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Single Image Super Resolution: Edge Based Techniques

Sonali Shejwal, V. K. Hadke, R. K. Deode

Department of E & Tc, TSSM's BSCOER, Narhe, University of Pune, India
E-mail: sonali.shejwal@gmail.com

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 enhanced 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 2^{nd} order directional derivative of the image intensity. ICBI as compared with bicubic interpolation and also the alternative interpolation formula like improved new edge directed interpolation (INEDI) provides notably higher values in terms of qualitative and chemical analysis. Comparative analysis of those algorithms performed on range of take a look at pictures on the premise of PSNR and RMSE metrics show effectiveness of edge based mostly 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)*

INTRODUCTION

The goal of super-resolution image reconstruction technology is to get high-resolution (HR) pictures from input low-resolution (LR) pictures. when this was initial self-addressed in 1984, super-resolution technologies are extensively studied and wide utilized in satellite imaging, medical image process, traffic police work, video compression, video printing and different applications [1]. The most goals are to extract the helpful info or needed 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 drawback for each still pictures and videos. Though the super-resolution reconstruction techniques for video are usually extensions to still image super-resolution, many various approaches projected are rumored [2]. In general, supported the kind of cues used, the super-resolution strategies is additional classified into two categories: motion-based techniques and, therefore, the motion-free approaches. Motion-based techniques use the relative motion between totally different low resolution observations as a cue in estimating the high resolution image, whereas motion-free super-resolution techniques might use cues like blur, zoom, and shading.

The basic plan behind SR is to mix the non-redundant info contained in multiple low-resolution (LR) frames to come up with a high-resolution (HR) image. A closely connected technique with SR is that the single image interpolation approach, which may be conjointly accustomed upmarket the LR image. The resolution of a digital image may be classified in many alternative ways that like, picture element resolution, spacial resolution, spectral resolution, temporal resolution, radiometric resolution etc. As there is no extra info provided, the standard of the only image interpolation is extremely a lot of restricted because of the ill-posed nature of the matter, and, therefore, the lost frequency elements cannot be recovered. Within the SR setting, however, multiple LR observations area unit out there for reconstruction, creating the matter higher unnatural. The non-redundant info contained in these LR pictures is often introduced by sub picture element shifts between them. These sub picture element shifts could occur because of uncontrolled motions between the imaging system and scene, e.g., movement of objects, or because of controlled motions, e.g., the satellite imaging system orbits the world with predefined speed and path.

APPROACHES OF SUPER-RESOLUTION

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

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

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 algorithms estimate the HR image by iteratively back projecting the error between simulated LR images and the observed ones [3]. Maximum a posteriori (MAP) approaches adopt the prior probability of target HR images to stabilize the solution space under a Bayesian framework [4, 5]. However, these approaches are computationally demanding.

Example Based Approach

Generic image priors square measure sometimes deployed to regularize the answer properly. The regularization becomes particularly crucial once meagre range of measurements is equipped, as within the extreme case, only one single low-resolution frame is ascertained. In such cases, generic image priors do not fulfill as a good regularization for SR [2]. Completely different from previous approaches wherever the previous is in a very constant kind regularizing on the full image, the example-based strategies develop the previous by sampling from alternative pictures, just like in a very native means.

Statistical or Learning Based Approach

Learning primarily based techniques estimate high frequency details from an oversized coaching set of time unit pictures that cipher the link between time unit and LR pictures [5]. These approaches effectively perceive missing details supported similarities between the LR image and also the examples within the coaching set. These approaches are applied to SR in varied ways that, together with generic detail synthesis for up sampling, edge-focused detail synthesis, imposing consistency on synthesized detail and targeting multiple low-resolution pictures [4]. One crucial drawback in learning-based super-resolution algorithms is that the illustration of the high-frequency element of associate time unit image. Different issues of learning-based approaches are associated with the actual fact that previous data used is not sometimes valid for discretionary scaling factors and also the undeniable fact that they are computationally expensive.

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 could easily reach real-time performances; however, they often introduce several artifacts [6–8].

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

Implementation of Super-Resolution Algorithms

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

Bicubic Interpolation

Bicubic interpolation is chosen over bilinear interpolation in image resampling, when speed is not a major concern. Bilinear interpolation, takes only 4 pixels (2x2) into account, where bicubic interpolation takes 16 pixels (4x4) [8]. 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 and f_{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 yields a surface $p(x,y)$ on the unit square $[0, 1] \times [0, 1]$ which is continuous with continuous derivatives. Convolution based interpolation is described mathematically as [6]:

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

The third order cubic convolution kernel is defined as:

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

Iterative Curvature Based Interpolation (ICBI)

ICBI method is executed in 4 different steps as shown in Figure 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].

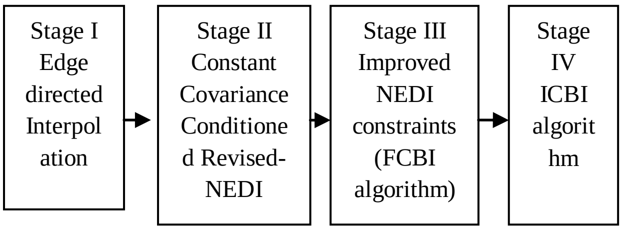

Fig. 1: *Development Stages of IBCI Method.*

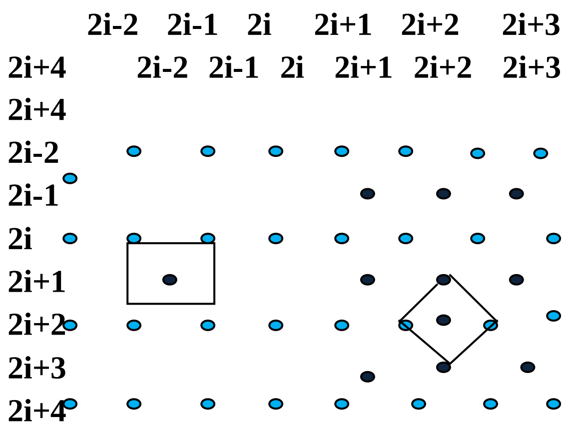

Fig. 2: *Two-Step Interpolation based on a Weighted Average of Four Neighbors [9].*

Computational cost of this procedure is quite high.

Edge Directed Interpolation

The 'edge-directed' interpolation algorithms 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 byad hoc rules obtain the missing values as weighted averages of valued neighbors, with weights derived by a local edge analysis as shown in Figure 2 [9].

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

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

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 (about 35%) as given and most important, the quality of the interpolation is the same as obtained with the NEDI method [7].

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.

Iterative Curvature Based Interpolation

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

FCBI Method

The two filling steps are performed by first initializing the new values with the FCBI algorithm, 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 Figure 3 [7].

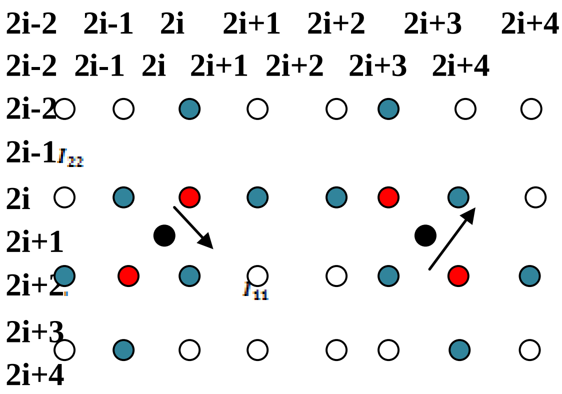

Fig. 3: FCBI Method - At Each Step FCBI Algorithm Fills the Central Pixel (Black) with the Average of the Two Neighbors in the Direction of The Lowest Second-Order Derivative (**$i.e., I_{11}$** *or* **I_{22}**) *[7].*

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

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

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

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

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

Energy Function

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

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

$U_c = curvature\ contiunity$ $U_e = curvature\ enhancement$

$U_i = isophote\ smoothing$

$U = energy\ term$

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.

EXPERIMENTAL EVALUATION

Test database of natural images selected from the morgue File 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.

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:

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

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

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

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

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

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 Image 1	19.53	27.00	22.62	18.92	21.89	20.57
Test Image 2	20.29	24.73	21.92	20.52	24.06	16.05
Test Image 3	19.56	26.65	28.48	9.63	41.11	2.25
Test Image 4	20.29	24.73	21.92	20.52	24.06	16.05
Test Image 5	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

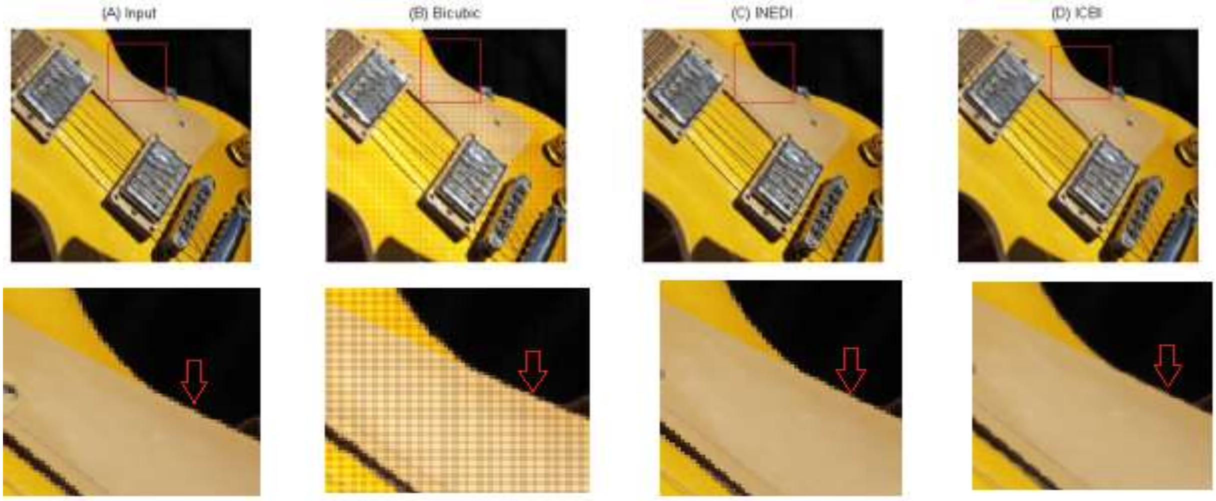

Fig. 4: *Test Image 1- (A) Input Image, Results Obtained with- (B) Bicubic Interpolation, (C) INEDI and (D) ICBI Method Respectively (Top Row: Complete Image, Bottom Row: Close-Up Views with Arrows Pointing towards Result of Interpolation Methods).*

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.*

Qualitative Results

Figures 4–6 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.

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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