2018 24th International Conference on Pattern Recognition (ICPR)
Beijing, China, August 20-24, 2018

Face Image Super-Resolution via K-NN Regularized Collaborative Representation with Importance Reweighting

Licheng Liu
The College of Electrical and Information Engineering
Hunan University
Changsha, China 410082
lichenghnu@gmail.com

Shutao Li
The College of Electrical and Information Engineering
Hunan University
Changsha, China 410082
shutao_li@hnu.edu.cn

***Abstract*—In visual recognition and surveillance system, human face is one of the most important factors. Unfortunately, due to the low-cost imaging sensors and the complexity imaging environment, the captured face images are always low-resolution (LR) and corrupted by noise. The noisy LR face images possess limited useful information, which will extremely degrade the performance of face recognition system. To address this issue, in this paper we presented a K-nearest neighbor (K-NN) Regularized Collaborative Representation (K-RCR) method to simultaneously enhance the resolution of face images and suppress the noise. The proposed K-RCR breaks the bottlenecks of patch based face super-resolution methods, which makes it to be a reality that denoising and super-resolution can be achieved in a unified framework. Specifically, the K-NN selection strategy is employed to use the most important K nearest neighbors in the training dataset to collaboratively represent the test patch, leading to a unique and stable solution for the least squares problem. Moreover, a diagonal weight matrix is incorporated into the objective function to equip it more robust to noise. Experimental results on the standard test face dataset, i.e., FEI, demonstrate the superiority of our proposed method over several state-of-the-art face image super-resolution methods.**

I. Introduction

High-resolution (HR) face images with rich image details and informative characteristics are greatly required in real-world scenarios such as satellite imaging, consumer photographs, magnetic resonance imaging, and video surveillance. Unfortunately, the captured images are always with low resolution (LR) and polluted by noise due to hardware constraints, storage limitations, poor environmental conditions, long distance between the objects and camera sensors, and other restrictions in electronic imaging systems [1]. Face image super-resolution, aiming to reconstruct a HR face image with high quality from its noisy LR observations, may be an effective way to solve this problem. Similar to other super-resolution methods [2], it also tries to recover the high-frequency components, e.g., edges and face contours and remove the undesirable effects, e.g., resolution degradation and noise, from the noisy LR face images.

The problem of face image super-resolution can be traced back to 2000, in which Baker and Kanade [3] presented a pioneering work on face image super-resolution called face hallucination. From then on, various methods have been exploited for face image super-resolution. For example, Liu *et al.* [4] proposed a global parametric Markov network based two-phase face hallucination approach from the probability point of view. These methods usually treat the face image as a whole and they are named as global face hallucination methods.

Besides, some traditional machine learning techniques have been introduced for face image super-resolution, including the Locality Preserving Projections (LPP) [5], the Principal Component Analysis (PCA) [6], the Canonical Correlation Analysis [7], and so on.

Recent years, local methods deal with small patches have received more and more attentions due to their powerful synthesis capacity in capturing face image details. Chang *et al.* [8] presented a neighbor embedding (NE) method for face image super-resolution based on the locally linear embedding (LLE) [9] framework. It assumes that the HR patch and its corresponding LR courtpart share the same neighborhood relationship. Later, Zhang *et al.* [10] further extended the neighbor embedding scheme into the Discrete Cosine Transform (DCT) frequency domain. Jiang *et al.* [11] proposed a coupled-layer NE for face hallucination, based on the assumption that the neighbor correlation can be learned from a common space.

According to the observation that human face is a structured object, that is, the target patch can be estimated by the training patches seated at the same position, in [12], the Least Square Regression (LSR) is introduced to model position patches for face hallucination. The LSR, however, is somehow unstable. Thus, additional regularization terms are needed to stabilize the linear system. A popular used prior is the l_1-norm induced sparsity prior [13], including the Adaptive Weighted Sparse Representation (AWSR) [14] and the Smooth Sparse Representation (SSR) [15], for face image super-resolution. Another important prior is the l_2-norm induced collaborative representation [16] or locality regularized collaborative representation [17]–[19], which uses all the training samples to reconstruct the target HR patch.

978-1-5386-3788-3/18/$31.00 ©2018 IEEE

An open question in image super-resolution is how to estimate the high frequency details from the LR images in noisy environment [20], [21]. An intuitive way is first using some denoising methods [22], [23] to remove the noise, then the super-resolution methods are applied on the denoised results to produce HR images. Unfortunately, the noise is impossible to be suppressed accurately and the denoising errors will be further amplified by the face hallucination operations.

In this paper, we presented a K-RCR based method for noisy face image super-resolution. Our target is to forecast the HR face image from its noisy LR observation without a pre-denoising process. To achieve this purpose, the collaborative representation with K-NN selection strategy is chosen for data representation. Besides, to make it robust to noise, a reweighting strategy is utilized to assess the importance of each feature in a patch. To this end, the influence of noise can suppressed while the contribution of useful informative pixel can be highlighted in representation, leading to more accurate coefficients to generate the target HR patch.

The remainder of this paper is organized as follows: The proposed K-RCR based face super-resolution method is p-resented in detail in section II. Section III shows some experimental results and Section IV draws a conclusion.

II. The Proposed K-RCR Framework

For position patch based face image super-resolution, the test and training images are all divided into small image patches firstly, then they are processed by various machine learning methods. More specifically, for an input LR face image $\mathbf{Y}^L$, it can be divided into overlapping patches with a sliding window scanning from left to right and top to down. Suppose that M patches can be extracted, denoted by $\{\mathbf{y}^L(p,q)|1 \le p \le P, 1 \le q \le Q\}$ with $M = PQ$, in which $\mathbf{y}^L(p,q)$ represents the vectorized patch at (p,q)th position extracted from the input LR face image. Accordingly, the LR and HR training images are also divided into patches based on the division strategy of input LR face images as $\{\mathbf{y}_k^L(p,q)|1 \le p \le P, 1 \le q \le Q\}_{k=1}^K$ and $\{\mathbf{x}_k^H(p,q)|1 \le p \le P, 1 \le q \le Q\}_{k=1}^K$, where $\mathbf{y}_k^L(p,q)$ and $\mathbf{x}_k^H(p,q)$ are the (p,q)th LR and HR position patches in the kth training images respectively, P is the total number of patches in each column, Q is the total number of patches in each row, and K is the number of training samples. To this end, for the (p,q)th position input LR patch $\mathbf{y}^L(p,q)$, two codebooks namely LR and HR dictionaries, $D^L(p,q) = (\mathbf{y}_1^L(p,q), \cdots, \mathbf{y}_K^L(p,q))$ and $D^H(p,q) = (\mathbf{x}_1^H(p,q), \cdots, \mathbf{x}_K^H(p,q))$ can be constructed by arranging the corresponding LR and HR training position patches as columns. The LR dictionary $D^L(p,q)$ is used to represent $\mathbf{y}^L(p,q)$, while the HR dictionary $\mathbf{x}_K^H(p,q))$ is used for reconstruct of the target HR patch based on the representation coefficients of $\mathbf{y}^L(p,q)$ over $D^L(p,q)$.

A. Face SR via K-RCR

Based on the observation that the LR and HR patch manifold share the same topology structure, the HR target patch can be estimated according to the explicit mapping learned from the observed LR space. Basically, the input LR patch is firstly represented by the LR dictionary, then the representation coefficients are applied on the HR dictionary to reconstruct the HR target patch. Linear combination is always considered,

$$\mathbf{y}^L(p,q) = \sum_{k=1}^{K} \alpha_k(p,q)\mathbf{y}_k^L(p,q) \tag{1}$$

where $\alpha_k(p,q)$ is the weight associated to $\mathbf{y}_k^L(p,q)$ in representing $\mathbf{y}^L(p,q)$.

Take into consideration of noise and reconstruction error, the representation coefficients can be achieved by solving the following minimization problem,

$$\min_{\boldsymbol{\alpha}(p,q)} \left\|\mathbf{y}^L(p,q) - D^L(p,q)\boldsymbol{\alpha}(p,q)\right\|_2^2. \tag{2}$$

where $\boldsymbol{\alpha}(p,q)$ is the representation coefficient vector.

The solution of Eq. (2) is usually unstable, especially for the case that the data dimension is larger than the dictionary size.

To stabilize the linear system, sparsity constraint has been added into the objective function.

$$\min_{\boldsymbol{\alpha}(p,q)} \left\|\mathbf{y}^L(p,q) - D^L(p,q)\boldsymbol{\alpha}(p,q)\right\|_2^2 + \lambda\left\|\boldsymbol{\alpha}(p,q)\right\|_1. \tag{3}$$

in which $\|\cdot\|_1$ is the l_1-norm computing the summation of absolute values and λ is the model parameter controlling the sparsity.

Recent years, Zhang *et al.* [24] revealed that it is the collaborative representation but not the l_1-norm induced sparsity representation that makes the model powerful for data representation. Motivated by this, the collaborative representation model is also introduced for face image super-resolution.

$$\min_{\boldsymbol{\alpha}(p,q)} \left\|\mathbf{y}^L(p,q) - D^L(p,q)\boldsymbol{\alpha}(p,q)\right\|_2^2 + \lambda\left\|\boldsymbol{\alpha}(p,q)\right\|_2^2. \tag{4}$$

Due to the differentiable l_2-norm on both data fidelity term and coefficient, Eq. (4) admits an analysis solution which can be calculated much faster than the sparsity.

Since the collaborative representation uses all the training samples in the dictionary to collaboratively represent the test patch, one limitation is that it is sensitive to noise.

Considering that each feature (pixel) in the patch may be affected differently by noise, so that we should allow different pixels offer different contribution in representation. Recall that, in the data fidelity term in Eq. (4), each pixel is treated equally, which is unsensible, because for a patch corrupted by noise sampled from Gaussian distribution, the interference value for each pixel cannot be the same but should be different. This leads to the following reweighted collaborative representation.

$$\min_{\boldsymbol{\alpha}(p,q)} \left\|\Gamma\big(\mathbf{y}^L(p,q) - D^L(p,q)\boldsymbol{\alpha}(p,q)\big)\right\|_2^2 + \lambda\left\|\boldsymbol{\alpha}(p,q)\right\|_2^2. \tag{5}$$

where Γ is a diagonal weight matrix.

The motivation of incorporating a diagonal matrix into the objective function can be explained as follows: since the contribution of each pixel offered in the objective function should be determined by its noise degree, we intend to use a weight $\gamma_{i,i}$ (the i-th diagonal element of Γ) to reflect the noise level of i-th pixel to a certain extent. In other words, the i-th diagonal element $\gamma_{i,i}$ should choose the value from $[0, 1]$ denoting the cleanliness of i-th pixel. That is, the weight $\gamma_{i,i}$ is assigned to be a small value (0 or approach to 0) if the corresponding pixel y_i^L is contaminated by heavy noise, while $\gamma_{i,i}$ is assigned to be a large value (1 or close to 1) if the corresponding pixel y_i^L is relatively less affected by noise. By using such reweighting strategy, one can see that, the contributions of the pixels with high level noise can be suppressed while the contributions of the pixels corrupted by low level noise will be highlighted. This encourages the proposed model to exploit more useful information from the informative pixels for representation.

The work in [25] argued that the representation coefficients tread to be locally. That is, the input data is more likely to be encoded by the training samples which are similar to the test one, while the training samples that dissimilar to the test one may play unimportant roles in representation. Therefore, it is sensible to just choose the K-nearest neighbors of the test patch for data representation, leading to the final proposed K-RCR based face image super-resolution model,

$$\min_{\boldsymbol{\alpha}(p,q)} \left\|\Gamma(\mathbf{y}^L(p,q) - \sum_{k\in N(\mathbf{y}^L(p,q))} \boldsymbol{\alpha}_k(p,q)\mathbf{y}_k^L(p,q))\right\|_2^2 + \lambda\left\|\boldsymbol{\alpha}(p,g)\right\|_2^2 \quad (6)$$

where $N(\mathbf{y}^L(p,q))$ denotes the index set of the K-nearest neighbors (K-NNs) of $\mathbf{y}^L(p,q)$ in the LR dictionary.

Denote by $D_K^L(p,g)$ as the sub-dictionary constituted by the K-NNs of $\mathbf{y}_k^L(p,q)$ in the LR space. Therefore, Eq. (7) can be reformulated as the following form,

$$\min_{\boldsymbol{\alpha}(p,q)} \left\|\Gamma(\mathbf{y}^L(p,q) - D_K^L(p,g)\boldsymbol{\alpha}(p,q)\mathbf{y}_k^L(p,q)\right\|_2^2 + \lambda\left\|\boldsymbol{\alpha}(p,g))\right\|_2^2 \quad (7)$$

It is worth noting that we introduce the K-NN selection strategy to preserve the manifold structure and use reweighting tactics to differ the importance of each pixel. If the weight matrix is set to be an identity matrix, it means that all the pixels are treated equally, and all the neighbors are selected, then the proposed K-RCR reduces to conventional collaborating representation model.

The solution of Eq. (7) can be calculated easily, since the objective function is convex and differentiable. Basically, calculating the derivatives with respect to $\boldsymbol{\alpha}(p,q)$ and setting it to zero, the optimal solution can be obtained as,

$$\hat{\boldsymbol{\alpha}}(p,q) = \left(\left(D_K^L(p,q)\right)^T\Gamma^2 D_K^L(p,q) + \lambda I\right)^{-1}\left(D_K^L(p,q)\right)^T\mathbf{y}^L(p,q)$$

Once the optimal coefficient vector $\hat{\boldsymbol{\alpha}}(p,q)$ is obtained, the corresponding (p,q)th position HR patch is constructed as,

$$\mathbf{y}^H(p,q) = D_K^H(p,q)\hat{\boldsymbol{\alpha}}(p,q) \quad (8)$$

where D_K^H is the corresponding sub-dictionary of D^H indexed by the K-NNs.

Fig. 1: Some face images in FEI face dataset. Each column represents two face images for one person with relaxed or serious expressions.

The final HR face image can be generated by aggregating all the obtained HR patches with the overlapping pixel values be averaged.

III. Experimental Results

In this section, we describe in detail the experiments performed to evaluate the effectiveness and robustness of the proposed K-CRR based method for face image super-resolution. The proposed method is compared with several state-of-the-art methods and the objective qualities of the hallucination results is evaluated by two quantitative measures, namely Peak Signal Noise Ratio (PSNR) and Structural SIMilarity (SSIM) [26]. Generally, the higher the SSIM value, the better is the face super-resolution quality. The maximum value of SSIM is 1, indicating a perfect estimation result. Compared to the measure of PSNR, SSIM score can better reflect the structure similarity between the reconstructed image and the reference image.

The compared methods include three popular face hallucination methods, namely the Least Square Regression (LSR) [12] method, the Locality-constrained Representation (LcR) [17] method, and the Tikhonov Regularized Neighbor Representation (TRNR) [25] based method. The dataset used in our experiment is FEI face database, which will be described in detail in the next part.

A. Datasets Description

1) The FEI dataset contains 400 frontal face images for 200 persons with 100 men and 100 women. As a result, there are two images for each person, in which one is with neutral expression while the other is with similing expression. To keep the consistency, all the face images are aligned and cropped into size of 120×100 pixels based on the eye positions. We randomly partition the face images into two categories: training and testing, where 360 images associated with 180 persons are used as training data while the remaining 40 images associated with 20 persons are utilized as test images. Note that the test images and the training images are absolutely non-overlapped. Some examples of the face images in FEI dataset are shown in Fig. 1.

TABLE I: Averaged PSNR scores for the 40 test face images in FEI database corrupted by Gaussian noise with different standard deviations, respectively.

Dataset		LSR	LcR	TRNR	K-RCR
	$\sigma = 8$	25.38	26.15	26.53	**28.04**
	$\sigma = 10$	23.85	24.67	24.91	**27.16**
FEI	$\sigma = 12$	22.50	23.46	23.49	**26.29**
	$\sigma = 15$	20.84	21.82	21.66	**24.92**
	$\sigma = 18$	19.50	20.53	20.17	**24.51**

TABLE II: Averaged SSIM scores for the 40 test face images in FEI database corrupted by Gaussian noise with different standard deviations, respectively.

Dataset		LSR	LcR	TRNR	K-RCR
	$\sigma = 8$	0.6193	0.6671	0.7262	**0.8053**
	$\sigma = 10$	0.5416	0.5985	0.6536	**0.7745**
FEI	$\sigma = 12$	0.4737	0.5341	0.5837	**0.7461**
	$\sigma = 15$	0.3870	0.4497	0.4882	**0.6996**
	$\sigma = 18$	0.3275	0.3854	0.3705	**0.6780**

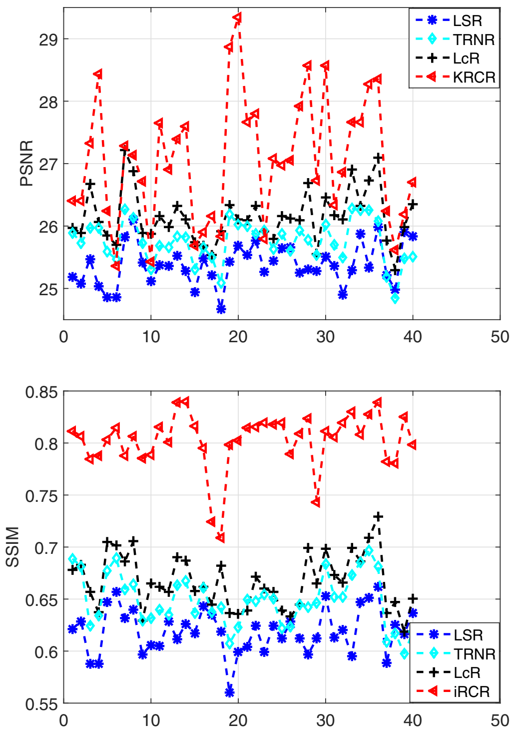

Fig. 2: The PSNR and SSIM values for the noisy images with Gaussian noise ($\sigma = 8$) in FEI dataset. The numbers in horizontal axis represent the index of test images.

B. Implementation and Parameter Settings

All parameter settings for the compared methods reported in this paper are set with the optimal parameters suggested by the original papers or carefully tuned by ourselves to achieve their best performance. Particularly, for position patch based methods, the patch size and overlap between neighbor patches are crucial to obtain reliable results. On one hand, too small patch size will result in too weak co-occurrence geometrical structure information between LR and HR space. On the other hand, too large patch size will lead to smooth outputs and lose some visual details and also will cause high computational complexity. According to [17], considering both the performance and running time, the patch size and overlap are set as 12×12 pixels and 4 pixels for the HR patches respectively, and there are 3×3 pixels for the LR patches with one pixel be overlapped. The locality regularization parameter τ is set as 0.04 for the LcR method, while it is set to be 0.01 in TRNR method to obtain their corresponding optimal performance. The numbers of K-NNs are set as 150 for both the TRNR and the proposed K-RCR methods. For the proposed K-RCR method, we empirically set $\lambda = 0.12$.

C. Results on FEI dataset

To test the robustness of all the methods. The standard test face image are first downsampled by a factor of 4, blurred by a 4×4 average blur kernel, and added by Gaussian noise with different noise variance to generate the LR face images. Then the noisy LR face images are processed by the compared methods.

Table I and Table II, respectively, tabulate the averaged PSNR and SSIM scores of all the forty test face images polluted by Gaussian noise with different standard deviations, in which the largest values are highlighted in bold. What is more, the PSNR and SSIM values of each test image in FEI dataset corrupted by Gaussian noise with standard deviation $\sigma = 8$ are plotted in Fig. 2. From Table I, Table II and Fig. 2, one can see that, the LSR with no regularization term on coefficients gained worse face hallucination results than the LcR and TRNR methods in which the locality prior is used to constrain the encoding coefficients. In contrast, our proposed K-RCR obtains the highest PSNR and SSIM values for all the cases. It indicates that the proposed K-RCR based method achieves promising performance in simultaneously removing Gaussian noise and super-resolving face images, since it considers both noise patterns and neighborhood information in the objective function.

Besides of the PSNR and SSIM values, some super-resolution results are shown in Fig. 3 to give some visual compressions. Fig. 3 exhibits the results of 6 face images contaminated by Gaussian noise with different standard deviations from different super-resolution methods. In Fig. 3, from left to right, they are the noisy face images, the results of LSR, LcR, TRNR, K-RCR, and the ground truths, respectively, from top to bottom, they are the super-resolution results of face image corrupted by Gaussian noise with standard deviation $\sigma = 8, 10, 12, 15, 18$. Obviously, the performance of all the comparison methods are declined, when noise level becomes high. This is because many informative information will be

(a) (b) (c) (d) (e) (f)

Fig. 3: Comparison of super-resolution performance of different methods for LR images corrupted by Gaussian noise with different standard deviations in FEI dataset. From left to right, each column denotes the noisy LR face images, the results of LSR, the results of LcR, the results of TRNR, the results of K-RCR, and the ground truths. From top to bottom, each row represents the LR face image corrupted by Gaussian noise with standard deviation $\sigma = 8$, 10, 12, 15, 18, and the corresponding hallucinated faces generated by different methods.

lost and more noise be amplified during the super-resolution processing in the high noise level environment. However, the proposed K-RCR based method still obtains the best visual impressions.

IV. Conclusion

In this paper, we presented an K-RCR based face image super-resolution method to simultaneously enhance the resolution of face images and suppress the Gaussian noise. By incorporating the K-NN selection strategy into the objective function, K-RCR can select the most relevant patch samples (nearest neighbors of the test sample in the training dataset) to reconstruct the HR version of the observed LR image patch, thus generating discriminant HR face image with detailed features. In addition, to equip the proposed K-RCR based method more robust to noise, a diagonal weight matrix is introduced into the loss function, which subtly suppress the influences of noisy pixels while highlight the contributions of informative pixels. Experiments on the simulated noisy faces in public FEI dataset demonstrate that the proposed K-RCR based approach achieved better performance than several comparison state-of-the-art face image super-resolution methods.

Although just the Gaussian noise is taken into account to assess the robustness of the proposed method in the experiments, the noise is not limited to Gaussian noise but can be any other noise, such as gamma noise or mixture noise, if the weight matrix Γ is properly set.

ACKNOWLEDGMENT

This work was supported in part by the National Natural Science Foundation of China under grant 61702169, the National Natural Science Fund of China for International Cooperation and Exchanges under Grant 61520106001, and the Fundamental Research Funds for the Central Universities under Grant 531107050878.

REFERENCES

[1] L. Liu, C. L. P. Chen, Y. Zhou, and X. You, "A new weighted mean filter with a two-phase detector for removing impulse noise," *Information Sciences*, vol. 315, no. 0, pp. 1–16, 2015.

[2] L. Christian, T. Lucas, H. Ferenc, C. Jose, C. Andrew, A. Alejandro, A. Andrew, T. Alykhan, T. Johannes, and W. Zehan, "Photo-realistic single image super-resolution using a generative adversarial network," in *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 105–114.

[3] S. Baker and T. Kanade, "Hallucinating faces," in *In Proceedings of Fourth IEEE International Conference on Automatic Face and Gesture Recognition, 2000.*, pp. 83–88.

[4] C. Liu, H.-Y. Shum, and C.-S. Zhang, "A two-step approach to hallucinating faces: global parametric model and local nonparametric model," in *Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2001. CVPR 2001.*, vol. 1, pp. I–192–I–198.

[5] X. Zhang, S. Peng, and J. Jiang, "An adaptive learning method for face hallucination using locality preserving projections," in *in Processing of 8th IEEE International Conference on Automatic Face & Gesture Recognition*, pp. 1–8.

[6] J. S. Park and S. W. Lee, "An example-based face hallucination method for single-frame, low-resolution facial images," *IEEE Transactions on Image Processing*, vol. 17, no. 10, pp. 1806–1816, 2008.

[7] H. Huang, H. He, X. Fan, and J. Zhang, "Super-resolution of human face image using canonical correlation analysis," *Pattern Recognition*, vol. 43, no. 7, pp. 2532–2543, 2010.

[8] H. Chang, D.-Y. Yeung, and Y. Xiong, "Super-resolution through neighbor embedding," in *Proceedings of the 2004 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2004. CVPR 2004.*, vol. 1, pp. 275–282.

[9] S. T. Roweis and L. K. Saul, "Nonlinear dimensionality reduction by locally linear embedding," *Science*, vol. 290, no. 5500, pp. 2323–2326, 2000.

[10] W. Zhang and W. K. Cham, "Hallucinating face in the dct domain," *IEEE Transactions on Image Processing*, vol. 20, no. 10, pp. 2769–2779, 2011.

[11] J. Jiang, R. Hu, Z. Wang, Z. Han, and J. Ma, "Facial image hallucination through coupled-layer neighbor embedding," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 26, no. 9, pp. 1674–1684, 2016.

[12] X. Ma, J. Zhang, and C. Qi, "Hallucinating face by position-patch," *Pattern Recognition*, vol. 43, no. 6, pp. 2224–2236, 2010.

[13] A. M. Bruckstein, D. L. Donoho, and M. Elad, "From sparse solutions of systems of equations to sparse modeling of signals and images," *SIAM Review*, vol. 51, no. 1, pp. 34–81, 2009.

[14] Z. Wang, R. Hu, S. Wang, and J. Jiang, "Face hallucination via weighted adaptive sparse regularization," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 24, no. 5, pp. 802–813, 2014.

[15] J. Jiang, J. Ma, C. Chen, X. Jiang, and Z. Wang, "Noise robust face image super-resolution through smooth sparse representation," *IEEE Transactions on Cybernetics*, vol. 47, no. 11, pp. 3991–4002, 2017.

[16] Y. Zhang, J. Zhang, and Q. Dai, "CCR: Clustering and collaborative representation for fast single image super-resolution," *IEEE Transactions on Multimedia*, vol. 18, no. 3, pp. 405–417, 2016.

[17] J. Jiang, R. Hu, Z. Wang, and Z. Han, "Noise robust face hallucination via locality-constrained representation," *IEEE Transactions on Multimedia*, vol. 16, no. 5, pp. 1268–1281, 2014.

[18] ——, "Face super-resolution via multilayer locality-constrained iterative neighbor embedding and intermediate dictionary learning," *IEEE Transactions on Image Processing*, vol. 23, no. 10, pp. 4220–4231, 2014.

[19] L. Liu, S. Li, and C. L. P. Chen, "Quaternion locality-constrained coding for color face hallucination," *IEEE Transactions on Cybernetics*, vol. PP, no. 99, pp. 1–12, 2017.

[20] L. Yue, H. Shen, Q. Yuan, and L. Zhang, "A locally adaptive l1-l2 norm for multi-frame super-resolution of images with mixed noise and outliers," *Signal Processing*, vol. 105, no. 0, pp. 156–174, 2014.

[21] L. Liu, C. L. P. Chen, S. Li, Y. Y. Tang, and L. Chen, "Robust face hallucination via locality-constrained bi-layer representation," *IEEE Transactions on Cybernetics*, vol. PP, no. 99, pp. 1–13, 2017.

[22] C. L. P. Chen, L. Liu, L. Chen, Y. Y. Tang, and Y. Zhou, "Weighted couple sparse representation with classified regularization for impulse noise removal," *IEEE Transactions on Image Processing*, vol. 24, no. 11, pp. 4014–4026, 2015.

[23] L. Liu, L. Chen, C. L. P. Chen, Y. Y. Tang, and C. M. Pun, "Weighted joint sparse representation for removing mixed noise in image," *IEEE Transactions on Cybernetics*, vol. 47, no. 3, pp. 600–611, 2017.

[24] L. Zhang, M. Yang, and X. Feng, "Sparse representation or collaborative representation: Which helps face recognition?" in *2011 IEEE International Conference on Computer Vision (ICCV)*. IEEE, pp. 471–478.

[25] J. Jiang, C. Chen, K. Huang, Z. Cai, and R. Hu, "Noise robust position-patch based face super-resolution via tikhonov regularized neighbor representation," *Information Sciences*, vol. 367C368, pp. 354–372, 2016.

[26] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: from error visibility to structural similarity," *IEEE Transactions on Image Processing*, vol. 13, no. 4, pp. 600–612, 2004.