}{N-ni}, & otherwise \end{cases}\ . \tag{7}$$

If the label of a pair (β_i , β_j) is given as same, (β_i , β_j) belong to O . We can also simplify Equation (6) as follows:

$$\begin{aligned} g(B) &= \sum_{i=1}^{N}\sum_{j=1}^{N}\left(\left\|\beta_i-\beta_j\right\|_2^2 M_{ij}+\eta\left\|B\right\|_F^2\right) \\ &= Tr\left(BSB^T\right)-Tr\left(BMB^T\right)+\eta\left\|B\right\|_F^2 \\ &= Tr\left(BLB^T\right)+\eta\left\|B\right\|_F^2 . \end{aligned} \tag{8}$$

where $B = [\beta_1, \beta_2, ..., \beta_N]$, $L = S - M$, $S = \mathrm{diag}\{s_1, s_2, ..., s_N\}$, and the diagonal elements of S are the sums of the row elements of M , that means $s_j = \sum_{i=1}^{N} M_{ij}$. Although the objective function in Equation (5) is usually not convex for P and B simultaneously, it is convex to one of them when the other is fixed. We iteratively optimize P and B by using the following two-stage method.

3.1 Learn B with Fixed P

when P is fixed, Equation (5) can be rewritten as:

$$J_{\beta_k} = \arg\min\left\{\sum_{k=1}^{N}\left\|Px_k - PD_k\beta_k\right\|_F^2 + \gamma\left\|\beta_k\right\|_1 + \lambda_3 g(B)\right\} s.t. PP^T = I . \tag{9}$$

Here, β_k can be alternately optimized with fixed β_i, $i \neq k$.

Let $B_{\wedge k} = [\beta_1, ..., \beta_{k-1}, 0, \beta_{k+1}, ..., \beta_N]$, $B_{\wedge} = B - B_{\wedge k} = [0, ..., 0, \beta_k, 0, ..., 0]$. $g(B)$ can be rewritten as

$$\begin{aligned} g(B) &= Tr\left(BLB^T\right)+\eta\left\|B\right\|_F^2 \\ &= Tr\left((B_\Lambda + B_{\Lambda k})L(B_\Lambda + B_{\Lambda k})^T\right)+\eta\left\|B\right\|_F^2 \\ &= Tr\left(B_\Lambda L B_\Lambda{}^T + B_\Lambda L B_{\Lambda k}{}^T + B_{\Lambda k} L B_\Lambda{}^T + B_{\Lambda k} L B_{\Lambda k}{}^T\right)+\eta\left\|B\right\|_F^2 \\ &= Tr\left(\beta_k Z L(\beta_k Z)^T + \beta_k Z L B_{\Lambda k}{}^T + B_{\Lambda k} L(\beta_k Z)^T + B_{\Lambda k} L B_{\Lambda k}{}^T\right)+\eta\left\|B\right\|_F^2 . \end{aligned} \tag{10}$$

where $B_\Lambda = \beta_k Z$, $Z = [0, ..., 0, 1, 0, ..., 0]$. $B_{\Lambda k}$ does not include β_k , and it can be regarded as a constant. Equation (9) can be rewritten as

$$\begin{aligned} J_{\beta_k} = \arg\min\Bigg\{&\sum_{k=1}^{N}\left\|Px_k - PD_k\beta_k\right\|_F^2 + \gamma\left\|\beta_k\right\|_1 + \lambda_3\Big(Tr\Big(\beta_k Z L(\beta_k Z)^T + \\ &\beta_k Z L B_{\Lambda k}{}^T + B_{\Lambda k} L(\beta_k Z)^T + B_{\Lambda k} L B_{\Lambda k}{}^T\Big)+\eta\left\|B\right\|_F^2\Big)\Bigg\} s.t. PP^T = I . \end{aligned} \tag{11}$$

It can be seen that all terms of Equation (11) are differentiable to β_k , except $\left\|\beta_k\right\|_1$. Therefore, following the work in [20-21], we can adopt fast iterative shrinkage-thresholding algorithm (FISTA) [22] to solve Equation (11).

3.2 Learn P with Fixed B

According to the coefficient matrix B obtained in Section 3.1, for updating the projection matrix P, the objective function can be rewritten as

$$J_P = \arg\min\left\{\sum_{k=1}^{N}\left\|Px_k - PD_k\beta_k\right\|_F^2 + \lambda_1 h\left(P,X,D,B\right) + \lambda_2\left\|X - P^T PX\right\|_F^2\right\} s.t. PP^T = I\ . \quad \textbf{(12)}$$

where $h\left(P,X,D,B\right)$ is a variation of the Fisher discriminant criterion, which is effective for discovering the discriminant of geometric structure and increasing the separability of reconstruction residues [19], and is defined as $h\left(P,X,D,B\right) = Tr\left(S_w - S_b\right)$. For this definition,

$$\begin{aligned} S_w &= \frac{1}{N}\sum_{i=1}^{c}\sum_{j=1}^{ni}\left[Px_{ij} - PD_{ij}\delta_i\left(\beta_{ij}\right)\right]\left[Px_{ij} - PD_{ij}\delta_i\left(\beta_{ij}\right)\right]^T \\ &= \mathrm{P}\left\{\frac{1}{N}\sum_{i=1}^{c}\sum_{j=1}^{ni}\left[x_{ij} - D_{ij}\delta_i\left(\beta_{ij}\right)\right]\left[x_{ij} - D_{ij}\delta_i\left(\beta_{ij}\right)\right]^T\right\}P^T \\ &= \mathrm{P}\tilde{S}_w P^T. \end{aligned} \quad \textbf{(13)}$$

$$\begin{aligned} S_b &= \frac{1}{N(c-1)}\sum_{i=1}^{c}\sum_{j=1}^{ni}\sum_{s\neq i}^{c}\left[Px_{ij} - PD_{ij}\delta_s\left(\beta_{ij}\right)\right]\left[Px_{ij} - PD_{ij}\delta_s\left(\beta_{ij}\right)\right]^T \\ &= P\left\{\frac{1}{N(c-1)}\sum_{i=1}^{c}\sum_{j=1}^{ni}\sum_{s\neq i}^{c}\left[x_{ij} - D_{ij}\delta_s\left(\beta_{ij}\right)\right]\left[x_{ij} - D_{ij}\delta_s\left(\beta_{ij}\right)\right]^T\right\}P^T \\ &= P\tilde{S}_b P^T. \end{aligned} \quad \textbf{(14)}$$

Where x_{ij} represents the j-th training sample of the i-th class, and $\tilde{S}_w$ and $\tilde{S}_b$ are the residual scatter matrices of within-class and between-class, respectively. The minimization of Equation (12) is written as

$$\begin{aligned} J_P &= \arg\min\left\{\sum_{k=1}^{N}\left\|Px_k - PD_k\beta_k\right\|_F^2 + \lambda_1 Tr\left(P\left(\tilde{S}_w - \tilde{S}_b\right)P^T\right) + \lambda_2\left\|X - P^T PX\right\|_F^2\right\} \\ &= \arg\min Tr\left\{\sum_{k=1}^{N}P\left(\left(x_k - D_k\beta_k\right)\left(x_k - D_k\beta_k\right)^T + \lambda_1\left(\tilde{S}_w - \tilde{S}_b\right) + \lambda_2 XX^T\right)P^T + X^T X\right\} \\ &= \arg\min Tr\left(P\tilde{J}P^T\right). \end{aligned} \quad \textbf{(15)}$$

Since the last item $X^T X$ has no effect on the update of P, P can be determined by applying singular value decomposition to $\tilde{J}$, i.e. $P \leftarrow SVD\left(\tilde{J}\right)$. P is composed by the t eigenvectors associated with the first t smallest eigenvalues of $\tilde{J}$.

By now the proposed method can be implemented by the iterative solution. The description and implementation steps are as follows:

Step1: Initialize P by using the PCA method;

Step2: Fix P, calculate the initial coefficient according to: $J_{\beta_k} = \arg\min\left\{\left\|Px_k - PD_k\beta_k\right\|_F^2 + \gamma\left\|\beta_k\right\|_1\right\}$.

Step3: Update coefficient matrix B via Equation (11).

Step4: Update the projection P via Equation (15).

Step5: Go to step 3 until the maximum number iteration is reached.

4 Experiments and Analysis

We evaluate the proposed method on the ORL [23], Georgia Tech [24] and FERET [25] face database for face recognition task. The experimental platform is Intel (R) Core (TM) i5-7500 CPU(3.40GHz). In all experiments, $\gamma = 0.005$.

4.1 The ORL Database

The ORL database contains 400 face images of 40 subjects, each subject has 10 face images with some variations in poses, facial expressions and details, and the images are converted into the size of 56×46. Parameters λ_1, λ_2 and λ_3 are set to 0.2, 0.6 and 0.2 respectively. Some face images from the ORL database are shown in Fig. 1. In the first experiment, a random subset with r images of each subject is used as training samples, and r takes the values 3, 4, 5 and 6 in turn. The remaining images are taken as test samples. The experiments are repeated 10 times to calculate the average recognition rate. The results obtained by PCA-SRC, LDA-SRC, NEP-SRC, DR-SRC, SDR-SRC [19] and our method are shown in Table 1, the indices include the mean recognition rate and the corresponding dimensionality (the number in parentheses).

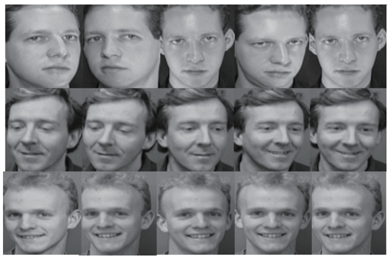

Fig. 1. Some images from the ORL face database

From Table 1, it can be seen that our method performs better among all comparison methods, and the change of dimensionality affects their recognition performance. When the number of training samples for each subject is 3, 4, 5 and 6, the proposed method consistently records the highest recognition rates of 91.04%, 92.87%, 94.40% and 96.19%, respectively, and the corresponding dimensionality are 120, 120, 80 and 120. LDA-SRC, PCA-SRC, and NPE-SRC have lower recognition rates than other comparison methods since their dimensionality reduction process is not related to SRC. The recognition rates of the last three methods are overall higher than the first three methods. The reason is that the learned dimensionality reduction matrix effectively utilizes the discriminative information of the training sample set and strengthens the discrimination between the samples after projection. In particular, the proposed method obtains 0.19%~3.19% higher recognition rate than the SDR-SRC method, and the classification accuracy of it has reached more than 90%, which further proves that the combination of projection matrix and SRC is more reasonable for face recognition tasks.

Table 1. The average recognition rates of different methods on the ORL face database

Method\r	3	4	5	6
LDA-SRC	81.75(60)	86.25(80)	80.00(60)	91.25(140)
PCA-SRC	84.42(80)	88.16(60)	89.50(60)	92.75(80)
NPE-SRC	82.14(80)	87.08(80)	88.50(60)	91.87(60)
DR-SRC	85.71(80)	88.33(140)	90.50(60)	93.37(60)
SDR-SRC	87.85(80)	91.50(120)	93.75(60)	96.00(60)
OUR	91.04(120)	92.87(120)	94.40(80)	96.19(120)

4.2 The Georgia Tech Database

The Georgia Tech face database (GT) has 750 images from 50 subjects. All people in the database were represented by 15 color images with cluttered background. The images show frontal or tilted faces with variations in facial expression, illuminations and scale. In our experiment, the images are converted to gray type with the size of 40 × 30, and the background are all removed. Parameters λ_1, λ_2 and λ_3 are set to 0.05, 0.2 and 0.1 respectively. Fig. 2 shows some sample images of this database. A random subset with r (3, 5, 7 and 9) images of each subject are used as training samples, and the rest are the test set. All methods are carried out 10 times, the average recognition rate and the corresponding dimensionality are reported in Table 2.

Fig. 2. Some images from the GT face database

Compared the experimental results of the first three groups, PCA-SRC is superior to others. In the latter three group results, DR-SRC method have the minimum recognition rate, which indicate that the class information of samples plays an important role in the classification task. When the number of training samples for each subject is 3, 5 and 7, the average recognition rates of the proposed method is higher than other comparison methods, and when the number of training samples for each subject is 9, SDR-SRC method achieves the highest recognition rate of 77 %, our method is second.

Table 2. The average recognition rates of different methods on the GT face database

Method\r	3	5	7	9
LDA-SRC	46.16(80)	52.60(60)	59.75(80)	69.66(60)
PCA-SRC	48.83(120)	53.20(160)	66.50(140)	70.00(80)
NPE-SRC	42.66(80)	45.80(80)	59.25(60)	65.00(60)
DR-SRC	50.33(100)	56.80(140)	68.75(100)	74.33(60)
SDR-SRC	51.33(60)	60.40(120)	72.50(80)	77.00(60)
OUR	55.98(80)	64.92(100)	72.60(80)	75.70(80)

4.3 The FERET Database

The FERET database consists of 14,051 images with different poses, illuminations and expressions. In our experiments, a subset of FERET is used, which includes 1400 face images from 200 subjects. Each subject offered seven face images and those were marked with 'ba', 'bj', 'bk', 'be', 'bf', 'bd' and 'bg', respectively. The images are converted into the size of 40×40. Parameters λ_1, λ_2 and λ_3 are set to 0.05, 0.8 and 1 respectively. Fig. 3 shows some images from the FERET database. We randomly select 3, 4 and 5 face images of each subject as training samples and the rest as test samples. The experimental results are shown in Table 3. It can be seen that the recognition rate of our method is higher than other comparison methods. As expected, our method actively utilizes sample diversity, and the constraint added to the objective function makes the projected subspace more discriminative, which holds the classification more accurate.

Fig. 3. Some images from the FERET face database

Table 3. The average recognition rates of different methods on the FERET face database

Method\r	3	4	5
LDA-SRC	47.25(80)	58.50(100)	69.75(180)
PCA-SRC	50.87(120)	66.33(60)	70.75(140)
NPE-SRC	42.75(80)	56.66(100)	66.75(100)
DR-SRC	51.50(100)	68.30(60)	73.75(200)
SDR-SRC	55.75(60)	71.00(120)	76.50(140)
OUR	56.19(80)	74.80(120)	76.90(120)

4.4 Residual Curve

For SRC based facial recognition method, the object class is determined by the minimal residual of test sample between the class sample. The residual curve of one test sample can visually reveal the recognition result and the robustness to all classes. Therefore, after obtaining the projection matrix using DR-SRC and our method on the GT face database, we randomly select a test sample and project it into a low-dimensional space to observe the classification residual of each class of SRC method. The residual curves of the GT face database are shown in Fig. 4. It can be seen that the residuals of the two methods are relatively small for class 3 and 7. Our method accurately classified the test sample into the 3-th class, while DR-SRC incorrectly classified the sample into the 7-th class. For ORL and FERET face databases, the first and the 28-th class are selected as test samples, and the residual curves are shown in Fig. 5 and Fig. 6, respectively. It can be seen that our method accurately classified the test sample, while the DR-SRC method incorrectly classified the test sample.

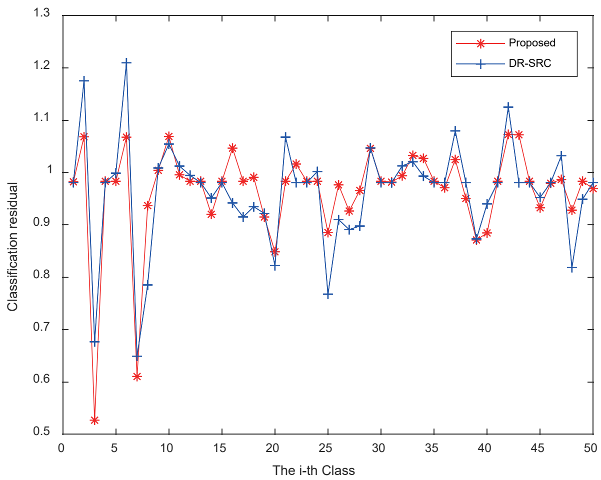

Fig. 4. Classification residual of each class of the GT face database

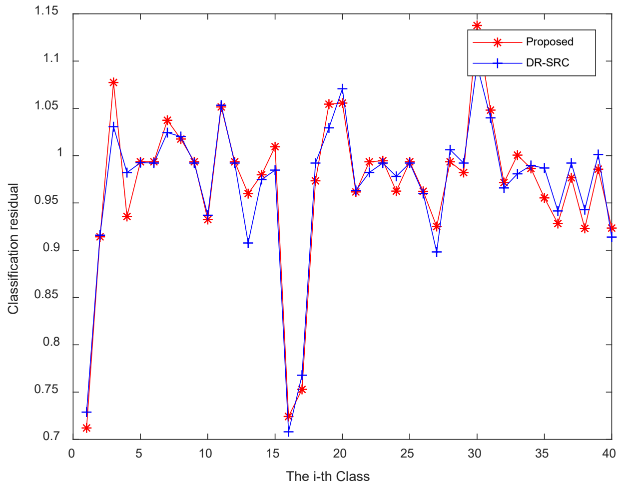

Fig. 5. Classification residual of each class of the ORL face database

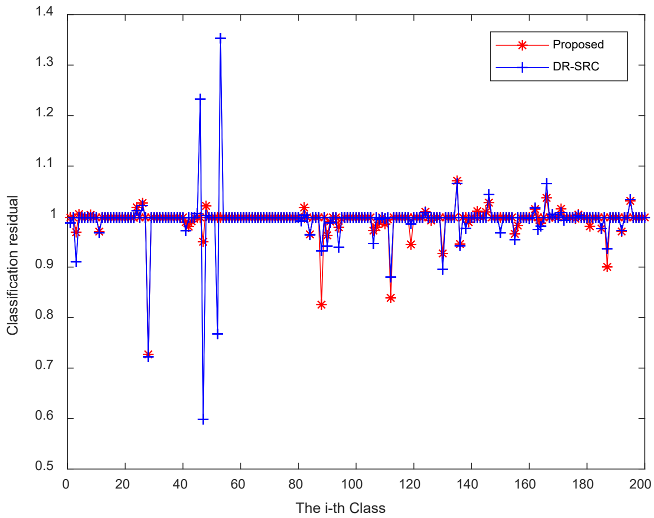

Fig. 6. Classification residual of each class of the FERET face database

4.5 Discussion and Analysis

Through the observation of above experimental results from different databases, the followings can be summarized:

(1) Compared with LDA-SRC, PCA-SRC and NPE-SRC methods, the experimental results of DR-SRC, SDR-SRC and our method are better. In most cases, our method is able to obtain higher recognition rate than other comparison methods. Therefore, the dimensionality reduction method is suitable for SRC, which project high-dimensional data into a low-dimensional space by learning the projection matrix, and the extracted low-dimensional features can obtain a better recognition effect.

(2) When the number of training samples is relatively small, the recognition effect of our proposed method is significantly improved in most cases. However, the superiority of our method decreases with the number of training samples increases.

5 Conclusion

The face recognition method based on sparse representation can achieve good classification performance under sparse constraints, but due to the high computational cost of SRC and traditional dimensionality reduction methods are not directly related to SRC. To improve the classification performance of SRC, we strengthened the connection of the dimensionality reduction process and SRC. The coefficient constraint term is introduced into the objective function, and the distance relationship between the coefficients of each sample is considered. Then, the high-dimensional face image is projected into the low-dimensional subspace by optimizing the dimensionality reduction matrix. The effectiveness of the proposed method is verified on the ORL, GT and FERET databases with promising results. However, the method in this paper is still challenging to recognize occluded face images, which would be an interesting topic for the future research.

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