

Investigating Image Super Resolution Techniques: What to Choose?

Shahryar Shafique Qureshi, Xue Ming Li, Toufee Ahmad

Beijing Key Laboratory of Network System and Network Culture, Beijing University of Posts and Telecommunications,
Beijing, 100876, P.R.China.

its.shahryar@gmail.com, engrtoufeeahmad@gmail.com

Abstract—Super resolution image reconstruction refers to a process of creating a high resolution image from a single or multiple low resolution image(s). The main goal is to extract the useful information or required image details. Several super resolution reconstruction techniques have been proposed, which can be mainly divided into two families: (1) Multi image super resolution (2) Single image super resolution. In this paper we present comprehensive overview of the well known super resolution techniques for both mentioned families. We also discuss the recent developments, some applications of super resolution, simulation results and the future research challenges. We conducted several experiments on different images for the purpose of their quantitative and qualitative comparison.

Keywords—Image Reconstruction; Iterative Back-Projection; Projection Onto Convex Sets; Super resolution; Compressed Sensing

I. INTRODUCTION

Images with high pixel density are always desirable in almost all imaging applications. e.g. medical imaging, satellite imaging, video surveillance, high definition television broadcasting, microscopy, digital mosaicing etc. For such applications scientists have applied software resolution enhancement techniques, which termed as Super Resolution (SR) reconstruction techniques. The goal of super resolution technique is to reconstruct a high resolution image from a single or multiple low resolution image(s).

SR techniques can be broadly categorized into two families: 1) Classical multi-image Super resolution/Multiple image Super resolution. 2) Single Image Super resolution, also called Example/Learning Based super resolution. In multi-image super resolution high resolution (HR) image is reconstructed from the multiple observations of the same low resolution (LR) input image. In order to reconstruct a HR image, the LR frames are shifted with respect to the HR grid differently from each other and with sub-pixel increments. As each LR frame has inimitable information which cannot be obtained from other LR frames and this is subjugated to get a HR image.

While in the single image SR technique only a single image is available to work on and the problem is even more under constrained, as the image detail is limited. In SR literature these Single image SR techniques are usually know by Example or Learning Based SR. Basically in Example based SR techniques the high frequency information of the given single LR image is enhanced by retrieving the most likely high frequency information from the given training image samples based on the local features of the input LR image.

This section starts with some introductory remarks, then in section II we will see a general observation model for an imaging system. Which is then followed by an overview of SR techniques for both multi and single image super resolution in section III and IV respectively. In section V some simulation results of the SR techniques are given. In the end section VI presents the concluding remarks and future challenges for the super resolution image reconstruction.

II. OBSERVATION MODEL FOR SUPER RESOLUTION IMAGE RECONSTRUCTION

In this section we formulate an observation model for SR image reconstruction problem, which establish a relationship between the desired HR image and the observed LR images. We consider that the desired HR image is represented by X , a vector of image samples $X = [X_1, X_2, \dots, X_N]^T$ where N is given by $N = L_1 N_1 \times L_2 N_2$. It is assumed that X is to be sampled at or above the Nyquist rate from a continuous scene supposed to be a bandlimited. For the observed LR images, both horizontal and vertical directions are subsampled by factors of L_1 and L_2 respectively and is of size M_1 and M_2 . y_k denotes the k-th LR image and is represented by $y_k = [y_{k,1}, y_{k,2}, \dots, y_{k,M}]^T$ where $k=1,2,\dots,p$ and M is given by $M = M_1 \times M_2$. The observed LR images y_k are the warped, blurred, down sampled and noisy version

of the desired HR image X . The observation model can be mathematically formulated as:

$$y_k = D_k B_k W_k X + n_k \quad (1)$$

D_k is a $M \times N$ decimating (sub sampling) matrix, W_k is warp matrix of size $N \times N$ and B_k is blur matrix of size $N \times N$.

The warp matrix W_k refers to the motion models (global or local) degradation caused when acquiring k-th image. The blurring matrix B_k can be either linear space invariant (LSI) or linear space variant (LSV). Blurring may be resulting effect of relative movement between the observing image and imaging system and point spread function (PSF) of the LR sensor. Both W_k and B_k are multiplied with the downsampling matrix D_k which results in an aliased LR images. Finally white Gaussian noise n_k is encountered during the image acquisition process. In the above observation model the operations W_k , B_k , D_k can be combined into a transform matrix H_k and is written as:

$$y_k = H_k X + n_k \quad (2)$$

Researchers in [1]-[4] discussed another observation model and warping step is executed before the blurring. When the imaging blur is spatio-temporally and only global translational motion is involved among multiple observed LR images the blur matrix and warp matrix are computable. Use of the second model is more appropriate when the imaging blur is spatio temporally variant.

III. MULTI IMAGE SUPER RESOLUTION TECHNIQUES

Multi-image super resolution is a well studied problem now and several methods have been proposed by the researchers. [5] introduced the idea of image super resolution and they used signal processing techniques to reconstruct the HR image by receiving additional information from multiple LR images. Since then SR is a hot research area and many superior SR techniques have been reported. Most of the SR techniques consist of three steps: registration, interpolation and restoration. The registration stage is the process of estimation of relative shifts between LR images compared to the reference LR image with fractional pixel accuracy. Thus all LR images are registered in the same coordinate system. Then non-uniform interpolation is applied to obtain a uniformly spaced HR image from non-uniformly spaced composite of LR images. Finally in the restoration step the blur and noise is removed. These steps are implemented separately or simultaneously depending upon the reconstruction method adopted.

Multi-image SR techniques can be further divided into two categories i.e. Frequency domain techniques and Spatial domain techniques. In frequency domain techniques the

Fourier transform property is used which make it highly attractive to the global translation models. It also takes the advantage of utilizing sampling theory to enable effect restoration made possible by availability of multiple observation models. In the last decade spatial domain techniques have gained more popularity as they allow more observation and degradation models. Also they allow the inclusion of priori constraints into the reconstruct process.

A. Frequency Domain Techniques

The frequency domain techniques have proved that HR image can be reconstructed from the LR image sequences through aliasing removal. So far research done in this domain is based on the influential work of Tsai and Huang [5]. The frequency domain techniques are based on three principles (i) the shifting property of Fourier Transform (FT) (ii) the aliasing relationship between continuous FT of an HR image and the discrete FT of the LR images (iii) and bandlimited HR image. These principles are used to formulate a system of equations to create Discrete Fourier Transform (DFT) coefficients of the observed LR image and relate it to a sample of Continuous Fourier Transform (CFT) of an unknown image. Consider the continuous HR image is denoted by $f(x, y)$ and $F(u, v)$ be its CFT. Then the translated images can be represented as:

$$f_r(x, y) = f(x + \Delta x_r, y + \Delta y_r) \\ r = 1, 2, \dots, R$$

CFT of original image translation is given by $F_r(u, v)$. The shifted images are impulse sampled to yield observed images as:

$$y_r[m, n] = f(mT_x + \Delta x_r, nT_y + \Delta y_r)$$

where $m = 1, 2, \dots, M-1$ and $n = 1, 2, \dots, N-1$.

DFT is denoted by $\gamma_r[k, l]$ and may be computed for each observed images and it is related to the CFT of the original image through aliasing relation as:

$$\gamma_r[k, l] = \alpha \sum_{p=-\infty}^{\infty} \sum_{q=-\infty}^{\infty} F_r \left(\frac{k}{MT_x} + p f_{s_x}, \frac{l}{NT_y} + q f_{s_y} \right) \quad (3)$$

where $\alpha = 1/T_x T_y$, $f_{s_x} = 1/T_x$ and $f_{s_y} = 1/T_y$ are sampling rates in x and y dimensions. CFT of the original scene can be related to CFTs of the shifted versions through the shifting property as:

$$F_r(u, v) = e^{j2\pi(\Delta x_r u + \Delta y_r v)} F(u, v) \quad (4)$$

According to the third property in the frequency domain technique the original HR image is assumed as bandlimited so

the above Eq. (4) can be used to rewrite the aliasing relationship in Eq. (3) in the Matrix vector form as:

$$Y = \Phi F \quad (5)$$

where Y is $R \times 1$ column vector with r^{th} element being DFT coefficients $\gamma_r[k, l]$ of observed image $y_r[m, n]$. Φ is a matrix which relates the DFT of the observation data to the sample of the unknown CFT of $f(x, y)$ contained in the $4L_u L_v \times 1$ vector F . So the SR reconstruction require determining the DFTs of the observed data, Φ , solving Eq. (5) and reconstruct the desired HR image via inverse DFT. This technique is further extended by Kim and Bose [6] applied to LR images with same blur and noise characteristics, resulting in weighted least square formulation. Their method proved to be more computational efficient to solve system of equations in frequency domain in presence of noise. Later on they extended their research to minimize the errors in registration (Φ) by adopting Recursive total least square method [7]. Another idea of using DCT instead of DFT was proposed by Rhee and Kang [8] to reduce computational complexity and memory requirement.

The frequency domain techniques are theoretical simple and has less hardware complexity. Also the relationship between LR images and HR images is clearly demonstrated. Aliasing is much easier to describe and handle-in. Due to the nature of FT, frequency domain techniques are limited to only global translation motion and space invariant degradation models. It is difficult to apply the spatial domain apriori knowledge for regularization in frequency domain techniques.

B. Spatial Domain Techniques

1) *Non-uniform Interpolation*: This technique is based on the non-uniform sampling theory and thus allowing reconstruction of functions from samples, taken at non-uniformly distributed locations. Clark et.al. [9] was the first one to introduce this idea and it was further extended by Kim and Bose [10] for 2-D bandlimited discrete signals. To estimate the HR image, this technique follows 3 steps: Registration, Non-uniform interpolation and Restoration (deblurring process). In the registration step the relative motion information (i.e. relative shifts) is estimated between LR images compared to reference LR images with sub-pixel accuracy. Then the next step is to apply non-uniform interpolation because the registered HR image does not always match up to a uniformly spaced grid so, non-uniform interpolation results a uniformly spaced HR image. In the restoration step noise and blurring effect in HR image is removed and any of the deconvolution methods can be used that consider presence of noise. This technique has advantage of less computational complexity and makes possible the real-time applications. However there are some limitations like all the LR images should have same blur and noise characteristics. Also the errors occurred in the interpolation

step are ignored by restoration step, so optimality of the whole reconstruction algorithm is not guaranteed.

2) *Projection Onto Convex Sets (POCS)*: Projection Onto Convex Sets (POCS) is a space domain technique which provides a solution to the blurring caused by sensor point spread function (PSF) in LR images and was firstly introduced by Stark and Oskoui [11]. It allows the inclusion of priori knowledge into reconstruction process. The estimated reconstruction is successively projected on different convex constraints sets. Those sets are representing the reconstructed image characteristics like, smoothness, finite energy, positivity and fidelity to data. Assume the following convex constraint sets which are based on observed LR image pixel at each frame [12] [13].

$$C_{m_1 m_2 k} = \left\{ z(n_1, n_2) : \left| r_k^{(z)}(m_1, m_2) \right| \leq \delta_0 \right\} \quad (6)$$

$$1 \leq m_1 \leq M_1, 1 \leq m_2 \leq M_2, k = 1, 2, \dots, P$$

where

$$r_k^{(z)}(m_1, m_2) = y_k(m_1, m_2) - \sum_{n_1=1}^{N_1} \sum_{n_2=1}^{N_2} z(n_1, n_2) h(m_1, m_2; n_1, n_2) \quad (7)$$

and δ_0 represents the statistical confidence that we have in observation and determined from the statistic of noise process. h is defined as PSF function. The projection of an arbitrary image $z(n_1, n_2)$ onto $C_{m_1 m_2 k}$ given in [14]. POCS are well-liked because of their simple algorithms, use priori information of solution and robust performance in the presence of missing or inconsistent data. These techniques have some disadvantages i.e. high computational cost, slow convergence, the solution is in general non-unique and it depends on the initial guess.

3) *Iterative Back-projection (IBP)*: The main idea of this technique is iteratively back-projecting the reconstruction error into the reconstructed image thus minimizing the reconstruction error. It was firstly presented by Irani and Peleg [15] and they improved the image resolution together with a method for image registration with sub-pixel accuracy and deblurring simultaneously. A set of simulated LR images is created from the estimated HR image using the image blur model. The estimated HR is then corrected with difference (error) between the simulated LR images and observed LR images. In this process iterating can be stopped until a set number of iterations or when the back-projected differences become insignificant. Iterative update scheme to estimate the HR image is represented by:

$$\hat{x}^{n+1}[n_1, n_2] = \hat{x}^n[n_1, n_2] + \sum_{m_1, m_2 \in \gamma_k^{m_1, n_1}} \left(y_k[m_1, m_2] - \hat{y}_k^n[m_1, m_2] \right) \times h^{BP}[m_1, m_2; n_1, n_2]$$

This technique uses a back-projection operator h^{BP} . It can be choose arbitrarily and has affect on the characteristics of the solution when there are possible solutions. Therefore it can be

used to incorporate constraints such as smoothness or other desired property of the solution. In [16] Irani and Peleg have improved their work considering a more general motion model. Zomet et.al. [17] extended their research by taking the median of the errors in different back-projected images. This technique is very easy to understand but SR reconstruction is not unique due ill posed nature of inverse problem. The inclusion of priori constraints in IBP technique is difficult comparative to POCS.

IV. SINGLE IMAGE SUPER RESOLUTION TECHNIQUES

In the SR literature most of the research done is in the area of multiple image super resolution and in recent years a few techniques have been proposed concerning the estimations of HR image from a single LR image. Single image SR has an intuitive limitation that it is successful only if the input database (training set) contains a HR image which is similar to the one which is being enhanced. For that purpose statistical learning is studied. Some traditional resolution enhancement methods (smoothing, interpolation, sharpening) have been used to improve the image quality. Smoothing is done by using spatial filters e.g. weiner, guassian and median filter. Interpolations methods have been widely used. e.g. Nearest neighbour, bilinear, bicubic and cubic spline [18]. Comparatively smoothing methods, interpolation methods are more favorable but they may also blur the edges and scrub out the image details. The image sharpening methods [19] [20] were introduced to amplify the higher frequency in the image and assuming that noise is not amplified. These methods are successful in creating sharper images but (may) also include haloing artifacts. Lately some sophisticated Example or Learning based methods [21]-[25] have been introduced. The goal is to recover the missing high frequency details that are not completely found any individual LR image. It is assumed that missing HR information is available in HR database patches and learned from the corresponding LR/HR resolution pairs of examples in the database.

A. Fast NN-based Method by Freeman et.al.

The example based SR method proposed by Freeman et. al. [23] is considered as state of the art. The concept is to learn correspondence/relationship between HR and LR image patches from Training data (database of LR and HR image pairs) and use the Markov Random Field (MRF) to model these patches in an image and to propagate information between patches using Iterative Belief propagation algorithm so as to minimize the discontinuities at the HR patch boundaries. Their work is basically continuity of the framework developed for low-level vision by Freeman et.al. [22] [26] [27].

The fact that belief propagation converged to a solution of the Markov network very quickly (typically 3 or 4 iteration)

Table I. PSNR comparison of different methods

Test Image	Bicubic Interpolation		IBP		POCS	
	PSNR	MSE	PSNR	MSE	PSNR	MSE
Elaine	21.34	477.617	21.54	456.121	24.38	237.181
Mandrill	20.97	520.092	17.29	1213.613	21.26	486.497

prompted authors (Freeman et.al) that much more simpler and time efficient approach can be used i.e. One Pass algorithm. The results of One pass algorithm are nearly as good as there of the iterative algorithm base on Markov network.

B. LLE Method by Chang et.al.

Motivated by the recent manifold learning methods, Cheng et. al [28] proposed a single image SR technique which is based on Locally Linear Embedding (LLE). This technique assumes that small patches in the low and high resolution images form manifolds with similar local geometry in two distinct spaces. Multiple training samples can be used to contribute simultaneously for the creation each image patch in HR image. In their approach they mapped local geometry of LR patch space to HR patch space, generating HR patch as a linear combination of neighbours. So there is no need that generation a HR patch should only depend on the nearest neighbour in the training set, instead it depends simultaneously on multiple nearest neighbours in a way similar to LLE for manifold learning. Due to this attribute strategy this technique requires smaller training database as compared to the other learning based super resolution techniques. However if the number of k nearest neighbour is fixed for reconstruction the results might be blurred because of over or under fitting.

C. Super Resolution from Sparse Representation of patches of LR images.

In recent research, sparse representation has been applied to inverse problems related to single input image [29]-[33]. The idea is to represent image patches as sparse linear combination of elements from an over-complete image patch dictionary. For each patch of the LR input a sparse representation is computed and then this representation is used to generate the corresponding HR output. Yang et.al. in [34] verified the effectiveness of sparsity as a prior for learning based super resolution. They choose to work with two coupled dictionaries. i.e. HR image patches as D_h and LR image patches as $D_l = LD_h$. The sparse representation if a LR image patch as D_l is used to generate the corresponding HR patch from D_h . A local model for sparse representation of each local patch is used, the patches are overlapped such that the resulting HR patches agree on the overlap areas. The global reconstruction constraint is used to eliminate artifacts from resulting HR image and make it consistent with the LR input image. Furthermore they extended their work [35] for both general image SR and special cases of face hallucination, their approach is naturally robust to noise. Relying on the theory of compressed sensing [36] has proposed solution for image

super resolution problem. In their research they used greedy matching pursuit algorithm to solve for HR image and their method does not require a training data set. They implement the constraint that HR image be sparse in the wavelet domain and used this property to solve for the desired image.

V. SIMULATION RESULTS

We performed different experiments for this paper on Pentium IV, 2GB RAM with 2.0 GHz machine. MATLAB has been used for implementation of all algorithms. We tested different approaches including POCS, IBP, Bilinear Interpolation on different images. For this purpose, two test images 'ELAINE' and 'MANDRILL' have been selected. A high resolution image was reconstructed from the low resolution images using above approaches. The reconstructed images using different approaches are shown in figure 1(b-d). Table (1) gives the quantitative comparison for both of the test images in terms of PSNR and MSE. We showed experimentally that apart from the computational and technical complexity of spatial domain methods, they are more superior as compare to the frequency domain method. Within the class of spatial domain techniques POCS give more promising results than IBP.

VI. CONCLUSIONS AND FUTURE RESEARCH

Image SR is currently the most spotlight image processing research area for scientists. It has more optimized the image acquisition process and provided improved content visualization and object recognition. Furthermore the hardware limitations of the imaging process are overcome. We have presented the SR imaging techniques for both Multi images and Single image categories. There is still room for further improvement and optimization. Learning based approach has a lot of potential for the researchers, so progressive work is needed in this area and also on the machine learning approaches for single image SR. while in case for sparse representation it should be investigated the number of raw sample patches needed to build a dictionary satisfying the sparse representation prior. Another future challenge is to explore the paradigms for compression imaging based on single image SR.

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

Figure 1 : Simulation Results: column (a) HR Test Images, (b) Results using Bicubic Interpolation, (c) Results using IBP, (d) Results using POCS Method