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A NOVEL NEIGHBOR EMBEDDING SUPER RESOLUTION USING ICA AND IMPROVED NLIBP

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Abstract- In this paper, a novel technique for neighbor embedding single image super resolution (SR) is proposed. An evolutionary algorithm known as Imperialist Competitive Algorithm (ICA) is applied for neighbor embedding single image super resolution. ICA is used for minimizing the reconstruction error of reconstruction weights for neighbors of each low-resolution patch in the low-resolution training image set as a cost function. Additionally, we use improved non-local iterative back-projection (NLIBP) based on edge detection as a post-processing method which perfectly reserves edges in the reconstructed images. The method is applied on various color images and also compared to existing approaches. The results show that the proposed algorithms can more accurately enlarge the low-resolution image than other approaches. The proposed algorithm improves the PSNR by 2.8db on average and reduces the RMSE by 3.2 on average. Visual quality of enlarged images is improved as well.

Keywords: Neighbor Embedding, Imperialist Competitive Algorithm (ICA), Improved Non-Local Iterative Back-Projection (NLIBP).

I. INTRODUCTION

The super-resolution (SR) methods can be divided into two classes: one class is multiple-frame SR [1, 2], which a high-resolution (HR) image generated from multiple low-resolution (LR) images and the other one is single-frame SR [3-6], which a HR image generated from a single LR image, with the help of training set images. This paper addresses the problem of recovering a super-resolved image from a single low-resolution input.

Neighbor embedding algorithm has been widely used in example-based super-resolution reconstruction from a single frame, which assumes that neighbor patches embedded are contained in a single manifold. Chang et al. (2004) first propose neighbor embedding super-resolution method, which assumes patches of high and low-resolution images, can form manifolds with similar local geometry in the two different feature spaces. First, they compute the reconstruction weights of each low-resolution patch's neighbors in low-resolution training image set by minimizing the reconstruction error.

Second, they estimated the high-resolution embedding from the training image pairs by preserving local geometry. Finally, they enforce local compatibility between adjacent high-resolution patches. Instead of using the super resolution problem directly with highly computationally complex algorithms, ICA algorithm can be applied to find optimal weights of each low-resolution patch's neighbors and promote the output results. ICA is used to solve different optimization problems in various areas of engineering and science.

The following are some of the applications of this algorithm: Designing controller for industrial systems, Designing Intelligent Recommender Systems, Solving optimization problems in communication systems, Solving scheduling and production management problems, Training and analysis of Artificial Neural Networks, Nash Equilibrium Point Achievement, Design and thermodynamic optimization of plate-fin heat exchangers, and so on [7-10].

In this paper, we apply ICAs approaches for finding the optimum value for the reconstruction weights of each low-resolution patch's neighbors in low-resolution training image set, by minimizing the reconstruction error as a cost function in Neighbor Embedding methods. Moreover, we try to find the reconstructed image which sharp edges are well preserved and no jaggy artifacts affect reconstruction quality. Experimental results show that this approach can effectively obtain high-resolution image and make the super-resolution algorithm of the image more practical.

This paper is organized as follows. In section II we briefly give a review of improved NLIBP algorithm based on edge detection and ICA. In section III we outline the methodology of this ICA and improved NLIBP algorithm to solve the neighbor embedding super resolution problem, followed by the experiments and analysis in section IV. The conclusion forms the last section.

II. REVIEW OF IMPROVED NLIBP ALGORITHM AND ICA

A. Improved NLIBP Algorithm

Dong et al. proposed the non-local iterative back-projection (NLIBP) method [11] in which the non-local image redundancies was used to lead the back-projection procedure. However, for images with large area, the NLIBP method may generate some undesirable artifacts. Pixels along strong edges can effectively use the non-local redundancies, and the absolute difference between the original pixel and the reconstructed pixel becomes smaller. Nevertheless, this is not always true to pixels allocated in flat areas, because it may include some dissimilar pixels in the data fusion.

Therefore, the reconstruction quality will be threatened when the input image has large flat areas with shading background or many disorderly fine textures. Because both the sharpness of edges and the smoothness of the total image are significant quality metrics for the image SR reconstruction, the improved non-local iterative back projection algorithm is to arrange the non-local post processing to avoid the difficulties existed in the NLIBP algorithm [8].

So in the improved algorithm, it controls the use of non-local post-processing by detecting whether there are some strong edges existed in the pixel's 7×7 square neighborhood. It uses canny edge detection algorithm to exploit strong edges. Pixels, whose 7×7 square neighborhood exists strong edges, will be blurred. In addition, this is the case where non-local post processing is needed to keep the edges well preserved. The initial Bicubic interpolation image is exploited to reconstruct the flat area. More details on the mechanism of improved NLIBP can be found in [11, 12].

B. ICA Algorithm

In computer vision, Imperialist Competitive Algorithm (ICA) [13] is a method that is used to solve optimization problems. Population individuals, which are called countries, are divided into two types: colonies and imperialists that all together form some empires. Imperialistic rivalry between these empires forms the basis of ICA. All the empires try to win this game and take ownership of colonies of other empires. At each step of the algorithm, based on their authority, all the empires have a chance to govern of one or more of the colonies of the weakest empire [13].

Algorithm continues with the steps until a stop condition is satisfied. Imperialistic rivalry hopefully converges to a condition in which there is only one empire and its colonies are in the same position and have the same cost as the imperialist. The ICA algorithm can be summarized as follows [13]:

1- Procreate some random solution in the search space and generate initial empires.
2- Assimilation: Colonies move towards imperialist states in different in directions.
3- Mutation: Random changes occur in the specifications of some countries.
4- Position replacement between a colony and Imperialist. If there is a colony has lower cost than imperialist take the control of empire by changing the existing imperialist.
5- Imperialistic competition: All imperialists compete to take possession of colonies of each other.
6- Remove the weak empires. Powerless empires lose their power gradually and they will finally be eliminated.
7- If the stop condition is content, stop, if not go to 2.

III. PROPOSED ALGORITHM

In this section, we will describe the idea of the proposed method. Our contribution consists of two steps. Firstly, we generate HR image through neighbor embedding via ICA algorithm. We use ICA method to find the optimal value for the reconstruction weights of each low-resolution patch's neighbors in low-resolution training image set by minimizing error of reconstructing which can produce the optimal result (better PSNR). Then, improved non-local back projection is applied as a post-processing method for minimizing the reconstruction error significantly in iterative manner and gives good result.

The post-processing method, which is used in our contribution, integrates canny edge detector with NLIBP which improves visual quality with very fine edge details. The parameters of canny edge detection algorithm include MAX, which is maximum threshold value for hysteresis, MIN value which is the minimum, and SIGMA which is used for generating the Gaussian kernels [12]. As follows, we briefly review method in [14]. Then, we describe our proposed method. Chang et al. [14] first proposed idea of neighbor embedding for super-resolution reconstruction. According to [14] target high-resolution image Y_t of a low-resolution image X_t is estimated using a training set of low resolution images X_s and corresponding high-resolution images Y_s.

Each low- or high-resolution image is as a set of overlapping image patches. The numbers of patches for X_t and Y_t are the same, and the number of each low-resolution image in X_s and the corresponding high-resolution image in Y_s also have the same number of patches. The groups of image patches denote corresponding to x_s, y_s, x_t and y_t as $\{x_s^p\}_{p=1}^{N_s}$, $\{y_s^p\}_{p=1}^{N_s}$, $\{x_t^q\}_{q=1}^{N_t}$ and $\{y_t^q\}_{q=1}^{N_t}$. Neighbor embedding algorithm for SR reconstruction can be summarized as follow [14]:

1- For each patch x_t^q in image X^t do:

a) Find the set N_q of K nearest neighbors in X_s.

b) Calculate the reconstruction weights of the neighbors for minimizing the error of reconstructing x_t^q as following equation [14].

$$\varepsilon^q = \| x_t^q - \sum_{x_s^p \in N^q} w_{qp} x_s^p \|^2 \tag{1}$$

where, w_{qp} is the weight for x_s^p , subject to the following constraints [14]:

$$\begin{cases} \sum_{x_s^p \in N_q} w_{qp} = 1 \\ w_{qp} = 0 \quad \text{for} \quad x_s^p \notin N_q \end{cases} \tag{2}$$

c) Compute the high-resolution embedding y_t^q as Equation (3) [14] using the appropriate high-resolution features of the K nearest neighbors and the reconstruction weights.

$$y_t^q = \sum_{x_s^p \in N_q} w_{qp} y_s^p \tag{3}$$

2- Create the target high-resolution image Y^t.

For minimizing ε^q, define a local Gram matrix G_q for x_t^q as the following equation [14].

$$G_q = (x_t^q 1^T - X)^T (x_t^q 1^T - X) \tag{4}$$

where, 1 is a column vector of ones and X is a $D\times K$ matrix with its columns being the neighbors of x_t^q. Moreover, we gather the weights of neighbors to form a K-dimensional weight vector W_q and then solve the linear system of equations $G_qW_q = 1$.

In the proposed method, we proposed the use of ICA for calculate the reconstruction weights of each low-resolution patch's neighbors in low-resolution training image set instead of using local Gram matrix G_q. According to ICA, we start by generating a set of candidate random solutions, which shows the reconstruction weights in the optimization problem search space. The generated random weights are called the initial Countries. Countries in this algorithm are considered the peer of Chromosomes in GAs and Particles in Particle Swarm Optimization (PSO) and it is an array of values of a candidate solution of optimization problem.

The power of each country is determined by cost function of the optimization problem. In our method, we define ε^q as the cost function. Based on their cost function value (value of ε^q), some of the best initial countries (the weights with the least cost function value), become Imperialists and govern other countries and form the initial Empires and this [13]. Algorithm continues with the Assimilation, Revolution, and Competition steps until a stop condition is satisfied. In this way, the algorithm has low complication, while preserving the performance.

After finding optimal value of the reconstruction weights as mentioned above, and construct the output high-resolution image, post processing method is used in order to generate a sharper high resolution image. We extract strong edges existed in the initial high resolution by canny edge detection algorithm with parameters selected follows. Improved NLIBP algorithm is an efficient method that is conducted on the pixels that belong to the strong edge area and repeated iteratively to minimize the energy of the error. Our algorithm can be summarized as follows:

1- Construct the initial high-resolution image by neighbor embedding based ICA as follows:

a) For each patch x_t^q in image X^t do:

i. Find the set N_q of K nearest neighbors in X_s.

ii. Define $\varepsilon^q = \| x_t^q - \sum_{x_s^p \in N^q} w_{qp} x_s^p \|^2$ as cost function for calculating the reconstruction weight of the neighbors for minimizing the error of reconstructing x_t^q as the following equation:

$$\varepsilon(w), \quad w = (w_{qp1}, w_{qp2}, ..., w_{qpd}) \tag{5}$$

i. Start ICA technique for finding optimum reconstruction weights.

ii. If the stop condition is satisfied, stop, if not continue.

iii. Compute the high-resolution embedding y_t^q.

b) Generate the target high-resolution image Y^t.

2- Edge area extraction approach is exploited to divide the initial high resolution image into two parts: at area and edge area.

3- Then, NLIBP is conducted on the pixels that belong to the strong edge area to preserve the edge of the HR image. According to the edge information detected in Step 2. Only pixels, whose 7×7 square neighborhood exist edges, will be followed by a non-local post-processing introduced in Section II to keep the edges well preserved.

4- The initial HR image is exploited to reconstruct the flat area of the HR image.

The flowchart of our proposed algorithm can be seen in Figure 1.

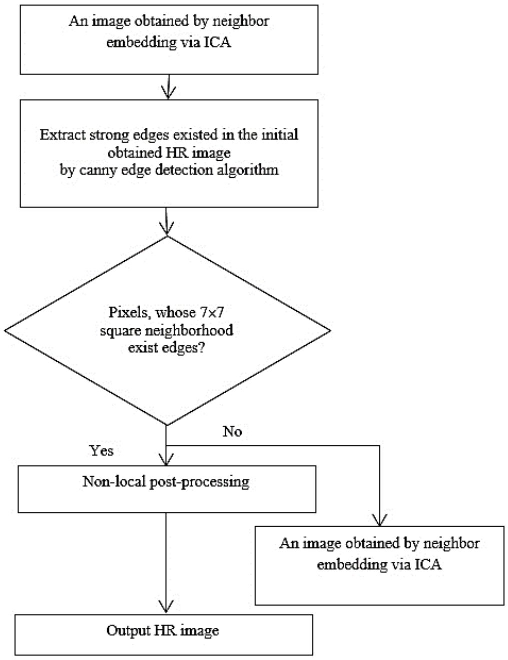

Figure1. The proposed SR framework

IV. EXPERIMENTAL RESULT

This section will show the performance of the proposed method and perform comparisons between Bicubic interpolation and Chang's method [14]. Four images shown in Figure 2 are taken and tested. In our method, initial input LR image was generated from original HR image. To get input LR images, each HR is degraded by blurring, and down-sampled with factor 2 to product a testing input image. In our experiment, the size of the input HR images is 256×256.

The LR image is viewed as the test images and the HR image is viewed as the ground-truth images. We attempt to obtain the corresponding reconstruction images with the single input LR image. For all the experiments, when any one image is seen as a testing image, the rest acts as the generation of training samples. For low-resolution images, we find $M \times M$ patches with an overlap of N pixels between adjacent patches. If we want to magnify a low resolution image by S times in each dimension, then we use $SM \times SM$ patches in the high-resolution image with an overlap of SN pixels between adjacent patches. In our experiment, we select parameters of neighbor embedding as follows: low resolution patch *size* = 3, *overlap* =1 and K = 5.

As mentioned above, we use ICA for finding the reconstruction weights of each low-resolution patch's neighbors in low-resolution training image set. In addition, we adopt canny edge detection algorithm to extract strong edges in our method, and we believe that persuasive results can be got by some other more appropriate edge detection algorithms. Considering that, only hard edges are cared in our algorithm. Maximum and Minimum threshold value for hysteresis and SIGMA are set to 1, 0.04 and 1.2 respectively, which give the most favorable result among groups of thresholds we have tested.

The result of this edge detector is a binary image in which the white pixels closely approximate the true edges of the original image. The obtained results of canny edge detector on four testing images can be seen in Figure 3. In our proposed algorithm, for improved NLIBP algorithm, the initial estimation is generated by a neighbor embedding via ICA algorithm. In addition, the size of patches for block matching is set to 7×7 pixels. The threshold for similarity between patches is set to 10, and the parameter t, a parameter to control the decaying speed, is set to 0.6.

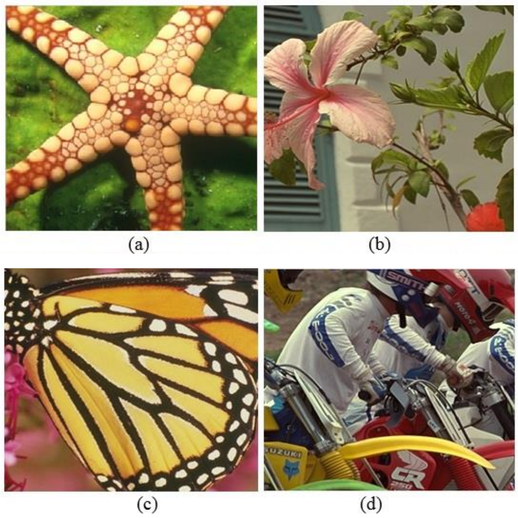

Figure 2. Test images, (a) Starfish, (b) Flower, (c) Butterfly, (d) Bike

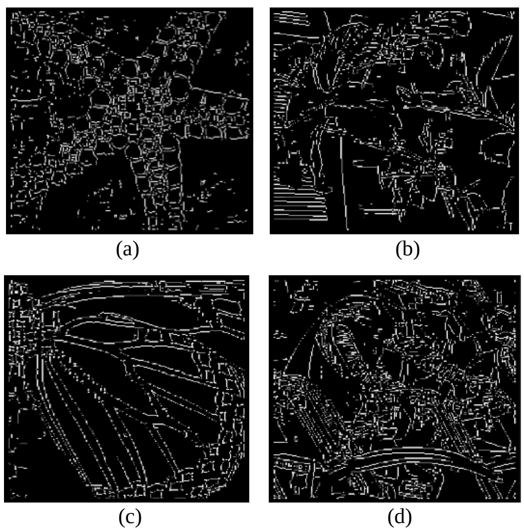

Figure 3. Edge region extraction, (a) Starfish edge image, (b) Flower edge image, (c) Butterfly edge image, (d) Bike edge image

Peak signal-to noise ratio (PSNR) and Root mean square error (RMSE) have been used as objective measures of super-resolution; however, the outstanding method of presenting results is clearly subjective to visual quality. In Table 1, we compare the PSNR value between Bicubic interpolation, neighbor embedding method in [14], and our proposed method. In Table 2, we compare the RMSE value between Bicubic interpolation, neighbor embedding method in [14] and our proposed method.

For all testing images, the results show that our method achieve higher PSNR value and lower RMSE value than other methods. The results of applying different super resolution methods to obtain 2X magnification to a starfish image, a flower image, a butterfly image and a bike image can be seen in Figure 4, Figure 5, Figure 6, and Figure 7, respectively. As we can see from it, our proposed method can achieve better visual effects and the obtained results are sharper in the edge area when compared with other techniques.

Table 1. PSNR comparison

Image	Bicubic interpolation	Our approach	Chang's method [14]
Starfish	25.6129	31.7972	28.3736
Flower	26.1858	31.3775	28.5701
Butterfly	22.7827	29.1351	25.8291
Bike	21.9979	26.8569	24.1312

Table 2. RMSE comparison

Image	Bicubic interpolation	Our approach	Chang's method [14]
Starfish	13.3627	6.5566	9.7243
Flower	12.5099	6.8812	9.5068
Butterfly	18.5096	8.9081	13.0342
Bike	20.2583	11.5797	15.8481

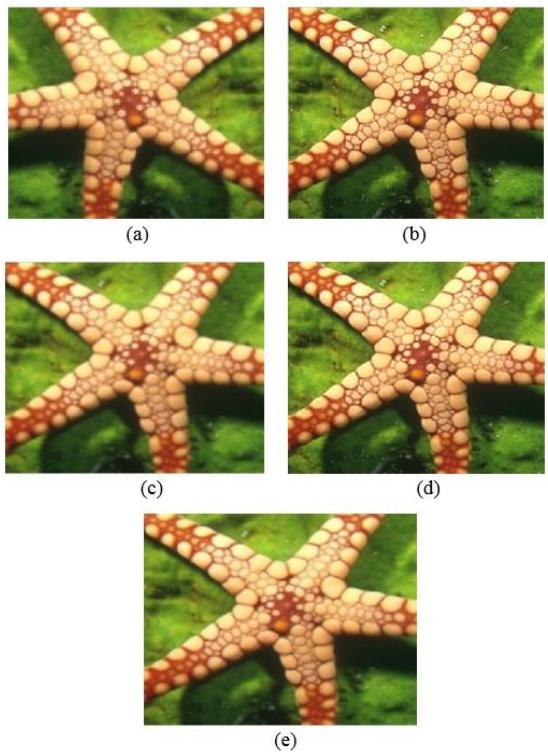

Figure 4. (a) Input LR image, (b) Original HR image, (c) Bicubic interpolation, (d) Our method, (e) Chang's method [14]

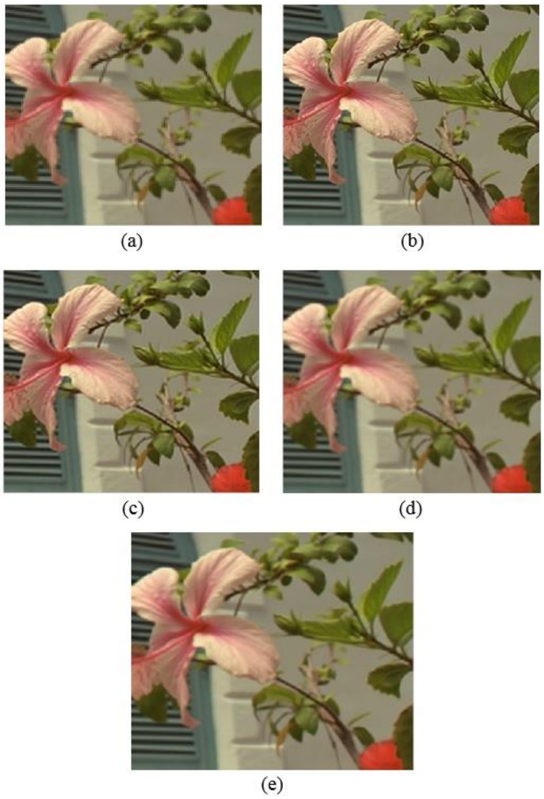

Figure 5. (a) Input LR image, (b) Original HR image, (c) Bicubic interpolation, (d) Our method, (e) Chang's method [14]

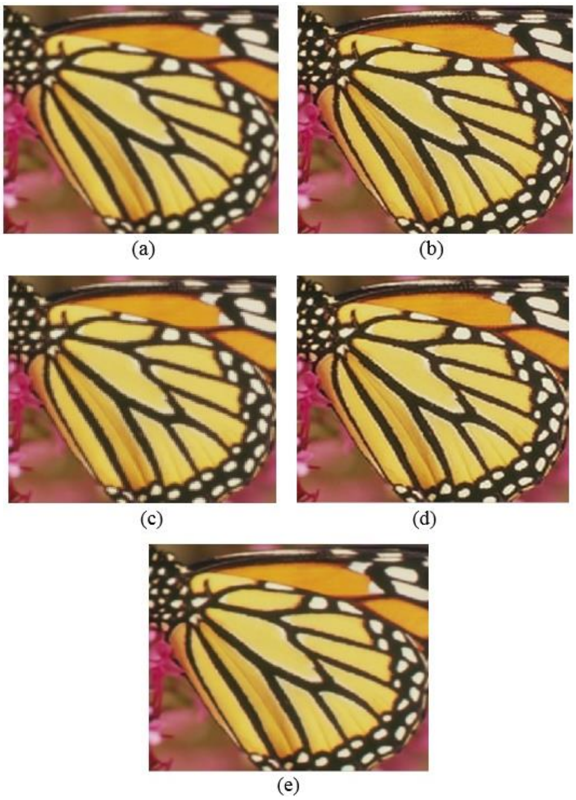

Figure 6. (a) Input LR image, (b) Original HR image, (c) Bicubic interpolation, (d) Our method, (e) Chang's method [14]

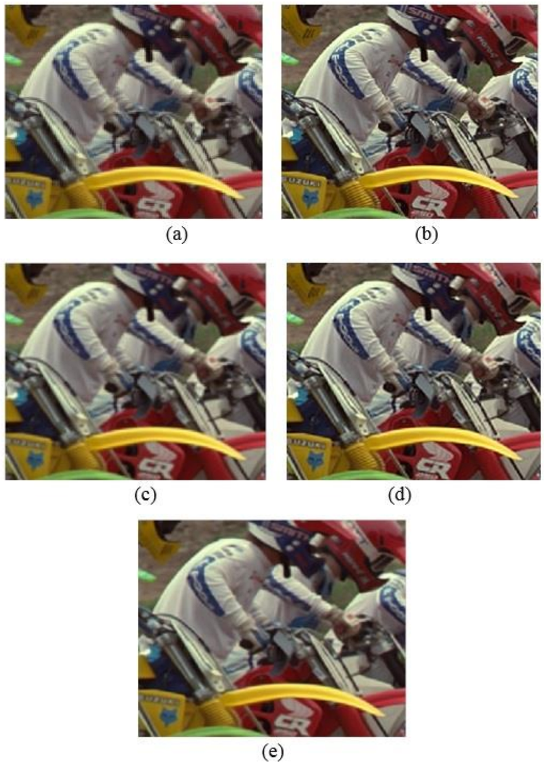

Figure 7. (a) Input LR image, (b) Original HR image, (c) Bicubic interpolation, (d) Our method, (e) Chang's method [14]

V. CONCLUSIONS

In this work, a novel super resolution algorithm is proposed to enhance the images. The proposed method uses ICA algorithm in neighbor embedding method for minimizing the reconstruction error of HR image by optimizing the weights of each low-resolution patch's neighbors in low-resolution training image set. It also applies an improved NLIBP as a post processing method for reducing jaggiest of the reconstructed image resulting sharp edges. Experimental results illustrate the effectiveness of the back-projection error correction and high frequency in obtaining a high-resolution image.

Results of the proposed technique are compared to Bicubic interpolation and neighbor embedding technique as in [14]. The obtained results show that the proposed algorithm can achieve better results than the other ones. The proposed method improves the PSNR by 2.8 db on average and diminishes the RMSE by 3.2 on average. As a result, ICA in neighbor embedding method and improved NLIPB can reconstruct high quality images in both aspects of objective quality and subjective perception with edge perseveration.

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