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Multi-view face hallucination using SVD and a mapping model

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Multi-view face hallucination (MFH) presents a challenge issue in face recognition domain. In this paper, an efficient method based on singular value decomposition (SVD) and a mapping model is proposed for multi-view face hallucination. Based on an approximately same linear mapping relationship across different views, two corresponding matrices obtained from the SVD of the low resolution (LR) image for the high-resolution (HR) multi-view face images can be constructed via the mapping model using global reconstruction. Experiments show that our proposed multi-view face-hallucination scheme is effective and produces promising super-resolved results.

1. Introduction

Face hallucination is a technique to construct a high-resolution (HR) image from a low-resolution (LR) face image [30,33,40], and has become an active issue in computer vision and pattern recognition [9,10,21,24 46,48]. Face-hallucinating technique is especially important for video surveillance, in which LR images are usually captured at a far distance.

The pioneering study on face hallucination was proposed by Baker et al. [4], and has become an important and hot topic in image processing right now. Yang et al. [43] proposed a sparse-coding approach to reconstruct the HR patch, which is produced via using the same combination coefficients as corresponding neighboring HR patches. Wang and Tang [41] designed a holistic face-hallucination scheme which utilizes eigentransformation to represent a LR input face as a linear combination of LR training samples. In [35], Park et al. [35] proposed an example-based super-resolution algorithm based on the eigentransformation-based framework [41]. Liu et al. [26] proposed a hybrid method based on global and local constraints for the task of face hallucination. Li and Chang [25] proposed a novel super-resolution algorithm by aligning coupled manifolds for face hallucination. In [32], a framework using patches at the same position and the optimal weights for the training position-patches are combined for hallucinating HR face. Based on the assumption that two similar face images should have similar local-pixel structures, a novel face-hallucination method was developed in [13]. Akyol and Gokmen [1] utilized both the shape and texture components to hallucinate HR image. Recently, based on similarity constraints, a new

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face-hallucination approach was proposed for HR face image reconstruction [27]. Jiang et al. designed a novel face super-resolution scheme based on multilayer locality-constrained iterative neighbor embedding algorithm, aiming at preserving the manifold-consistency between the reconstructed HR and the original HR image [19]. In [20], a Locality-induced Support Regression (LiSR) method was proposed for face super-resolution. Tian and Ma introduced a technical review for SR image and video reconstruction approached in [39]. In [7], a deep learning method was proposed for single image super-resolution (SR) via learning an end-to-end mapping between LR-HR images. Based on a residual convolutional neural network, Oktay et al. [34] proposed an image super-resolution (SR) for HR 3D volumes reconstruction. Recently, Yue et al. [45] provided a comprehensive view of SR containing reconstruction algorithms, parameter selection and optimization methods. Recently, generative adversarial networks (GAN)-based methods can be performed to generate photo-realistic natural images and faces [11,44]. During the generation of facial images, the main idea of GAN-based methods is to train two adversarial networks: a generator (G) aims to generate facial images, and a discriminator (D) seeks to distinguish generated (fake) images from real facial images. However, there still exists the model collapse problem when the generator (G) learns to map different inputs to the same point and then GAN-based methods may fail to produce satisfactory facial images. Yu and Porikli [44] designed a discriminative generative network, called ultra-resolution by discriminative generative networks (UR-DGN), to generate HR frontal facial images. Nevertheless, the defect is that generative facial images are sensitive to rotations [6], which is not suitable for the task of multi-view face hallucination (MFH).

Based on boundary equilibrium generative adversarial networks, a single face image super-resolution method propose is designed [12]. In [5], Chen et al. proposed a deep end-to-end trainable Face Super-Resolution Network (FSRNet) for reconstructing very LR face images. Through feature learning into an adversarial network, an end-to-end model is designed to fulfill cross-spectral face hallucination [38]. Zhuang et al. [49] proposed a two-stage face hallucination scheme to reconstruct HR face image from the LR face via integrating locality preserving projection (LPP) and radial basis function (RBF) regression simultaneously. In [2], a Generic Shape-Illumination Manifold (gSIM) framework was designed to hallucinate faces across different poses and scales. Later, an efficient framework for matching linear subspaces in images of different scales was designed [3]. More recently, Farrugia and Guillemot proposed a coupled sparse support (CSS) face-hallucination framework via estimating the local geometrical structure on the high-resolution manifold [8]. Based on the relationship between target patch and training patches in the high-resolution feature space, two regularization models are designed to produce HR facial images [37]. In [22], Jiang et al. proposed a novel context-patch method by thresholding locality-constrained representation with reproducing learning to hallucinate HR faces. Based on locality-constrained linear coding, an effective bi-layer representation face-hallucination method is proposed to super-resolve the HR facial images based on training samples [29].

However, most existing algorithms are only limited to frontal faces. Multi-view face hallucination (MFH) is a more difficult issue and only several schemes have been proposed. Li et al. [28] presented a framework based on Gabor wavelet features to deal with the pose variation issue for face hallucination. Jia et al. [16] proposed a Bayesian framework based on tensor for face hallucination; however, probability model and tensor based MFH methods are generally complicated with high computational complexity. In [31], Ma et al. proposed an efficient MFH in two stages: multi-view LR faces are firstly generated by using face transformation, then resolution enhancement step to combine high-frequency details for the multi-view LR faces. Hui and Lam [14] proposed an effective two-step patch-based MFH method. In [47], Zeng and Huang proposed a super-resolution method by learning a crop of nonlinear mappings in the coherent feature space between non-frontal low resolution (NFL) images of various poses and their related frontal high resolution (FH) images. Recently, a multi-view face hallucination based on sparse representation was proposed [15]. More recently, Jin and Bouganis [23] developed a patch-wise prior based method to hallucinate LR facial images in PCA subspace for robust blurring kernel estimation. For multi-view face super-resolution, Deshmukh and Rani [6] proposed a Fractional-Grey Wolf Optimizer-based (FGWO) framework via kernel weighted regression.

For our previous work [17], we only focus on frontal-view face hallucination. In this letter, based on an assumption that there exists an approximately same linear mapping relationship across different views, HR multi-view face images can then be constructed. We proposed a method to combine SVD with a mapping model to fulfill the MFH task, which is effective and produces promising results.

The rest of the paper is organized as follows. In Section 2, we will present Singular Value Decomposition and the mapping model. Section 3 introduces a novel framework of Multi-view face hallucination (MFH) and experimental results are presented in Section 4. The paper closes with a conclusion and discussion in Section 5.

2. SVD and mapping model

Suppose that a HR face is denoted as I_h and the corresponding down-sampled LR face is denoted as I_l. The HR and LR faces can be decomposed by SVD as follows:

$$I_h = U_h W_h V_h^T \text{ and } I_l = U_l W_l V_l^T \tag{1}$$

These two matrices U_l and V_l for I_l can be up-sampled to develop two new matrices U_l' and V_l' that have the same size as U_h and V_h, respectively. Define two mapping matrices P_u and P_v, as follows:

$$U_h = U_l' P_u, \text{ and } V_h = V_l' P_v. \tag{2}$$

Then the matrices P_u and P_v can be approximately obtained via pseudo-inverse technique as below:

$$\tilde{P}_u = \left(U_l'^T U'_l + \lambda E\right)^{-1} U_l'^T U_h, \text{ and } \tilde{P}_v = \left(V_l'^T V_l' + \lambda E\right)^{-1} V_l'^T V_h, \tag{3}$$

where λ is a small positive number and E is a unit matrix. Then a reconstruction of U_h and V_h, denoted as $\hat{U}_h$ and $\hat{V}_h$, respectively, can be calculated:

$$\hat{U}_h = U_l' \tilde{P}_u, \text{ and } \hat{V}_h = V_l' \tilde{P}_v. \tag{4}$$

For the face-hallucination issue, a HR image can be estimated from a LR face using the matrices $\hat{U}_h$ and $\hat{V}_h$, which can be computed based on a pair of LR-HR training faces.

Assuming that an LR image I_l will be hallucinated to generate a HR image with a magnification factor of α. By using the LR input face, an amount of M LR face images resembling I_l, also with the corresponding HR faces as references, are retrieved from a database with pairs of LR-HR faces. These M pairs of LR-HR training faces, denoted as I_l^i and I_h^i ($i = 1, 2, \ldots, M$), should have a comparable structural appearance to the LR input image after alignment. Every single of the similar HR faces can be super-resolved using the mapping matrices of its corresponding LR face images, i.e.

$$\hat{U}_h^i = U_l'^i \tilde{P}_u^i, \text{ and } \hat{V}_h^i = V_l'^i \tilde{P}_v^i, \tag{5}$$

where $1 \leq i \leq M$.

Then, for face hallucination, the mapping matrices $\tilde{P}_u$ and $\tilde{P}_v$ can be calculated using the corresponding mapping matrices $\tilde{P}_u^i$ and $\tilde{P}_v^i$, computed from the M pairs of LR and HR faces. A linear combination of mapping matrices is expressed as below:

$$\tilde{P}_u = \sum_{i=1}^{M} \beta_i \tilde{P}_u^i, \text{ and } \tilde{P}_v = \sum_{i=1}^{M} \gamma_i \tilde{P}_v^i, \tag{6}$$

where β_i and γ_i are the corresponding coefficients for $\tilde{P}_u$ and $\tilde{P}_v$, respectively.

By using SVD, matrices U_l and V_l of the LR input face I_l can also be up-sampled via interpolation to produce two new matrices U_l' and V_l', with the same size as U_h and V_h for the reconstructed HR face I_h, respectively. Now, the approximated matrices $\hat{U}_h$ and $\hat{V}_h$ can be calculated as follows:

$$\hat{U}_h = U_l' \tilde{P}_u, \text{ and } \hat{V}_h = V_l' \tilde{P}_v. \tag{7}$$

Since the leading singular values in the diagonal matrix $\hat{\mathrm{W}}_{\mathrm{h}}$ can be obtained from a linear relationship $s_h \cong \alpha s_l$ [17,18], the HR face $\hat{I}_h$ can be generated using the computed matrices $\hat{U}_h$ and $\hat{V}_h$, and its diagonal matrix $\hat{W}_h$, as below:

$$\hat{I}_h = \hat{U}_h \hat{W}_h \hat{V}_h^T. \tag{8}$$

The following $E(i)$ can be utilized to measure the hallucination error, and the optimal hallucinating weights β_i and γ_i can be solved by minimizing the following convex function [17]:

$$\varsigma = \underset{\beta_i, \quad \gamma_i}{argmin} \{E(i)\} = \underset{\beta_i, \quad \gamma_i}{argmin} \left\{ \sum_{i=1}^{M} \left\| I_h^i - \hat{I}_h \right\|^2 \right\}, \quad \text{s.t.} \quad \hat{I}_h \downarrow \alpha = I_l. \tag{9}$$

3. Multi-view face hallucination (MFH) design

Assuming that an input LR face $I_{z,\,l}$ at view *z; z* denotes multi-view face images. MFH aims to hallucinate the desired HR faces from I_z. These M pairs of HR and LR training faces are represented as $I_{z,l}^i$ and $I_{z,h}^i$ ($i = 1, \ldots, M$), respectively. The linear combination of the corresponding mapping matrices calculated from the M pairs of HR and LR faces at view z, can be obtained as same as in (6):

$$\tilde{P}_{z,u} = \sum_{i=1}^{M} \beta_{z,i} \tilde{P}_{z,u}^i, \text{ and } \tilde{P}_{z,v} = \sum_{i=1}^{M} \gamma_{z,i} \tilde{P}_{z,v}^i. \tag{10}$$

From (10), we can see that HR face$\mathrm{I}_{\mathrm{z,\,h}}$ at view z can be constructed if the weights $\beta_{z,\,i}$ and $\gamma_{z,\,i}$ are procured. In practice, they are difficult to be procured precisely [31,47]. Inspired by [31], we assume that there exists approximately same linear mapping relationship across different multiple views. Therefore, the weights obtained at the face view z' (e.g. frontal view) in (6) are used to generate two new matrices, and rewrite (10) as follows:

$$\tilde{P}_{z,u} = \sum_{i=1}^{M} \beta_i \tilde{P}_{z,u}^i, \text{ and } \tilde{P}_{z,v} = \sum_{i=1}^{M} \gamma_i \tilde{P}_{z,v}^i. \tag{11}$$

With the aid of linear combination of training faces at view z in Eq. (11), we can then hallucinate LR image from one view to multi-view points. Fig. 1 shows the proposed MFH framework. For clarity, the proposed scheme for multi-view face hallucination scheme is summarized as Algorithm 1.

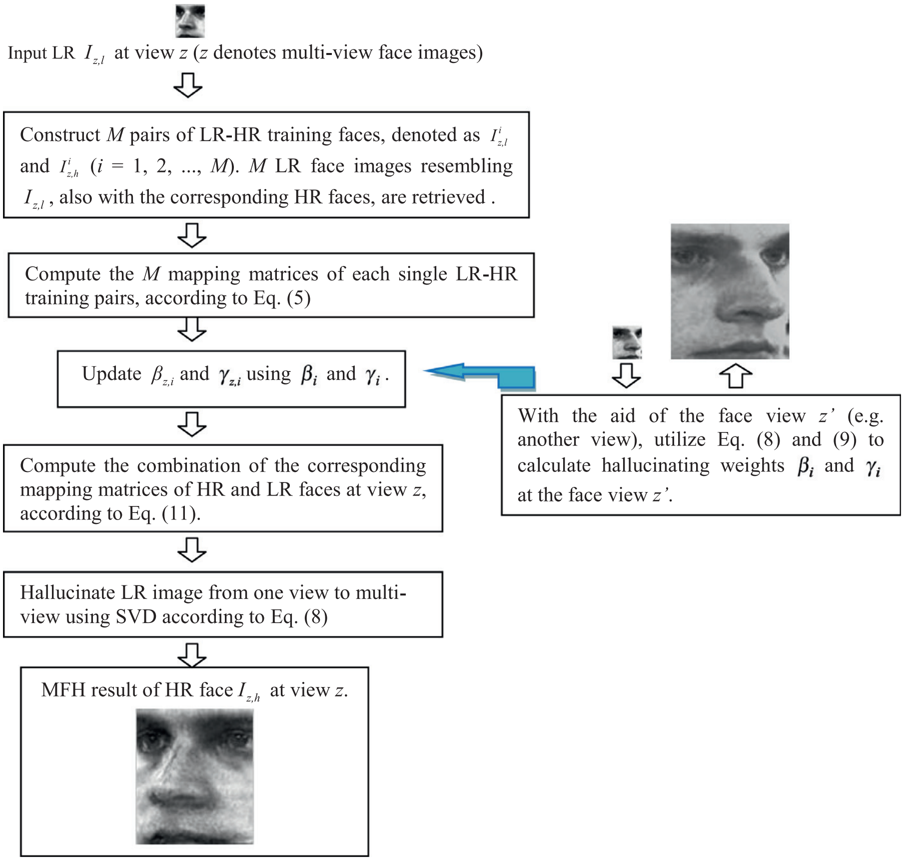

Fig. 1. The proposed MFH framework based on SVD and a Mapping Model.

4. Experimental results

All facial images were aligned based upon the position of the two eyes, and the LR images were down-sampled and the reconstruction was run from these downgraded images. Each of the testing facial images was assessed using the "leave-one-out" method.

4.1. Experiment 1

To evaluate the validity of our proposed method, five poses at −22.5°, 22.5°, 0°(frontal view), −45°, and 45° are utilized to verify the performance of the proposed algorithm. The CMU database contains 68 × 5 images, each of the face images is aligned using the location of the two eyes, and every original HR face is cropped into a size with 108 × 124 pixels. The parameter λ in (3) is experimentally set at 0.001. And the reference number of face examples is set with 3. In the Multi-view face hallucination (MFH) experiments, all the algorithms are tested by hallucinating the HR faces with a magnification factor of $\alpha = 4$. Two widely used image quality assessments, PSNR (peak signal-to-noise ratio) and SSIM (structural similarity) [42], are utilized to assess the performance of individual MFH approach.

Fig. 2 shows some samples of the multi-view face hallucination results produced using different MFH approaches. It can be seen from Fig. 2(a) that Jia's method [16] generates blurry results as compared to the ground truth faces in Fig. 2(d). The results of Ma's algorithm [31] in Fig. 2(b) generate a slight better visual quality than Jia's method. Fig. 2(c) gives the hallucinated faces based on Jin's method [23], while Fig. 2(d) shows the results of multi-view face super resolution according to Deshmukh's algorithm [6]. Figs. 2(e) are the results produced by using our proposed method, which can effectively hallucinate the fine individual facial details, and can generate sharp edges and corners (e.g. eye regions).

Table 1 provides the PSNR and SSIM of three different multi-view face hallucination methods. As shown in Table 1, our algorithm outperforms other existing state-of-the-art multi-view face hallucination approaches. In addition, as a commonly known assessment quantity, PSNR is not always well consistent with human visual perception. Therefore we provide a curve of SSIM of each CMU individuals in detail. Fig. 3 illustrates the curve of SSIM across all CMU faces for different MFH algorithms with a magnification factor of 4. According to the curve of SSIM, it can be seen that the proposed algorithm can achieve a better performance statistically.

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

Fig. 2. MFH results hallucinated using different methods with a magnification factor of 4 (α=4): (a) Jia's method [16], (b) Ma's method [31], (c) Jin's method [23], (d) Deshmukh's method [6], (e) our proposed method, (c) Ground truth image.

Table 1
The average PSNR and SSIM of different MFH algorithms.

Algorithms		Jia's method	Ma's method	Jin's method	Deshmukh's method	Our method
Left 45° to Frontal	PSNR	21.5601	21.6002	21.6213	21.5918	21.6367
	SSIM	0.5525	0.5543	0.5592	0.5564	0.5614
Left 22.5° to Frontal	PSNR	21.9729	22.2119	22.3419	22.2405	22.4702
	SSIM	0.5577	0.5585	0.5680	0.5576	0.5725
Right 22.5° to Frontal	PSNR	21.9820	21.6705	22.3893	22.0166	22.5822
	SSIM	0.5606	0.5633	0.5687	0.5632	0.5775
Right 45° to Frontal	PSNR	21.4006	21.6292	22.3571	22.0047	22.6726
	SSIM	0.5449	0.5557	0.5635	0.5603	0.5708

Algorithm 1 Multi-view face hallucination Using SVD and a mapping mode.

1. Input: an LR face $I_{z,\,l}$ at view z (z denotes multi-view face images).
2. Construct M pairs of LR-HR training faces, denoted as $I^{i}_{z,l}$ and $I^{i}_{z,h}$ ($i = 1, 2, \ldots, M$). M LR face images resembling $I_{z,\,l}$, also with the corresponding HR faces, are retrieved.
3. Compute the M mapping matrices of each single LR-HR training pairs, according to Eq. (5).
4. With the aid of the face view z' (e.g. frontal view), calculate the linear combination of the mapping matrices according to Eq. (6) and compute the approximated matrices $\hat{U}_h$ and $\hat{V}_h$ according to Eq. (7), respectively.
5. Use Eqs. (8) and (9) to calculate hallucinating weights β_i and γ_i at the face view z'.
6. Update $\beta_{z,\,i}$ and $\gamma_{z,\,i}$ using β_i and γ_i; compute the combination of the corresponding mapping matrices of HR and LR faces at view z, according to Eq. (11).
7. Hallucinate LR image from one view to multi-view using SVD according to Eq. (8)
8. Output: HR face $I_{z,\,h}$ at view z.

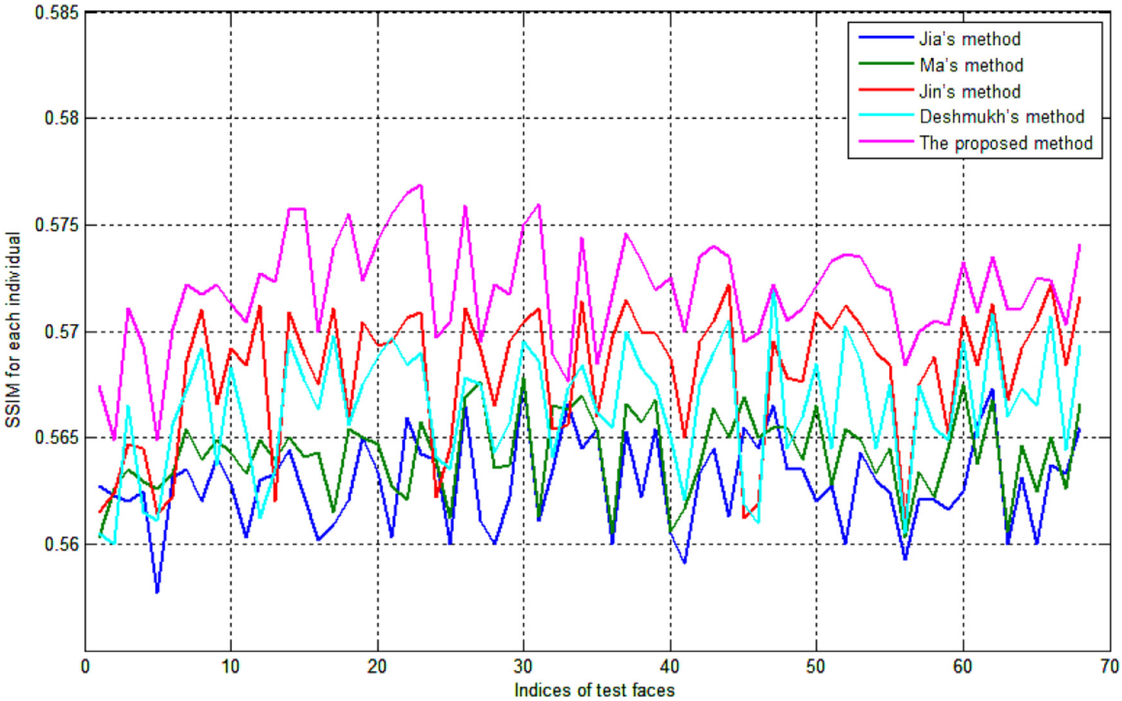

Fig. 3. SSIM curve across all the CMU faces for different MFH algorithms with a magnification factor of 4.

4.2. Experiment 2

In reality, we often confronted with parts of the face including chin, particle ears, hair and facial contour line, and were concurrent with other poses of looking down and looking up, which can be seen as faces rotated along the z-axis in Euclidian space (with yaw degrees). Therefore, our algorithm is still suitable for this situation and valid in this practical application. Note that, compared to the faces rotated along the y-axis in Euclidian space (with tilt degrees), it's a much more challenging issue right now. To our best knowledge, the database specially designed for multi-view faces is not publicly available currently. Therefore, it's hard to provide the related performance. However, in order to further evaluate the effectiveness and robustness of our method, we have included one more widely used face dataset, i.e. the FERET face database [36]. In this experiment, 70 individuals are randomly selected form the FERET face database, i.e. there are 70×5 images. Each of the face is also aligned using the location of the two eyes, and all original HR facial images are cropped to a size of 80×80. In detail, for each individual, faces of five poses from the cropped FERET face database with parts of the face including chin, particle ears, hair and facial contour line, are contained and performed. Two typical examples are shown in Fig 4.

Fig. 5 illustrates the curve of SSIM of every testing faces for different MFH methods with a magnification factor of 4, respectively. From Fig. 5 we can see that the proposed method, compared with other typical state-of-the-art approaches, can produce plausible and promising results.

Fig. 4. Cropped faces of two different subjects with five poses from the FERET face database. From left to right: assigned as −45°, −22.5°, 0°(frontal view), 22.5°, and 45° in the experiment.

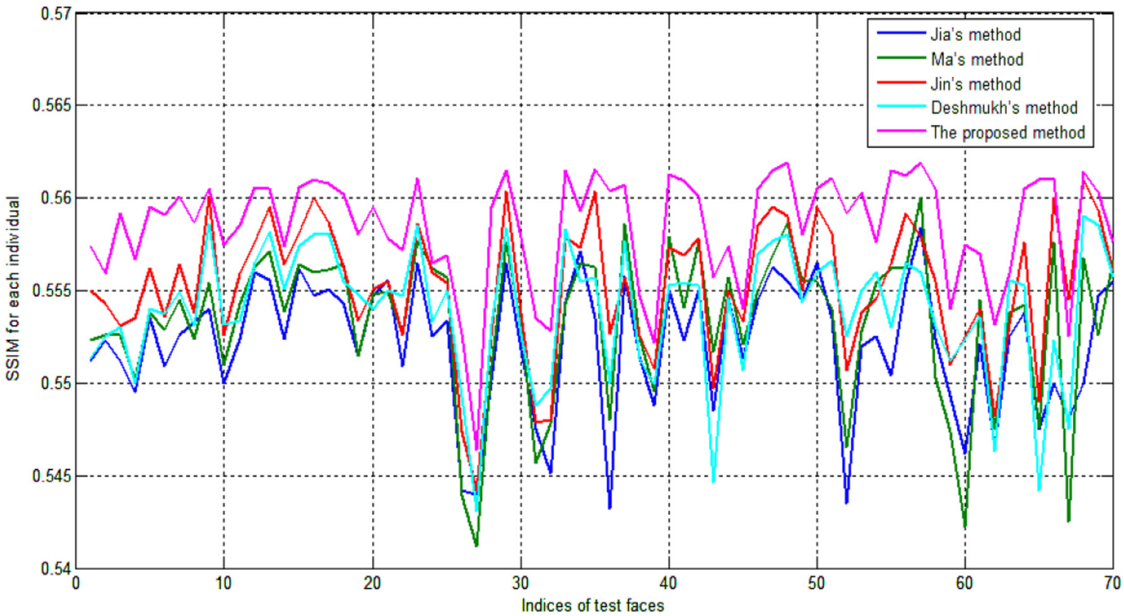

Fig. 5. SSIM curve across all the 70 FERET faces for different MFH algorithms with a magnification factor of 4.

5. Conclusion and discussion

In this communication, we have proposed a novel MFH method for the hallucination of LR face images. Based on the assumption that the linear mapping manifold across various facial views is similar, two corresponding matrices generated by SVD of the LR face for the HR multi-view face images can be estimated. Thereby, the proposed scheme can hallucinate the holistic pattern and subtle structure of faces. And contrasted with typical state-of-the-art MFH methods, experimental results have shown that the proposed algorithm can generate HR faces with high-frequency details.

In the future, we will investigate a more challenging MFH issue with larger multi-view angles and sub-region occlusion with the aid of 3D face reconstruction.

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