

Face Image Super Resolution via Adaptive-Block PCA

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Abstract: A novel single face image Super Resolution (SR) framework based on adaptive-block Principal Component Analysis (PCA) is presented in this paper. The basic idea is the reconstruction of a High Resolution (HR) face image from a Low Resolution (LR) observation based on a set of HR and LR training image pairs. The HR image block is generated in the proposed method by using the same position image blocks of each training image. The test face image and the training image sets are divided into many overlapping blocks, then these image blocks are classified according to the characteristics of the image block and then PCA is operated directly on the non-flat image blocks to extract the optimal weights and the hallucinated patches are reconstructed using the same weights. The final HR facial image is formed by integrating the hallucinated patches. Experiments indicate that the new method produces HR faces of higher quality and costs less computational time than some recent face image SR techniques.

Keywords: SR, face image, adaptive-block, PCA.

Received October 30, 2013; accepted November 20, 2014; Published online December 23, 2015

1. Introduction

The goal of Super Resolution (SR) image reconstruction technology is to generate High Resolution (HR) image from its Low Resolution (LR) inputs. It has a wide range of applications such as: Remote sensing, medical image processing, video surveillance. The generation of LR image loses lots of detail information, so the SR task is an ill-posed problem [5, 16].

In general, most contemporary super-resolution algorithms can be classified into three categories. One is the Interpolation Algorithm. Many image Interpolation Algorithms were development. These methods need to get tradeoffs between computational complexity and reproduction quality. Bicubic or bilinear interpolators are the common methods. Edge-directed interpolation methods are proposed across-edge interpolation. They can preserve the edge. However, these methods do not consider the generation of LR. The output results have blurring effects.

The second kind of method for image SR is reconstruction-based algorithms. The basic idea of reconstruction-based super-resolution is to exploit additional information from successive LR frames with sub-pixel displacements and then to synthesize an HR image. Iterative Back-Projection (IBP) [15] algorithms estimate the HR image by iteratively back projecting the error between simulated LR images and the observed ones. Maximum A Posterior (MAP) [3] approaches adopt the prior probability of target HR images to stabilize the solution space under a Bayesian framework. Projection On Convex Sets (POCS) [6]

tends to consider the solution as an element on a convex set defined by the input LR images.

The third kind of method for image SR is learning-based approaches. In recent years, the common learning-based face super-resolution algorithms usually involve two steps. The first step generates global face image keeping the main characteristics of the ground truth image using probabilistic method in MAP frame or manifold learning method such a Locally Linear Embedding (LLE); the second step produces residual image to compensate the results of the first step. However, the two-step frame work or residue compensation may not be indispensable in all circumstances [7, 9]. Since, the local model has higher reconstruction precision than global model; face hallucination is achieved by only using local model.

The success of example-based super-resolution methods hinge on two major factors: Collecting a large and representative database of low-resolution and high-resolution image pairs and learning their mapping [12, 13]. Example-based super-resolution methods often entail the need of a large dataset to encompass as much image variation as possible [6] with ensuing computational load in the learning process. Moreover, the mapping learned from a general database may not be able to recover the true missing high-frequency details from the low-resolution image if the input frame contains textures that do not appear in the database.

Since, the hallucinating face was proposed, the face SR problem is highly concerned by researchers and learning-based approaches are prevailing. As face images exhibit geometrical structures unique to generic images, it is very important to represent and

reconstruct the structural feature. Baker and Kanade [1] developed a hallucination method based on the property of face images. Liu [11] proposed a two-step face image SR method that divided the SR problem into reconstructing global information and local information, both of which can be learnt from training sets. The two-step framework is a useful framework upon which many SR algorithms are built. Wang and Tang [17] fit the input face image as a linear combination of LR training face images in the eigentransformation domain. The HR image is generated by replacing the LR training images with corresponding HR ones and retaining the same combination coefficients. A well-known manifold learning method, Chang [2] developed the neighbor embedding algorithm based on the assumption that the training low and high-resolution images form manifolds with similar local geometry in two distinct feature spaces. Jian [10] applied the perspective of compressed sensing to super-resolution. The HR image produced by the sparse representation approach might not satisfy the acquisition process assumed. The final result was generated by additional residue compensation step using back-projection method. Zhuang and Zhang [18] proposed the locality preserving hallucination algorithm combining LPP and Radial Basis Function (RBF) regression together to hallucinate a global HR face. Details of the synthesized high-resolution face were further improved by residue compensation based on neighbor embedding [10].

Face image can be reconstructed from the optimal linear combination of the training face images because of the structural similarity. However, because facial image contains abundant information and each has its own characteristics, global reconstruction tends to result in low reconstruction precision and unsatisfactory results. A reconstruction based on adaptive block PCA is proposed in this paper instead of a complicated model. Position in the face image is used as well as image features to reconstruct new image [8]. The traditional PCA operates directly on a whole image represented as a vector and acquires a set of projection vectors to extract global features from given training patterns. Our method operates instead directly on a set of image blocks of the original image and acquires a set of projection sub-vectors for each image blocks to extract corresponding local sub-features and then synthesizes them into global features for SR reconstruction.

2. The Research Method

2.1. Problem Formulation

Viewing a two-Dimensional (2D) image as a vector, the process of getting a low-resolution face image from the high-resolution one can be formulated as: $Y = N * Q * X + V$, Where X represents a HR image, Y represents a LR image, N represents the down

sampling operator, Q represents a blurring filter and V represents the noise. The task of SR is to recover X from the observed Y as accurate as possible, which is extremely ill-posed, since many HR images X can satisfy the above reconstruction constraint for a given LR image Y .

Many video applications, such as: Surveillance or monitoring systems must extract and enhance small faces from a sequence of low-resolution frames [17]. Face detection is one of important research issue, as extensively surveyed by Jian [10]. Because algorithmic face detection is beyond the scope of this work, we assume that facial images were previously extracted and cropped, as shown in Figure 1-a LR facial image, Figure 1-b resolution-enhanced facial image by bicubic interpolation and Figure 1-c desired HR facial image.

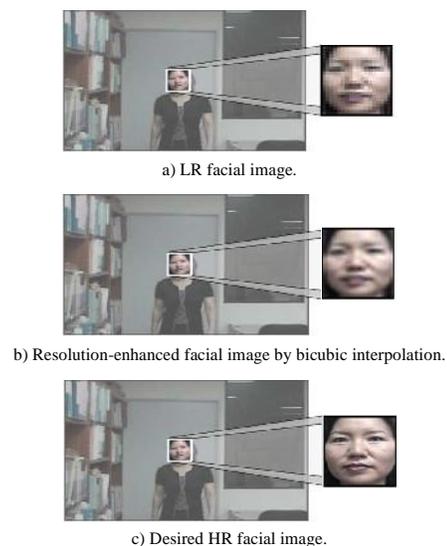


Figure 1. Example of a LR face image from a single frame image.

2.2. PCA Algorithms

Principal Component Analysis (PCA) is a very effective approach of extracting features in recent years [17]. The image data is projected from the high dimension space to a low dimension space, so as to achieve dimension reduction and save the main information of the image data. In our method, PCA represents face images using a weighted combination of eigenfaces. PCA is applied to the low-resolution face image. In the PCA representation, different frequency components are uncorrelated. Eigenfaces with large eigenhigh-frequency details [17], as shown in Figure 2. PCA is optimal for the face representation because the K largest eigenfaces account for most of the energy and are most informative for the face image set in Figure 3. The eigenface number K controls the detail level of the reconstructed face.

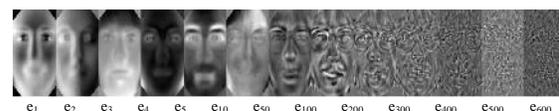


Figure 2. Eigenface examples sorted by eigenvalues.

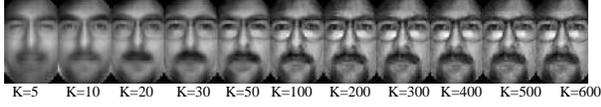


Figure 3. Face reconstruction using a different number of eigenfaces, K is the eigenface number.

Many studies on face space have shown that a face image can be reconstructed from eigenfaces in the PCA representation [17]. Like the multi-resolution analysis, PCA also decomposes the face image into different frequency components. The difference is that the PCA method utilizes the face distribution to decompose face structure into uncorrelated frequency components. So, it can encode face information more concisely.

2.3. Proposed Algorithm

Traditional PCA algorithm is performed on the original images directly and obtains the global features, which are vulnerable to external ambient temperature, psychological and physiological factors. Such global procedure cannot obtain enough information because the local part of the face is quite different. It is necessary to extract more detailed local features. In order to take full advantage of both the global information and the local characteristics of facial images, the images are partitioned into blocks [4, 14, 17]. Position in the face image is used as well as image features to reconstruct new image [17, 18]. Therefore, the idea of block PCA is proposed in this paper. We exploit PCA to get the coefficient mapping by which the SR results can be obtained.

Firstly, the LR test image x_j , the low-resolution image sets l and the high-resolution image sets h denoted by a vector are divided into a set of equally-sized blocks in overlapping ways. A set of low-resolution training image pairs $l = \{l_i\}_{i=1}^M$ and high-resolution pairs $h = \{h_i\}_{i=1}^M$ are given, where M is the number of the low-resolution training samples. Then, all those blocks sharing the same original feature components are respectively collected from the training set to compose corresponding training block sets.

Secondly, the whole HR image plane is divided into square blocks of the same size as the initial block division set. They can be represented as a set of small overlapped image block which are considered as matrix $\{l_{ij}\}_{j=1}^k, \{h_{ij}\}_{j=1}^k$, where k is the number of the blocks in the image. The low-resolution image input x_l is also represented as a set of small overlapped blocks which is $x = \{x_j, j = 1, 2, \dots, k\}$. Then, the features of each block are analyzed to refine the block division set and to label the block pattern.

Suppose that, the size of LR image is $b \times b$ and the size of HR image is $B \times B$, the size of LR image block in LR face image is $d \times d$, the overlapping pixel in the horizontal and vertical directions is $d1$. Similarly, the size of image block in HR face image is $(n \times d) \times (n \times d)$, the overlapping pixel in the horizontal and vertical directions is $(n \times d1)$, n is the magnification factor. The

number of the blocks in the image k can be calculated as:

$$k = \left(1 + \frac{b-d}{d-d1}\right)^2 = \left(1 + \frac{B-n*d}{n*d-n*d1}\right)^2 \quad (1)$$

The high-and low-resolution block pair is shown in Figure 4.

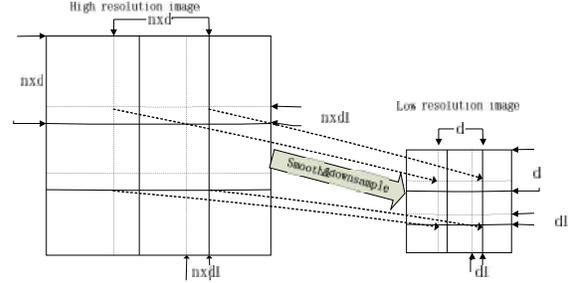


Figure 4. The high-resolution and LR block pair.

A structure matrix is used to examine the smoothness around a pixel, where the structure matrix for a single pixel $I(x, y)$ in image I is defined as:

$$S(x, y) = \sqrt{\nabla I_x(x, y)^2 + \nabla I_y(x, y)^2} \quad (2)$$

$\nabla I_x(x, y)$ is the gradient values in the horizontal directions, and $\nabla I_y(x, y)$ is the gradient values in the vertical directions.

$$\nabla I_x(x, y) = I(x-1, y+1) + 2I(x, y) - I(x+1, y+1) - I(x-1, y-1) - 2I(x, y-1) - I(x+1, y-1) \quad (3)$$

$$\nabla I_y(x, y) = I(x-1, y-1) + 2I(x-1, y) - I(x-1, y+1) - I(x+1, y-1) - 2I(x+1, y) - I(x+1, y+1) \quad (4)$$

Thus, the structure matrix of block x_j can be defined as:

$$S_j = \frac{1}{n_j} \sum_{(x,y) \in x_j} S(x, y) \quad (5)$$

Where n_j is the number of pixels in block x_j . The eigenvalue $|j_1^j|$ and $|j_2^j|$ of matrix S_j are a measurement of gradient strength. The larger eigenvalue corresponds to the direction with the stronger gradient, whereas the smaller one corresponds to the direction with the weaker gradient. The smoothness j of block x_i is defined as:

$$t_j = |j_1^j| + |j_2^j| \quad (6)$$

If $j < T$ (T is threshold), x_j is flat block, else x_i is non-flat block.

If x_j is non-flat block, it should be divided into sub-blocks of the same size $x_j = \{x_1, x_2, \dots, x_{k1}\}$. The size of sub-block in LR face image is $d' \times d'$, the size of sub-block in HR face image is $(n \times d') \times (n \times d')$. k_1 can be calculated by Equation 1.

If x_j is flat block, it keep the initial size. The process of adaptive-block is shown in Figure 5.

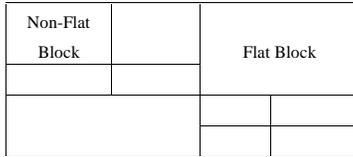


Figure 5. The process of adaptive-block.

Thirdly, for the j^{th} sub-block of the flat block, it is approximated by a linear combination of the low-resolution image block sets using the PCA method in the same place of images, and PCA is performed on each of such LR training image block sets.

The face image SR reconstruction based on PCA is shown in Figure 6.

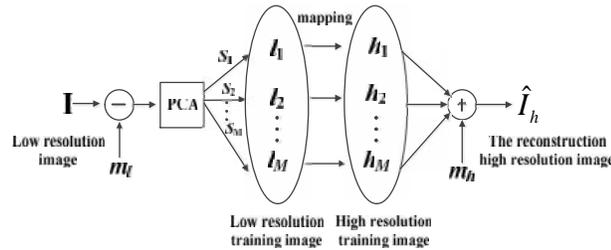


Figure 6. Face image SR based on PCA.

Then, according to the second step, we construct PCA for the j^{th} block set to seek its eigenvectors V_j . We first define the j^{th} mean block matrix m_j as:

$$m_j = \frac{1}{M} \sum_{i=1}^M l_{ij} \quad (7)$$

Removing the mean face from each image block, we have:

$$L_j = [l_{1j} - m_j, \dots, l_{Mj} - m_j] \quad (8)$$

A set of eigenvectors, also called eigenfaces, are computed from the eigenvectors of the ensemble covariance matrix of the transpose matrix of L_j .

$$C_j = L_j^T L_j \quad (9)$$

Then find independently each set of projection sub-vectors by means of the following eigenvalue-eigenvector system under the constraints.

$$V_j V_j^T = I_j, j = 1, 2, \dots, k \quad (10)$$

$$C_j V_j = V_j \lambda_j \quad (11)$$

Where I_j is an identity matrix and λ_j is a diagonal matrix composed by the first p largest non-negative eigenvalues of C_j in a descending order and thus their corresponding first p local eigenvectors compose the V_j . PCA decomposes face images into different frequency components. Eigen faces with large eigenvalues characterize the low-frequency components. Eigen faces with small eigenvalues characterize the high-frequency details. PCA is optimal for the face representation because the first p local eigenfaces account for most of the energy and are most informative for the face image set.

Therefore, the orthonormal eigenvector matrix of C_j can be computed from:

$$E_j = L_j V_j \lambda_j^{-1/2} \quad (12)$$

For the j^{th} sub-block x_j a weight vector can be computed by projecting it onto the eigenvector:

$$w_j = E_j^T (x_j - m_j) \quad (13)$$

Apply PCA to x_j , the reconstructed face image block r_j can be represented by:

$$r_j = E_j w_j + m_j = L_j V_j \lambda_j^{-1/2} w_j + m_j = L_j S_j + m_j \quad (14)$$

Where

$$S_j = V_j \lambda_j^{-1/2} w_j = [S_{j1}, S_{j2}, \dots, S_{jM}]^T \quad (15)$$

Equation can be rewritten as:

$$r_j = L_j S_j + m_j = \sum_{i=1}^M S_{ji} l_{ij} + m_j \quad (16)$$

This shows that the input low-resolution face image block can be reconstructed from the optimal linear combination of the M low-resolution training face image blocks. Here, S_j describes the weight that each training face block contributes in reconstructing the input face block. The sample face block that is more similar to the input face block has a greater weight contribution as shown in Figure 7. Keeping the coefficients and replacing each low-resolution image l_{ij} with its corresponding HR image block h_{ij} and replacing m_j with the high-resolution mean face block M_j , finally we have:

$$R_j = \sum_{i=1}^M S_{ji} h_{ij} + M_j \quad (17)$$

Where R_j is expected to be an approximation to the j^{th} block of real HR face image. All of the sub-block images are integrated to form the non-flat image block.

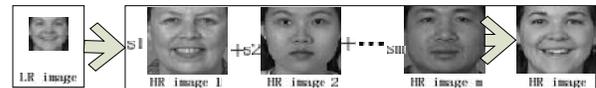


Figure 7. A novel face can be approximated by a linear combination of training faces.

In the other hand, for the flat block, it can be reconstructed by bilinear interpolation. The advantage of adaptive block is the less calculation time.

Finally, all the HR blocks are integrated to form the final global HR image according to the original position. Pixels of the overlapping regions in the final result are obtained by averaging the pixels value in the overlapping regions between two adjacent blocks.

3. Experiments Results and Analysis

The experiments are performed on FERET face database. This experiment is designed to verify the effectiveness of SR methods under well-defined

environment and limited facial variations. 200 normal expression images of different persons which are illustrated in Figure 8 are randomly selected. These face images are aligned manually by using the locations of three points: Centers of left and right eye balls and center of the mouth. The size of HR face image is 80×80.



Figure 8. FERET face database.

150 images for training and 50 images for testing are selected. The test images are obtained by 2 times down-sampling and blurred using a 5×5 Gaussian filter. So, the size of LR face image is 40×40.

- Compare the Performance of Different Numbers of Training Samples: Figure 9 illustrates one example of hallucinating face images using different numbers of training samples. The image block initial size of low-resolution is 4×4 and the overlapping pixel is 2. HR image block initial size is 8×8 and the overlapping pixels are 4. Figure 9-a is the LR face image when the magnification factor is 2. Figures 9-b and e are the reconstructed face image when the number of training database is 50, 100, 120, and 150. Table 1 is the PSNR values of the reconstructed image.

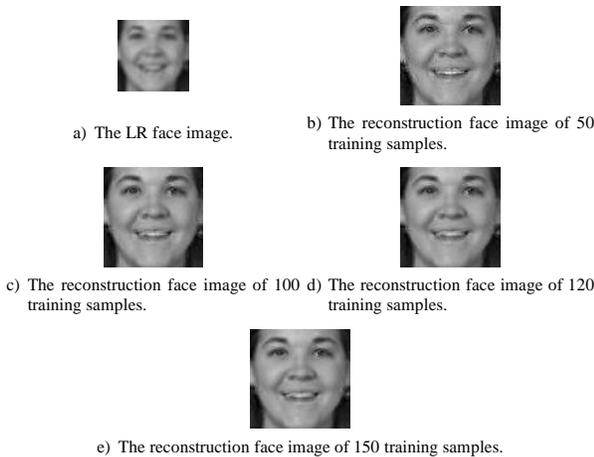


Figure 9. The hallucinating face images using different numbers of training samples.

Table 1. The PSNR of different numbers of training samples.

PSNR	K=50	K=100	K=120	K=150
Image 1	28.16	28.97	29.22	29.42
Image 2	27.34	28.06	28.19	28.47
Image 3	27.21	28.05	28.30	28.44
Image 4	28.59	29.47	29.63	29.87

Experiments show that the proposed method gains higher PSNR with the increasing training samples. The results are much different with different numbers of training sets. The results are not much different if the number is above 100, suggesting that our method is capable of achieving satisfactory results based on even a relatively small training set. However, when the

training set is too small, a lot of the individual characteristics fail to be rendered.

- Compare the Performance of Different Magnifications: Figures 10 and 11-a show the LR face image with the magnification factor equals 4 and 2; Figures 10 and 11-b show the reconstruction face image by the proposed method; Figures 10 and 11-c show the original HR face image. Table 2 is the PSNR values of the reconstructed image.

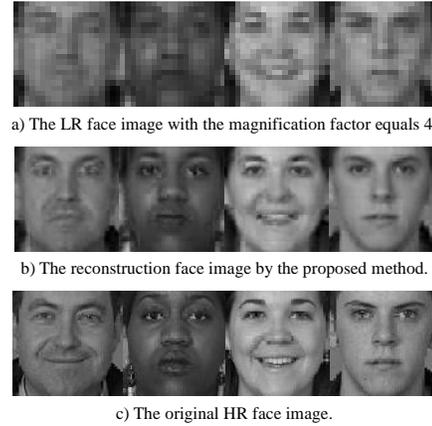


Figure 10. Face image SR performance with the magnification factor equals 4.

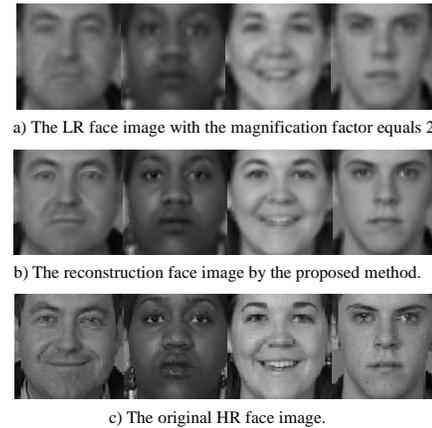


Figure 11. Face image SR performance with the magnification factor equals 2.

Table 2. The PSNR of different magnifications.

PSNR	Magnification=2	Magnification=4
Image 1	29.63	26.74
Image 2	28.47	26.06
Image 3	28.44	25.22
Image 4	29.87	27.18

Experiments show that the reconstruction quality when the factor equals 2 is better than that when the factor equals 4. Because the greater the magnification, the more number of training samples are needed. Only more training samples can ensure more prior knowledge and the reconstruction quality will be good.

- Compare the Performance of Different Initial Size of Block: Figures 12-a, b, c and d show four examples of hallucinating face images when the

initial size of the image block are 2×2 , 4×4 , 8×8 , 16×16 . The number of training face images is 150 and the magnification is 2. Table 3 is the PSNR values of the reconstructed image.

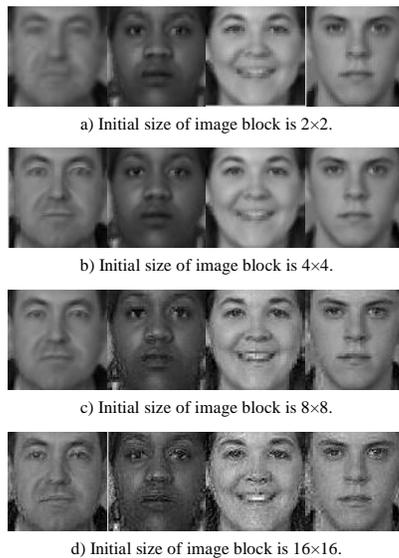


Figure 12. The performance of different size of block when the initial size of image block is 2×2 , 4×4 , 8×8 , 16×16 .

Table 3. The PSNR of different size of block.

PSNR	2×2	4×4	8×8	16×16
Image 1	29.63	26.74	28.33	23.85
Image 2	28.47	26.06	28.02	24.47
Image 3	28.44	25.22	27.31	23.14
Image 4	29.87	27.18	28.99	25.27

Experiments show that when the initial size of face image block is too small or too large, the effect of the reconstructed image is not good. Only the appropriate block size for face reconstruction has a good contribution. When a patch is too small, it loses the geometrical information of a human face, so the super-resolution reconstruction image becomes blurry [14]. On the other hand, as a patch becomes larger, it needs much more training images to extract reliable generalized basis.

- Compare the Performance of the Proposed Method with Other Face SR Algorithms: We compare the performance of the proposed SR method by comparing it with other representative face SR algorithms, which are bilinear interpolator, bicubic interpolator, Wang's method [17], Chang's neighbor embedding [2] method and the method with the fixed size of block. The optimal block size of 8×8 is chosen in neighbor embedding method, in which the corresponding low-resolution size is 4×4 . The number of the neighbour patches for reconstruction in neighbor embedding is 150. In our method, the initial size of the LR image block is 4×4 and when the block is non-flat, the size of sub-block is 2×2 .

Figures 13-a, b, c, d, e, f, g and h show the following results sequentially: LR images, Bilinear interpolator results, bicubic interpolator results, PCA method results [17], neighbor embedding

method results [2], the method results with the same size image block, which can be called method 1, our method results and original HR image. The optimal block size of 4×4 is chosen in neighbor embedding method, and the number of the neighbour patches for reconstruction in neighbor embedding is 150. Table 4 is the PSNR values of the reconstructed image.

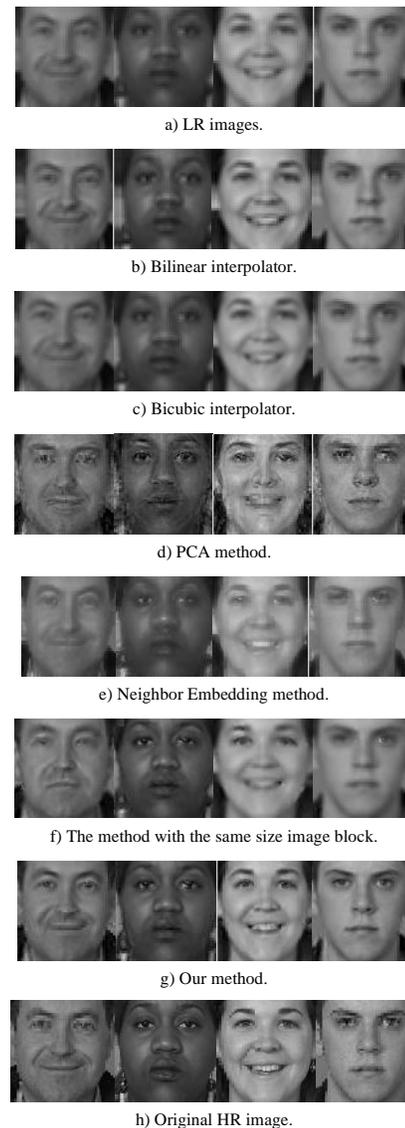


Figure 13. Comparative face image SR performance between the proposed method and other face SR algorithms.

Table 4. The PSNR of different methods

PSNR	Bilinear	Bicubic	PCA [17]	NE [2]	Method1	Our Method
Image 1	29.63	28.33	26.74	23.85	28.95	29.63
Image 2	28.47	28.02	26.06	24.47	28.21	28.47
Image 3	28.44	27.31	25.22	23.14	28.01	28.44
Image 4	29.87	28.99	27.18	25.27	29.11	29.87

Experiments show that the result of Wang's method [17] can hardly maintain global smoothness and visual rationality, especially on locations around face contour and margin of the mouth. Chang method [2] generates more detailed facial features than Wang's method, but some subtle characteristics are still blurred. The

performance of bilinear interpolator is the worst, but the final results by bicubic interpolation are more facial details. The reconstructed face image by the method with the fixed size of block is not better than our method, including less facial details. Our method can well reconstruct the face image with more facial details which are quite close to the original images and the proposed method gains the highest PSNR over other approaches, Compare with the other methods, our method is of the best quality.

- Compare the Performance of Special Images: The performance when the training sets contain face images with eyes/nose/mouth and test face images without eyes/nose/mouth is studied in the proposed method. Figure 14-a shows the LR face image which has no eyes/nose/mouth; Figure 14-b shows the reconstructed face image with the proposed method; Figure 14-c shows the initial HR face image. Table 5 is the PSNR values of the reconstructed image.

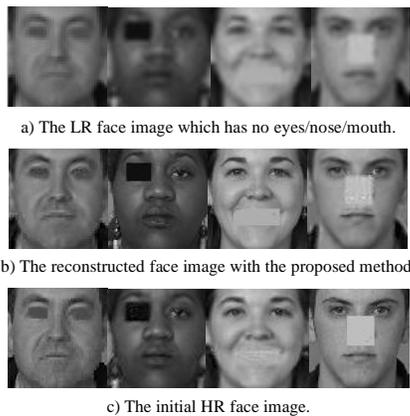


Figure 14. The occluded face image SR performance.

Table 5. The PSNR of special face images.

PSNR	Special images	Normal Images
Image 1	29.51	29.63
Image 2	28.02	28.47
Image 3	27.42	28.44
Image 4	28.76	29.87

Experiments show that the test face images are without eyes/nose/mouth, but the reconstructed face image will have the outline of the eyes/nose/mouth, which is not quite clear. The results preserve the characteristics of the training images since the input image is approximated by training images in the proposed method.

4. Conclusions

A single face image SR method based on adaptive-block PCA is designed in the study. Experiments show that the proposed method costs less computational time and generates results with the best image quality compared to some recent algorithms. Since, the input image is approximated by blocks in algorithm; our method preserves the characteristics of the low-

resolution image input [1]. If the input face images have noise, our method will enlarge the noise instead of removing it and global image based our method is able to retain the characteristics of the training set. In this case, if the input face images have noise or glasses but the training images do not, these hallucination methods can remove the noise or glasses. Non-feature information contributes to super-resolution, and construction coefficients obtained by common algorithms do not contain the non-feature information. Thus, the loss of some detailed facial information inevitably occurs in the first step and additional residue compensation is indispensable in such circumstances. In addition, global reconstruction tends to result in low reconstruction precision. That is the reason why common method usually follows a two-step framework and requires residue compensation. In comparison to other methods, our method is much simpler and easy to implement. Because the degradation process is diverse in real world but the degradation matrix assumed in algorithm is fixed, the hallucination results may not be satisfactory to all the real world images, which is also a limitation of other face hallucinations. One possible direction for future research may be to broaden the applications of face hallucination in the real world setting.

Acknowledgments

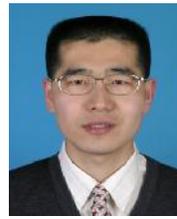
This work was supported in part by the National Science Foundation of China under grant no. 61671069. It was also partially supported by the Importation and Development of High-Caliber Talents Project of Beijing Municipal Institutions under Grant No. CIT&TCD201304119 and the National Science and Technology Major Project under Grant No. 2011ZX05039-004-02.

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