Super Resolution from Single Image: Survey

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***Abstract*— Super resolution technology provides an effective way to increase image resolution from a single or multiple low resolution input image(s). Amongst various single image super resolution algorithms, edge adaptive algorithms are used to improve the accuracy of the interpolation characterizing the edge features in a lager region and for real-time performance. A new algorithm for image Iterative curvature based interpolation (ICBI) performs iterative correction of the interpolated pixels obtained by the 2nd order directional derivative of the image intensity. Super resolution in spatial and wavelet domain also obtains better results as it has advantage uses in both domains. ICBI in comparison with super resolution in spatial and wavelet domain and the other interpolation algorithms such as Improved New Edge Directed Interpolation (INEDI), Fast Curvature Based Interpolation (FCBI) and bilinear interpolation provides notably higher values in terms of subjective and objective tests. PSNR of images shows effectiveness of algorithm.**

***Keywords*— Edge adaptive algorithms, Interpolation, Peak Signal to Noise Ratio (PSNR), Spatial and wavelet domain, Super Resolution (SR).**

I. 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 (2) Single image super resolution.

Many researchers have tackled the super-resolution reconstruction problem for both still images and video. Although the super-resolution reconstruction techniques for video are often extensions to still image super-resolution, many different approaches [3], [4] have also been proposed. In general, based on the type of cues used, the super-resolution methods can be 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 frames to generate a high-resolution image. A closely related technique with SR is the single image interpolation approach, which can be also used to increase the image size. However, since 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 low-resolution 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 summarized as follows: Section II gives the basic approaches of super resolution Section III describes interpolation based algorithm of single image super resolution in spatial domain and super resolution in spatial and wavelet domain. Section IV describes the experimental tests showing its advantages. A brief conclusion is given in Section V.

II. APPROACHES OF SUPER RESOLUTION

Many techniques have been proposed over the last two decades [3] 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. However, these frequency domain approaches are very restricted in the image observation model they can handle, and real problems are much more complicated.

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

A. 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. Early super-resolution methods solve the problem in the frequency domain but are usually restricted to global translational motion and linear space-invariant blur [1]. Most contemporary algorithms solve the super-resolution problem in the spatial domain. Iterative back-projection [4] 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. Projection on convex sets (POCS)[6] tends to consider the solution as an element on a convex set defined by the input LR images. However, these approaches are computationally demanding.

B. 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]. A recently emerging methodology for regularizing the ill-posed super-resolution reconstruction is to use examples, in order to break the super-resolution limit caused by inadequate measurements. 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 [18] in a local way.

C. 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 [7], [8]. These approaches effectively "hallucinate" missing details based on similarities between the LR image and the examples in the training set. These approaches have shown great promise and have been applied to SR in various ways, including generic detail synthesis for up sampling, edge-focused detail synthesis [7], imposing consistency on synthesized detail [7, 8], and targeting multiple low-resolution images. Recent work in [9] used a combined multi-image and learning-based strategy, where the training set is obtained from the low-resolution input itself. This particular approach is reliant on redundancies in the input image which is shown to be more beneficial in sharpening edges than in synthesizing details. 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.

D. Interpolation Based Approach

Image upscaling (and more generally image interpolation) methods are implemented in a variety of computer tools like printers, digital TV, media players, image processing packages, graphics renderers, and so on. The problem is quite simple to be described: need to obtain a digital image to be represented on a large bitmap from original data sampled in a smaller grid, and this image should look like it had been acquired with a sensor having the resolution of the upscaled image or, at least, present a "natural" texture. Methods that are commonly applied to solve the problem (i.e., pixel replication, bilinear, or bicubic interpolation) do not fulfill these requirements, creating images that are affected by visual artifacts like pixelization, jagged contours, and over smoothing.

Simplest edge-adaptive methods [15], which could easily reach real-time performances, are not, however, able to create natural looking images and often introduce relevant artifacts. More effective non iterative edge-adaptive methods like new edge-directed interpolation (NEDI) [16] or improved NEDI (iNEDI) [17] present a relevant computational complexity, even higher than that of many learning-based methods. An image upscaling method explains in [14] able to obtain artifact-free enlarged images preserving relevant image features and natural texture. Other optimization methods [10] are often able to obtain good edge behavior, even if sometimes at the cost of texture flattening.

The constraint used in ICBI technique, based on the continuity of the second order derivatives (that prove to be related to the NEDI constraint), is simple and extremely effective in removing artifacts; The main contributions of this algorithm [14] for image upscaling based on the iterative smoothing of second-order derivatives [iterative curvature based interpolation (ICBI)].

II. OVERVIEW OF SUPER RESOLUTION ALGORITHMS

A. Bilinear Interpolation

Bilinear interpolation is an extension of linear interpolation for interpolating functions of two variables on a regular 2D grid. Bilinear interpolation is a resampling method that uses the distance weighted average of the four nearest pixel values to estimate a new pixel value. The four cell centers from the input raster are closest to the cell center for the output processing cell will be weighted and based on distance and then averaged. Suppose that we want to find the value of the unknown function f at the point $P = (x, y)$ as shown in Fig.1. It is assumed that we know the value of f at the four points $Q_{11} = (x_1, y_1)$, $Q_{12} = (x_1, y_2)$, $Q_{21} = (x_2, y_1)$, and $Q_{22} = (x_2, y_2)$.

First do linear interpolation in the x-direction. These yields-

$$f(R_1) = \frac{x_2 - x}{x_2 - x_1} f(Q_{11}) + \frac{x - x_1}{x_2 - x_1} f(Q_{21}) \quad (1)$$

Where $R_1 = (x, y_1)$-

$$f(R_2) = \frac{x_2 - x_1}{x_2 - x_1} f(Q_{12}) + \frac{x - x_1}{x_2 - x_1} f(Q_{22}) \quad (2)$$

Where $R_2 = (x, y_2)$ Proceed by interpolating in the y-direction.-

$$f(P) = \frac{y_2 - y}{y_2 - y_1} f(R_1) + \frac{y - y_1}{y_2 - y_1} f(R_2) \quad (3)$$

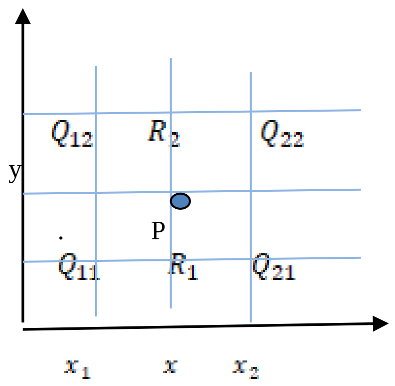

Fig. 1 Bilinear Interpolation

P = Desired Point Q = Known Points (four closest pixels) R = Point on the line with the known points

This gives the desired estimate of $f(x, y)$

$$f(x,y) = \frac{1}{(x_2-x_1)(y_2-y_1)}\{f(Q_{11})(x_2-x)(y_2-y)+f(Q_{21})(x-x_1)(y_2-y)+f(Q_{12})(x_2-x)(y-y_1)+f(Q_{22})(x-x_1)(y-y_1)\}$$

(4)

B. Development Stages of Iterative Curvature Based Interpolation (ICBI) method

This is organized in 4 steps. Edge directed interpolation (EDI) gives the basic description of the image upscaling methods based on grid doubling and hole filing. NEDI algorithm showed EDI drawbacks can be removed by changing the constant covariance constraint. Improved NEDI algorithm demonstrates the relationship between the constraints and second order derivatives used in ICBI algorithm. In ICBI algorithm describes [14] a detailed method of obtaining a high quality image using improve techniques as shown in Fig. 2.

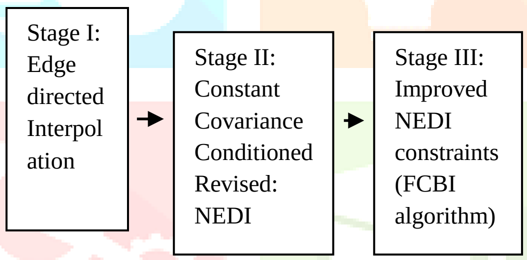

Fig. 2 Development stages of IBCI method

Iterative Curvature Based Interpolation method:

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 (Fig .3).

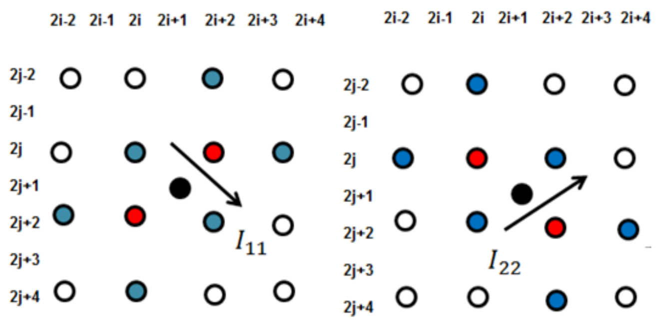

Fig. 3 FCBI method - At each step (here, it is shown the first), the FCBI algorithm fills the central pixel (black) with the average of the two neighbors in the direction of the lowest second-order derivative (I_{11} or I_{22}). I_{11} and I_{22} are estimated using for each one the eight-valued neighboring pixels (identified with different colors) [14].

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

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

(5)

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

$\frac{I(2i+2,2j) + I(2i,2j+2)}{2}$, otherwise. (6)

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

$U(2i+1,2j+1) = aU_c(2i+1, 2j+1) + bU_e(2i+1, 2j+1) + cU_i(2i+1, 2j+1)$ (7)

By using this pixel energy, the first step of the iterative interpolation correction (adjusting pixel values with two odd indexes) is finally implemented as a simple greedy minimization. Iteration is lower than a fixed threshold, or the maximum number of iterations has been reached. The number of iterations can also be fixed in order to adapt the computational complexity to timing constraints. After the second hole-filling step (assigning values to all the remaining empty pixels), 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.

C. Single Image Super Resolution in Spatial and Wavelet Domain

Interpolation techniques like pixel replication and bilinear interpolation up sample an image without considering any details of input image. These methods work well in smooth region but edges and some textures get blurred. In wavelet-domain based techniques of image interpolation the foremost challenge is to estimate unknown coefficients of three high frequency sub bands. Basic interpolation method in wavelet domain is Wavelet Zero-Padding. In this method [18] low resolution image is multiply with scaling factor S, which works as top left quadrant (LL) of final high resolution image. In other three quadrants of high-resolution image (HH, HL and LH), zeros are padded. Steps are as follows:**Step 1: Low Resolution Image:** Get the low resolution as input image.

Step 2: Up sampling of the Image:

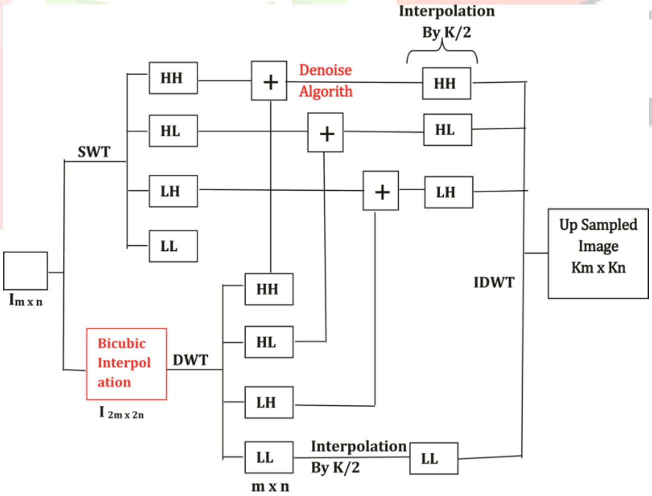

Fig.4 Image Upscaling

As shown in Fig 4 , apply Stationary Wavelet Transform (SWT) on low-resolution image of size m x n which produce four sub bands (LL, LH, HL, HH) with size of m x n each. SWT is same as Discrete Wavelet Transform (DWT) but SWT generates each sub band of the size of image while in DWT each sub band is half the size of image on the algorithm presented in [19].

Step 3 and 4: Gaussian Filter and Down sampling

After up sampling due to point spread function (PSF) image can be look blurred little bit. So Gaussian filter merely work like smoothing kernel.

Step 5 and 6: Reconstruction the error and up sampling the error

Up sampling the error is most important step. For reconstructing super resolution image, error must be back projected and for that error matrix must be up-sampled to meet super resolution image.

Step 7: Back projecting error

Finally error matrix generated in step 6 is added with high-resolution image generated in step 3. Repeat the above procedure as shown in the flowchart till we acquire satisfactory results. Within three iterations appropriate result comes.

III. EXPERIMENTAL EVALUATION

A. Subjective Test

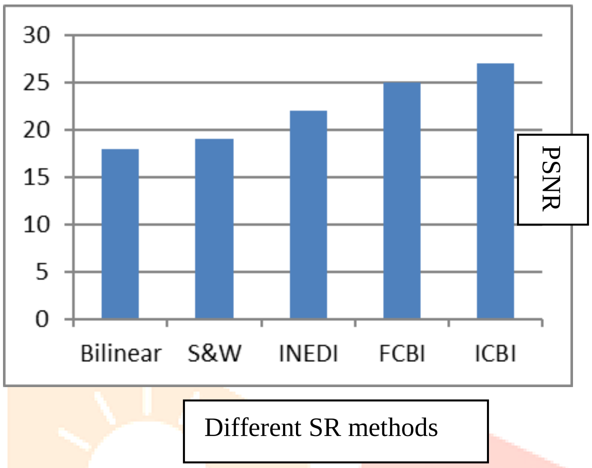

Fig. 5 Average qualitative scores of PSNR obtained by comparing pairs of differently enlarged images.

By looking at the quantitative results, it must also be considered that some of the methods are tested. In order to achieve the maximum PSNR is necessarily the best thing to do to have very good images. As shown in Fig. 5 ICBI obtains maximum PSNR value.

B.Objective Test

Fig. 6 shows images obtained after upsampling and which are equal to the corresponding size of original image. By looking at the qualititative results, it also be considered that some of the methods here are tested. ICBI obtains good results.

IV. . CONCLUSION

In this paper, several approaches of single image super resolution such as reconstruction based, learning based and interpolation based are discussed. Reconstruction based approach is relatively sensitive to registration errors and learning based approach is computationally expensive. Comparative analysis of different SR methods proves that a new improved interpolation based (ICBI) algorithm obtains satisfactory results in terms of both subjective and objective tests and also causes fewer artifacts.

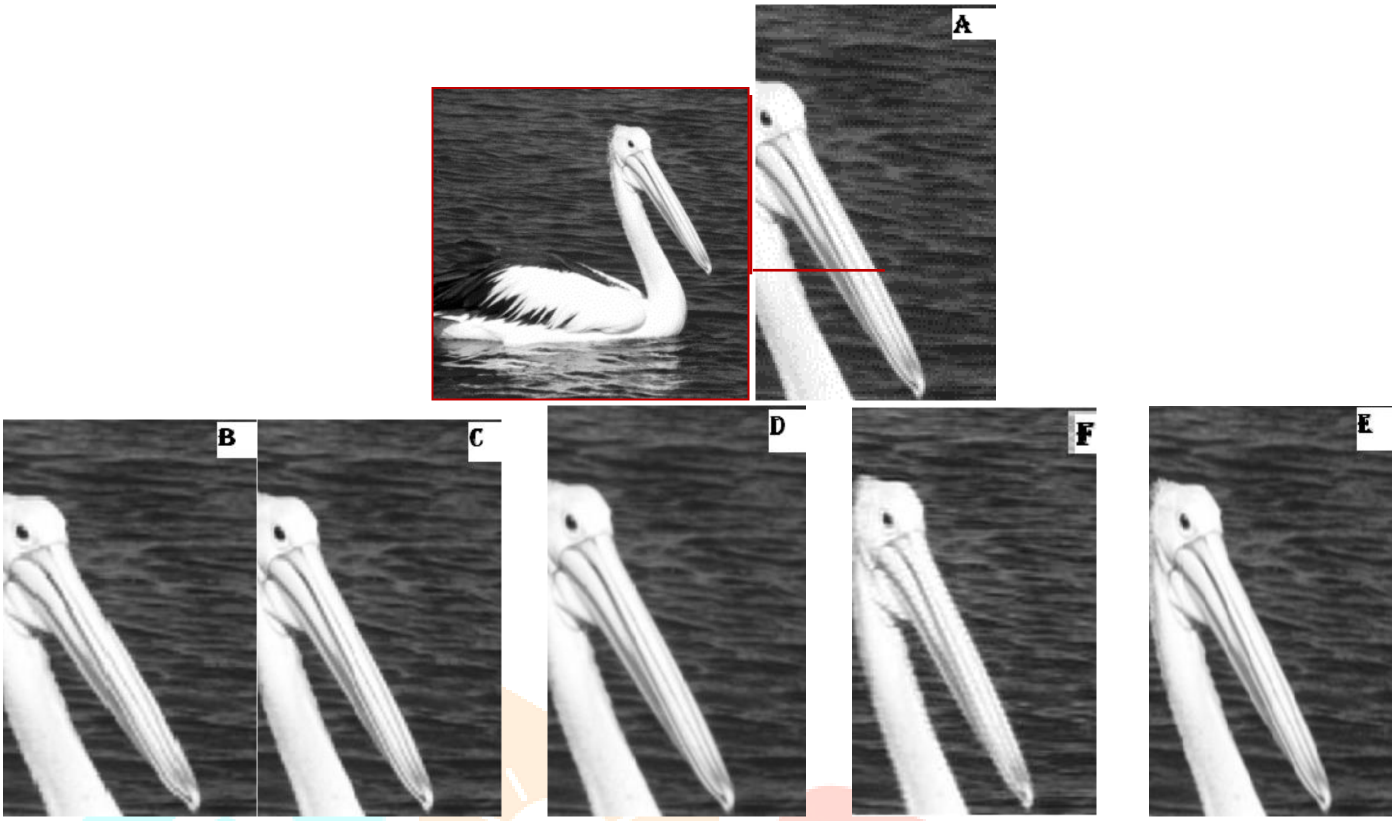

Fig. 6 Comparing with different methods (A) Enlargement of a natural image using pixel replication (in this case by a 4×factor) (B) Bilinear interpolation (C) NEDI and (D) INEDI provide better results (E) ICBI technique. (F) Results obtained with spatial and wavelet domains.

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