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Super-resolution reconstruction of face images based on pre-amplification non-negative restricted neighborhood embedding

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Abstract. The traditional super-resolution (SR) reconstruction algorithm based on neighborhood embedding preserves the local geometric structure of image block manifold to reconstruct high-resolution (HR) manifold. However, when the magnification is large, the low resolution (LR) image is seriously degraded and most of the information is lost after down-sampling. The neighborhood relation of the LR manifold can not reflect the inherent data structure. In order to solve the problem effectively, we propose a face image SR algorithm based on pre-amplification non-negative restricted neighborhood embedding. In the training phase, the LR image is pre-amplified so that there are more similar manifold structures between the HR and LR resolution images. The constraints of the reconstructed coefficients are loosened and the HR image blocks are iteratively updated to obtain the reconstructed weights. The experimental results show that the proposed method has a better reconstruction effect compared with some traditional learning algorithms.

Key words: super resolution, neighborhood embedding, nonnegative restriction, face reconstruction.

1. Introduction

With the rapid development of face recognition technology, a large number of monitoring systems are currently installed in a variety of places. In practice, the resolution of the face image obtained from the monitoring system is very low due to the limited network bandwidth, the small server storage and the long distance. The SR reconstruction technology can be a good solution to this problem which refers to the process of reconstructing HR images from a series of LR images or a single LR image. It is widely used in remote sensing, digital HDTV, public safety, medical image analysis and so on. Face image SR reconstruction is an important application of image SR technology which can provide more face details for face image recovery, face recognition, face expression analysis and more.

The manifold learning based method is a hot research topic in the field of face image SR reconstruction technology. Because the face can be seen as a manifold structure, the face SR reconstruction algorithm based on manifold learning has been widely concerned. Chang et al. [1] proposes a learning SR algorithm based on neighborhood embedding which introduced neighborhood embedding into SR reconstruction for the first time. However, it does not dig the potential of the algorithm in depth. Since then, many authors have conducted extensive studies in this field [2–4]. In the neighborhood embedded SR reconstruction algorithm, the key factor affecting the quality of the reconstruction is whether the nearest neighbor block can be found accurately and whether the reconstructed weight coefficients can be calculated. In paper [3], it is pointed out that the performance of the algorithm can be improved by selecting the better features and establishing a more accurate formula for calculating the reconstructed coefficient weights. In addition, in paper [5], non-local similarity is used in image restoration under sparse models. It proposes that similar blocks have the same dictionary elements in sparse decomposition, which can be used to solve sparse representation coefficients. In paper [6], it is proposed to reconstruct the face image using Bayesian formula for the first time. Liu et al [7] integrates a global parameter model and a local nonparametric model for image reconstruction.

In recent years, it has been found that the location information is very important for face analysis and synthesis. In [9], an outstanding method for reconstructed face images using the training image blocks with the same location is presented. However, when the number of training sample is larger than that of the image block, the reconstruction weights are not unique. To solve this problem, a sparse regularization method is proposed to obtain the optimal reconstruction weights of face hallucination in paper [10]. In addition, paper [11] proposes a position patch based face hallucination method, which uses local geometric constraints in the reconstructed objective function. Han et al propose a nearest feature line based approach for face SR reconstruction. Papers [10, 17] solve the problem that the solution is not unique when the number of training samples is larger than the dimension of the face block. This method is to sparse regularization of the objective function of face reconstruction to obtain the optimal weight of face SR, so as to reduce the reconstructed error. In paper [18], a method based on local geometric constraint location blocks is introduced in block representation functions. In the computation of the reconstructed weights, the method takes into account the prior information of the location

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of the image blocks, and introduces the local geometric constraints. When describing the linear geometric relationship between the image block and its neighboring blocks, the weights have a direct effect on the quality of the reconstructed image. In the LINE algorithm [12], the weights satisfy the constraint that the sum is equal to 1. However, because there is no constraint on the symbol, the weight may be negative. It directly results in the possibility of negative brightness when reconstructing a HR image block, which is inconsistent with the fact that the brightness value can not be negative. In addition, many methods over pursue smaller reconstruction errors, which lead to overfitting phenomenon, so that the quality of the reconstructed face images is degraded. To sum up, how to preserve the neighborhood relations between HR and LR images and how to obtain the optimal reconstruction weights are two crucial issues in face reconstruction.

In order to solve the above problems, this paper presents a face image SR algorithm based on pre-amplification non-negative restricted neighborhood embedding which not only introduces the pre-amplification non-negative restriction, but also improves the neighborhood embedding. In particular, non-negative coefficients are used to represent HR block in the iterative calculation process, which effectively enhances the reconstructive effect of the final HR block.

2. Neighborhood embedding based SR reconstruction

The traditional neighborhood embedding (NE) algorithm adopts the idea of local linear embedding (LLE) algorithm in manifold learning [13] which assumes that there is a similar local geometry between the HR image block and the LR image block. According to this hypothesis, the LR input image block is expressed as the linear combination of the K-nearest neighbors in the training set, and then the neighborhood relation is mapped to the corresponding HR image block to obtain the corresponding HR image. The traditional NE algorithm mainly includes two stages: sample training and image reconstruction. The sample training stage includes the following two steps:

Step 1. Blur and down-sample the selected HR training images $\boldsymbol{I}_{HR}^{train}$ to obtain the corresponding LR training images.

Step 2. Block the HR training image and the LR training image to obtain a HR training image block set $\boldsymbol{I}_{HR}^{train} = \{\boldsymbol{y}_s^p\}_{p=1}$ and a LR training image block set respectively, where $p = 1, 2, 3, \dots, N_s$, N_s represents the number of training blocks. It should be noted that the HR training image block and the LR training image block are one-to-one correspondence.

The image reconstruction stage consists of the following four steps:

Step 1:

① Block the input LR test image I_{LR}^{input} to obtain a LR test image block set, where $p = 1, 2, 3, \dots, N_t$, N_t represents the number of LR test image blocks.

② For each image block x_t^q, find the LR K neighborhoods N_q^l in the LR training image block set X_{LR}^{train}.

Step 2:

Use x_t^q to linearly represent x_t^q.The reconstruction error ε^q between the input image block and the image block reconstructed by using K neighborhoods is guaranteed minimum. Then solve the reconstruction coefficients.

Step 3:

Obtain the HR output image block set $Y_{HR}^{output} = \{y_t^q\}_{q=1}^{N_t}$ according to Eq. (1), where y_t^q represents the output block corresponding to the input block x_t^q.

$$y_t^q = \sum_{y_s^p \in N_q^h} w_{qp} y_s^p, \tag{1}$$

where N_q^h represent the HRK-nearest neighbors corresponding to N_q^l, y_s^p represents the HR training image block corresponding to x_s^p.

Step 3:

Concatenate all the image blocks in Y_{HR}^{output} to obtain a HR output image I_{HR}^{output}. (For the pixels in overlapping area, take the average).

In the traditional neighborhood embedding algorithm, when the magnification is large, the neighborhood relation between the HR image blocks and LR image blocks can not be maintained, which leads to the sharp decline of the reconstruction quality. In addition, the traditional algorithm can not guarantee the reconstructive quality in the condition of high magnification due to its robustness to noise is not strong [14].

3. The proposed algorithm

In order to keep the neighborhood relation between HR and LR image blocks in traditional neighborhood embedding algorithm, Pre-amplification non-negative constraints are introduced into the traditional neighborhood algorithms. On the other hand, the K-nearest neighbor blocks are estimated using the HR image block search mechanism. Then the optimal weights are obtained by iterative calculation to improve the reconstruction quality.

3.1. Pre-amplification non-negative restriction. In the traditional neighborhood embedding algorithm, the reconstruction coefficient satisfies the condition that the sum of the coefficients in the formula (2) is 1. The coefficients obtained by calculating may be positive or negative [15]. Positive coefficients produce superposition effects, while negative coefficients produce offset effects. If the superposition effect and the offset effect exist simultaneously, the reconstruction error ε^q will increase. In addition, when the magnification is large, the LR image is degraded seriously. As a consequence, the low-frequency information contained in the LR image has a low correlation with the high-frequency information contained in the HR image. Eventually it leads to a substantial decline in the quality of the reconstructed image. In order to solve the above problems, this paper uses the method based on pre-amplification non-negative restriction neighborhood embedding. In the training phase, as a transition, the LR image is pre-amplified into medium-resolution (MR) image. Then we obtain the mapping relations between the MR image and the HR image by training. In the reconstruction phase, the input LR image is amplified in advance. Then the weight coefficient satisfying the non-negative constraint is calculated to obtain the HR images.

Assume that the input image I_{LR}^{input} set is magnified α times. In the training phase, the temporary LR image set I_{LR}^{temp} is obtained by performing fuzzy operation and down-sampling α times operation on the HR training image set I_{HR}^{train}. Then, we pre-amplify I_{LR}^{temp} T times to get the training set of LR image. Finally, the I_{HR}^{train} and I_{LR}^{train} are divided into blocks to obtain HR training image blocks Y_{HR}^{train} and LR training image blocks X_{LR}^{train}, respectively.

In the reconstruction phase, it do not directly block I_{LR}^{input} but pre-amplified I_{LR}^{input} T times to obtain I_{MR}^{temp}. Then I_{MR}^{temp} is divided into blocks and the results is used as the input image block set. For each input image block, we look for K nearest neighbors in X_{LR}^{train}. Based on the non-negative constrained iterative neighborhood embedding algorithm, the reconstruction coefficient is obtained. The output image blocks can be obtained by Eq. (1). Finally, through the splicing of the image, we get the output HR image.

The pre-amplification of the input image can ensure that the neighborhood relationship between the high and LR images is better maintained when the magnification is large, thus improving the reconstruction quality. Therefore, the reconstruction quality has been effectively improved.

In the reconstruction phase, the traditional neighborhood embedding algorithm uses formula (2) to solve the reconstruction coefficients:

$$\varepsilon^q = \left| x_t^q - \sum_{x_s^p \in N_q^l} w_{qp} x_s^p \right|^2 s.t. \sum_{x_s^p \in N_q^l} w_{qp} = 1 \tag{2}$$

where x_t^q represents the input image block, N_q^l represents the set of LR k-nearest neighbors of x_t^q, x_s^p represents the p-th nearest neighbor of x_t^q in training set, w_{qp} represents the p-th nearest neighbor reconstructive coefficient of the image block x_t^q.

When the constraint that the sum of all the weights is equal to 1 is satisfied, the negative weights may appears because there is no sign constraint on these weights. It means that when reconstructing a HR image block, there may be a negative brightness value. It is clearly inconsistent with the fact that the brightness values are not negative. Therefore, the over pursuit of minimal reconstruction error will lead to overfitting phenomenon, which makes the reconstructed face images degraded in quality.

In order to solve the above problems, the algorithm in this paper modifies the constraints in formula (2) as follows:

$$\varepsilon^q = \left\| x_t^q - \sum_{x_s^p \in N_q^l} w_{qp} x_s^p \right\|^2 s.t. w_{qp} \geq 0 \tag{3}$$

where $w_{qp} \geq 0$, which indicates that the coefficients satisfy the non-negative requirement. So we call it non-negative neighborhood embedding. Eq. (3) is a Non-Negative Least Squares (NNLE) problem that can be solved by iteration.

3.2. Iterative neighborhood embedding. The prior information of face location is very important in face reconstruction. According to the literatures [18], this paper presents a new method for using blocks based on local geometric constraints in the expression function of blocks. In order to obtain more accurate reconstruction weights, the prior information of the image block position is taken into account and local geometric constraints are added in this method. The detailed formula is as follows:

$$\varepsilon^q = \left\| x_t^q - \sum_{j=1}^{\bar{N}} w_j \bar{x}^j \right\|_2^2 + \lambda \sum_{j=1}^{\bar{N}} \left(w_j d_j \right)^2 s.t. w_j \geq 0 \tag{4}$$

where λ is a regularization parameter which is used to balance the local relationship between the reconstruction error and the solution. represents the reconstruction weight coefficient of the block with the same location. $d = \left[d_1, \ldots, d_{\frac{T}{N}} \right]$ is the local adaptation with $\bar{N}$ dimension which represents the similarity degree of freedom between the each training block and the input LR block. The detailed expression is as follows:

$$d_j = \left\| \bar{x}_j - x_t^q \right\|_2, \ j = 1, \ldots, \bar{N}. \tag{5}$$

Different degrees of freedom are set for different training blocks. The training blocks close to the input LR block will be selected and the training blocks far away from the LR block will be penalized, according to which local constraints is achieved. In addition, in the neighborhood embedding algorithm, the pre-amplification technique reduces the inconsistency between the manifolds of LR and HR. Then, iterative calculation strategy is introduced into the method based on local geometric constraint position blocks. The iterative update is used to represent the LR block and estimate the HR block, so that the geometry of the HR manifold can be better preserved. The detailed process is as follows.

By using the following Eq. (6), the local constraints in the HR space can be computed and the distance between the HR block and each block in the HR training set can be estimated. Then, the reconstructed weight coefficients are estimated and the new better estimation of the HR block can be obtained.

$$\begin{aligned} \langle \hat{w}, \hat{y}_t \rangle = \operatorname{argmin}_{w, y^t} \Big\{ \Big\| x_t^q - \sum_{k \in N_K(y_t^q)} w_k x_k \Big\|_2^2 + \\ + \tau \left\| dist \odot w \right\|_2^2 \Big\} s.t. w_k \geq 0 \end{aligned} \tag{6}$$

where, represents point multiplication $N_K(y_t^q)$, represents the k-*th* nearest neighbors of the HR block y_t^q to be estimated in the HR block, i. e.,

$$N_K(y_t^q) = support(dist|_K) \tag{7}$$

where $dist \in R^{\bar{N}}$ is the distance between the image block and y_t^q in the HR image block set and $dist|_K$ represents the smallest k units of *dist*.

$$dist_j = \left\| \bar{y}_j - y_t^q \right\|_2, \ 1 \leq j \leq N \tag{8}$$

w and y_t^q in Eq. (6) can be iteratively solved respectively. When the n-*th* block is processed, the bicubic interpolation result of

Table 1
Face Image SR algorithm Based on Pre-amplification Non-negative Restricted Neighborhood Embedding (PNRNE)

Algorithm 1: PNRNE SR algorithm of face image
Input: LR training block set and HR training block set Inputting image block set **Set parameters:** The size of the HR image block; The size of the temporary LR image block; The number of overlapping pixels between HR and LR image blocks; The neighbor's number; Local Restricted coefficient; Iterative number **Step 1**: Calculate the weight coefficient iteratively according to the formula (4). **Step 2:** Estimate the distance between the HR block and each block in the HR training set using the formula (7, 8). Then obtain the k-nearest neighbors in the HR block set. **Step 3:** Substitute the distance between the HR blocks obtained by Step 2 intothe formula (6) Update and by minimizing formula (6) and compute and iteratively. **Step 4:** Reconstruct the corresponding HR block using the optimal weight coefficient obtained by Step 3 according to formula (9). **Step 5:** Splice the HR blocks to obtain the final HR image.

the LR block is set to the initial value of $y_t^q(n)$. By minimizing the formula (6) to continually update $w(n)$ and $y_t^q(n)$, the optimal reconstruction weight $\hat{W}$ of the LR block can be applied to Eq. (9) as

$$y_t = \sum_{\bar{y}_k \in N_K(y_t^q)} \hat{w}_k x_k. \tag{9}$$

The order of the above processing is from top to bottom and from left to right based on the position of the block in the image. According to document [17], there is compatibility between adjacent blocks. Therefore, for the overlapping regions of adjacent blocks, we perform simple averaging operations.

3.3. Overall algorithm. According to the detailed analysis of the above, we can get the general idea of this algorithm. Firstly, based on pre-amplification non-negative restriction, neighborhood relations between HR and LR blocks are most likely to be preserved. Then, the HR image block search mechanism is used in the neighborhood embedding stage, by which the neighboring blocks are estimated and iteratively updated to obtain the optimal reconstruction weights. As the consequence, reconstruction quality has been effectively improved. The detailed processes of the overall algorithm are listed in Table 1. Meanwhile, the flowchart of the proposed method is given in Fig. 1.

4. Experiments

4.1. Evaluation criteria and experimental design. The experiments adopt the widely used evaluation criteria, including mean square error (MSE) and peak signal-to-noise ratio (PSNR). The MSE is mainly used to compare the error between the original HR image and the reconstructed image which is defined as

$$MSE(\hat{x}, x) = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} \left(\hat{x}_{i,j} - x_{i,j}\right)^2 \tag{10}$$

where $\hat{x}_{i,j}$ and $x_{i,j}$ represent the pixel value at the position (i, j) of the reconstructed image and the original HR image, respectively. Mand N are the number of rows and columns of the image. The smaller MSE indicates that the reconstructed image is closer to the original HR image, so the reconstructive effect is better. PSNR provides an objective criterion for measuring image distortion or noise level. So the peak signal-to-noise ratio can be used to evaluate the distortion of the reconstructed image for the original HR image which is defined as:

$$PSNR(\hat{x}, x) = 10 log_1 0 \frac{Max\_I^2}{MSE(\hat{x}, x)} \tag{11}$$

where Max_I^2 represents the maximum value of the image pixel which is generally set to 255. The evaluation results are

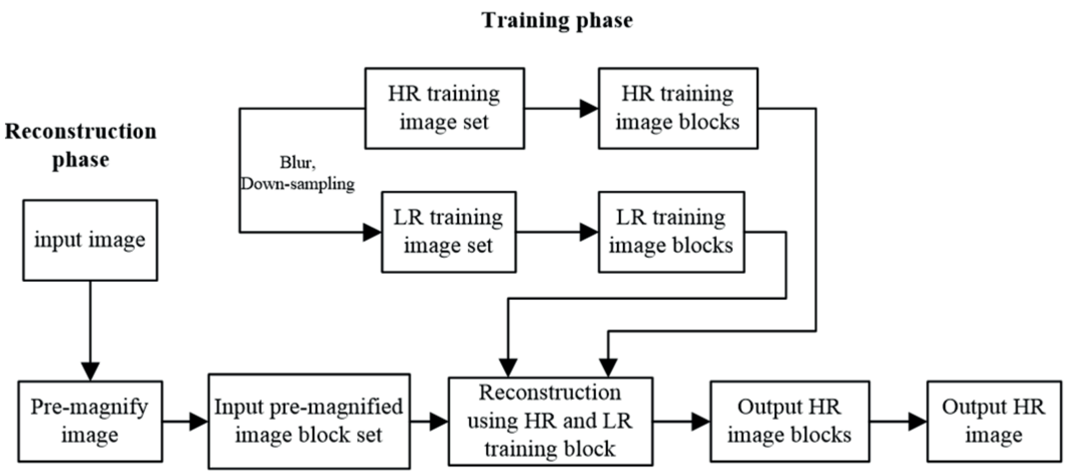

Fig. 1 The flowchart of the proposed algorithm

expressed in units of DB. The larger PSNR indicates that the reconstructed image is less distorted than the original HR image. Obviously, the reconstruction effect is better.

Although MSE and PSNR can demonstrate the reconstruction results to some extent, more experiments show that the traditional MSE and PSNR values are not completely consistent with the subjective visual perception because they only reflect the overall statistical properties of image error. In order to be more consistent with the visual experience, an evaluation criteria based on structural and characteristic similarity is proposed, which is called structural similarity (SSIM). The specific definition is as follows:

$$SSIM(\hat{x}, x) = [l(\hat{x}, x)]^{\alpha}[c(\hat{x}, x)]^{\beta}[s(\hat{x}, x)]^{\gamma}, \quad (\alpha > 0, \beta > 0, \gamma > 0) \tag{12}$$

where the parameters $l(\hat{x}, x)$, $c(\hat{x}, x)$ and $s(\hat{x}, x)$ respectively compare the brightness, contrast and structure between the original HR image and the reconstructed HR image. α, β and γ are used to adjust the relative importance of the three parameters which are defined as

$$l(\hat{x}, x) = \frac{2\mu_x\mu_{\hat{x}} + C1}{\mu_x^2 + \mu_{\hat{x}}^2 + C1}, \quad c(\hat{x}, x) = \frac{2\sigma_x\sigma_{\hat{x}} + C1}{\sigma_x^2 + \sigma_{\hat{x}}^2 + C1},$$

$$s(\hat{x}, x) = \frac{\sigma_{x\hat{x}} + C3}{\sigma_x\sigma_{\hat{x}} + C3},$$

where $\mu_{\hat{x}}$ and μ_x are the average luminance of $\hat{x}$ and x, $\sigma_{\hat{x}}$ and σ_x are the standard deviation of $\hat{x}$ and x, $\sigma_{x\hat{x}}$ is the covariance of $\hat{x}$ and x. $C1$, $C2$, $C3$ are smaller constants to avoid the case where the denominator is zero. The larger shows that the two images have higher structural similarity, which indicates that the reconstructed image quality is better.

The experiments use the public face database CAS-PEAL-R1 in literature [19] which has 30871 face images of 1040 person. From the front subset, the face images of neutral expression and normal lighting of each object are selected for the experiments. In all 1040 positive face images, 1000 images are randomly selected for training. The remaining 40 images are used for testing. The 4×4 mean filter was used to smooth the HR object. The corresponding LR image can be obtained by down-sampling 4 times if the SR reconstruction magnification is 4. Then these LR images are pre-amplified to get LR training images. In the experiments, the HR image block size is set to 12×12 and the temporary LR image block size is set to 3×3. In order to ensure the local compatibility and smoothness of the adjacent image blocks, there are four and two pixels overlap in the high and low image blocks, respectively. According to the experience obtained from a large number of experiments, the number of iteration is set to 5.

4.2. Experimental results and analysis. In the proposed algorithm of this paper, there are two important parameters that directly affect the effect of the algorithm, which are nearest neighbor number K and the regularization parameter. In order to find out the influence of these two parameters on SR reconstruction, a large number of experiments are carried out and the average maximum PSNR and SSIM of all tested face images are calculated. For each round of the experiments, one parameter is fixed, and the other parameter is changed according to a certain rule. The effects of these two parameters on the experimental results are shown in Figs 2 and 3.

For the nearest neighbor block K, theoretically, the more nearest neighbor blocks selected from the training set, the better the obtained HR image effect should be. However, this also means longer running times and higher running costs. The effect of K on the final reconstruction results is shown in Fig. 2. As can be seen from the figure, when K increases from

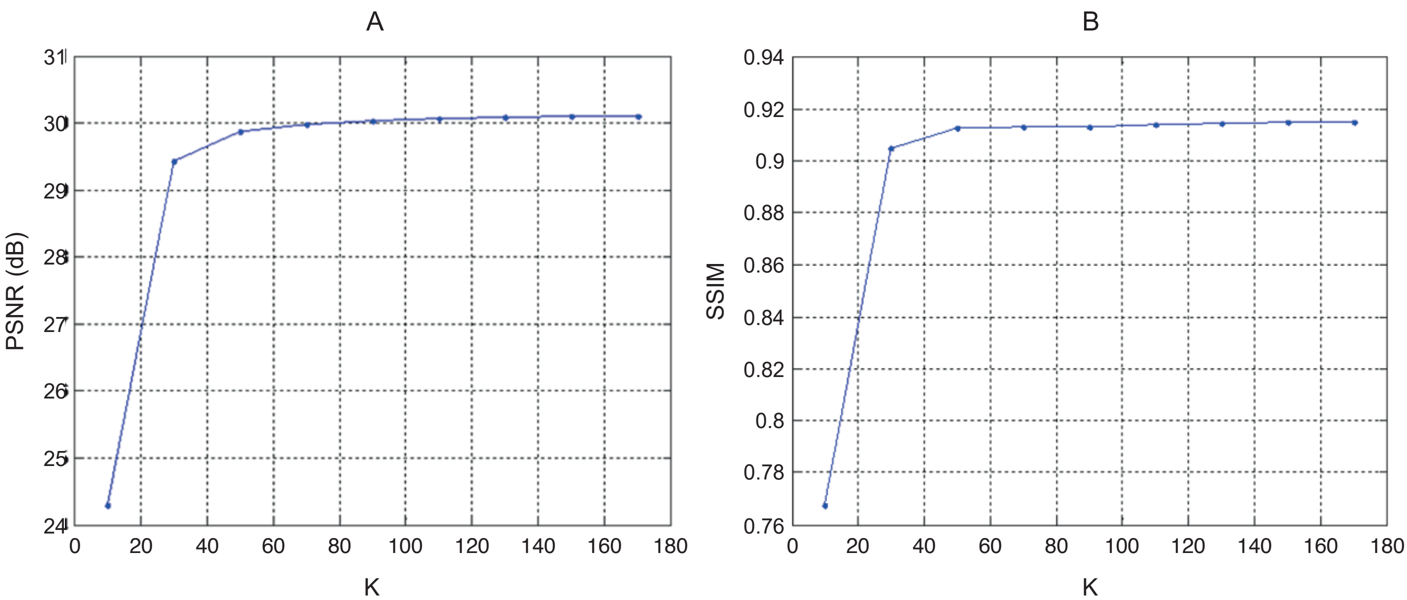

Fig. 2. The effect of Kon reconstructive image quality

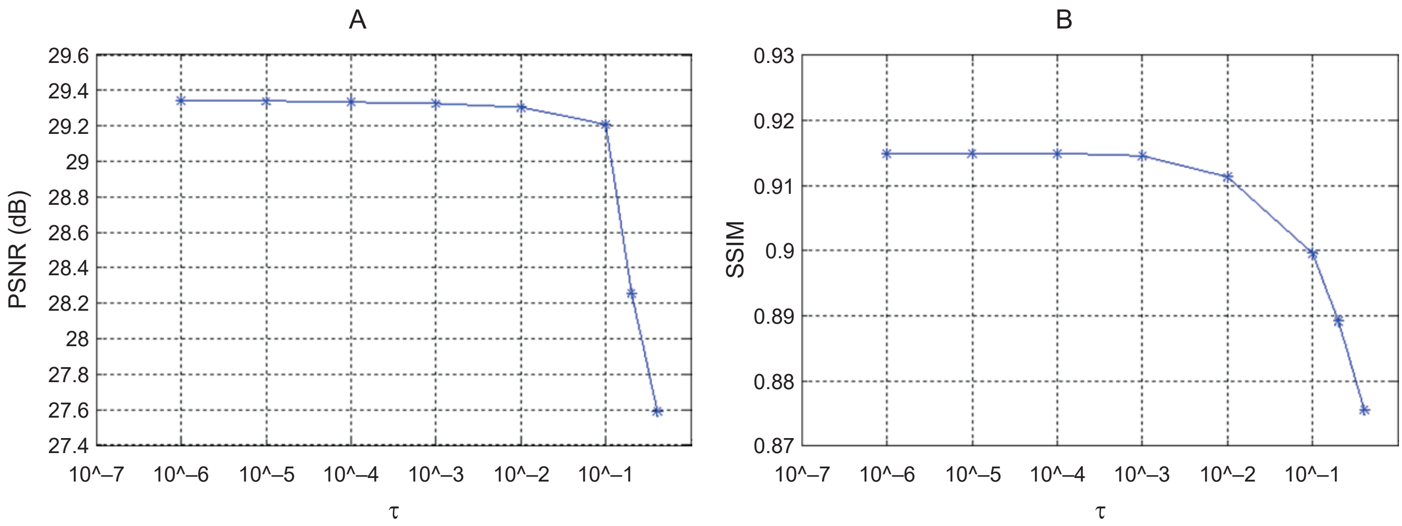

Fig. 3. The effect of τ reconstructive image quality

10 to 50, the PSNR and SSIM increase significantly with the increasing of K. When the value of K is greater than 150, K has almost no effect on the reconstruction results. Therefore, by comprehensive consideration, the value of K is set to 155 in the experiments.

In the proposed algorithm in this paper, τ is a regularization parameter, which is used to balance the contribution between the reconstruction error and the local block. In order to reveal the role of the regularization parameter τ effectively, we carried out experiments also. The effect of this parameter on the quality of reconstructed face images is shown in Fig. 3.

As can be seen from Fig. 3, the regularization parameter τ has a very significant influence on the quality of the reconstructive HR images. If τ is too small, it indicates that the penalty locality constraints is too much. If the τ is too large, it means that the local information is over learning, which will lead to a decrease in the quality of the reconstructed result. In the experiments, we set that $\tau = le - 5$. In order to demonstrate the effectiveness of the proposed algorithm, the proposed method is compared with other typical algorithms which are

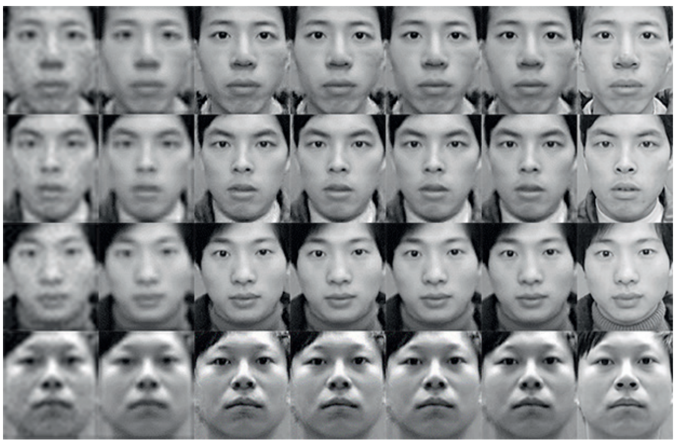

Fig. 4. Experimental results of 4 times SR reconstruction of test images

bicubic algorithm, neighbor embedding-based (NE-based) [6], locality-constraint representation algorithm(LcR) [11], sparse representation algorithm(SR) [17], and locality-constraint iterative neighbor embedding (LINE) [12] respectively.

First of all, we perform the SR reconstruction on 40 face images using the above 4 different algorithms and our method. In the experiments, the multiple of SR reconstruction is 4and the multiple of pre-amplification is set to 2. Table 2 is the detailed experimental results which give the PSNR and SSIM values of different algorithms. From the table, we can see that the proposed algorithm has a better reconstruction effect than other algorithms.

Table 2
The PSNR and SSIM values of different algorithms

SR algorithm	**MSE**	**PSNR(dB)**	**SSIM**
Bicubic	276.20	24.23	0.8180
NE-based [6]	106.43	27.86	0.8859
LcR [11]	97.29	28.25	0.8972
SR [17]	86.91	28.74	0.9024
LINE [12]	75.87	29.33	0.9143
Proposed	63.54	30.10	0.9148

To further evaluate the effects of the proposed SR reconstruction algorithm, we conduct qualitative experiments, in which three face images are reconstructed by different algorithms. Figure 4 demonstrates the experimental results. From the figure, the images of first column are degraded LR images, and the images in column 2, 3, 4, 5, 6 are the HR image reconstructed by Bicubic, NE-based [6], LcR [11], SR [17], and proposed method, respectively. The images in column 7 are the original HR images. It can be seen that our algorithm has the best reconstruction effect. The reconstructed HR image contains more details of the image and is closer to the original HR image.

5. Conclusion

In view of the shortcomings of the traditional neighborhood embedding algorithm, this paper proposes a novel SR reconstruction algorithm based on pre-amplification non-negative restricted neighborhood embedding. During the training phase, pre-amplification techniques are used for the transition. When the magnification is large, the neighborhood relation of HR and LR image blocks can be maintained well. Inspired by the idea of "the whole is equal to the sum of parts", the reconstruction error is reduced by using non-negative restriction. Then, the nearest neighbor search mechanism is introduced, and the HR block obtained by bicubic interpolation algorithm is used as the initial value. Finally, the distance between HR training image blocks is calculated and the nearest neighbor of HR block is searched. According to the distance, the weights are penalized to obtain the weights and the corresponding HR blocks. After several iterations, the reconstructive HR image block can be obtained. The experimental results show that the proposed algorithm is superior to the traditional algorithm in subjective visual effect and objective evaluation.

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References

[1] C. Hong, Y. Dityan, and X. Yimin, Super resolution through neighbor embedding [C], *IEEE ComputerSociety Conference on Computer Vision and Pattern Recognition*,Washington DC, USA, 2004: 275–282.
[2] X.B. Gao, K.B. Zhang, D.C. Tao, et al., Image super-resolution with sparse neighbor embedding [J]. *IEEE Transactions on Image Processing*, 2012, 21(7):3194–3205.
[3] K. Su, Q. Tian, Q. Xue, et al., Neighborhood issue in singleframe image super-resolution [C], *IEEE International Conference on Multimedia and Expo*, 2005:1122–1125.
[4] D. Wysoczański, J. Mroczka, and A.G. Polak, Performance analysis of regularization algorithms used for image reconstruction in computed tomography[J]. *Bull. Pol. Ac.: Tech*., 2013, 61(2): 467–474.
[5] J. Mairal, F. Bach, J. Ponce, et al., Non-local sparse models for image restoration [C]. *IEEE International Conference on Computer Vision*, 2009: 2272–2279.
[6] S. Baker and T. Kanade, "Hallucinating faces," in Proc. 4th IEEE Int. Conf. Autom. Face Gesture Recognit., Mar. 2000, pp. 83–88.
[7] C. Liu, H.-Y. Shum, and C.-S. Zhang, "A two-step approach to hallucinating faces: Global parametric model and local nonparametric model," in *Proc. IEEE Comput. Soc. Conf. CVPR*, vol. 1, Dec. 2001, pp. I-192-I-198.
[8] N. Wang, D. Tao, X. Gao, X. Li, and J. Li, "A comprehensive survey to face hallucination", *Int. J. Comput. Vis*., vol. 106, no. 1, pp. 1–22,2013.
[9] M. Xiang, Z. Jun-ping, and Q. Chun, Hallucinating face by position-patch [J]. Pattern Recognition, 2010, 43(6): 2224–2236.
[10] C. Jung, L. Jiao, B. Liu, and M. Gong, "Position-patch based face hallucination using convex optimization", *Signal Processing Letters*, IEEE, vol. 18, no. 6, pp. 367–370, 2011.
[11] J. Jiang, R. Hu, Z. Han, T. Lu, and K. Huang, "Position patch based face hallucination via locality-constrained representation", in *ICME*, 2012, pp. 212–217.
[12] J. Jiang, R. Hu, Z. Han, Z. Wang, T. Lu, and J. Chen, "Locality constraint iterative neighbor embedding for face hallucination", in *Proc. IEEE ICME*, Jul. 2013, pp. 1–6.
[13] S.T. Roweis and L.K. Saul, "Nonlinear dimensionality reduction by locally linear embedding", *Science*, vol. 290,no. 5500, pp. 2323–2326, 2000.
[14] K. Zhang, X. Gao, D. Tao, etal., Single image super-resolution with non-local means and steering kernel regression [J]. *IEEE Transactions on Image Processing*, 2012, 21(11):4544–4556.
[15] D.D. Lee and H.S. Seung, Learning the parts of objects by nonnegative matrix factorization [J]. *Nature*, 1999, 401(6755): 788–791
[16] Z. Han, J. Jiang, R. Hu, T. Lu, and K. Huang, "Face image superresolution via nearest feature line", in *ACM MM*, 2012, pp. 769–772.
[17] J. Yang, J. Wright, T.S. Huang, and Y. Ma, "Image superresolution via sparse representation", *IEEE Trans. Image Process*., vol. 19, no. 11, pp. 2861–2873, Nov. 2010
[18] J. Jiang, R. Hu, Z. Wang, and Z. Han, "Noise robust face hallucination via locality-constrained representation", *IEEE Trans. Multimedia*, vol. 16, no. 5, pp. 1268–1281, Aug. 2014.
[19] W. Gao, B. Cao, S. Shan, X. Chen, D. Zhou, X. Zhang, and D. Zhao, "The cas-peal large-scale Chinese face database and baseline evaluations", *IEEE TSMC*, Part A, vol. 38, no. 1, pp. 149–161, 2008.