NONLOCAL BACK-PROJECTION FOR ADAPTIVE IMAGE ENLARGEMENT

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ABSTRACT

This paper presents a novel non-local iterative back-projection (NLIBP) algorithm for image enlargement. The iterative back-projection (IBP) technique iteratively reconstructs a high resolution (HR) image from its blurred and downsampled low resolution (LR) counterpart. However, the conventional IBP methods often produce many “jaggy” and “ringing” artifacts because the reconstruction errors are back projected into the reconstructed image isotropically and locally. In natural images, usually there exist many non-local redundancies which can be exploited to improve the image reconstruction quality. Therefore, we propose to incorporate adaptively the non-local information into the IBP process so that the reconstruction errors can be reduced. Experimental results demonstrated that the proposed NLBP can reconstruct faithfully the HR images with sharp edges and texture structures. It outperforms the state-of-the-art methods in both PSNR and visual perception.

Index Terms— Image interpolation, back-projection, image restoration, non-local method

1. INTRODUCTION

Reconstructing a sharp high resolution (HR) image from its low resolution (LR) counterpart has a wide range of applications such as medical imaging, remote sensing, computer vision, and consumer electronics. The LR image can be viewed as a downsampled version of the smoothed HR image. The classical linear interpolators, such as bilinear, bi-cubic and cubic spline, have a low complexity but suffer from blurred edges and annoying artifacts. Adaptive image interpolation algorithms have been recently proposed. Edge-directed interpolation techniques interpolate the image along the edge direction, which can be estimated explicitly or implicitly [1-4]. The method in [5] uses a 2D autoregressive model to model the image structure and reconstructs the image via soft-decision estimation. The above image interpolation methods, however, do not consider the blurring effects in the LR image formation process. Usually, they will be followed by a de-blurring operation to restore the sharp edges in the HR image.

The iterative back-projection (IBP) technique [6] can accomplish the HR image interpolation and de-blurring simultaneously. Its underlying idea is that the reconstructed HR image from the degraded LR image should produce the same observed LR image if passing it through the same blurring and downsampling process. The IBP technique can minimize the reconstruction error by iteratively back-projecting the reconstruction error into the reconstructed image. However, the IBP techniques often produce many “jaggy” and “ringing” artifacts around edges. This is mainly because that the reconstruction errors are back projected isotropically in IBP, ignoring the fact that edge structures are usually anisotropic. To enforce the iterative process converges to a desired HR image with better edge preservation, Dai et al [7] used bilateral filtering [9] to guide the back-projection process. However, only the local correlation is exploited by the bilateral filters. Moreover, the bilateral filters compute the pixel similarity in a pixel based manner, which may not be robust to edge preservation.

In natural images, there are often many patterns appearing repeatedly over the image. Such non-local redundancies can be very helpful to improving the image quality. Inspired by the success of non-local means filtering in image denoising [8], we propose to adopt the non-local processing into IBP to enhance the image enlargement result. An HR image is initially interpolated by bicubic interpolation, followed by a nonlocal post-processing. The IBP iteration, which is regularized by a non-local regularizer, is then applied to minimize the reconstruction error. The so called non-local IBP (NLIBP) method effectively incorporates the non-local redundancy into back-projection. The non-local similarity is computed based on the patches centered on the given pixels, thus it is more robust to image structure reconstruction.

The rest of this paper is organized as follows. Section 2 presents the initial image interpolation with non-local post-processing. The NLIBP algorithm is presented in Section 3. Section 4 presents the experimental results. Section 5 concludes the paper.

2. NON-LOCAL IMAGE INTERPOLATION

This section presents a novel image interpolation method to generate an initial HR image, which will be served as the initial HR image for the following NLIBP process. Generally, a better initial estimate of the HR image will lead to better final results with less NLIBP iteration.

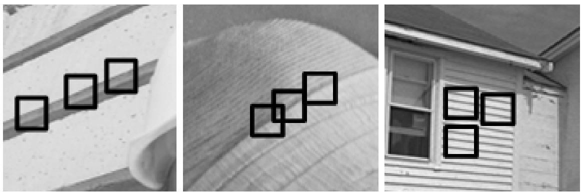

Figure 1. Examples of image repetitive structures.

According to the sampling theory, it is impossible to reconstruct faithfully the edges and textures whose frequency exceeds the Nyquist sampling limit. The problem is aggravated by the human visual system because it is sensitive to edges. Fortunately, natural images often contain repeated patterns and structures. Some examples are shown in Fig. 1. A natural idea is to employ such non-local redundancies to improve the image interpolation quality. In this section, we develop a simple but efficient non-local post-processing technique for this purpose. It consists of three steps: initial image interpolation, block matching and non-local data fusion. Any existing interpolation method can be used for the initial interpolation. For simplicity, we employ the bicubic interpolator for initial interpolation.

2.1 Block matching for similar pixel grouping

The initially interpolated HR pixels can be viewed as the noisy estimates of the unknown missing samples, where the interpolation error can be modeled as the noise. To improve the initial interpolation, therefore, the interpolated HR pixels can be fused with the similar LR pixels to it to reduce the interpolation noise. Before the fusion, the similar pixels to the given pixel should be grouped. The block matching is used to this end.

Let $\hat{y}(i_0, j_0)$ be an initially interpolated HR pixel at location (i_0, j_0) , and $N_y(i_0, j_0)$ be its squared neighborhood, e.g. a 7×7 window. Denote by $y(i, j)$ an LR pixel and by $N_y(i, j)$ the square neighborhood of it. The distance between the two patches, i.e. $N_y(i_0, j_0)$ and $N_y(i, j)$, is defined by

$$d_{(i,j)} = \left\| N_y(i_0, j_0) - N_y(i, j) \right\|_2 \tag{1}$$

where $\|\cdot\|$ is the L_2 norm operator. If the distance d is below a preset threshold, this means that the two patches are similar and hence we group $y(i, j)$ into a set $S_{(i_0, j_0)}$, which contains $\hat{y}(i_0, j_0)$ and the similar pixels to it. Although the block matching process can be performed over the whole image, it will be computationally prohibitive. In practice, we limit the searching into a relatively large window, such as a 21×21 window.

2.2. Data fusion

After grouping the similar LR pixels to the interpolated HR pixel $\hat{y}(i_0, j_0)$ into $S_{(i_0, j_0)}$, we can then update $\hat{y}(i_0, j_0)$ as the weighted average of all the elements in $S_{(i_0, j_0)}$:

$$\hat{y}^{'}(i_0, j_0) = \sum_{y(i,j)\in S_{(i_0,j_0)}} \omega(i, j) y(i, j) \tag{2}$$

where the weight $\omega(i, j)$ depends on the similarity between patches $N_y(i_0, j_0)$ and $N_y(i, j)$ with constraints $0 \le \omega(i, j) \le 1$ and $\sum_{y(i,j)\in S_{(i_0,j_0)}} \omega(i, j) = 1$. As in non-local means denoising, we set $\omega(i, j)$ as the exponential function of distance $d_{(i,j)}$

$$\omega(i, j) = \frac{1}{C(i, j)} e^{-\frac{d_{(i,j)}}{t}} \tag{3}$$

where $C(i, j)$ is the normalization constant

$$C(i, j) = \sum_{y(i,j)\in S_{(i_0,j_0)}} \omega(i, j) \tag{4}$$

and t is a parameter to control the decaying speed.

Note that the initial estimate of the missing pixel, i.e. $\hat{y}(i_0, j_0)$, is involved in the fusion and its weight is $1/C(i, j)$, which is the maximal one among all the weights. After the non-local data fusion, the initial interpolation can be improved with less artifacts and interpolation error.

3. NON-LOCAL ITERATIVE BACK-PROJECTION

The formation of an LR image I_l from the unknown HR image I_h can be formulated as follows

$$I_l = D\left(I_h * G\right) \tag{5}$$

where D is the down-sampling matrix, $*$ is the convolution operator and G is the point spread function (PSF) which is generally a smoothing kernel. The task is to reconstruct the HR image I_h from the observed LR image I_l . One underlying criterion is that the reconstructed HR image, denoted by $\hat{I}_h$, should produce the same LR image I_l if passing it through the same image formation process (5). The reconstruction error of $\hat{I}_h$ is defined as

$$e\left(\hat{I}_h\right) = I_l - D\left(\hat{I}_h * G\right) \tag{6}$$

The IBP technique was proposed in [6] to reconstruct the HR image from a set of LR images by minimizing the reconstruction error *e* iteratively. In the case that there is only one input LR image, each iteration consists of the following two steps:

(1) Compute the reconstruction error $e(\hat{I}_h^{(t)})$ of image $\hat{I}_h^{(t)}$ in the t^{th} iteration using Eq. (6);

(2) Update $\hat{I}_h^{(t)}$ with the reconstruction error:

$$\hat{I}_h^{(t+1)} = \hat{I}_h^{(t)} + F\left(I_l - D\left(I_h^{(t)} * G\right)\right) * p \qquad (7)$$

where $F(\cdot)$ is an interpolator and p is a back-projection kernel that controls the speed of the convergence. As discussed in [6], the smaller the $\|\delta - G * p\|_1$ is, the faster the algorithm converges, but the less numerical stability of the algorithm is.

It was proved in [6] that $\hat{I}_h^{(t)}$ converges to an HR image I_h^c which satisfies Eq. (5) with an exponential rate. However, $\hat{I}_h^{(t)}$ may converge to an HR image with "jaggy" and "ringing" artifacts because the IBP propagates the reconstruction error without considering the edge direction and strength. To reduce the artifacts, Dai et al proposed to use the bilateral filter to update the reconstruction error [7]. The bilateral filter based IBP (BFIBP) can reconstruct the HR image with sharper edges. However, the performance of BFIBP is limited because it only exploits the local image correlation.

In this paper, we exploit the non-local image redundancy to improve the HR image reconstruction quality. The non-local information is not only used to generate the initial interpolation as discussed in the Sec. 2, it is but also used to guide the IBP error propagation. The proposed NLIBP method is performed as follows.

First, the reconstruction error image $e(\hat{I}_h^{(t)})$ is up-sampled with bicubic interpolator to obtain an HR error image. Directly updating the reconstructed HR image $\hat{I}_h^{(t)}$ with the isotropically interpolated HR error image $e(\hat{I}_h^{(t)})_h$ will cause "jaggy" and "ringing" artifacts. To guide the error propagation with non-local information, the HR error image $e(\hat{I}_h^{(t)})_h$ is post-processed using the non-local filters calculated in the initial image interpolation step, as described in Sec. 2. The non-local post processing of the HR error image $e(\hat{I}_h^{(t)})_h$ yields a sharp reconstruction error image. Then the post-processed reconstruction error is back projected to the reconstructed HR image $\hat{I}_h^{(t)}$ with kernel p to yield an updated HR image $\hat{I}_h^{(t+1)}$.

The above two procedures are iteratively implemented until $\left\|e(\hat{I}_h^{(t)})\right\|_1$ is below a predefined threshold. We use the same non-local filter through out the entire iterative process. This improves the computational efficiency significantly but without sacrificing much the HR reconstruction accuracy.

4. EXPERIMENTAL RESULTS

Figure 2. The test images.

Table 1. The PSNR (dB) results.

Images	Forema	Sailboat	Tower	Leaves
Bicubic	32.48	31.01	26.26	27.36
IBP	34.32	32.44	28.32	30.08
BFIBP	34.75	32.54	28.47	30.68
NLIBP	**35.21**	**33.35**	**28.94**	**31.06**

In this section, we evaluate the performance of NLIBP by using several benchmark test images, which are shown in Fig. 2. The bicubic interpolator, the IBP method [6] and the BFIBP method [7] are used for comparison. For a fair comparison, the initial non-local interpolation proposed in Section 2 is used for IBP, BFIBP and NLIBP. In simulation, we passed the original images through a Gaussian PSF kernel with standard deviation 1, and then downsampled the smoothed image with a factor of 2. The simulated LR image is inputted to the four schemes to reconstruct the HR image.

Table 1 lists the PSNR results of the four methods on the four test images. It can be seen that the proposed NLIBP outperforms all the other methods, including BFIBP which stands for state-of-the-art. Fig. 3 and Fig. 4 show the cropped Sailboat and Leaves images reconstructed by the four methods. As can be seen in Fig. 3 and Fig. 4, the bicubic interpolator produces very blurred results. The IBP increases the contrast, but there are clearly visible "jaggy" and "ringing" artifacts in the reconstructed images. The BFIBP method eliminates most of the "jaggy" and "ringing" artifacts. However, as shown in Fig. 3 (d) and Fig. 4 (d), the edges reconstructed by BFIBP are not very sharp and there are some visually unpleasant artifacts. The proposed NLIBP method produces the most visually pleasant results, reconstructing sharp and clean edges with much less artifacts.

5. CONCLUSION

In this paper, we proposed a novel non-local iterative back-projection algorithm for image enlargement. The non-local redundancies among natural images were exploited to produce sharp image edges and remove the artifacts caused by the iterative back-projection process. The non-local information is incorporated into the back-projection of reconstruction errors to avoid the cross-edge error propagation. The experimental results show that the proposed techniques produce sharper edges and fewer artifacts than previous techniques.

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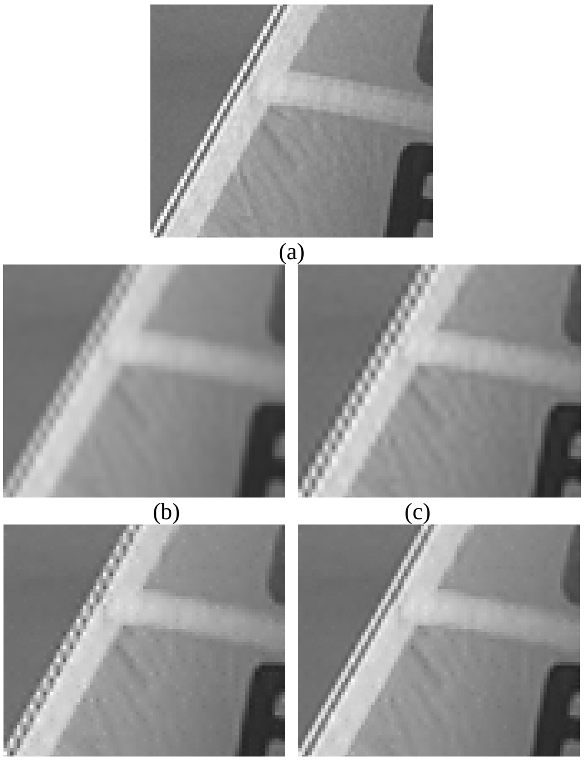

(a) (b) (c) (d) (e)

Figure 3. (a) Partial original image Sailboat; and the reconstructed images by (b) bicubic; (c) IBP; (d) BFIBP and (e) NLIBP.

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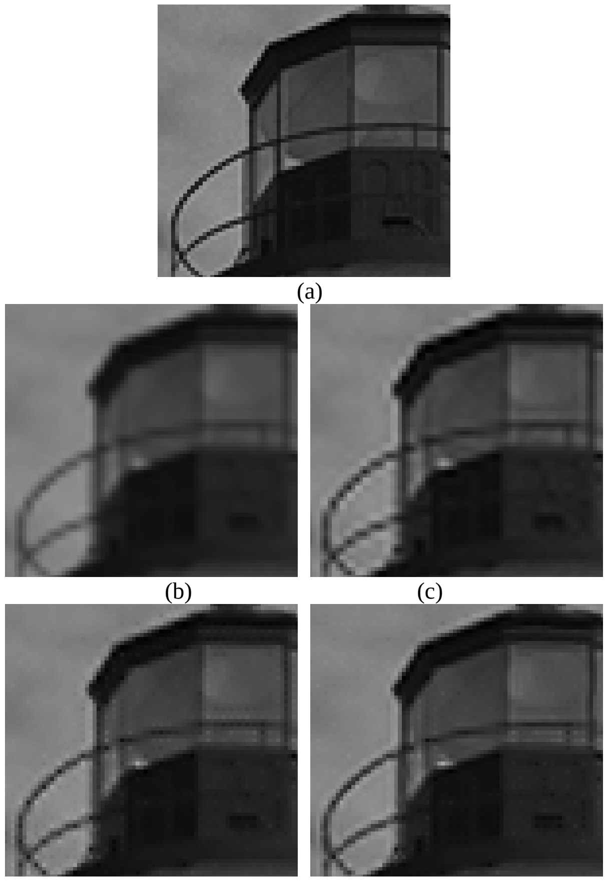

(a) (b) (c) (d) (e)

Figure 4. (a) Partial original image Tower; and the reconstructed images by (b) bicubic; (c) IBP; (d) BFIBP and (e) NLIBP.