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Image Super-Resolution Reconstruction Method Based on Sparse Residual Dictionary

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Abstract

In order to improve the resolution of degraded images, an image super-resolution reconstruction method based on sparse residual dictionary is proposed. Firstly, the fuzzy matrix and down-sampling are used to degrade the high-resolution image set to get the corresponding low-resolution image set, and the Bicubic interpolation method is used to reconstruct the low-resolution image, and the high-resolution residual image set is obtained by comparison. The residual image contains the high frequency information of the image. Secondly, using the method of sparse dictionary learning, the residual maps are trained as a sample, and the sparse residual dictionary pair through joint dictionary training. Finally, the sparse coefficient of the image calculated by using the low-resolution dictionary and the low-resolution image to be reconstructed, and the similarity between the low-resolution and high-resolution image blocks and the sparse representation of the corresponding real dictionary strengthened, so as to realize the image super-resolution reconstruction. The experimental results show that the proposed algorithm performs well in both subjective and objective evaluation of reconstructed images.

Keywords: Interpolation; Joint Dictionary Training; Sparse Dictionary;

1. Introduction

Image super-resolution (SR) reconstruction uses a single or a set of low-resolution (LR) to reconstruct a high-

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resolution (HR) image based on certain assumptions or prior information [1]. Since the input of low-resolution images provides limited information, image super-resolution reconstruction is a typical ill-conditioned inverse problem that requires relevant prior information [2]. Existing super-resolution methods can be roughly divided into three categories: based on interpolation [3], based on reconstruction [4] and based on learning [5]. The interpolation method based on polynomial approximation with full representation, the method is simple and fast, but the image blur quality is poor. The reconstruction-based method can effectively maintain the boundary sharpness and suppress false by applying a set of linear constraints to unknown high-resolution pixel values. Shadow, but when the magnification factor is large, the reconstruction effect is poor. IBP (Iterative Back Projection) is a common SR method based on reconstruction, which constrains the estimated high-resolution image by modeling the degradation process [6]. The learning-based method is a commonly used method by learning and training image and making full use of the image with the prior knowledge inherent in the image [7].

In recent years, with the deep research of compressed sensing and machine learning and the super-resolution method based on learning, many scholars have carried out research and made a series of achievements. Yang et al. [5] combined the theory of compressed sensing with sparse coding to propose an image super-resolution algorithm based on sparse representation. This method uses a set of external training images to learn a pair of LR/HR dictionaries to solve low-resolution image blocks. In the LR dictionary, the sparse coefficients are combined with the HR dictionary to reconstruct the high-resolution image. In the follow-up study, Yang et al. [8] proposed a super-resolution (ScSR) algorithm based on sparse coding and joint dictionary learning, further enhanced the reconstruction quality and speed of image super resolution. Clasner et al. [9] proposed a super-resolution algorithm for single image based on image self-similarity, which generates sample library through interpolation of the input image at different scales, but with poor adaptive ability, the reconstructed image artifacts are serious. Marco et al. [10] proposed that the super-resolution reconstruction recovers the high frequency information of the image, and proposes an adjacent embedded super-resolution algorithm based on the back-projection residual map to reconstruct the high-resolution image by constructing a pair of new dictionary. Zhu et al.further improved the dictionary and proposed to use the K-SVD algorithm constructs the learning dictionary from the image self-similar block. In the reconstruction stage, the image is sparsely encoded using a simple Orthogonal Matching Pursuit (OMP) algorithm, which improves the quality and speed of reconstruction.

Dictionary learning plays a key role in the super-resolution reconstruction algorithm based on learning. Dictionaries based on learning methods are usually generated by random sampling of images with similar statistical features in the training image set, which can be divided into two categories from their sources: internal dictionary and external dictionary [11,12,13]. The image usually has a lot of self-similarity, and the internal dictionary constructed by the self-similar redundant blocks of the input image itself. The super-resolution method based on the internal dictionary results in too many artifacts in the super-resolution reconstruction because of the information provided by the image itself is limited. The external dictionary is generated by randomly sampling the external training image set. It contains rich feature information and can reconstruct the high-resolution image very well. Different from the internal dictionary, the external dictionary is pre-established, can greatly reduce the calculation amount and time of the reconstruction process [11].

Aiming at the problems of obvious artifacts and low execution efficiency in fast single image super-resolution reconstruct based on self-learning and sparse representation, this paper proposes an image super-resolution algorithm based on residual dictionary learning [14]. Before learning the dictionary, the HR image in the external training image set is preprocessed, and the residual image is extracted. Then a residual dictionary is obtained by using the super-resolution (ScSR) dictionary training method based on sparse coding and joint dictionary learning [15]. The residual maps are used as a sample to train the dictionary of sparse residual, which improves the structure of the dictionary to reduce the complexity of dictionary training and enhance the dictionary's expression of high frequency information and eliminate reconstruction artifacts. Then the sparse coefficient is solved, and the obtained sparse coefficient is combined with the residual dictionary to be applied to the reconstruction stage, which effectively reduces the operation time. The experimental results show that the proposed algorithm not only effectively reduces the dictionary training time and image reconstruction time, but also further improves the quality of reconstructed images.

2. Image Super-Resolution Reconstruction Method Based On Sparse Residual Dictionary

For the given training set $X^H = \{x_1, x_2, \cdots x_n\}$ of external HR images, the corresponding LR image set $Y^L = \{y_1, y_2, \cdots y_n\}$ was obtained by fuzzification and down-sampling operations for each image, and the residual dictionary was introduced into the image super-resolution reconstruction process based on sparse representation with the idea of residual maps. By preprocessing the external training HR image that any image in the external HR image set is first subjected to processed by fuzzification and down-sampling which to obtain the corresponding LR image Y^H, and the image Y^H is interpolated and enlarged to obtain the image $I(Y^H)$ reconstructed by corresponding interpolation. Finally, the new HR residual image is obtained by found the difference $X^H - I(Y^H)$ between the HR image X^H and the interpolated image $I(Y^H)$. This step is similar to a high-pass filtering. The resulting residual map contains the structural information and high-frequency details of the image, as shown in Fig.1. Compared with the traditional dictionary learning method, the residual dictionary filters out the low-frequency part in the training stage, and only trains the high-frequency part of the image, which not only reduces the computational complexity of dictionary training, but also improves the reconstruction ability of the dictionary. Finally, the new HR residual image was processed for noise reduction and the ScSR algorithm [8] was used to train the high and low resolution dictionary, and the final result HR image Y^H was reconstructed. The algorithm process is shown in Fig.2.

Fig.1. Residual map (HR, LR, Interpolation reconstruction, Residual).

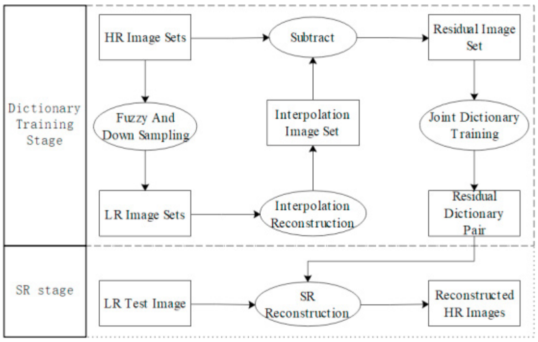

Fig.2. The flow chart.

The specific algorithm steps are as follows:

Step 1. Preprocessing: Degrading the HR training image set to get LR image set, including down-sampling, fuzzy matrix, and then using Bicubic interpolation method to reconstruct the LR image set, get the corresponding interpolation image set (including image texture and structure information), and extract HR residual image set as dictionary training samples.

Step 2. Dictionary pair training: Using ScSR algorithm, the HR residual image set is sparsely coded and trained by model (1), and the high and low resolution residual dictionary pairs are obtained.

$$\min_{\{D_H, D_L, \alpha\}} \frac{1}{N}\left\|X^H - D_H\alpha\right\|_2^2 + \frac{1}{M}\left\|Y^L - D_L\alpha\right\|_2^2 + \lambda\left(\frac{1}{N} + \frac{1}{M}\right)\|\alpha\|_1 \tag{1}$$

Where N and M represent the dimensions of the HR and LR dictionary vector form, respectively.

Step 3. Image reconstruction: First, the LR test image is divided into blocks and the sparse coefficient is solved. Then the corresponding HR image block is obtained by the sparse coefficient. Finally, the HR image to be estimated is obtained by the weighted average processing of the HR image block.

In Step 1, the interpolation method estimates the interpolation pixels by weighting the local pixels. This method has low computational complexity and high speed, and is often used as the basis of other methods. However, the reconstructed image is often too smooth and has ringing and sawtooth effects. Traditional interpolation methods include Nearest Neighbor Interpolation, Spline Interpolation, Bilinear Interpolation and Bicubic interpolation. The Bicubic Interpolation method is the most effective because of its best effect.

In step 2, the dictionary training for a given HR residual image, the first degradation operation to get the LR rate residual image, the size of $k*k$, and then the high and low residual image X is cut into x_i, size is $L*L$. Using the four filter operators of the formula (3) to process each image block can produce four eigenvectors, namely:

$$\mathrm{M}_{ij(L*L)} = x_i \otimes f_j, i = 1,2,\cdots K^2, j = 1,2,3,4 \tag{2}$$

$$f_1 = [-1,0,1], f_2 = f_1^T, f_3 = [1,0,-2,0,1], f_4 = f_3^T \tag{3}$$

Where x_i represents the i-th block image block, f_j is the filter, and M_{ij} is the filtered feature map of image block x_i. Each feature map is synthesized into a column vector β_{ij} with the size of L^2*1. Then, the four column vectors are connected to the composite column vector γ_i as a new representation of the image block, that is $\gamma_i = (\beta_{i1};\beta_{i2};\beta_{i3};\beta_{i4})$, and the size is $4L^2*1$; finally, the column vectors of all the image blocks are merged into a matrix Θ as the latest final representation of the image:

$$\Theta = (\gamma_1, \gamma_2, \cdots, \gamma_{K^2}) \tag{4}$$

Where Θ is the size $4L^2*K^2$, there are K^2 blocks of image block. In this way, the feature representation of each image block also encodes its domain information, which will better predict the neighborhood information of the final SR reconstructed image. Dictionary training is shown in Fig.3.

In step 3, image reconstruction is shown in Fig.4.

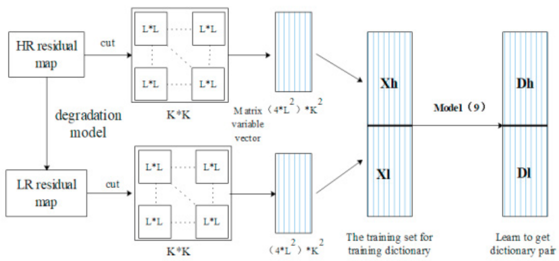

Fig.3. Dictionary Training.

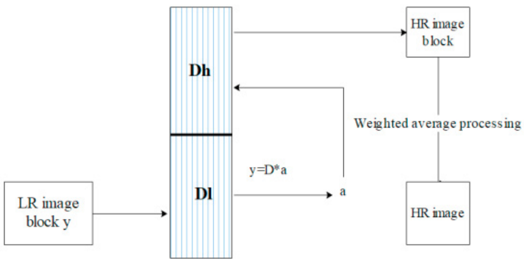

Fig.4. Image Reconstruction.

3. Experiment Analysis

In the simulation experiment, 24 satellite images with a resolution of 1024×1024 were selected as HR image set (Fig.5), and the degraded image set was LR image set (Fig.6). After interpolation reconstruction (Fig.7), the image set of residual image was extracted (Fig.8) as the dictionary training sample set. As can be seen from the residual image, the texture structure information of the image was mainly kept. The training sample of the dictionary is 100,000, the image block size is 5×5, and the sparse regularization is 0.15, the upper sampling factor is 2, and the dictionary size is 1024. In the experiment, Bicubic interpolation was used as the benchmark algorithm to compare the advantages and disadvantages of the ScSR method [8] and the method in this paper. Using baby, butterfly, bird, Lena and head as test objects, Fig.10 shows the reconstructed high-resolution image, and Table 1 shows the comparison of algorithm reconstruction time. At the same time, the reconstructed image's Peak signal-to-noise Ratio (PSNR) and Structural SIMilarity (SSIM) relative to the original high-resolution image are calculated. The results are shown in Table 2 and Table 3.

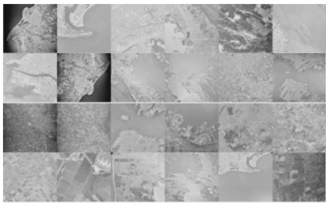
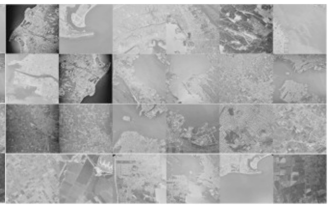

Fig.5. HR image. Fig.6. LR image.

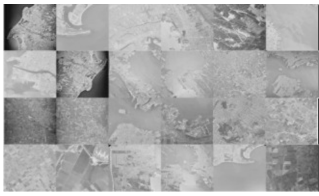
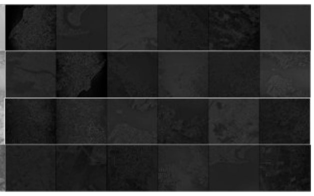

Fig.7. Interpolation SR image. ;Fig.8. Residual image.


(a) lena (b) baby


(c) bird (d) butterfly

(e) head

Fig.9. Reconstruction results (Bicubic; ScSR; algorithm from left to right).

Table 1. Reconstruction time of different algorithms.

Picture	Bicubic	ScSR	algorithm
lena	0.114	47.951	0.2334
baby	0.109	49.702	0.3537
bird	0.121	42.241	0.2403
butterfly	0.105	41.661	0.2379
head	0.117	47.227	0.2416

Table 2. Comparison of reconstructed image PSNR values.

Picture	Bicubic	ScSR	algorithm
lena	32.447	33.920	33.920
baby	36.499	37.484	38.154
bird	36.107	38.389	38.55
butterfly	27.239	28.952	28.952
head	34.431	35.053	35.525

Table 3. Comparison of reconstructed image SSIM values.

Picture	Bicubic	ScSR	algorithm
lena	0.8872	0.9109	0.9044
baby	0.9854	0.9912	0.9922
bird	0.9503	0.9701	0.9711
butterfly	0.8954	0.9304	0.9090
head	0.8268	0.8513	0.8610

It can be seen from the visual intuition of Figure 9 that the effects of the reconstruction of the three algorithms are not much different, and the artifacts and aliasing effects appear in the edge part. The algorithm reduces the blur in detail, the edge sawtooth effect is improved, and the high-frequency information is more prominent and the effect is better.

As can be seen from Table 1, in terms of reconstruction time, the image reconstruction time of various SR methods is only compared without considering dictionary training time, and the reconstruction time of this algorithm is much better than that of ScSR algorithm. As can be seen from Table 2 and Table 3, the reconstructed image PSNR obtained by this algorithm is slightly higher than that obtained by interpolation and ScSR algorithm, and slightly lower than that obtained by ScSR algorithm in SSIM, indicating that part of the texture structure is missing. In general, this paper saves time and takes care of reconstruction quality, and improves the effect of image reconstruction to some extent.

4. Conclusion

In this paper, the problem of super-resolution reconstruction of single image is studied in depth. The image as the training HR dictionary is preprocessed by interpolation method. The image of the HR image is subtracted from the original HR image to obtain the difference image containing high frequency detail information. The residual figure as a joint training samples dictionary to get the high and low resolution, to improve the structural dictionary, and strengthen the low resolution and high resolution image block and the corresponding real dictionary of sparse representation of similarity, and reduces the complexity of the dictionary training and enhance the dictionary to the high frequency information expression, eliminate reconstruction artifacts, further improve the quality of reconstruction image. At the same time, the image magnified by the interpolation method is too smooth, and the obtained difference image cannot reflect the low frequency information of the image and is partially missing in the texture structure. The experimental results show that compared with the traditional methods, the proposed method saves time to a certain extent, and the objective evaluation indexes PSNR and SSIM are Improved.

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