Comparative Analysis of Edge Based Single Image Superresolution

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ABSTRACT: **Super-resolution image reconstruction provides an effective way to increase image resolution from a single or multiple low resolution images. There exists various single image super-resolution based on different assumptions, amongst which edge adaptive algorithms are particularly used to improve the accuracy of the interpolation characterizing the edge features in a larger region. A recent algorithm for image iterative curvature based interpolation (ICBI) performs iterative procedure of the interpolated pixels obtained by the 2nd order directional derivative of the image intensity. ICBI in comparison with bicubic interpolation and the other interpolation algorithm such as improved new edge directed interpolation (INEDI) provides notably higher values in terms of qualitative and quantitative analysis. Comparative analysis of these algorithms performed on number of test images on the basis of PSNR and RMSE metrics show effectiveness of edge based techniques.**

Keywords **–Interpolation, Iterative curvature based interpolation (ICBI), improved new edge directed interpolation (INEDI), Peak Signal to Noise Ratio (PSNR), Root Mean Square Error (RMSE), Super-resolution (SR).**

1. Introduction

The goal of super-resolution image reconstruction technology is to generate high-resolution (HR) images from input low-resolution (LR) images. After this was first addressed in 1984 [1], super-resolution technologies have been extensively studied and widely used in satellite imaging, medical image processing, traffic surveillance, video compression, video printing and other applications. The main goal is to extract the useful information or required image details. Super-resolution reconstruction techniques have been mainly divided into two families: (1) multi image super-resolution and (2) single image super-resolution.

Many researchers have tackled the super-resolution reconstruction problem for both still images and videos. Although the super-resolution reconstruction techniques for video are often extensions to still image super-resolution, many different approaches proposed are reported in [2]. In general, based on the type of cues used, the super-resolution methods can be further classified into two categories: motion-based techniques and the motion-free approaches. Motion-based techniques use the relative motion between different low resolution observations as a cue in estimating the high resolution image, while motion-free super-resolution techniques may use cues such as blur, zoom, and shading.

The basic idea behind SR is to combine the non-redundant information contained in multiple low-resolution (LR) frames to generate a high-resolution (HR) image. A closely related technique with SR is the single image interpolation approach, which can be also used to upscale the LR image. The resolution of a digital image can be classified in many different ways such as, pixel resolution, spatial resolution, spectral resolution, temporal resolution, radiometric resolution etc. As there is no additional information provided, the quality of the single image interpolation is very much limited due to the ill-posed nature of the problem, and the lost frequency components cannot be recovered. In the SR setting, however, multiple LR observations are available for reconstruction, making the problem better constrained. The non-redundant information contained in these LR images is typically introduced by sub pixel shifts between them. These sub pixel shifts may occur due to uncontrolled motions between the imaging system and scene, e.g., movement of objects, or due to controlled motions, e.g., the satellite imaging system orbits the earth with predefined speed and path.

This paper is organized as follows: Section 2 gives the basic approaches of super-resolution. Section 3 describes interpolation based algorithms for single image super-resolution in spatial domain. Section 4 describes the experimental results and comparative analysis. Conclusions are provided in Section 5.

2. Approaches of Super-resolution

Many techniques have been proposed over the last two decades [2] representing approaches from frequency domain to spatial domain, and from signal processing perspective to machine learning perspective. Early works on super-resolution mainly followed the theory of [1] by exploring the shift and aliasing properties of the Fourier transform.

Approaches addressing the SR problem can be categorized as reconstruction based, example based, learning based and interpolation based.

2.1 Reconstruction Based Approach

The basic idea of reconstruction-based super-resolution is to exploit additional information from successive LR frames with sub pixel displacements and then to synthesize an HR image or a sequence. Most of the algorithms solve the super-resolution problem which is in spatial domain. Iterative back-projection [3] algorithms estimate the HR image by iteratively back projecting the error between simulated LR images and the observed ones. Maximum a posteriori (MAP) [5] approaches adopt the prior probability of target HR images to stabilize the solution space under a Bayesian framework. However, these approaches are computationally demanding.

2.2 Example Based Approach

Generic image priors are usually deployed to regularize the solution properly. The regularization becomes especially crucial when insufficient number of measurements is supplied, as in the extreme case, only one single low-resolution frame is observed. In such cases, generic image priors do not suffice as an effective regularization for SR [2]. Different from previous approaches where the prior is in a parametric form regularizing on the whole image, the example-based methods develop the prior by sampling from other images, similar to in a local way.

2.3 Statistical or Learning Based Approach

Learning based techniques estimate high frequency details from a large training set of HR images that encode the relationship between HR and LR images [5]. These approaches effectively hallucinate missing details based on similarities between the LR image and the examples in the training set. These approaches have been applied to SR in various ways, including generic detail synthesis for up sampling, edge-focused detail synthesis [4], imposing consistency on synthesized detail and targeting multiple low-resolution images. One crucial problem in learning-based super-resolution algorithms is the representation of the high-frequency component of an HR image. Other problems of learning-based approaches are related to the fact that prior information used is not usually valid for arbitrary scaling factors and the fact that they are computationally expensive.

2.4 Interpolation Based Approach

In the SR problem there is a requirement to obtain a digital image, which is to be represented on an enlarged grid from original data sampled on a smaller grid. This image should be look like it had been captured with a sensor having the resolution of the upscaled image or, at least, present a natural texture. Methods like bilinear or bicubic interpolation which are commonly applied to solve this problem are less effective to fulfill these requirements as many times these methods results into creating images that are affected by artifacts like jagged contours, and over smoothing. Even edge-adaptive methods [8] could easily reach real-time performances; however, they often introduce several artifacts.

Whereas more effective non iterative edge-adaptive methods like new edge-directed interpolation (NEDI) [9] or improved NEDI (iNEDI) [10] leads to computational complexity even higher than that of many learning-based methods. Other optimization methods as given in [2] are often able to obtain good edge behavior, even if sometimes at the cost of texture flattening. An image upscaling method iterative curvature based interpolation (ICBI) technique as explained in [7] is able to obtain artifact-free enlarged images preserving relevant image features and natural texture.

3. Implementation of Super-resolution Algorithms

In this paper implementation of three interpolation based approaches is performed and compared. These methods are described as follows:

3.1 Bicubic Interpolation

Bicubic interpolation is chosen over bilinear interpolation in image resampling, when speed is not a major concern. Bilinear interpolation [8], takes only 4 pixels (2x2) into account, where bicubic interpolation takes 16 pixels (4x4). Images obtained with bicubic interpolation are smoother and have few interpolation artifacts. In this method function values f and its derivatives f_x , f_y andf_{xy} are known at 4 points as (0,0);(1,0);(0,1) and (1,1) respectively. Then the interpolated surface is given as:

$$p(x,y) = \sum_{i=0}^{3} a_{ij} \;\; x^i y^j \qquad (1)$$

This interpolation considers 16 coefficients of a_{ij}. This procedure yeids a surface $p(x,y)$ on the unit square [0, 1] $\times$ [0, 1] which is continuous with continuous derivatives. Convolution based interpolation [6] is described mathematically as:

$$f(x) = \sum_{k \in z} f_k \; \varphi(x-k) \qquad (2)$$

The third order cubic convolution kernel is defined as:

$$\varphi_{cc3}(x) = \begin{cases} \frac{3}{2}|x|^3 - \frac{5}{2}|x|^2 + 1 \\ -\frac{1}{2}|x|^3 + \frac{5}{2}|x|^2 - 4|x| + 2 \\ 0 \end{cases} \qquad (3)$$

3.2 Iterative Curvature Based Interpolation (ICBI)

ICBI method is executed in 4 different steps as shown in Fig. 1. Edge directed interpolation (EDI) gives the basic description of the image upscaling method based on grid doubling and hole filling. Improved NEDI algorithm demonstrates the relationship between the constraints and second order derivatives used in ICBI algorithm [7].

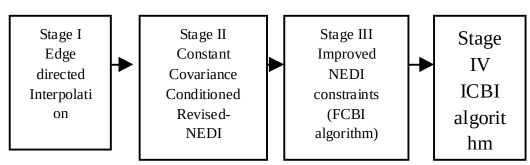

Fig. 1 Development stages of IBCI method

3.2.1 *Edge Directed Interpolation:*

The ‘edge-directed’ interpolation algorithms[9] when applied each time, approximately double the image size into an enlarged grid (indexed by 2i and 2j) from copying the original pixels (indexed by i and j), and then filling the gaps by ad hoc rules obtain the missing values as weighted averages of valued neighbors, with weights derived by a local edge analysis as shown in Fig.2.

For example, for the first step, the interpolated value is usually computed as:

$$I_{2i+1,2j+1} = \overrightarrow{\alpha}.(I_{2i,2j,}I_{2i,2j+2,}I_{2i+2,2j,}I_{2i+2,2j+2}) \quad (4)$$

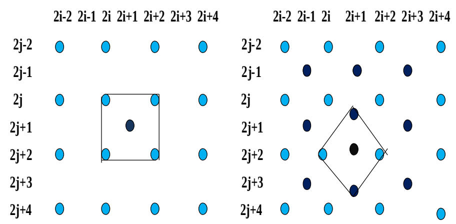

Fig. 2 Two-step interpolation based on a weighted average of four neighbors [9].

Computational cost of this procedure is quite high.

3.2.2 *Constant Covariance Conditioned Revised*

In this case, the brightness changes only perpendicular to the edge and it means that the over constrained system solved to obtain the parameters is badly conditioned due to the rank deficiency of the problem [10].

$$I_{2i+1,2j+1} = \vec{\beta}(I_{2i,2j} + I_{2i+2,2j+2}\ ,I_{2i,2j+2} + I_{2i+2,2j+2}) \quad (5)$$

The solution of this step is faster (about35%) as given in [7] and most important, the quality of the interpolation is the same as obtained with the NEDI method.

3.2.3 *Improved NEDI Constraints*

If the condition 5 holds in a neighborhood and across scales, it is reasonable that an algorithm iteratively refining interpolated pixels by locally minimizing a function that should be zero. Then this constraint would be effective to obtain a good result. From (5):

$$\beta_1(I_{2i,2j} - 2I_{2i+1,2j+1} + I_{2i+2,2j+2}) + \beta_2(I_{2i,2j+2} - 2I_{2i+1,2j+1} + I_{2i+2,2j+2}) = (1- \ 2\ (\beta_1 + \beta_2))I_{2i+1,2j+1} \quad (6)$$

One way to guarantee that this condition is locally true is to assume that local approximations of the second-order derivatives along the two perpendicular directions$(I_{2i,2j} - 2I_{2i+1,2j+1} + I_{2i+2,2j+2})$and $(I_{2i,2j+2} - 2I_{2i+1,2j+1} + I_{2i+2,2j})$ divided by the local intensity are $I_{2i+1,2j+1}$ constant. If assume that the local gain is null $(\beta_1 + \beta_2 = 1/2)$, can impose simply the constancy of the second-order derivative estimates. This condition is actually introduced in the ICBI method.

3.2.4 *Iterative Curvature Based Interpolation*

ICBI method obtains by using Fast curvature based interpolation (FCBI) method and energy function.

3.2.4.1 *FCBI Method* : The two filling steps are performed by first initializing the new values with the FCBI algorithm [7], i.e., for the first step, computing local approximations of the second-order derivative $\tilde{I}_{11}(2i+1, 2j+1)$ and $\tilde{I}_{22}(2i+1, 2j+1)$ along the two diagonal directions using eight-valued neighboring pixels as shown in Fig .3.

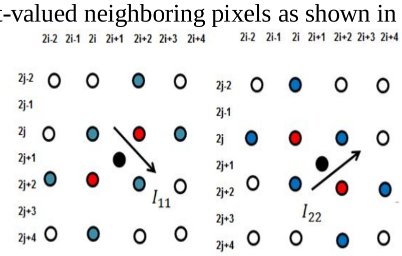

Fig. 3 FCBI method - At each step FCBI algorithm fills the central pixel (black) with the average of the two neighbors in the direction of the lowest second-order derivative ($i.e.$, I_{11}or I_{22}). [7]

$$\tilde{I}_{11}(2i+1, 2j+1) = I\,(2i-2, 2j+2) + I\,(2i, 2j) + I\,(2i+2, 2j-2) - 3I\,(2i, 2j+2) - 3I\,(2i+2, 2j) + I\,(2i, 2j+4) + I(2i+2, 2j+2) + I(2i+4, 2j)$$

$$\tilde{I}_{22}(2i+1, 2j+1) = I\,(2i, 2j-2) + I\,(2i+2, 2j) + I\,(2i+4, 2j+2) - 3I\,(2i, 2j) - 3I\,(2i+2, 2j+2) + I\,(2i-2, 2j) + I(2i, 2j+2) + I(2i+2, 2j+4) \quad (7)$$

And then assigning to the point the average of the two neighbors in the direction where the derivative is lower:

$$\frac{I\,(2i,2j) + I\,(2i+2,2j+2)}{2}, \text{ if } \tilde{I}_{11}(2i+1, 2j+1) < \tilde{I}_{22}(2i+1, 2j+1)$$

$$\text{Otherwise } \frac{I\,(2i+2,2j) + I\,(2i,2j+2)}{2} \quad (8)$$

3.2.4.2 *Energy Function*: The main energy term defined for each interpolated pixel should be minimized by small changes in second order derivatives:

$$U\,(2i+1, 2j+1) = aU_c\,(2i+1, 2j+1) + bU_e\,(2i+1, 2j+1) + cU_i\,(2i+1, 2j+1) \quad (9)$$

U_c = *curvature continuity*
U_e = *curvature enhancement*
U_i = *isophote smoothing*
U = *energy term*

a, b, c were *chosen by trial and error in order to maximize the perceived image quality.*

The ratio between a and b determines a trade-off between edge sharpness and artifacts removal. The value of c is not critical.

After the second hole-filling step i.e. FCBI ; the iterative procedure is repeated in a similar way, just replacing the diagonal derivatives in the energy terms with horizontal and vertical ones and iteratively modifying only the values of the newly added pixels. Due to the iterative procedure, this method is termed as ICBI.

4. Experimental Evaluation

Test database of natural images selected from the morgueFile online archive [7]. Test images' size is 256x256 pixels and it uses TIFF format. Test images are both color and gray-scale images. Results are shown for Test image 1-5 namely, piano.tiff, lady.tiff, bird.tiff, duck.tiff and flower.tiff. Subjective and objective tests are performed in order to compare quantitatively the quality of the images resulted with different methods.

4.1 Quantitative Results

The quality metrics used to verify the quality of upscaled images with the SR methods are root mean square error (RMSE) and peak signal to noise ratio (PSNR). Defining the term mean square error (MSE) as:

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \qquad (10)$$

Where, $I(i,j)$ is the original image

K (i, j) is the output image and image size is *m x n*

$$RMSE = \sqrt{MSE} \qquad (11)$$

$$PSNR = 20\ log_{10}\,[(MAX_I) - (MSE)] \qquad (12)$$

Table 1 show quantitative results of interpolation based single image SR methods. Good quality images achieve the maximum PSNR and minimum RMSE. It implies that ICBI performs better over other two methods. It is also verified in our experimental evaluation that ICBI requires less computational time as compared to other methods.

Table 1. PSNR and RMSE results for interpolation based single image super resolution methods

	Bicubic [6]		**INEDI [9]**		**ICBI [7]**	
	PSNR (dB)	RMSE	PSNR (dB)	RMSE	PSNR (dB)	RMSE
Test Image1	19.53	27.00	22.62	18.92	21.89	20.57
Test Image2	20.29	24.73	21.92	20.52	24.06	16.05
Test Image3	19.56	26.65	28.48	9.63	41.11	2.25
Test Image4	20.29	24.73	21.92	20.52	24.06	16.05
Test Image5	19.53	27.00	22.62	18.92	21.89	20.57
Average values	**19.19**	**28.12**	**23.27**	**18.3**	**26.11**	**16.31**

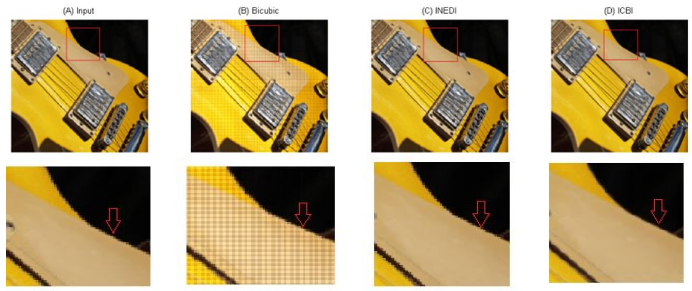

Fig.4 Test Image 1- (A) Input image, Results obtained with- (B) Bicubic interpolation, (C) INEDI and (D) ICBI method respectively (Top row: Complete image, Bottom row: close-up views with arrows pointing towards result of interpolation methods)

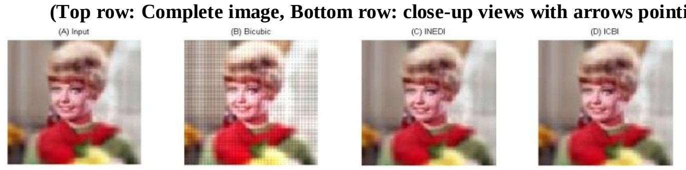

Fig.5 Test Image 2- (A) Input image, Results obtained with- (B) Bicubic interpolation, (C) INEDI and (D) ICBI method respectively

Fig.6 Test Image 3- (A) Input image, Results obtained with- (B) Bicubic interpolation, (C) INEDI and (D) ICBI method respectively

4.2 Qualitative Results

Fig. 4, 5 and 6 show the up sampled, high quality images obtained with different SR methods. It can clearly be seen by comparing the images upscaled by the same factor (considered factor 2) with different methods. Even the qualitative results on the test images show effectiveness of ICBI method.

5. CONCLUSION

In this paper, several methods of edge based single image super resolution such as bicubic interpolation, INEDI and ICBI are discussed. Bicubic interpolation is relatively sensitive to edge features whereas INEDI is computationally expensive. Comparative analysis of different interpolation based SR methods shows that a new improved interpolation based ICBI algorithm demonstrates significant improvements in terms of both qualitative and quantitative analysis and also causes fewer artifacts.

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