ITERATIVE IMAGE INTERPOLATION FOR IRREGULARLY SAMPLED IMAGE

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Abstract: For irregularly sampled color images, an iterative interpolation algorithm utilizing a wavelet shrinkage denoising technique is proposed. Exploiting the non-local information from neighboring blocks, the reconstruction performance converges as the iteration of the proposed algorithm is repeated. Experimental results show that the proposed algorithm outperforms the conventional algorithms in terms of subjective quality and objective measures. The proposed algorithm correctly reconstructs the edge and provides perceptually good performance with randomly chosen 25% pixels.

1 INTRODUCTION

Irregularly sampled signals can be found in many application areas such as seismic data (Duijndam, 2001); (Herrmann, 2008) and medical imagery (Lustig, 2007); (Lustig, 2008). The reconstruction algorithms for irregularly sampled signals can be divided into two groups: nonlinear algorithms, and iterative algorithms. The nonlinear interpolation methods have been proposed to solve the problem in the early 1990s (Marvasti, 1987); (Marvasti, 1993). One of such nonlinear algorithms is the Delaunay triangulation method (Delaunay, 1934); (Lertrattanapanich, 2004). Recent kernel regression algorithms also provide a data adaptive filtering algorithm (Takeda, 2006); (Takeda, 2007). However, these methods apply low-pass filtering to observed samples and produced poor results due to blurring artifacts.

The iterative recovery method has been proposed by Wiley (Wiley, 1978) which requires low-pass filtering of unequally spaced samples. For band-limited signals, under some restrictions the irregularly sampled signals can recover the missing signals after iterations (Sandberg, 1963). However, these restrictions cannot be satisfied in general. The recent framework using sparsity constraints and iterative estimation produced improved performance (Guleryuz, 2006a); (Guleryuz, 2006b). Li proposed an iterative interpolation algorithm for irregularly sampled signals utilizing this framework and the block-matching based denoising algorithm (Li, 2008).

However, in (Li, 2008), the transform based denoising algorithm usually produces the undesirable artifacts in a flat area since the denoising algorithm fails to consider edge information. Even though the flat area has no edges, ringing artifacts are produced in the originally homogeneous region. This error-prone area can be localized using an edge detection algorithm, and the smoothing algorithm can be applied to the localized area. In the proposed method, the block-based transform based denoising algorithm with some modification is applied and the non-local means algorithm (Buades, 2005) is used to remove the ringing artifacts in flat areas.

2 PREVIOUS WORKS

Suppose a two dimensional plane and the scattered points in the plane. For a set of points, drawing lines from each point to its nearest points form a set of vertices. These triangular patches include no intersection from the other lines. This triangulation is commonly known as Delaunay triangulation. It is well known that the Delaunay triangulation is a geometrically dual with a Voronoi diagram in R^2. In other words, the Voronoi tessellation has the intersection lines normal to the Delaunay

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triangulation (Delaunay, 1934); (Lertrattanapanich, 2004). For 2-D signals, there exists fast algorithms to form the Delaunay triangulation which has the maximized minimum angle of each triangle over the ordered sets of all triangulations, and the Delaunay triangulation is known to be suitable for image interpolation (Lertrattanapanich, 2004). In Qhull algorithm (Barber, 1996), the Delaunay triangulation is computed with sparsely observed 2-D samples. Fig. 1 shows irregularly sampled and interpolated images using the Delaunay triangulation with cubic polynomials.

(a)

(b)

Figure 1: The Delaunay triangulation interpolation for the irregularly sampled image: (a) the observed image (25%) (b) the interpolated image.

Fig. 1 shows that the Delaunay interpolation algorithm fails to correctly restore the edges around the roof in the house and also produces severe noises in a homogeneous region.

A recent algorithm improved the reconstructed image using an iterative procedure (Li, 2008). In this algorithm, the block matching and 3-D filtering algorithm (BM3D) is used (Dabov, 2007). The BM3D denoising method collects a group of non-local blocks similar to the current block and stacks them in 3-D arrays. The stacked 3-D arrays are transformed using a transform technique (e.g., DCT and wavelet), and the transform coefficients are filtered using the shrinkage of transform spectrum or thresholding operator. Then, the inverse transform is applied. In the patch-based interpolation method (Li, 2008), the BM3D algorithm is used as the sparsity constraints and the observed pixels are put back into the resulting image (Abma, 2006); (Guleryuz, 2006a); (Guleryuz, 2006b).

3 PROPOSED INTERATIVE INTERPOLATION

The proposed image interpolation algorithm for the irregularly sampled signals exploits the concept of the Guleryuz's method and the BM3D (Dabov, 2007) similar to the patch-based interpolation method (Li, 2008). The overall procedure of the proposed algorithm is shown in Fig. 2. In the BM3D block, the wavelet shrinkage algorithm (Chambolle, 1998); (Donoho, 2006); (Donoho1995) was used. In addition, the SSIM metric (Wang, 2004) was used to find similar blocks and a Gaussian kernel was used in computing the resulting image. In particular, the proposed algorithm successfully removed some undesirable artifacts in a flat area by excluding neighboring blocks, which are substantially different from the current block, in computing the weighted average.

In the initial interpolation, the Delaunay triangulation based interpolation is performed to estimate the missing pixels using the observed neighboring pixels. Since the Delaunay triangulation based interpolation uses a cubic interpolation kernel to estimate the missing pixels, blurred edges and stained areas usually appear. Then, a modified BM3D is applied, where the wavelet shrinkage algorithm (Chambolle, 1998); (Donoho, 2006); (Donoho1995) was used.

After similar blocks are collected, the blocks are stacked together to form a cube. In the 3D wavelet denoising method, a 3-D additive wavelet transform (or over-complete wavelet transform) is applied to the stacked blocks. Then, thresholding is applied to the wavelet coefficients.

In this process, the coefficients smaller than the threshold are set to zero. It is noted that the threshold value is set to 30. After the inverse 3-D wavelet transform is applied, the weights for aggregation of the stacked blocks are computed. Then, the stacked blocks produced by the wavelet shrinkage algorithm are averaged and the Gaussian kernel.

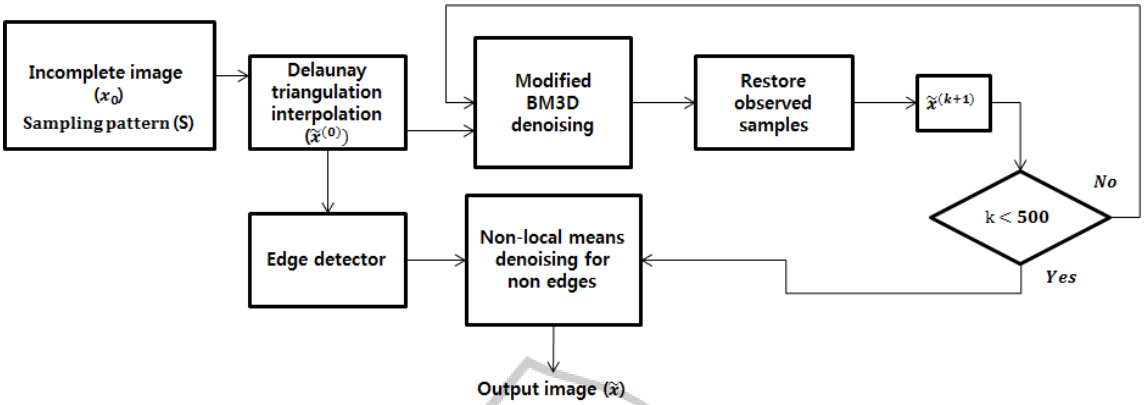


Figure 2: The overall procedure of the proposed algorithm.

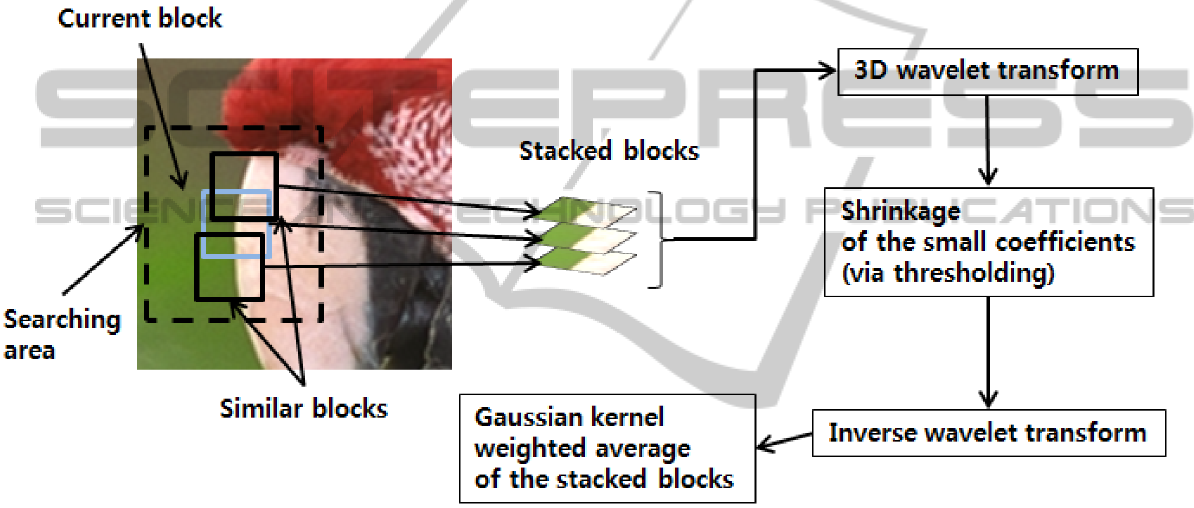


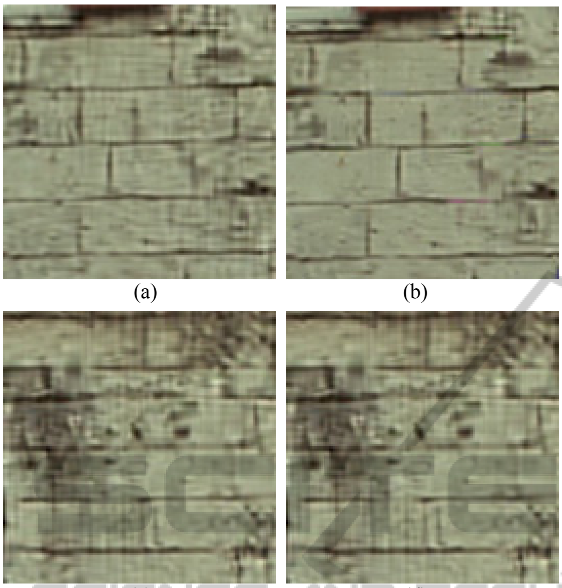
Figure 3: Modified BM3D with wavelet shrinkage denoising.

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

Figure 4: The parts of the results as the iteration is performed: (a) the observed image (25%) (b) the initial interpolation (c) the fifth iteration (d) the 100th iteration.

This modified BM3D method is applied to every pixel. Due to the 3D wavelet transform, the observed pixels are also modified in the output of the modified BM3D method. Thus, the observed pixels are placed back into the output of the modified BM3D method.

As the iteration (modified BM3D followed injecting the observed samples) is repeated, the edges with noises or the stained areas are cleaned as shown in Fig. 4. However, the resulting image still contains undesirable artifacts in a flat area and produces ringing artifacts in the homogeneous region. This is caused by some blocks which are substantially different from the current block.



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

Figure 5: The results after denoising: (a) image before denoising (b) image after denoising (c) image before denoising (d) image after denoising.

To address this problem, after applying an edge detection operator to the initial interpolation image, a modified non-local means (NLM) denoising algorithm (Buades, 2005) is applied on the homogeneous region. In the proposed algorithm, the Laplacian of Gaussian (LoG) edge detector is used to find edge positions (Chen, 1987).

The non-local means algorithm (Buades, 2005) utilizes the similarity between two blocks which is measured as a decreasing function of the weighted Euclidean distance and the NLM algorithm uses the weighted average of the center pixels in the neighboring blocks for the current center pixel in the current block.

However, it is more desirable that some neighboring blocks are excluded in computing the weighted average because some blocks are substantially different from the current block. Therefore, in the proposed method, SSIM values between the current block and neighboring blocks are computed and only the blocks whose SSIM value is greater than 0.8 were used. This routine successfully removed the ringing artifacts in the homogeneous region as shown in Fig. 5.

Table 1: PSNR results for processing single channel independently.

Images	Delaunay	SKR	PBI	Proposed
Kodim01	23.40	23.28	25.14	**25.29**
Kodim02	30.45	30.44	31.60	**31.95**
Kodim03	31.39	31.51	32.79	**33.57**
Kodim04	30.62	30.24	31.56	**31.88**
Kodim05	23.39	23.33	**24.67**	24.65
Kodim06	25.00	24.86	**26.63**	26.47
Kodim07	30.13	29.92	31.61	**31.63**
Kodim08	21.01	21.21	23.97	**24.29**
Kodim09	29.33	29.70	31.33	**31.70**
Kodim10	29.34	29.38	30.82	**31.38**
Kodim11	26.52	26.46	**27.79**	27.67
Kodim12	30.23	30.39	32.34	**32.73**
Kodim13	21.33	21.02	**21.44**	21.16
Kodim14	26.26	25.83	**27.00**	26.91
Kodim15	29.02	29.90	31.21	**31.52**
Kodim16	28.88	28.60	30.37	**30.65**
Kodim17	29.02	29.04	**29.98**	29.89
Kodim18	24.99	24.74	**25.39**	25.14
Kodim19	25.18	24.97	28.25	**29.50**
Kodim20	28.41	28.09	29.93	**30.13**
Kodim21	25.75	25.47	26.57	**26.45**
Kodim22	27.70	27.39	28.62	**28.83**
Kodim23	31.74	31.53	32.76	**33.28**
Kodim24	23.91	23.57	**24.54**	24.30
Average	27.21	27.12	28.60	**28.79**

4 EXPERIMENTAL RESULTS AND DISCUSSIONS

In this paper, the proposed irregular interpolation method is compared with three conventional methods: the Delaunay method, the steering kernel regression (SKR) method (Takeda, 2006); (Takeda, 2007), and the patch-based interpolation (PBI) method (Li, 2008). Table 1 shows the PSNR results. It is noted that the proposed interpolation algorithm for the irregularly sampled image outperforms the conventional interpolation algorithms on average.

Figs. 6 – 7 show visual comparison of some sub-images: KODIM03 and KODIM10. Figs. 6 – 7 show that the proposed interpolation algorithm recovers the original images from the irregularly sampled image with high quality, and the proposed algorithm provides visually pleasing results. From Fig. 6, there are several edge distortions (the yellow cap) in the results of the Delaunay and the PBI methods, while the SKR and proposed methods restore the edges better than the other methods. However, the SKR method produces severe blurring, while the proposed algorithm produces better results. In Fig. 7, the diagonal edges exist along the yacht's sail and the proposed algorithm reconstructs the diagonal edges with high quality.

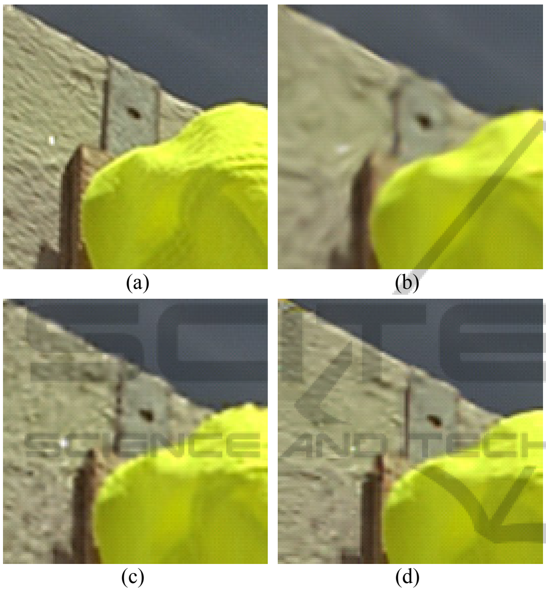


Figure 6: The visual comparison using KODIM03: (a) the original image (b) the SKR method (c) the PBI method (d) the proposed algorithm.

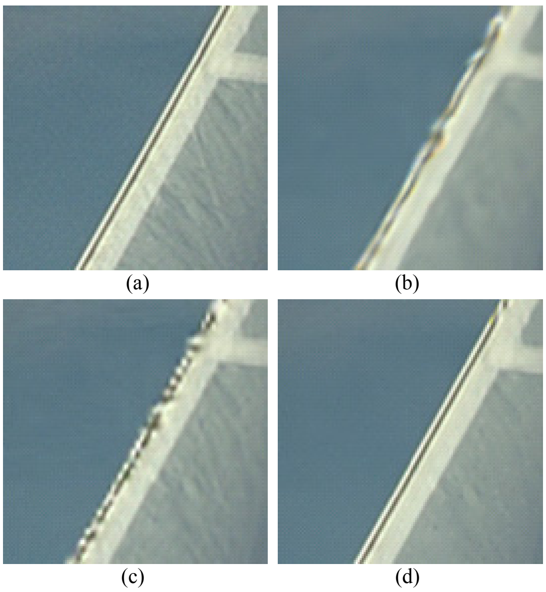


Figure 7: The visual comparison using KODIM10: (a) the original image (b) the SKR method (c) the PBI method (d) the proposed algorithm.

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