Performance Evaluation of Edge-Directed Interpolation Methods for Noise-free Images

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ABSTRACT

Many interpolation methods have been developed for high visual quality, but fail for preserving image structures. Edges carry heavy structural messages for visual tasks. Importance of edge preservation imposes edge-directed interpolation (EDI) methods a center of focus. How to measure edge-preserving ability has not been mentioned. In this paper, two metrics are proposed to measure the ability by edge-preserving ratio from accuracy and robustness. Performance of four edge-directed interpolation with two traditional methods are evaluated on two groups of standard images with other six commonly-used metrics. Experimental results show that EDI methods are better than traditional methods with highly improved edge-preserving ratio.

Categories and Subject Descriptors

D.2.8 [**Metrics**]: [performance measures]

General Terms

Performance, Measurement, Verification

Keywords

Edge-directed interpolation, edge-preserving ratio

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1. INTRODUCTION

High-resolution (HR) images with fine structures can improve readability in visual applications. Limited by sensor and optics manufacturing technology, image interpolation becomes feasible and promising [1]. Many methods have been developed and built into 3D accelerator hardware, but most of us are able to recognize these weaknesses, including blurring edges, blocking artifacts and coarse details [2]. A fundamental deficiency of these approaches is that strong dependencies among pixels are tacitly ignored. These dependencies are important visual messages about the structures, such as shape, texture, *et al* [3-4]. Because of the importance of edge-preserving in visual tasks, EDI methods become a center of focus [5-13].

EDI methods take advantage of edge information in low-resolution (LR) images. The first EDI is based on rendering and correction [5]. It smoothes parallel to edges, and tends to produce noisy artifact. *Li* [6] proposed an new edge-directed interpolation (NEDI) method which takes geometric duality to estimate covariance of targeted HR area from that of local window pixels in LR. By a fourth-order linear interpolation, it obtained HR images of 2^n size with well-maintained structures.

Its basis is correlation between LR and HR image which is sensitive to noise and easy to produce artifacts in high frequency region. [7] tackled NEDI from window shape, edge pixel handling, error propagation and global brightness invariance. [8] adopted a training window structure to eliminate the predication accumulation problem and extending the covariance matching into multiple directions to suppress the covariance mismatch problem. These methods overcome defects and restrict error propagation of NEDI. Image quality is improved with cost of computational complexity.

The second disadvantage of NEDI is its computational complexity. [9] developed fast edge-oriented algorithm by partitioning images into homogeneous areas and edge areas. [10] classified interpolation procedure into diagonal and non-diagonal process based on detected edges. *Zhang* [11] took directional filter and data fusion (DFDF) to reduce ringing artifacts and time cost. *Andrea* [12] introduced an iterative curvature-based interpolation (ICBI) method for real-time application. *Zhou* [13] applied edge-adaptive idea into cubic convolution method [14] and presented an directional cubic convolution interpolation (DCCI) method with optimal parameters by training. [9-13] simplify the procedure of estimating edge orientation and try to decrease time cost.

The last disadvantage of NEDI may be its 2^n integer magnification factor. To magnify a region of interest, the procedure is step by step in reality. Meanwhile, errors could be dynamically propagated during iteration and distort final image quality. Strategies to restrict error propagation and enhance robustness should be taken into consideration.

Edge structures play an important role in visual tasks. How to measure the edge-preservation ability of interpolation methods has not been mentioned. In this paper, two metrics are proposed to measure this kind of ability with edge-preserving ratio from accuracy and robustness. Performance of four edge-directed interpolation (NEDI [6], DFDF [11], ICBI [12] and DCCI [13])with Bi-linear and Bi-cubic are evaluated on two groups of standard images. This paper is organized as follows. Section 1 overviews the EDI methods. Section 2 presents two novel metrics to measure edge-preserving ability. Section 3 describes theories of these four EDI methods. Section 4 details the experiments. Section 5 demonstrates interpolation results. Section 6 discusses performance and draws conclusion.

2. EDGE-PRESERVING RATIO

Edge is discontinuities of image intensities corresponding to different illumination and material properties. It carries heavy structural messages for human vision systems to detect abnormalities and make decisions. Edge detection is to preserve structure properties with reduced amount of data. Canny [15] is a standard edge detector for its good detection, localization and single response. Based on Canny operator, edge maps of the standard and interpolated image are extracted and denoted as EMs and EMi with same threshold. Two metrics, EPRa and EPRr, are defined.

$$EPRa = \frac{num(EMs \cap EMi)}{num(EMs)} \tag{1}$$

$$EPRr = \frac{num(EMs \cap EMi)}{num(EMs \cup EMi)} \tag{2}$$

The operator *num* sums the amount of points with true value after intersection or union. EPRa measures edge structures preserved in EMi as that in EMs , and EPRr measures robustness of methods with less induced edge points. Comparing with EMs from original image, when pseudo edge structures are introduced in EMi, values of EPRa and EPRr decrease. This kind of edge structures may mislead image understanding and visual analysis. Orientations of edge points are crucial information which is omitted measuring, since determining edge orientation is full of uncertainty for its rough classification [16] and high complexity [17].

3. EDGE-DIRECTED INTERPOLATION

EDI methods mainly involves two filling steps. Taking factor of 2^1 for instance, before main steps, HR image is initialized with known pixels in LR from left to right and top to bottom (dark pixels). Then red pixels indexed by two odd values are determined by optimal weights of its four pixels from diagonal neighborhood in the first step. White pixels are filled with its vertical and horizontal neighbors (red and dark pixels) with similar rule in the second step. If factor is 2^n, HR image is obtained involving n iterations.

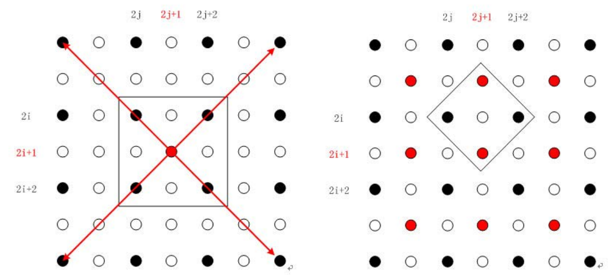

Figure 1: Two main steps in EDI methods

NEDI assumes the covariance from a local window of LR image is invariant in a large window and at different scales. The coefficients are solved by a least-square approximation. Value of center points is settled by merging values of four neighbor pixels. DFDF directly partitions neighbors of unknown points into two observation subsets in orthogonal directions. By modeling the two approximation values as two noisy measurement of an optimal value, more robust value estimation is fused via linear minimum mean square error estimation by statistical analysis. ICBI relaxes constraints by solving two blending weights. Taking the first step for instance, computing local approximations of the second order derivatives along the 45° and 135° diagonals, the value of red pixel is assigned with the average value of two neighbors in the same diagonal where the second-order derivative is lower. After two main steps, an iterative greedy procedure minimizes the global energy function by modifying pixel values. DCCI classifies point orientations into dedicated categories. Pre-values of missing pixels are by cubic-convolution method. Then gradients are computed from two orthogonal directions. Strong edges are distinguished by a threshold. The whole interpolation includes gradient computation, edge classification and optimal weight determination.

4. EXPERIMENTS

4.1 Materials

KODAK [19] and STILL [20] contain 20 images with resolution of 512×768 and of 512×512 respectively. Experiments are based on factor of 2^1 and standard images are downsampled by taking pixel from left-top corner in each 2×2 lattice. To avoid error boundary effects, 16 pixels around each border are excluded.

4.2 Metrics

EPRa and EPRr evaluate edge-preserving ability from accuracy and robustness. Higher EPRa means better edge-preservation, and higher EPRr shows more power to restrict artifacts. SNR, PSNR, SSIM [3], FSIM [4], MI [18], and TC are selected in addition. SNR and PSNR are based on error sensitivity model from pixel level. SSIM and FSIM measure image similarity from feature level. MI calculates the amount of information. TC measures time cost.

4.3 Software

Codes of DFDF, ICBI and DCCI are with no modification. NEDI is refined for occurrences of singularity. Bi-linear and Bi-cubic are built-in MATLAB. All codes run on a PC of Win7 OS (Intel (R) Core (TM), i3-2120 CPU @ 3.30 GHZ, 3.29 GHZ, and 1.98 GB DDR RAM).

5. RESULTS

5.1 Quantitative Results

Different methods are with different colors and markers in Figure 2 and Figure 3. Bi-linear is black star ($*$), Bi-cubic is in blue of left direction symbol ($>$), NEDI is with green diameter ($\diamond$), DFDF is with red dot (.), ICBI is brilliant blue of addition signal ($+$) and DCCI is with pink circle ($\circ$).

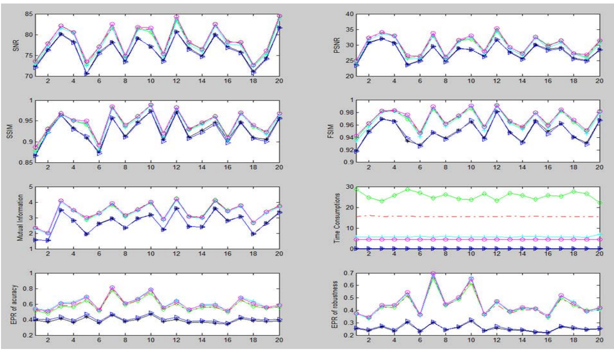

Figure 2: Metrics for KODAK

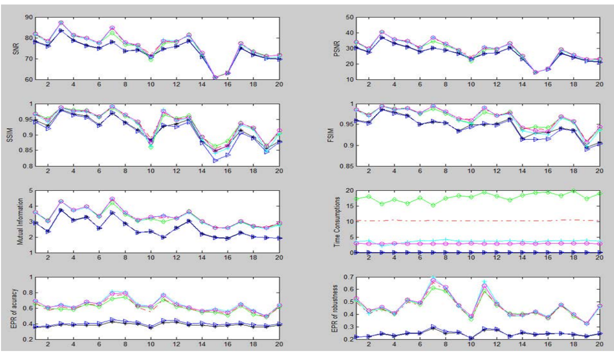

Figure 3: Metrics for STILL

MI and proposed EPR metrics distinguish EDI methods from traditional methods. Strength of Bi-linear and Bi-cubic is their less time consumptions. With proper programming and hardware, EDI methods can decrease time cost.

Unbiased analysis is achieved by averaging quantitative metrics. Best results are in bold in Table 1 and Table 2. EDI methods are better. Improvement of SNR and PSNR is from 2.00dB to 2.58dB, MI is up to 0.70, EPRa is enhanced from 0.21 to 0.36, and EPRr is increased from 0.21 to 0.23.

From objective analysis, it can conclude that EDI methods are better than Bi-linear and Bi-cubic except higher TC.

Table 1: Unbiased analysis for KODAK

	Bi-linear	Bi-cubic	NEDI	DFDF	ICBI	DCCI
SNR	76.38	76.19	78.37	78.42	77.95	**78.61**
PSNR	27.82	27.63	29.81	29.85	29.39	**30.05**
SSIM	0.93	0.93	0.94	0.94	0.94	**0.95**
FSIM	0.95	0.95	0.97	0.97	0.97	0.97
MI	2.68	2.67	3.35	**3.37**	3.30	3.36
TC	**0.02**	**0.02**	25.47	15.60	5.80	4.45
EPRa	0.39	0.41	0.58	0.59	**0.62**	0.61
EPRr	0.25	0.26	0.44	0.44	0.45	0.45

Table 2: Unbiased analysis for STILL

	Bi-linear	Bi-cubic	NEDI	DFDF	ICBI	DCCI
SNR	73.87	73.69	75.89	76.21	75.91	**76.27**
PSNR	26.47	26.29	28.48	28.81	28.50	**28.87**
SSIM	0.92	0.91	0.94	0.94	0.93	0.94
FSIM	0.95	0.94	0.97	0.97	0.96	0.97
MI	2.55	2.54	3.25	3.29	3.26	**3.30**
TC	**0.02**	**0.02**	17.78	10.29	3.62	2.93
EPRa	0.38	0.40	0.61	0.61	**0.65**	0.64
EPRr	0.24	0.25	0.46	0.45	0.47	0.47

Proposed EPR metrics verify the edge-preserving capacity of EDI methods.

5.2 Visual analysis

Visual analysis is only correct way to quantify image quality and 2 images from each group are selected. There are Butterfly and Parrot in KODAK, and Lena and Barbara in STILL. Figure 4 and Figure 5 demonstrate interpolation results from different methods. Interpolated Butterfly shows less staircase patterns from EDI methods. Bi-linear and Bi-cubic cause blurry, DFDF and DCCI show better visual structures. Interpolated Lena from DCCI shows less blocking artifact around the lighter region on hat. All EDI methods distort textures in Barbara around the neck since inadequate pixels represent fine structures.

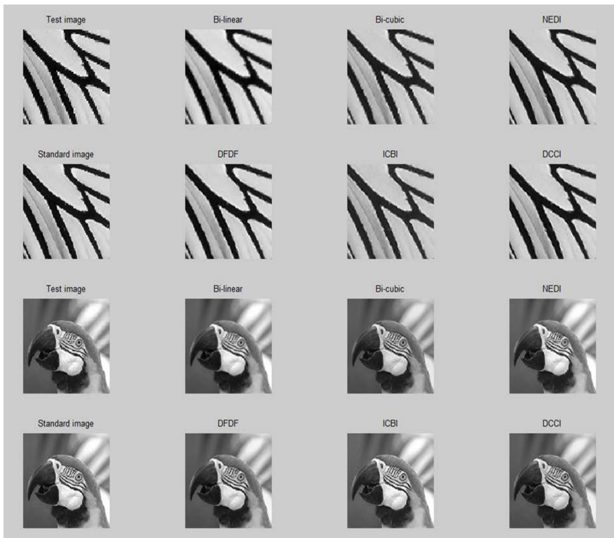

Figure 4: Butterfly and Parrot in KODAK

It can conclude that all interpolation methods obtain HR images with enriched details from visual analysis and EDI methods provide higher visual quality with crisper edges.

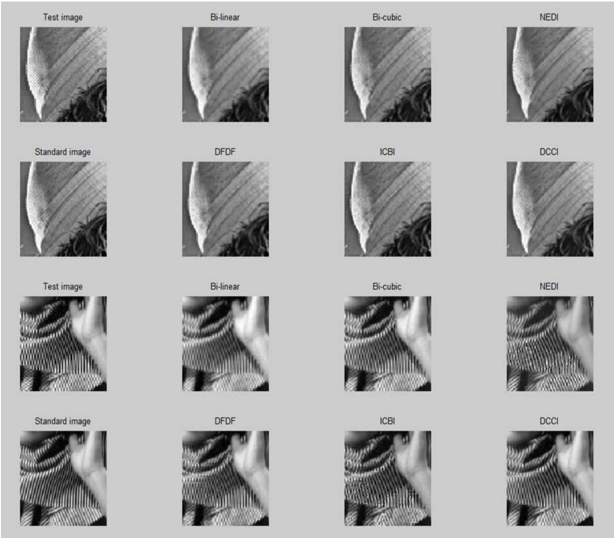

Figure 5: Lena and Barbara in STILL

Different from Bi-linear and Bi-cubic cause blurring, EDI methods may induce unnatural textures when LR images fail to present image structures.

5.3 Improvement of Edge-Preservation Ratio

In quantitative analysis, it can be observed that EPRa and EPRr are with higher improvement ratio which distinguish edge-preserving capacity of EDI methods from traditional methods. Correspondingly, interpolation results prove the rightness of proposed metrics of average values from traditional methods and EDI methods. Figure 6 shows mean value of EPRa and EPRr metrics from left to right. Up-row is for KODAK and bottom-row is STILL.

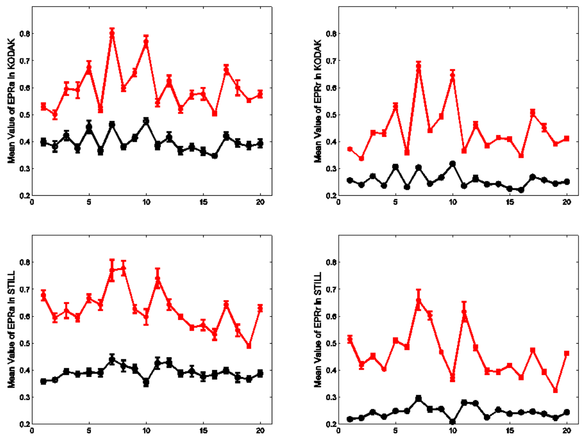

Figure 6: Error bars for EPR (Mean/STD)

For all twenty images in KODAK, the average EPRa of Bi-linear and Bi-cubic is 0.399 ± 0.036 (Mean±STD), of four EDI methods is 0.599 ± 0.082, and the improvement is up to 49.94%. And the average of EPRr of traditional methods is 0.257 ± 0.027, of four EDI methods is 0.444 ± 0.090, and the improvement is up to 72.78%.

For all twenty images in STILL, the average EPRa of Bi-linear and Bi-cubic is 0.391 ± 0.025 (Mean±STD), of four EDI methods is 0.626 ± 0.076, and the improvement is up to 59.88%. And the average of EPRr of traditional methods is 0.245 ± 0.022, of four EDI methods is 0.461 ± 0.087, and the improvement is up to 88.23%.

6. DISCUSSION AND CONCLUSION

One defect in experiment is how to down-sample standard images. Most sensors generate images by averaging over the unit cell. In addition, if down-sampled images exceed the Nyquist sampling limit, some small edges could be lost. And interpolation becomes meaningless when LR images are unable to represent image structures.

Image interpolation is intrinsically an ill-posed inverse problem. Even double-size an image, the number of known pixels is only 1/3 of that of unknown pixels. Fully interpolation for high visual quality is still challenging.

Traditional interpolation methods evaluate the unknown pixels indiscriminately in horizontal or vertical direction which discard characteristics of edges and textures. Blurring, blocking and loss of details are easily observed in interpolated images. EDI approaches consider edge messages, and adjust blending weights of neighbor pixels around missing points. Final intensities of missing points are settled based on the optimal weights and values of neighbor pixels.

This paper evaluated performance of four EDI methods with Bi-linear and Bi-cubic, and proposed two metrics to measure edge-preserving ability from accuracy and robustness. Totally six interpolation methods are performed on two groups of images with eight metrics. All methods are able to generate HR images with enriched details, and E-DI methods are better than traditional methods when pre-interpolated images with sufficient information to represent scenes. Among these EDI methods, the theoretical backgrounds of NEDI and DFDF are excellent, and implementation strategies of ICBI and DCCI are better. DCCI and ICBI overall outperforms NEDI and DFDF from objective metrics and visual analysis with lower and stable time cost regardless of image resolution and contents.

The performance evaluation in this paper focuses on noise-free images. In real applications, such as in medical imaging, artifacts and noise are prevalent. A preprocessing of artifact removal and noise suppression should be taken into account before the image interpolation. Image interpolation may be useful to improve the readability and entertainments, but it inevitably introduces uncertainties in image content. Restricting these uncertainties during interpolation procedure is also necessary.

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