Super-resolution Reconstruction Algorithm Based on Patch Similarity and Back-projection Modification

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Abstract—**We propose an effective super resolution reconstruction algorithm based on patch similarity and back-projection modification. In the proposed algorithm, we assume patch to be similar in natural images and extract the high-frequency information from the best similar patch to add into goal high-resolution image. In the process of reconstruction, the high-resolution patch is back-projected into the low-resolution patch so as to gain detailed modification. Experiments performed on simulated low-resolution image and real low-resolution image are proved that the proposed super-resolution reconstruction algorithm is effective and efficient to improve the resolution of image and achieve a better visual performance.**

Index Terms—**Super-resolution, patch similarity, back-projection modification, reconstruction**

I. Introduction

The goal of image super-resolution (SR) is to reconstruct an image with higher resolution than original low-resolution (LR) image captured by imaging device. In earlier works many SR methods have been proposed by several researchers[1-4]. There are two families of approaches for super-resolution: one is the classical super-resolution [5-8], the other is example-based super-resolution [9-12]. In the classical super-resolution, we obtain a high-resolution (HR) image from multiple low-resolution images. Unlike classical super-resolution, the idea of example-based super-resolution reconstruction method is to find correspondence between low and high resolution image patches, which are learned from an outside database or by image itself. Exampled-based image super-resolution is firstly explored by Freeman et.al. [9]. After several years, Tappen et al. use a patch-based model and require the output to be consistent with the input [13]. In 2009, Glasner et. al.[14] proposed a single image super-resolution reconstruction algorithm combined with classical and exampled-based method, but this method produces a small amount of ringing and jaggies.

In this paper, we proposed a new SR method that estimates the high-frequency component lost in the imaging process. The high-frequency image components are estimated by pairs of low- and high-frequency components, which are applied to the typically interpolated version of low-resolution image to gain the final super-resolved result. The effectiveness and validity of the proposed method are verified by applying it to standard images. Some introduction about image super resolution and image enhancement can be seen in references [16-18].

The rest of this paper is organized as follows. The details of the proposed method are explained in Section II, Section III describes our experimental results, and finally, conclusions are given in Section IV.

II. Proposed Super-resolution Method

In order to detail the proposed super-resolution reconstruction algorithm further, the basic idea and steps are described as follows:

Step1 Input a low-resolution image I_0.

Step2 I_0 is down-sampled by $\frac{1}{s}$ and blurred by a Gaussian kernel to gain a LR version L_0 of I_0 (s is the super-resolution reconstruction factor).

Step3 Then L_0 is interpolated by s to produce an interpolated image I'_0, which size is the same as I_0.

Step4 I_0 is divided into several patches and each

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patch is 5×5. For the first patch p_0 in I_0, we find the most similar patch $p_0^{'}$ (5×5) in image L_0. Mapping the center coordinate of $p_0^{'}$ to I_0, the mapping HR patch $p_0^{''}$ ($(5\times s)\times(5\times s)$) can be obtained in I_0.

Step5 $p_0^{''}$ is then back-projected and modified by the original patch p_0 in the input image I_0. When this iterative process is completed, we can get the reconstructed high-resolution version p_0^h of the first patch p_0 in I_0, and this patch is placed on the corresponding location of the HR image. In this step, the process of back-projection is illustrated in Fig. 1.

Step6 In addition, we can get the high-frequency image $H_0 = I_0 - L_0$. The corresponding high-frequency patch P_h ($(5\times s)\times(5\times s)$) is find in H_0, which central coordinate is the same to p_0. We add P_h to the patch $p_0^{''}$ in the reconstruction HR image.

Repeat above Step1-Step6, until all patches in the input image I_0 are processed completely, we can get the reconstruction high-resolution image I_H.

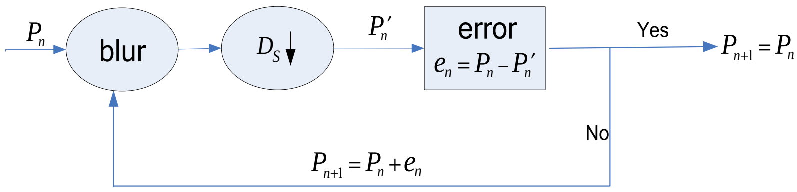


Figure 1. Illustration of back-projection modification

In above detailed steps, it is key that find the most similar block to the reference block in the process of construction, which can affect reconstruction result of super-resolution. For these reason, we also have tried many different block matching criterion in the experimental process to test which similarity criterion is suitable to our method, such as sum of squared differences (SSD), mutual information, mean value and brightness. The standard video sequence "Clarie" is used in our similarity criterion test. In this test, the size of patch is selected to be 6×6. The testing result is shown in Fig. 2.

(a) the 6th frame (b) reference image (c) SSD (d) mean value (e) mutual-information (f) brightness

Figure 2. Matching result of different similarity criterion

In Fig. 2, (a) is the 6th frame in "Clarie" video sequence, (b) is the reference image (the 8th frame in "Clarie" video sequence), (c) is the matching result by SSD, (d) is the result matched by mean value, (e) is the matching result by mutual-information, (f) is matched by brightness. From this comparison, we can see result matched by SSD is more acceptable by visual observation, so SSD matching criterion is adopted in the proposed method, which is explained in Eq. (1).

$$SSD = |x_1 - y_1|^2 + |x_2 - y_2|^2 + \cdots + |x_n - y_n|^2 \quad (1)$$

In Eq. (1), $x_1, x_2, \cdots, x_n$ and $y_1, y_2, \cdots, y_n$ represent corresponding pixel in two patch respectively.

III. Experiments

Normally, super-resolution reconstruction is performed on the true low-resolution image taken by the imaging device in natural condition. However, in order to verify the effectiveness of the proposed algorithm, we use this super-resolution algorithm on a simulated low-resolution image firstly, after that it performed on the true low-resolution image super-resolution reconstruction. These experiments can prove effectiveness of the proposed algorithm more complete and overall.

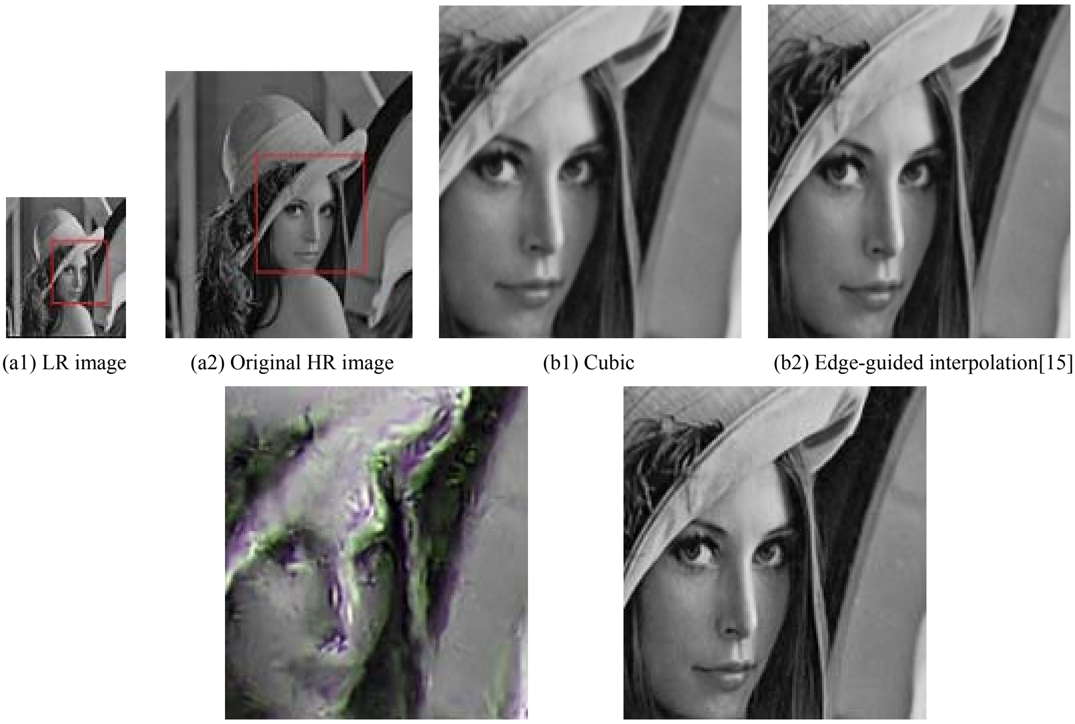
A. Simulated LR Image SR

(1)"Lena" (2×2)

This experiment is SR reconstruction up-scaled by 2 in

x and y direction respectively. Firstly, the original high-resolution image "Lena" (512×512) is convoluted by Gaussian kernel, the size of which is 3×3 and variance is 0.1. Then the blurred version of original “Lena” is down-sampled by 2 to get a low-resolution image (256×256). In order to show effectiveness of the proposed algorithm, we compare the quality of our result with the results produced by current state-of-art methods in Fig.3. Note that this comparable result is the local part of original image “Lena”, which is marked by red rectangular in Fig. 3(a1) and (a2).

In Fig. 3, (b1) is the SR result of cubic interpolation, which is too fuzzy, (b2) is better than (b1), but high-frequency information is still ambiguous (such as the edge of hat and eye), (b3) is too poor visual effect, and (b4) is the most similar to the original high-resolution image (such as eye and the edge of hat), which is also expected by us. The comparison in Fig.3 clearly reflects that the proposed SR reconstruction algorithm can effectively improve the visual and real resolution of reconstructed result.



(a1) LR image (a2) Original HR image (b1) Cubic (b2) Edge-guided interpolation[15]

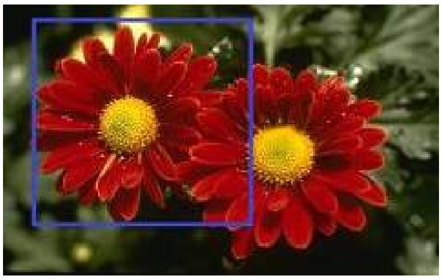
(b3) Freeman [9] (b4) The proposed SR algorithm

Figure 3. Comparison of “Lena”SR results (2×2)

(2) "Flower" (3×3)

This super-resolution experiment is also performed on a simulated low-resolution image. The original high-resolution image "Flower" (320×480) is convoluted by Gaussian PSF (point spread function) to get a blurred version of "Flower". The variance and size of convoluted kernel is 0.3 and 3 respectively. Then the blurred image is down-sampled by 2 to get a low-resolution image (160×240). In order to compare different reconstructed results better, there is only show the local SR part of reconstructed result, which is marked by blue rectangular in Fig. 4.

In Fig.4, it is obviously to see that (b1) is overall fuzzy, the visual performance of (b2) is slightly better than (b1), but the local edge in (b2) is still not clear. (b3) is reconstructed by an outside image database, so the detailed information is not the real information, as well as the visual effect is much poor. (b4) is the most similar to the original high-resolution image (such as the edge of petal and eye of flower). From this comparable result, we can see the proposed algorithm is the most effective and efficient one in SR reconstruction.



(a1) Original HR image "Flower"

(a2) Simulated LR image

(b1)Cubic

(b2) Edge-guided interpolation[15]

(b3) Freeman.et. al [9]

(b4) The proposed SR algorithm

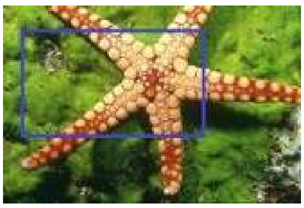
Figure. 4 Local comparable SR result of "Flower"(3×3)

B. Real Image SR

In order to further validate effectiveness of the proposed algorithm, a real low-resolution image is adopted in this section to achieve a complete super-resolution reconstruction.

In this experiment, a real colorful image "Starfish" (240×160) is SR reconstructed by 2 in x and y direction respectively. The local part of SR reconstructed result by various methods is shown in Fig. 5.

The original low-resolution image "starfish" used in this experiment is a good example, because it contains very detailed information. From comparable result in Fig.5, we can see that the best visual effect is reconstructed by the proposed SR algorithm, which clearly reflects the edge and detailed information in the image.



(a) Original LR image "Starfish"

(b1) Cubic

(b2) Edge-guided interpolation [15]

(b3) Freeman et. al. [9]

(b4) The proposed SR algorithm

Figure 5. Comparable SR result of “Starfish”(2×2)

C. computational Complexity

In addition, computational complexity is considered on the proposed algorithm, which is tested on a Dell computer, which CPU is 3.1GHz and RAM is 2G. The software platform was Matlab 2009. The time cost consumed by the proposed is 4.06s on a 256×256 color image, this time is larger than cubic interpolation, while is smaller than the method proposed in Ref. [9] and Ref. [15]. Obviously, the reconstruction result is much better than cubic interpolation, and the complexity of proposed algorithm is acceptable in real application.

IV. Conclusion

In this paper, a novel and effective super-resolution reconstruction algorithm based on patch similarity and back-projection modification was proposed. This method utilized the mapping relation between low-resolution patch and high-resolution patch in different image scales. In comparison with other established super-resolution image reconstruction approach, the proposed algorithm has more acceptable visual performance. At the same time, in this paper the proposed algorithm is only performed on a single image super-resolution reconstruction, it is also can be extended to a video super-resolution reconstruction. However, the limitation of this algorithm is that it can not reflect the true resolution of an image and can not reconstruct more details in a redundant information image. In future research, we plan to explore to incorporate the natural image characteristics to provide more high visual performance under natural image properties.

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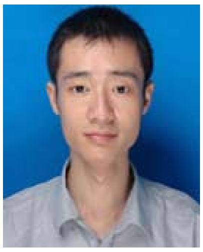

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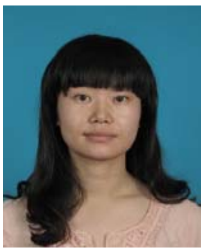

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