Robust low-resolution face recognition via low-rank representation and locality-constrained regression☆

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ABSTRACT

Recognizing face images in low-resolution (LR) scenarios have bigger challenges than recognizing those in high-resolution (HR) scenarios due to that LR images usually lack discriminative details. Previous methods ignore the existence of occlusions in the LR probe images. To alleviate this problem, we propose a low-rank representation and locality-constrained regression (LLRLCR) based method in this paper to learn occlusion-robust representations features for final face recognition tasks. For HR gallery set, LLRLCR uses double low-rank representation to reveal the underlying holistic data structures; for LR probe, LLRLCR uses locality-constrained matrix regression to keep regression error's structural information and to learn robust and discriminative representation features. The proposed method allows us to fully exploit the structure information in gallery and probe data simultaneously. Finally, after getting the occlusion-robust features, the face labels can be predicted via a simple yet powerful sparse representation based classifier engine. Experiments on some standard face databases have indicated that the proposed method can obtain promising recognition performance than some state-of-the-art LR face recognition approaches.

1. Introduction

Because of the wide range of applications (e.g., access control, identity authentication and security monitoring), face recognition (FR) has attracted considerable attention in past two decades [1-6]. However, in many real-world applications, due to the long distance between the subject and camera, the acquired face images usually have low-resolution (LR), making face recognition almost impossible. This refers to low-resolution face recognition (LR FR) problem [7]. Generally, there are three strategies to match a LR probe image with a high-resolution (HR) gallery one (as shown in Fig. 1): (i) match the

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(i) Downsampling the gallery and then matching.

(ii) Upsampling the probe and then matching.
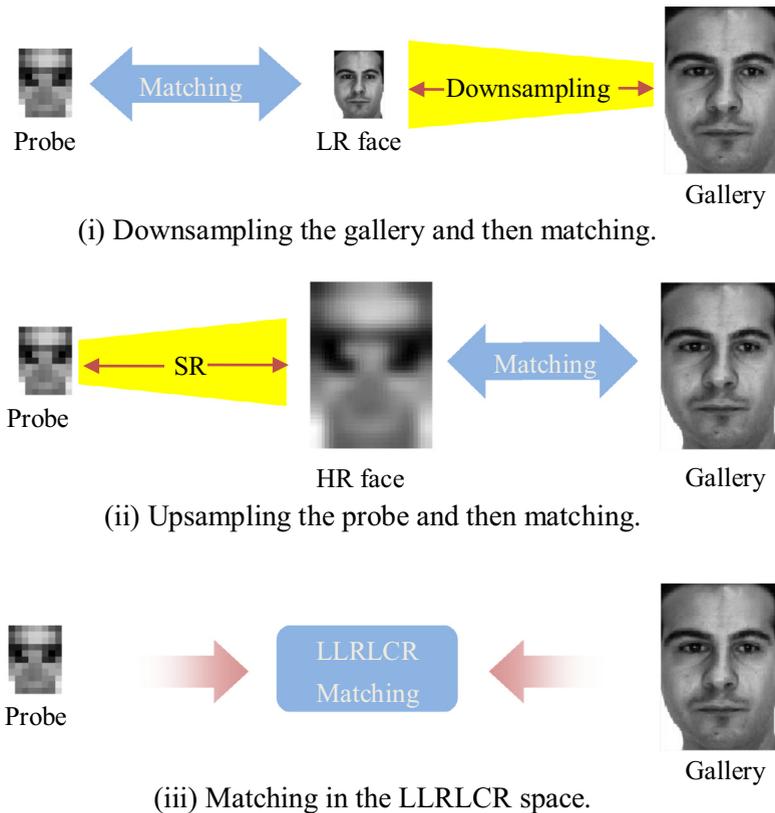

(iii) Matching in the LLRLCR space.

Fig. 1. Standard approaches to match an input LR probe to a HR gallery. (i) Match the down-sampled HR gallery with the LR probe; (ii) match HR gallery with the up-sampled LR probe; (iii) matching in the common space. The proposed method belongs to the third king of approach.

down-sampled HR gallery with the LR probe; (ii) match HR gallery with the up-sampled LR probe; (iii) map both the LR probe and the HR gallery into a common space and then implement matching.

1.1. Prior work

Super-resolution (SR) [8,9] technologies have been widely employed to enhance images resolution. Due to the super-resolution performance even with large magnification factor, learning-based SR approaches have obtained more considerations than interpolation-based ones. As we all known that Baker et al. [10] firstly proposed a face hallucination technology, which infers the HR image with the assistance of HR-LR training dictionary pairs under the Bayesian formulation. Wang et al. [11] coded the LR probe as a linear combination over the LR training dictionary with the help of eigentransformation technology. Huang et al. [12] applied canonical correlation analysis (CCA) to find a coherent subspace which maximizes the correlation between the principal component analysis (PCA) coefficients of corresponding LR and HR images. Recently, many literatures conclude that patch based methods can obtain better performance than global based ones. Following the well-known neighbor embedding (NE) method, Chen et al. [13] presented a low-rank variant based super-resolution method. Then, many researchers state that the position information is useful for face hallucination. Ma et al. [14] designed a position-patch based face hallucination model using all patches from the same position in a training dictionary. To deal with the over-fitting problem in [14], Jung et al. [15] and Jiang et al. [16] employed locality and sparsity prior to improve the super-resolution reconstruction results with only several principal training patches. Most recently, Jiang et al. [17] further presented a multilayer neighbor embedding scheme for efficient face hallucination.

These above mentioned super-resolution approaches aim at achieving good reconstructed image quality, they ignore the discriminative features, which are vital for the following face recognition process. Many resolution robust feature based methods have been proposed to enhance the discriminative ability on the common feature space. Hennings–Yeomans et al. [18] proposed to include the extracted face features in a SR method to simultaneously provide measures of fit of the results from both recognition and reconstruction perspectives. Huang et al. [19] built a nonlinear mapping between LR and HR features by radial basis functions with lower regression errors in a coherent feature space. Biswas et al. [20] proposed to use multidimensional scaling to transform the features of LR probe image and the HR gallery image into a distance-preserving feature space. Jiang et al. [21] developed a method based on coupled discriminant multi-manifold analysis (CDMMA) which learnt mapping simultaneously from the neighboring information as well as the local geometric structure implied by the
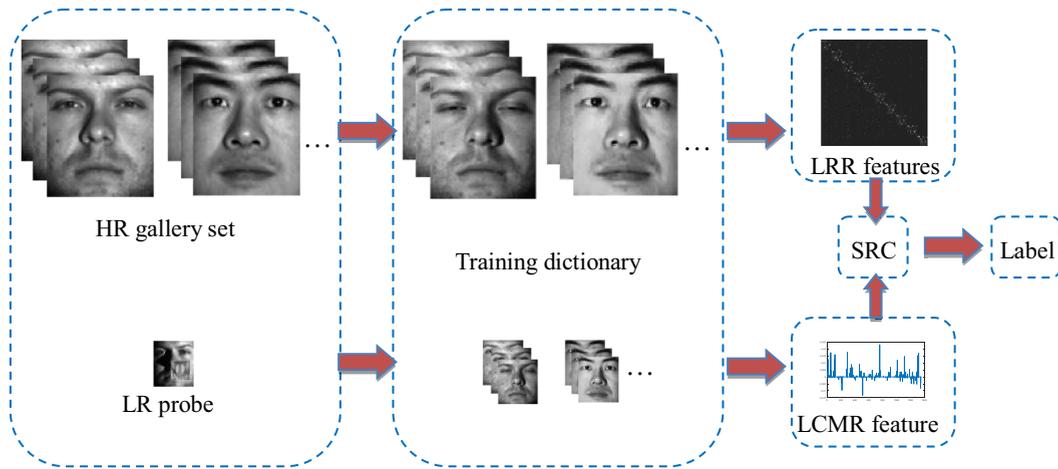
Fig. 2. The flowchart of the proposed method.

samples. Lu et al. [22] proposed a semi-coupled locality-constrained representation (SLR) approach [23] to learn the discriminative representations and the mapping relationship between LR and HR features simultaneously for LR FR.

1.2. Contributions

However, the above mentioned methods ignore the occlusions in the LR probe (which are usual in real-world applications) during the representation features learning stage, thus the learned resolution-robust features are sensitive to occlusion variations. For LR face recognition with occlusions, we propose a novel method called low-rank representation and locality-constrained regression (LRRLCR) in this paper. Here, LLRLCR aims at using double low-rank representation to reveal the underlying data global structures of gallery set. Also, considering the occlusions in the LR probe face images, LLRLCR imposes the nuclear norm constraint on the error term and introduces locality-constrained representation to learn robust and discriminative representation features. After acquiring the resolution-robust representation features both in LR and HR image space, we use a simple yet powerful sparse representation based recognition engine to predict the face label. Fig. 2 shows the flowchart of the proposed method. Experiments on benchmark face databases show the superiority of our method over some state-of-the-art LR face recognition algorithms.

1.3. Organizations

We organize our paper as follows. In Section 2, we present our method based on double low-rank representation and locality-constrained matrix regression. Section 3 evaluates the performance of the proposed methods on several commonly used face recognition databases and compares our proposed method with some state-of-the-art methods. The conclusions and feature work are given in Section 4.

2. The proposed LLRLCR

2.1. Double low-rank representation

For the gallery data, we want to get the robust and discriminative representation features for classification purpose: samples within the same class will have same structures, while between-class samples will have different structures. To this end, we can formulate our objective function as follows:

$$\min_{Z, E_i} \|Z\|_* + \lambda \sum\nolimits_{i=1}^{n} \|E_i\|_*, s.t. X = DZ + E \tag{1}$$

where $X = [x_1, x_2, \dots, x_n] \in \Re^{d \times n}$ is the gallery set, D is the given dictionary, $\|\cdot\|_*$ is the nuclear norm (i.e. the sum of the singular values) of a matrix. It should be noted that each error $E_i \in \Re^{p \times q}$ is a matrix ($d = pq$).

Inexact Augmented Lagrange multiplier (ALM), also called the alternating direction method, has been used to solve many low-rank problems [24]. To solve optimization problem (1), we first convert it to the following equivalent problem:

$$\min_{Z, E_i, J} \|J\|_* + \lambda \sum\nolimits_{i=1}^{n} \|E_i\|_*,$$
$$s.t. X = DZ + E, Z = J \tag{2}$$

The augmented Lagrange function L is given by:

$$L_\mu(Z, E_i, J, Y_1, Y_2) = \|J\|_* + \lambda \sum_{i=1}^n \|E_i\|_* + <Y_1, X - DZ - E> + <Y_2, Z - J> + \frac{\mu}{2}\left(\|X - DZ - E\|_F^2 + \|Z - J\|_F^2\right) \quad (3)$$

where $<A, B> = trace\,(A^T B)$, Y_1 and Y_2 are the Lagrange multipliers, and $\mu > 0$ is a penalty parameter. The above problem can be minimized with respect to Z, E and J, respectively.

Updating J

Given Z and E_i, the optimal solution can be obtained by

$$J^{k+1} = \arg\min_J \left(\frac{1}{\mu}\|J\|_* + \frac{1}{2}\left\|J - \left(Z + \frac{1}{\mu}Y_2\right)\right\|_F^2\right) \quad (4)$$

Its solution is [25]

$$J^{k+1} = UT_{\frac{1}{\mu}}[S]V \quad (5)$$

where $(U, S, V^T) = svd(Z + Y_2/\mu)$.

The singular value thresholding operator $T_\tau(\bullet)$ is defined as

$$T_{\frac{1}{\mu}}[S] = diag\left(\left\{\max\left(0, s_{j,j} - \frac{1}{\mu}\right)\right\}_{1 \le j \le r}\right) \quad (6)$$

where r is the rank of S.

Updating Z

Given J and E_i, the optimization problem can be reformulated as

$$Z^{k+1} = \arg\min_Z \frac{\mu}{2}\left(\left\|X - DZ - E + \frac{1}{\mu}Y_1\right\|_F^2 + \left\|Z - J + \frac{1}{\mu}Y_2\right\|_F^2\right) \quad (7)$$

This equation is a quadratic form in variable Z. Differentiating $L_\mu(Z)$ with respect to Z, and let it be zero, we can obtain the optimal solution as follows:

$$Z^{k+1} = \left(I + D^T D\right)^{-1}\left(D^T X - D^T E + J + \frac{D^T Y_1 - Y_2}{\mu}\right) \quad (8)$$

Updating E

Given J and Z, the objective function L_μ can be rewritten as:

$$\begin{aligned}
L_\mu(E) &= \lambda \sum_{i=1}^n \|E_i\|_* - <Y_1, E> + \frac{\mu}{2}\|X - DZ - E\|_F^2 \\
&= \lambda \sum_{i=1}^n \|E_i\|_* - \sum_{i=1}^n sum\left(Y_1^i \cdot E_i\right) + \frac{\mu}{2}\sum_{i=1}^n \|X_i - D(Z_i) - E_i\|_F^2 \\
&= \sum_{i=1}^n \left\{\lambda\|E_i\|_* + \frac{\mu}{2}\left\|X_i - D(Z_i) - E_i + \frac{1}{\mu}Y_1^i\right\|_F^2\right\},
\end{aligned} \quad (9)$$

where $D(Z_i) = z_{1i}D_1 + z_{2i}D_2 + \dots + z_{mi}D_m$, each D_j $(j = 1, \dots, m)$ is a matrix. Each E_i $(i = 1, \dots, n)$ in (11) is separable and can be solved one by one. Thus, the optimization problem can be reformulated as

$$E_i^{k+1} = \arg\min_{E_i} \frac{\lambda}{\mu}\|E_i\|_* + \frac{1}{2}\left\|E_i - \left(X_i - D(Z_i) + \frac{1}{\mu}Y_1^i\right)\right\|_F^2 \quad (10)$$

The optimal E_i^{k+1} can be obtained as follows:

$$E^{k+1} = UT_{\frac{\lambda}{\mu}}[S]V \quad (11)$$

where $(U, S, V^T) = svd(X_i - D(Z_i) + Y_1^i/\mu)$.

Here, we apply the following termination conditions: $\|X - DZ - E\|_\infty < \varepsilon$ and $\|Z - J\|_\infty < \varepsilon$, where ε is a given tolerance.

2.2. Locality-constrained matrix regression

To better reveal the occlusion in the probe data, we also use nuclear norm to characterize the reconstruction error. As in [16], we introduce a local manifold constraint via a similarity metric between the input patch and dictionary atoms to reveal prior information from nearest atoms. We formulate our model as follows:

$$\min_x \|y - D(x)\|_* + \lambda\|d \otimes x\|_2^2 \quad (12)$$

where $y \in \Re^{p \times q}$ is an input LR probe, $d = (d_1, \dots, d_N)^T$ is the distance vector, $D(x) = x_1 D_1 + x_2 D_2 + \dots + x_m D_m$ and each $D_j \in \Re^{p \times q}$ $(j = 1, \dots, m)$ is a matrix, $d_i = \|y - D_i\|_F^2$ is the locality metric.

For the convenience of expression, we rewrite the optimization problem of (12) as:

$$\min_{x,E} \|E\|_* + \lambda \|d \otimes x\|_2^2$$
$$s.t. y - D(x) = E,$$
(13)

The above problem can be solved via the alternating direction method of multipliers (ADMM) [5,6] with the following augmented Lagrangian function:

$$L_\mu(x, E) = \|E\|_* + \lambda \|d \otimes x\|_2^2 + Tr\left(Y_3^T (y - D(x) - E)\right) + \frac{\mu}{2} \|y - D(x) - E\|_F^2$$
(14)

where Z is the Lagrange multiplier and μ is a penalty parameter.

Updating x

Given E, the optimization problem can be reformulated as

$$L_\mu(x) = \|d \otimes x\|_2^2 + \frac{\mu}{2\lambda} \left\| y - D(x) - E + \frac{1}{\mu} Y_3 \right\|_F^2$$
(15)

Following [16], the solution of problem (15) can be derived analytically as

$$x^{k+1} = \left(G + \tau B^2\right) \backslash ones(m, 1),$$
(16)

Where $ones(m, 1)$ is an $m \times 1$ column vector of ones, the operator "\" denotes the left matrix division operation, $\tau = 2\lambda/\mu$, B is an $m \times m$ diagonal matrix with entries $B_{jj} = d_j$, and G is the covariance matrix $G = C^T C$ with

$$C = \left(y - E + \frac{1}{\mu} Y_3\right) ones(m, 1)^T - H,$$
(17)

where $H = [Vec(D_1), Vec(D_2), \ldots, Vec(D_m)]$ and $Vec(\cdot)$ denotes the vectorization operator.

Updating E

Given x, the optimization problem can be rewritten as

$$E^{k+1} = \arg\min_E \left(\frac{1}{\mu} \|E\|_* + \frac{1}{2} \left\| E - \left(y - D(x) + \frac{1}{\mu} Y_3\right) \right\|_F^2 \right)$$
(18)

Its solution is [25]

$$E^{k+1} = U T_{\frac{1}{\mu}}[S] V$$
(19)

where $(U, S, V^T) = svd(y - D(x) + Y_3/\mu)$.

Here, we apply the following termination condition: $\|y - D(x) - E\|_\infty < \varepsilon$, where ε is a given tolerance.

2.3. Recognition

We use HR low-rank representation matrix Z to form dictionary A, which denotes the representation features of gallery samples. With regard to the LR probe y, its locality-constrained matrix regression coefficient is denoted as x_y. Then the sparse reconstruction coefficients w of x_y over A can be computed by

$$\min_w \|x_y - Aw\|_2^2 + \eta \|w\|_1$$
(20)

Where η is the penalty parameter to balance the reconstruction error and sparsity. Formula (20) can be solved by Homotopy [26]. Then, the class-wise reconstruction error can be calculated through

$$e_i(x_y) = \|x_y - B_i \delta_i(w^*)\|_2^2$$
(21)

Here, δ_i is a function that gathers the coefficients corresponding to the i-th class, and the label of the input x_y is assigned to the class, which has the smallest reconstruction error.

The detailed LR face recognition procedure is summarized in Algorithm 1.

3. Experimental results and discussions

In the following text, some experiments are conducted to verify the effectiveness of our method for robust low-resolution face recognition. In our experiments, the HR images are used as the gallery, and the LR images (which is down-sampled from its HR versions) are used as the probe.

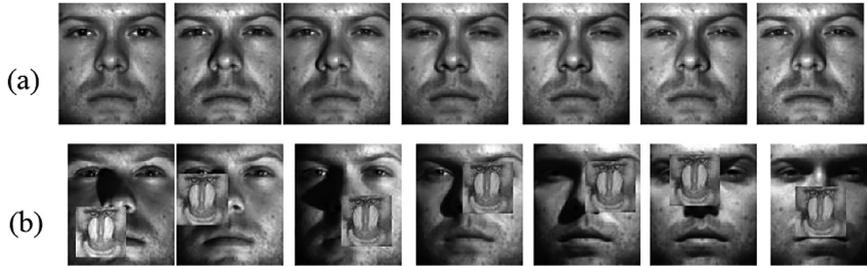**Fig. 3.** Samples from AR face database: (a) HR gallery set; (b) HR probe set.

Fig. 4. Samples from Extended Yale B face database: (a) HR gallery set; (b) HR probe set.

Table 1
The recognition rates (%) of the LLRLCR with baseline methods on the AR database.

Methods	HR + SRC	LR + SRC	LLRLCR
RR	35.83	15.07	**29.00**

Table 2
The recognition rates (%) of the LLRLCR with baseline methods on the Extended Yale B database.

Methods	HR + SRC	LR + SRC	LLRLCR
RR	91.89	56.14	**82.02**

3.1. Dataset description

AR database [27] contains 2600 face images for 100 people, including frontal faces with different facial expressions, lighting conditions and occlusions. Each subject takes twenty-six face images in two separate sessions. In our experiment, for each subject, we choose seven clean images from the first session to form training sets D_h and D_l, seven clean images from the second session to form HR gallery set X_h, and six images with sunglasses and scarfs from the first session to form LR probe set Y_l. It should be noted that all the probe images are outside the gallery set. The HR face images have a size of 44×32 pixels and are down-sampled by scaling factor of 4. The LR image is of size 11×8. Some samples are listed in Fig. 3.

Extended Yale B database [28] includes 38 human subjects under 9 poses and 64 illumination conditions. The database is divided into five Subsets according to different illumination variations. In this experiment, we use Subset 2 to form training sets D_h and D_l, Subset 1 to form HR gallery set X_h, and Subset 3 with slight illumination variations to form LR probe set Y_l. Each LR probe image is corrupted by a randomly located square block of a "baboon" image with an occlusion level of 20%. The HR face images have a size of 48×40 and the LR image is set as 12×10. Some samples are shown in Fig. 4.

3.2. Comparisons with the baselines

We first compare our method with two baselines: one is matching original HR probe images with HR gallery images, and the other is down-sampling HR gallery images to match given LR probe images. Both baselines use SRC [29] engine and are denoted as HR + SRC and LR + SRC respectively. It should be noted that the case HR + SRC is absent from real-world applications. The recognition rates of the two baseline methods and our method are tabulated in Tables 1 and 2. From Tables 1 to 2, we can see that: 1) There is a distinct performance drop (20.76% in AR database while 35.75% in Extended Yale B database) from HR + SRC case to LR + SRC one. This verifies that it is infeasible to match the input LR probe image to

Algorithm 1

LR face recognition process.

Input: Training datasets D_h, D_l. Gallery datasets X_h. Probe LR sample y.

1: For gallery set X_h, calculate its low-rank representation over D_h by Eq. (1) to form data matrix A;

2: Calculate the LR locality-constrained coefficient x_y of probe sample y over D_l by Eq. (12);

3: Classify y by Eq. (20) and Eq. (21):

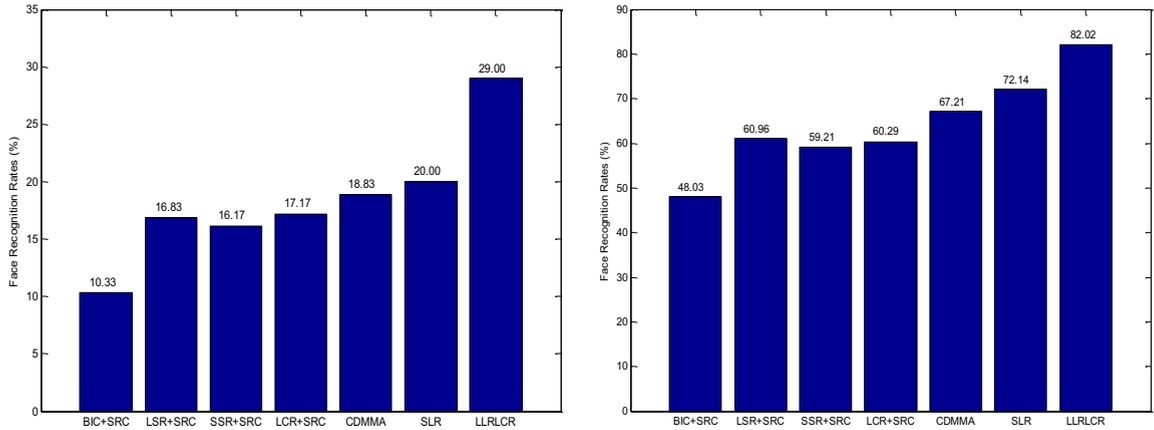**Output:** Class label i for input y.

Fig. 5. Recognition rates of different methods on different database: (a) AR face database, (b) Extended Yale B database.

Fig. 6. Hallucinated results based on different methods on AR database. From left to right are the Input LR image, the results of BIC, LSR [14], SSR [15], LCR [16] and the original HR image.

the down-sampled HR gallery one.; 2) The performance of LLRLCR is better than that of LR + SRC and our method obtains a comparable performance with that of HR + SRC.

3.3. Comparisons with the state-of-the-art methods

In this subsection, we try to compare our LLRLCR with some state-of-the-art low-resolution face recognition methods. The compared face recognition methods mainly fall into two cases: one is SR based recognition methods using HR version of the LR probe as input, including Bicubic interpolation (BIC), Ma et al.'s [14] position patch based super-resolution (LSR), Jung et al.'s [15] sparse representation based super-resolution (SSR) and Jiang et al.' [16] locality-constrained representation based super-resolution (LCR). The other is commonly used resolution-robust LR face recognition approaches using original
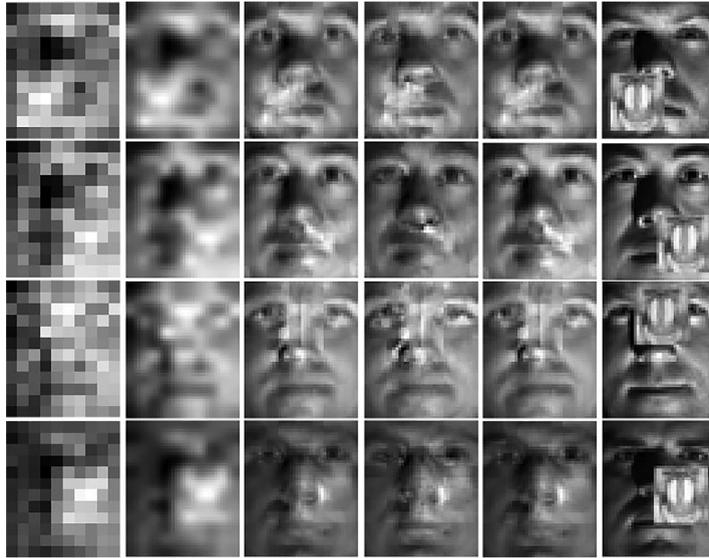
Fig. 7. Hallucinated results based on different methods on Extended Yale B database. From left to right are the Input LR image, the results of BIC, LSR [14], SSR [15], LCR [16] and the original HR image.
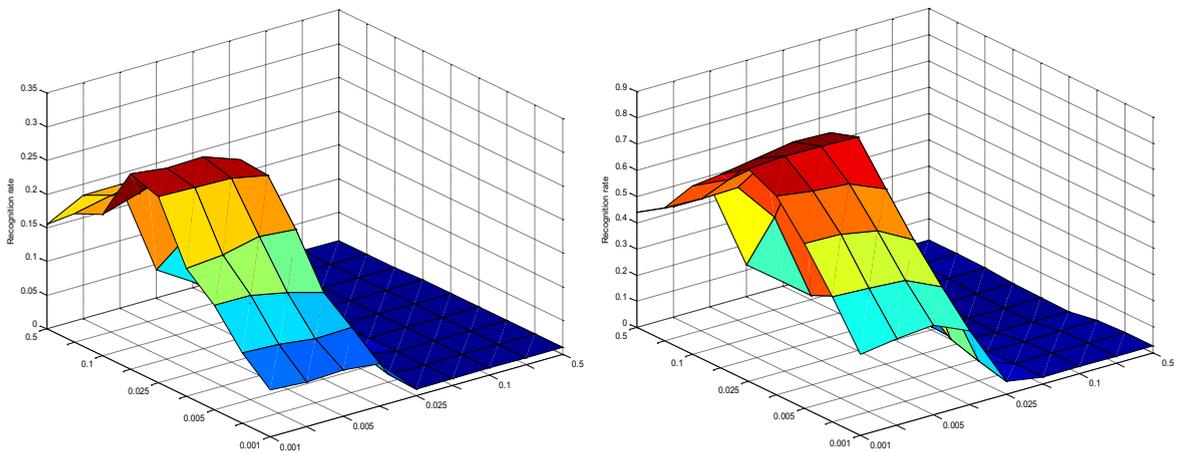

Fig. 8. The recognition rates of our method with different λ and η based on different database: (a) AR database, (b) Extended Yale B database.

observed LR probe as input, including CDMMA [21] and SLR [22] methods. It should be noted that for face recognition methods, the same gallery set is used. For hallucination methods, the same LR-HR training pairs are used. The recognition rates are reported in Fig. 5. We can observe that: 1) The SR based methods obtain unsatisfactory recognition rates. The reason may be that, due to the occlusions in LR probe images, these SR methods cannot well address the occlusions and learn the representation coefficients, result in the loss of discriminative details in the hallucinated images. Some SR results are listed in Fig. 6 and Fig. 7 for better illustration; 2) Our proposed LLRLCR can obtain better recognition performance than both SR based methods and common space based CDMMA method; 3) The SLR method, which also learns resolution-robust features for recognition, has a degraded performance when encountered with occlusions. These results confirm that by introducing the low-rank representation and locality-constrained matrix regression, our proposed LLRLCR can learn more robust and discriminative representation features, which further boost the face recognition performance.

3.4. Parameter analysis

In this subsection, we study the performance variation of LLRLCR with respect to different λ and η. Fig. 8 depict the accuracy of LLRLCR when λ and η take different values. From these figures, we can observe that the bigger the η is, the worse the performance will be. Larger and smaller λ will also lead to worse performance. We can conclude that the performance can achieve a stable level when $\lambda \in [0.01,0.1]$ and $\eta \in [0.001,0.1]$.

4. Conclusions

For low-resolution face recognition with occlusions, we have designed a low-rank representation and locality-constrained regression (LRRLCR) based model in this paper. LRRLCR aims at revealing the underlying structure information of the gallery data and learning robust and discriminative representation features of the probe data for recognition tasks simultaneously. Experiments performed on face datasets with occlusions have shown that our proposed LRRLCR can obtain better performance than some state-of-the-art approaches. Our future work will focus on combining our leaning method with deep neural networks.

Acknowledgments

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