

Recognition at a Long Distance: Very Low Resolution Face Recognition and Hallucination

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Abstract

In real-world video surveillance applications, one often needs to recognize face images from a very long distance. Such recognition tasks are very challenging, since such images are typically with very low resolution (VLR). However, if one simply downsamples high-resolution (HR) training images for recognizing the VLR test inputs, or if one directly upsamples the VLR inputs for matching the HR training data, the resulting recognition performance would not be satisfactory. In this paper, we propose a joint face hallucination and recognition approach based on sparse representation. Given a VLR input image, our method is able to synthesize its person-specific HR version with recognition guarantees. In our experiments, we consider two different face image datasets. Empirical results will support the use of our approach for both VLR face recognition. In addition, compared to state-of-the-art super-resolution (SR) methods, we will also show that our method results in improved quality for the recovered HR face images.

1. Introduction

In many video surveillance applications, as illustrated in Figure 1, we can only capture face images with very low resolution (e.g., face regions of size 16×16 pixels or less [9]). This is mainly because that the subject of interest is far away from the surveillance camera. On the other hand, the training images are typically with higher resolution. As a result, how to perform face detection or recognition for the above scenarios would be very challenging.

In this paper, we particularly focus on the problem of very-low resolution (VLR) face recognition. That is, we have VLR images as the test inputs, while the training ones are with higher resolution. As noted in [8], although conventional methods like [14, 3, 7] have been shown to achieve promising performance for face recognition, such methods typically require training and test face images of



Figure 1: Examples of very low resolution (VLR) face recognition¹.

the same size and with sufficient resolution (e.g., 32×32 pixels or higher [8]).

When solving the task of VLR face recognition, two possible solutions have been considered. Inspired by the recent success of image super-resolution (SR), one can synthesize the high-resolution (HR) image based on the VLR input using existing SR or face hallucination algorithms like [2, 18, 11]. After this image synthesis process is complete, the recognition or matching between the synthesized HR output and the HR training images can be performed accordingly. Different from the above SR-based strategy for VLR face recognition, one can alternatively downsample the HR training images into the targeted low resolution ones. Once the training images are downsampled into the VLR versions, they can be applied to recognize the VLR test images directly. However, as pointed out in [19, 4, 16], neither of the above strategies are able to achieve satisfactory recognition performance.

¹News report on 2013 Boston Marathon bombings. Image courtesy of New York Daily News: <http://www.nydailynews.com/news/national/tiny->

In this paper, we propose a joint face recognition and hallucination algorithm based on sparse representation. Unlike recent VLR approaches, our approach is able to describe cross-resolution face images by learning class-specific information. As a result, the synthesized HR images (from the VLR test input) would not only exhibit satisfactory visual quality, improved recognition performance can also be achieved. As verified later in our experiments, our method would perform favorably against existing SR and VLR face recognition approaches.

The remaining of this paper is organized as follows. We first discuss existing works on VLR face recognition in Section 2. A brief review of sparse representation is presented in Section 3. Section 4 introduces our proposed learning algorithm for joint face recognition and hallucination, while the optimization of the proposed algorithm (i.e., the training process) is detailed in Section 5. Our experiments on two face image datasets are presented in Section 6, and Section 7 concludes this paper.

2. Related Work

Existing VLR face recognition approaches typically aim at relating face images with different resolutions. For example, Abiantun *et al.* [1] adopted the kernel class-dependence feature analysis (KCFA) for determining a higher-order feature space, in which the HR and VLR images of the same subject exhibit higher correlation and is thus preferable for recognition. Different from the above correlation-based approach, Li *et al.* [10] proposed coupled locality preserving mappings (CLPMs) for observing a common feature space for VLR face recognition. Their work was later extended by Ren *et al.* [13], who decided to improve the representation capability of the observed common feature space by applying kernel tricks for non-linear mapping. On the other hand, Biswas *et al.* [5, 4] chose to derive a common feature space for HR and VLR face images using Multi-dimensional Scaling (MDS) techniques, so that they can perform recognition using projected HR training and VLR test images in the resulting feature space.

Different from the above approaches which associate VLR and HR images by explicitly observing a common feature space, Hennings-Yeomans *et al.* [8] proposed a joint SR and recognition algorithm (S^2R^2), which solves the face hallucination task by taking class (i.e., subject) information into consideration. Similarly, Zou *et al.* [19] proposed a discriminative SR (DSR) approach, with the goal of introducing additional discriminative abilities during the synthesis of targeted HR images. We note that, joint synthesis and recognition approaches like [8, 19] have shown improved performance for VLR face recognition. This is because that their methods were able to take both representative and dis-

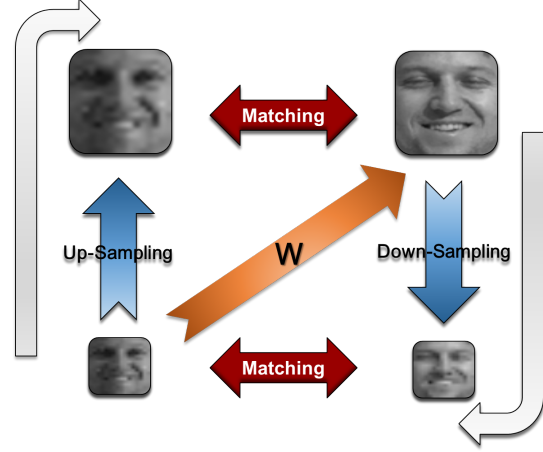


Figure 2: Illustration of our proposed method for joint face hallucination and recognition. Instead of performing recognition as standard approaches did (as indicated by the two gray arrows), we propose the learning of a person-specific face hallucination model \mathbf{W} with recognition guarantees.

criminative information into consideration. Take DSR [19] for example, it applies a MAP-based formulation for image hallucination and a distance-based metric for recognition. However, it is not clear whether the direct combination of these two *distinct* properties (i.e., reconstruction error and distance) in a unified framework would be preferable. This is the reason why we propose a joint face recognition and hallucination algorithm, in which both representation and classification terms are based on sparse representation. As verified later, our method not only performs favorably against state-of-the-art approaches on VLR recognition, improved image quality of the synthesized HR images can also be achieved.

3. A Brief Review of Sparse Representation Based Classification

Since our proposed algorithm for joint face recognition and hallucination is based on sparse representation based classification (SRC), we briefly review this technique in this section for the sake of clarity and completeness. SRC is proposed by Wright *et al.* [15], and it is applied for solving face recognition problems. SRC represents the test image \mathbf{x} as a sparse linear combination of a dictionary \mathbf{D} . Precisely, the sparse coefficient α of \mathbf{x} is calculated by solving the following L1-minimization problem:

$$\min_{\alpha} \|\mathbf{x} - \mathbf{D}\alpha\|_2^2 + \lambda \|\alpha\|_1. \quad (1)$$

After we obtain the sparse coefficient α , the test input \mathbf{x} is recognized as class k^* according to

$$k^* = \arg \min_k \|\mathbf{x} - \mathbf{D}\delta_k(\alpha)\|_2, \quad (2)$$

where $\delta_k(\alpha)$ is a vector whose only non-zero entries are the entries in α that are associated with class k . In other words, the test image \mathbf{x} is assigned to the class with the minimum class-wise reconstruction error. The motivation behind this classification strategy is that the test image \mathbf{x} should lie in the subspace spanned by face images of class k^* . As a result, most non-zero elements of α will be concentrated in the non-zero entries of $\delta_{k^*}(\alpha)$, which results in the minimum reconstruction error.

4. Our Proposed Method

We now detail how we address both face recognition and hallucination problems in a unified formulation, as depicted in Figure 2. Consider that we have N HR and VLR face image pairs as the gallery set, and the dimensions of HR and VLR face images are M and m , respectively. Based on sparse-representation based classification (SRC) [15], we utilize the HR face images as the HR dictionary $\mathbf{D}_H \in R^{M \times N}$, and the corresponding VLR face images as the LR dictionary $\mathbf{D}_L \in R^{m \times N}$.

Given K VLR face images as input training instances $\mathbf{I}_L = [\mathbf{x}_L^1, \dots, \mathbf{x}_L^K] \in R^{m \times K}$ (not in \mathbf{D}_L), and their corresponding HR images $\mathbf{I}_H = [\mathbf{x}_H^1, \dots, \mathbf{x}_H^K] \in R^{N \times K}$ as ground truth, we calculate the sparse coefficients of these VLR images as $\mathbf{A}_L = [\alpha_L^1, \dots, \alpha_L^K] \in R^{N \times K}$ using \mathbf{D}_L . With the sparse coefficients \mathbf{A}_L derived, our goal is to solve the following optimization problem:

$$\min_{\mathbf{A}_H, \mathbf{W}} E_H(\mathbf{I}_H, \mathbf{A}_H) + \tau E_R(\mathbf{I}_H, \mathbf{A}_H) + \gamma E_W(\mathbf{A}_H, \mathbf{A}_L, \mathbf{W}), \quad (3)$$

in which E_H and E_R denote the terms for face hallucination and recognition, respectively. In our proposed framework, this is realized by deriving the sparse coefficient \mathbf{A}_H for the HR images of interest. On the other hand, by learning the transformation \mathbf{W} , the E_W term aims at associating VLR and HR images by relating VLR and HR image features (i.e., \mathbf{A}_L and \mathbf{A}_H). Parameters τ and γ balance the associated terms. In the following subsections, we will give detailed definitions of each term. We will explain why solving (3) effectively and jointly addresses the tasks of face hallucination and recognition.

4.1. Person-Specific Face Hallucination

With the goal of synthesizing the HR image output, our face hallucination term E_H is defined as follows:

$$E_H(\mathbf{I}_H, \mathbf{A}_H) = \|\mathbf{I}_H - \mathbf{D}_H \mathbf{A}_H\|_F^2 + \lambda \|\mathbf{A}_H\|_1, \quad (4)$$

where $\mathbf{A}_H = [\alpha_H^1, \dots, \alpha_H^K]$ is the sparse coefficient matrix for \mathbf{I}_H . The parameter λ controls the sparsity, and we fix it as 0.1 as suggested in [15]. It can be seen that, this face hallucination term can be viewed as the learning of the sparse

representation for HR images. However, we note that we will derive the sparse coefficient \mathbf{A}_H not only for representation but also for recognition purposes.

In order to achieve the above goal of joint image representation and classification (i.e., for joint face hallucination and recognition), we have the term E_R introduce additional discriminating abilities. To be more specific, E_R is determined as follows:

$$E_R(\mathbf{I}_H, \mathbf{A}_H) = \sum_{i=1}^K \|\mathbf{x}_H^i - \mathbf{D}_H \delta_{ic}(\alpha_H^i)\|_2^2. \quad (5)$$

where δ_{ic} returns only the entries corresponding to the HR gallery images of subject c of an observed i -th training instance. It is obvious that, once \mathbf{A}_H is obtained, we have (5) solve the SRC face recognition problem by minimizing the class-wise reconstruction error for the input image. Thus, by solving (4) and (5) simultaneously, we will be able to perform class-specific face hallucination. In other words, joint face hallucination and recognition can be realized.

4.2. Adapting VLR to HR Face Images

During training, we only have VLR images \mathbf{I}_L and their sparse coefficients \mathbf{A}_L as the inputs (recall that \mathbf{D}_H and \mathbf{D}_L are the dictionaries of gallery HR/VLR images collected beforehand). When solving (3), we not only need to derive α_H for class-specific face hallucination, we also need to associate VLR and HR images so that \mathbf{A}_H can be properly inferred from \mathbf{A}_L .

To relate VLR and HR images, we propose to learn the mapping (or transformation) matrix \mathbf{W} . This transformation matrix will satisfy

$$E_W(\mathbf{A}_H, \mathbf{A}_L, \mathbf{W}) = \|\mathbf{A}_H - \mathbf{W} \mathbf{A}_L\|_F^2. \quad (6)$$

From the above equation, it can be seen that VLR and HR images are linearly related by the transformation \mathbf{W} . In other words, with \mathbf{W} observed, one can recover \mathbf{A}_H by $\mathbf{W} \mathbf{A}_L$ directly.

Based on the above discussions, the optimization problem of (3) can be rewritten as follows:

$$\min_{\mathbf{A}_H, \mathbf{W}} \sum_{i=1}^K (\|\mathbf{x}_H^i - \mathbf{D}_H \alpha_H^i\|_2^2 + \lambda \|\alpha_H^i\|_1 + \tau \|\mathbf{x}_H^i - \mathbf{D}_H \delta_{ic}(\alpha_H^i)\|_2^2 + \gamma \|\alpha_H^i - \mathbf{W} \alpha_L^i\|_2^2). \quad (7)$$

By solving our proposed formulation of (7) during the training stage, we can obtain the learning model \mathbf{W} and the sparse coefficient \mathbf{A}_H . The former associates cross-resolution images, while the later exhibits both representation and classification capabilities. In other words, as depicted in Figure 2, the tasks of face hallucination and recognition will be addressed simultaneously.

5. Optimization

5.1. Training

We now detail how we solve (7) during the training stage of our proposed framework. Recall that, we have dictionaries \mathbf{D}_H and \mathbf{D}_L which are pre-collected from the gallery HR and VLR images, respectively. In addition, we have input VLR training images \mathbf{I}_L (not in \mathbf{D}_L) and their ground truth HR ones \mathbf{I}_H . To initialize the optimization process for the training stage, we assume that $\mathbf{W} = \mathbf{I} \in \mathbb{R}^{N \times N}$, and we have \mathbf{A}_L computed from the input instances \mathbf{I}_L and \mathbf{D}_L accordingly. Then, we iterate between the following two steps for solving \mathbf{A}_H and \mathbf{W} when optimizing (7):

Updating \mathbf{A}_H : When solving \mathbf{A}_H , we consider that the transformation matrix \mathbf{W} is derived from the previous iteration and thus is fixed. In other words, given a pre-calculated \mathbf{W} , we can rewrite (7) for calculating the sparse coefficient matrix \mathbf{A}_H . To be more precise, this is achieved by solving the following problem:

$$\min_{\mathbf{A}_H} \sum_{i=1}^K \left\| \begin{bmatrix} \mathbf{x}_H^i \\ \tau^{1/2} \mathbf{x}_H^i \\ \gamma^{1/2} \mathbf{W} \mathbf{A}_L \end{bmatrix} - \begin{bmatrix} \mathbf{D}_H \\ \tau^{1/2} \delta_{ic}(\mathbf{D}_H) \\ \gamma^{1/2} \mathbf{I} \end{bmatrix} \alpha_H^i \right\|_2^2 + \lambda \|\alpha_H^i\|_1. \quad (8)$$

Since (8) has the same formulation as (4), we apply the existing techniques like Homotopy analysis [17] for solving \mathbf{A}_H .

Updating \mathbf{W} : With \mathbf{A}_H determined in the previous iteration, we can solve \mathbf{W} for updating the transformation matrix. In other words, given a fixed \mathbf{A}_H , we now simplify the problem of (7) as follows:

$$\min_{\mathbf{W}} \|\mathbf{A}_H - \mathbf{W} \mathbf{A}_L\|_F^2 \quad (9)$$

Let $Q(\mathbf{W})$ denote the objective function of (9). Since $Q(\mathbf{W})$ is an unconstrained quadratic problem, the optimal solution of (9) can be analytically derived by taking the derivative of Q with respect to \mathbf{W} and setting it equal to zero, i.e.,

$$\frac{\partial Q}{\partial \mathbf{W}} = (2\mathbf{A}_H \mathbf{A}_L^\top - 2\mathbf{W} \mathbf{A}_L \mathbf{A}_L^\top) = 0. \quad (10)$$

By the above derivation, the solution of (10) can be calculated as follows:

$$\begin{aligned} \mathbf{W} &= \mathbf{A}_H \mathbf{A}_L^\top (\mathbf{A}_L \mathbf{A}_L^\top)^{-1} \\ &= \sum_{i=1}^K \alpha_H^i \alpha_L^i (\sum_{i=1}^K \alpha_L^i (\alpha_L^i)^\top)^{-1}. \end{aligned} \quad (11)$$

In practice, the solution of (11) is unique since we typically have $K > N$ (see our experiments). More specifically, with

$K > N$, the non-singularity of $\mathbf{A}_L \mathbf{A}_L^\top$ can be guaranteed, and thus it is invertible.

It can be seen that, in (8) and (9), the optimization problem is convex with respect to the variable to be solved. As a result, one would expect the convergence of solutions \mathbf{A}_H and \mathbf{W} for terminating the iteration process. With the optimal \mathbf{A}_H and \mathbf{W} obtained, the training stage of our proposed algorithm is complete, and the projection matrix \mathbf{W} will be considered as our learned model for performing person-specific face hallucination and recognition.

5.2. Testing

Given a VLR test image $\mathbf{x}_{p,L}$, we first calculate its sparse coefficient feature $\alpha_{p,L}$ using the VLR gallery dictionary \mathbf{D}_L . Once the representation for this VLR image is derived, its HR version can be predicted by $\alpha_{p,H} = \mathbf{W} \alpha_{p,L}$ using our learned model \mathbf{W} directly. If one needs to visualize the recovered HR image (i.e., for face hallucination purposes), the output image $\mathbf{x}_{p,H}$ can be reconstructed by $\mathbf{D}_H \alpha_{p,H}$, which is based on the use of our face hallucination term (i.e., (4)).

On the other hand, if one needs to perform recognition for the synthesized HR image, the SRC-based term of (5) can be applied directly. In other words, we calculate class-wise image reconstruction errors as follows:

$$j = \underset{i}{\operatorname{argmin}} \|\mathbf{x}_{p,H} - \mathbf{D}_H \delta_i(\alpha_{p,H})\|_2, \quad (12)$$

where δ_i returns only the entries corresponding to the HR gallery images of subject i . Based on SRC, this determines the identity of $\mathbf{x}_{p,L}$ if the associated class-wise reconstruction error is minimum among all subjects.

6. Experiments

To evaluate the performance of our proposed method, we consider two databases in our experiments: CMU Multi-PIE [6] and FRGC [12]. We follow the setting of [8], and consider 6×6 and 24×24 pixels as the resolutions for VLR and HR images, respectively. Each face image is aligned with respect to the eyes, and the pixel values are re-scaled into the range of [0, 1]. For simplicity, we fix both parameters τ and γ in (7) as 1.0 for all experiments.

We consider two baselines approaches: recognition using HR images for both training and testing (denoted as *HR*), and that using VLR images for both training and testing (*VLR*). For VLR-to-HR recognition (i.e., HR images for training and VLR ones for testing), we consider: S^2R^2 [8], DSR [19], MDS [4], recognition using up-sampled HR test images via bicubic interpolation (*Bic*), *ScSR* [18], and the approach of Ma et al. [11], respectively. It is worth noting that, no VLR-to-HR approaches (including ours) will be expected to outperform the baseline method of *HR*, since it takes HR images for both training and testing.

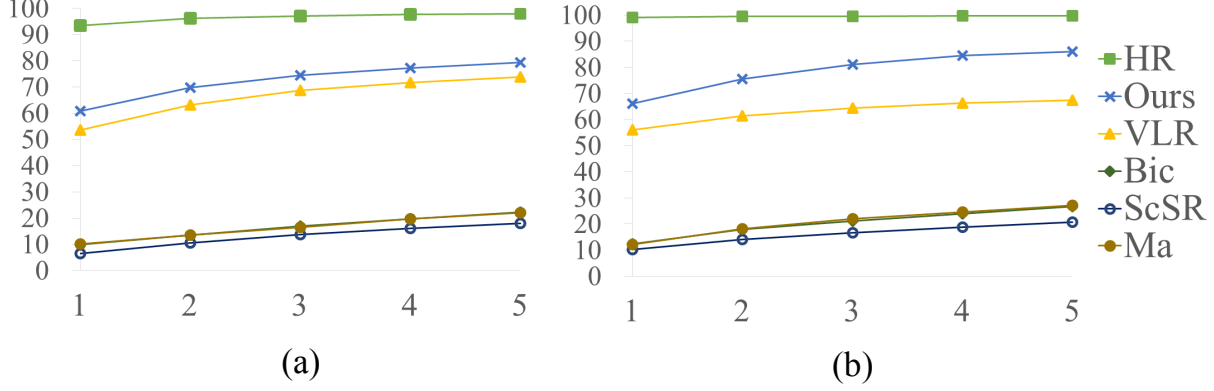


Figure 3: Cumulative matching characteristic (CMC) curves (i.e., accuracy vs. rank) for (a) FRGC and (b) CMU Multi-PIE databases.

For experiments on FRGC, we adopt images in FRGC Experiment 1 as used in [8]. And, only the subjects with more than 10 images in the gallery set will be selected for validation. When constructing the VLR/HR dictionaries (i.e., \mathbf{D}_L and \mathbf{D}_H), we choose four images from each subject while the remaining ones are used for training purposes (i.e., the learning of the transformation matrix \mathbf{W}). Once \mathbf{W} is learned, 6180 probe images of 221 subjects are used for performing recognition and hallucination. We compare the recognition results of different methods in terms of CMC curves in Figure 3(a). From this figure, we see that our recognition performance was superior to those using SR-based methods [18, 11], and we achieved the Rank-1 recognition rate as 60.83%, which was significantly higher than that of 53.60% with VLR only. It is also worth noting that, SR-based methods generally produced remarkably poorer results, even compared to VLR. This suggests that performing face hallucination followed by recognition is not preferable for VLR recognition.

We further consider a more challenge task using the CMU Multi-PIE database (session 1 of 249 subjects), which contains two different types of expression variations. For learning the transformation matrix \mathbf{W} , we select 12 images out of 20 illumination variation images of each subject for training. In particular, 3 out of 12 are randomly selected for constructing VLR/HR dictionaries, while the remaining images of each subject are used for learning \mathbf{W} . For testing, we have 3968 probe images for evaluation. As shown in Figure 3(b), our method again outperformed VLR and state-of-the-art SR-based methods. Our Rank-1 recognition rate was 66.08%, which was higher than that of 56.02% with VLR. In addition, we compare our results with S^2R^2 , DSR and MDS. Tables 1 and 2 list the Rank-1 recognition results, respectively. From both tables above, we can see that our approach performs favorably against state-of-the-

Table 1: Rank-1 recognition rate comparisons on FRGC.

VLR \rightarrow HR	Method	Rank-1
$6 \times 6 \rightarrow 24 \times 24$	S^2R^2 [8]	55%
$7 \times 6 \rightarrow 56 \times 48$	DSR [19]	56.5%
$6 \times 6 \rightarrow 24 \times 24$	Ours	60.83%
$7 \times 6 \rightarrow 56 \times 48$	Ours	65.92%

Table 2: Rank-1 recognition rates on Multi-PIE.

VLR \rightarrow HR	Method	Rank-1
$6 \times 6 \rightarrow 24 \times 24$	S^2R^2 [8]	62.8%
$8 \times 6 \rightarrow 48 \times 40$	MDS [4]	52%
$6 \times 6 \rightarrow 24 \times 24$	Ours	66.08%
$8 \times 6 \rightarrow 48 \times 40$	Ours	95.18%

art joint face hallucination and recognition methods.

To verify the effectiveness of our proposed method for person-specific face hallucination, we apply the metrics of PSNR and SSIM to evaluate the quality of the synthesized HR images. Table 3 lists and compares the results of face hallucination of different approaches. It is clear that we quantitatively outperformed existing approaches in terms of these two metrics. Finally, Figure 4 shows example hallucination output produced by different methods, which also confirms the use of our proposed method for synthesizing HR face images using VLR inputs.

7. Conclusions

We proposed a learning-based approach for joint face hallucination and recognition. We applied our proposed method for VLR face recognition problems, in which standard methods by either upsampling the VLR inputs or downsampling the HR training ones would fail to produce

Table 3: Comparisons of average PSNR and SSIM values on FRGC/CMU Multi-PIE databases.

Method	PSNR (dB)	SSIM
Bic	16.15/17.82	0.48/0.58
ScSR [18]	15.50/16.91	0.41/0.52
Ma [11]	15.87/17.63	0.49/0.59
Ours	21.81/20.89	0.82/0.77

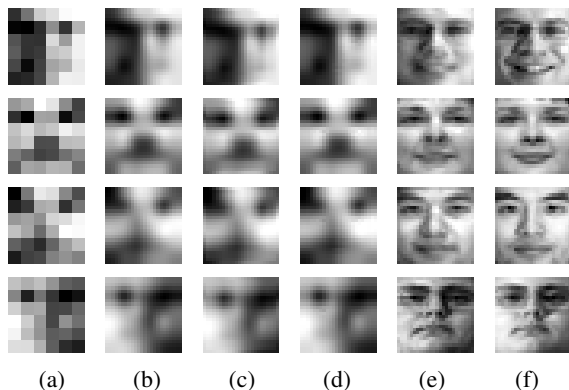


Figure 4: Example face hallucination results of (a) input VLR image, (b) Bicubic, (c) ScSR [18], (d) Ma et al. [11], (e) our proposed method, and (f) ground truth HR images.

satisfactory recognition results. By observing class information when modeling cross-resolution face image pairs, our proposed learning model exhibits excellent capabilities for person-specific face hallucination with recognition guarantees. Our experiments on FRGC and CMU Multi-PIE databases successfully verified the effectiveness of our proposed method for recognition, while the recovered HR images with improved quality (via PSNR and SSIM) can also be produced. For more challenging face recognition problems and as future research directions, we will extend our work to deal with VLR face images with pose variations, occlusion, or image misalignment.

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