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A COMPREHENSIVE REVIEW OF IMAGE SUPER RESOLUTION ALGORITHMS

Nikunj R. Patel
Student, Sardar Vallabhbhai Patel Institute of Technology, Vasad
Yagnik Rathod
Sardar Vallabhbhai Patel Institute of Technology, Vasad

Abstract

In the digital era, Image processing becomes more popular and most researched field. Most of the devices which needs the Image enhancement because of low profile hardware, we cannot upgrade the hardware so to achieve the high resolution we must develop the technique to enhance the Image via software, and Super Resolution is the technique to achieve High Resolution from the low resolution Image.

We can get the High Resolution Image from the Low resolution Image using the Super Resolution Technique. There are two basic approaches, we can use; Wavelet Domain technique and Spatial Domain technique for multi frame and Single frame. Up to this there are so many research work done multi Image Enhancement, but our job is to review the different techniques of Super Resolution (SR).

Keyword: *Super Resolution, Image Processing, Wavelet Domain, Spatial Domain.*

1. Introduction

High Resolution images are expected in many applications, likewise, Camera surveillance system, high definition television broadcasting, large distance video conferences and many others. These all areas are needed the enhanced image for viewing purpose but somehow it is not possible to capture the high resolution images because of limited storage, low transmission bandwidth and camera expense, and this is the only reason that we have to develop the algorithm based approaches to obtain the high resolution images from low resolution images. So to overcome from this problem we use some computational technique which helps us to enhance the image.

It is possible to obtain an High Resolution (HR) image from the Low Resolution (LR) images by using the signal processing technique called Super Resolution (SR)[1]-[2]. So this approach helps us to make image blur free and aliasing free. In other words, the SR process extrapolates the high frequency components and minimizing the aliasing and blurring. If the sub pixel shifted then each low resolution image contains different information. Therefore, the information that is contained in an under sampled image sequence can be combined to obtain an alias free high resolution image. Super resolution reconstruction from multiple snapshots provides far more detail information than any interpolated image from a single snapshot [3]

1.1 Super Resolution

A digital image is made up of small picture elements called pixels. Spatial resolution refers to the pixel density in an image and measures in pixels per unit area the image spatial resolution is firstly limited by the imaging sensors or the imaging acquisition device. In order to increase the spatial resolution of an imaging system, one straight forward way is to increase the sensor density by reducing the sensor size. However, as the sensor size decreases, the amount of light incident on each sensor also decreases, causing the so called shot noise. Also, the hardware cost of sensor increases with the increase of sensor density or correspondingly image pixel density. Therefore, the hardware limitation on the size of the sensor restricts the spatial resolution of an image that can be captured.

Another way to address this problem is to accept the image degradations and use signal processing to post process the captured images, to trade of computational cost with the hardware cost. These techniques are specifically referred as Super Resolution (SR) reconstruction.

Super-resolution (SR) are techniques that construct high-resolution (HR) images from several observed low-resolution (LR) images, thereby increasing the high frequency components and removing the degradations caused by the imaging process of the low resolution camera. 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 the 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., movements of objects, or due to controlled motions, e.g., the satellite imaging system orbits the earth with predefined speed and path. Each low-resolution frame is a decimated, aliased observation of the true scene. SR is possible only if there exists sub pixel motions between these low resolution frames, and thus the ill-posed upsampling problem can be better conditioned. In the imaging process, the camera captures several LR frames, which are downsampled from the HR scene with sub pixel shifts between each other. SR construction reverses this process by aligning the LR observations to sub pixel accuracy and combining them into a HR image grid.

1.2 Applications of Super Resolution

- Medical imaging (ie. CAT, MRI, etc).
- Satellite imaging
- Enlarging consumer photographs
- Video surveillance (ie. Car wash kidnapping)
- Converting NTSC video content to high-definition television

1.3 Methods of Super-resolution Techniques

There are mainly two different technique to achieve the super resolution and they are,

- Multi-frame Super-resolution
- Single-frame Super-resolution

2. Multi-frame Super-resolution

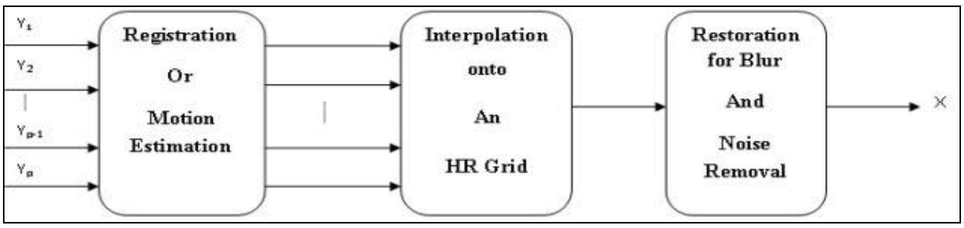
There are many different techniques are available for multi-frame super resolutions and here we include the main four methods and those are,

- Non uniform Interpolation Approach
- Frequency Domain Approach
- Regularized SR Reconstruction Approach

- Projection onto Convex Sets Approach

2.1 Non uniform Interpolation Approach

This approach is the most intuitive method for SR image reconstruction. The three stages presented are performed successively in this approach: i) estimation of relative motion, i.e., registration (if the motion information is not known), ii) non uniform interpolation to produce an improved resolution image, and iii) deblurring process (depending on the observation model). With the relative motion information estimated, the HR image on non-uniformly spaced sampling points is obtained. Then, the direct or iterative reconstruction procedure is followed to produce uniformly spaced sampling points [27]-[29]. Once an HR image is obtained by non-uniform interpolation, we address the restoration problem to remove blurring and noise. Restoration can be performed by applying any De-convolution method that considers the presence of noise. The reconstruction results of this approach appear in Figure 8. In this simulation, four LR images are generated by a decimation factor of two in both the horizontal and vertical directions from the 256 ×256 HR image. Only sensor blur is considered here, and a 20-dB Gaussian noise is added to these LR images. Ur and Gross [5] performed a non-uniform interpolation of an ensemble of spatially shifted LR images by utilizing the generalized multichannel sampling theorem of Papoulis [28] and Brown [29]. The interpolation is followed by a deblurring process, and the relative shifts are assumed to be known precisely here. Komatsu et al. [4] presented a scheme to acquire an improved resolution image by applying the Landweber algorithm [30] from multiple images taken simultaneously with multiple cameras. They employ the block-matching technique to measure relative shifts. If the cameras have the same aperture, however, it imposes severe limitations both in their arrangement and in the configuration of the scene. This difficulty was overcome by using multiple cameras with different apertures [6]. Hardie et al. developed a technique for real-time infrared image registration and SR reconstruction [7]. They utilized a gradient-based



1.0 FIGURE OF RESTORATION FOR BLUR AND NOISE REMOVAL

Registration algorithm for estimating the shifts between the acquired frames and presented a weighted nearest neighbour interpolation approach. Finally, Wiener filtering is applied to reduce effects of blurring and noise caused by the system. Shah and Zakhor proposed an SR colour video enhancement algorithm using the Landweber algorithm [8]. They also consider the inaccuracy of the registration algorithm by finding a set of candidate motion estimates instead of a single motion vector for each pixel. They use both luminance and chrominance information to estimate the motion field. Nguyen and Milanfar [9] proposed an efficient wavelet-based SR reconstruction algorithm. They exploit the interlacing structure of the sampling grid in SR and derive a computationally efficient wavelet interpolation for interlaced two-dimensional (2-D) data.

The advantage of the non-uniform interpolation approach is that it takes relatively low computational load and makes real-time applications possible. However, in this approach, degradation models are limited (they are only applicable when the blur and the noise characteristics are the same for all LR images). Additionally, the optimality of the whole reconstruction algorithm is not guaranteed, since the restoration step ignores the errors that occur in the interpolation stage.

2.2 Frequency Domain Approach

The frequency domain approach makes explicit use of the aliasing that exists in each LR image to reconstruct an HR image. Tsai and Huang [10] first derived a system equation that describes the relationship between LR images and a desired HR image by using the relative motion between LR images. The frequency domain approach is based on the following three principles: i) the shifting property of the Fourier transform, ii) the aliasing relationship between the continuous Fourier transform (CFT) of an original HR image and the discrete Fourier transform (DFT) of observed LR images, iii) and the assumption that an original HR image is bandlimited. These properties make it possible to formulate the system equation relating the aliased DFT coefficients of the observed LR images to a sample of the CFT of an unknown image. For example, let us assume that there are two 1-D LR signals sampled below the Nyquist sampling rate. From the above three principles, the aliased LR signals can be decomposed into the un-aliased HR signal

Let $x(t1,t2)$ denote a continuous HR image and $X(w1, w2)$ be its CFT. The global translations, which are the only motion considered in the frequency domain approach, yield the kth shifted image of $xk = (t1, t2) = x\ (t1+\delta k1 + t2 + \delta k2)$, where $\delta k1$ and$\delta k2$ are arbitrary but known values, and k =1,2,.., p. By the shifting property of the CFT, the CFT of the shifted image, X(w1, w2) can be written as

$$X(w1, w2) = \exp[j2\pi(\delta k1w1 + \delta k2w2)]\, X(w1, w2) \quad (1)$$

The shifted image xk (w1, w2) is sampled with the sampling period T1 and T2 to generate the observed LR image yk[n1, n2]. From the aliasing relationship and the assumption of bandlimitedness of X(w1, w2) (| X(w1, w2) | = 0 for |w1|>= (L1π / T1) ≥ π , |w2 | (L2π / T2), the relationship between the CFT of the HR image and the DFT of the kth observed LR image can be written as [31]

$$Y_k[\Omega_1, \Omega_2] = \frac{1}{T_1T_2}\sum_{n_1=0}^{L1-1}\sum_{n_2=0}^{L2-1} X_k \times \left(\frac{2\pi}{T_1}\left(\frac{\Omega_1}{N_1}+n_1\right), \frac{2\pi}{T_2}\left(\frac{\Omega_2}{N_2}+n_2\right)\right) \quad (2)$$

By using lexicographic ordering for the indices n1, n2 on the right-hand side and k on the left-hand side, a matrix vector form is obtained as:

$$Y = \Phi X \ (3)$$

where Y is a p × 1 column vector with the kth element of the DFT coefficients of yk = [n1, n2], X is a L1L2 × 1column vector with the samples of the unknown CFT of x(t1,t2), and Φ is a p × L1 L2 matrix which relates the DFT of the observed LR images to samples of the continuous HR image. Therefore, the reconstruction of a desired HR image requires us to determine Φ and solve this inverse problem

An extension of this approach for a blurred and noisy image was provided by Kim et al. [11], resulting in a weighted least squares formulation. In their approach, it is assumed that all LR images have the same blur and the same noise characteristics. This method was further refined by Kim and Su [12] to consider different blurs for each LR image. Here, the Tikhonov regularization method is adopted to overcome the ill-posed problem resulting from blur operator. Bose et al. [13] proposed the recursive total least squares method for SR reconstruction to reduce effects of registration errors (errors in Φ). A discrete cosine transforms (DCT)-based method was proposed by Rhee and Kang [14]. They reduce memory requirements and computational costs by using DCT instead of DFT. They also apply multichannel adaptive regularization parameters to overcome ill-posedness such as underdetermined cases or insufficient motion information cases.

2.3 Regularized SR Reconstruction Approach

Generally, the SR image reconstruction approach is an Ill-posed problem because of an insufficient number of LR images and ill-conditioned blur operators, Procedures adopted to stabilize the inversion of ill-posed problem are called regularization. In this section, we present deterministic and stochastic regularization approaches for SR image reconstruction. Typically, constrained least squares (CLS) and maximum a posteriori (MAP) SR image reconstruction methods are introduced.

2.3.1 Deterministic Approach

With estimates of the registration parameters, the observation model can be completely specified. The deterministic regularized SR approach solves the inverse problem by using the prior information about the solution which can be used to make the problem well posed. For example, CLS can be formulated by choosing an **x** to minimize the Lagrangian [63]

$$\left[\sum_{k=1}^{p} |y_k - w_k x|^2 + \alpha |Cx|^2\right]$$

Where the operator **C** is generally a high-pass filter, and ||-|| represents a*l*2 -norm., a priori knowledge concerning a desirable solution is represented by a smoothness constraint, suggesting that most images are naturally smooth with limited high-frequency activity, and therefore it is appropriate to minimize the amount of high-pass energy in the restored image. Katsaggelos et al. [15], [16] proposed a multichannel regularized SR approach in which regularization functional is used to calculate the regularization parameter without any prior knowledge at each iteration step. Later, Kang formulated the generalized multichannel deconvoultion method including the multichannel regularized SR approach [17]. The SR reconstruction method obtained by minimizing a regularized cost functional was proposed by Hardie et al. [18]. They define an observation model that incorporates knowledge of the optical system and the detector array (sensor PSF). They used an iterative gradient-based registration algorithm and considered both gradient descent and conjugate-gradient optimization procedures to minimize the cost functional. Bose et al. [19] pointed to the important role of the regularization parameter and a proposed CLS SR reconstruction which generates the optimum value of the regularization parameter, using the L-curve method [32].

2.4 Projection onto Convex Sets Approach

The POCS method describes an alternative iterative approach to incorporating prior knowledge about the solution into the reconstruction process. With the estimates of registration parameters, this algorithm simultaneously solves the restoration and interpolation problem to estimate the SR image. The POCS formulation of the SR reconstruction was first suggested by Stark and Oskoui [20]. Their method was extended by Tekalp et al. to include observation noise [21]. According to the method of POCS [26], incorporating a priori knowledge into the solution can be interpreted as restricting the solution to be a member of a closed convex set C_i that are defined as a set of vectors which satisfy a particular property. If the constraint sets have a nonempty intersection, then a solution that belongs to the intersection set $\boldsymbol{C_i} = \cap_{k=1}^{m} \boldsymbol{C_i}$ which is also a convex set, can be found by alternating projections onto these convex sets. Indeed, any solution in the intersection set is consistent with the a priori constraints and therefore it is a feasible solution. The method of POCS can be applied to find a vector which belongs in the intersection by the recursion

$X^{n+1} = P_m P_{m-1} \ldots P_2 P_1 x^n$

Where x_0 is an arbitrary starting point, and P_i is the projection operator which projects an arbitrary signal x onto the closed, convex sets, C_i (i =1,2,...,m). Although this may not be a trivial task, it is, in general, much easier than finding Ps, i.e., the projector those projects onto the solution set C_i in one step [20].

Assuming that the motion information is accurate, a data consistency constraint set based on the observation model is represented for each pixel within the LR images $y_k[m_1, m_2]$ [21], [22]

$$C_D^k[m_1,m_2] = \{x\,[n_1,n_2]: |r^{(x)}[m_1,m_2]| \le \delta_k[m_1,m_2]\}$$

$$where\ ^{(x)}[m_1,m_2] = y_k[m_1,m_2] - \sum_{n1,n2} x[n_1,n_2]W[m_1,m_2;n_1,n_2]$$

And $\delta_k[m_1, m2]$ is a bound reflecting the statistical confidence, with which the actual image is a member of the set $C_D^k[m_1,m_2]$ [22]. Since the bound $\delta_k[m_1, m2]$ is determined from the statistics of the noise process, the ideal solution is a member of the set within a certain statistical confidence.

In this simulation, four LR images are generated by a decimation factor of two in both the horizontal and vertical directions from the 256 x 256 HR image, and a 20 dB Gaussian noise is added to these LR images

Patti et al. [22] developed a POCS SR technique to consider space varying blur, nonzero aperture time, and non-zero physical dimension of each individual sensor element, sensor noise, and arbitrary sampling lattices. Tekalp et al. then extended the technique to the case of multiple moving objects in the scene by introducing the concept of a validity map and/or a segmentation map [23]. The validity map allows robust reconstruction in the presence of registration errors, and the segmentation map enables object-based SR reconstruction. In [24], a POCS-based SR reconstruction method where a continuous image formation model is improved to allow for higher order interpolation methods was proposed by Patti and Altunbasak. In this work, they assume a continuous scene within an HR sensor area is not constant. They also modify the constraint set to reduce the ringing artifact in the vicinity of edges. A set theoretic regularization approach similar to POCS formulation was investigated by Tom and Katsaggelos [25]. Using ellipsoidal constraint sets, they find the SR estimate which is the centroid of a bounding ellipsoid the advantage of POCS is that it is simple, and it utilizes the powerful spatial domain observation model. It also allows a convenient inclusion of a priori information. These methods have the disadvantages of non-uniqueness of solution, slow convergence, and a high computational cost

3. Single-frame Super-resolution

Super-resolution algorithms aim to construct a high-resolution image from one or multiple low resolution input frames [33]. They address an important problem with numerous applications. However, this problem is ill-posed because the ground truth is never known, and numerous algorithms are proposed with different assumptions of prior knowledge so that extra information can be exploited for generating high-resolution images from low-resolution ones. Existing super-resolution algorithms can be broadly categorized into three classes: reconstruction-based, interpolation-based, and example based approaches. Interpolation-based super-resolution methods assume that images are spatially smooth and can be adequately approximated by polynomials such as bilinear, bicubic or level-set functions [34, 33, 35]. This assumption is usually inaccurate for natural images and thus over-smoothed edges as well as visual artifacts often exist in the reconstructed high-resolution images. These edge statistics can be learned from a generic dataset or tailored for a particular type of scenes. With the learned prior edge statistics, sharp-edged images can be reconstructed well at the expense of losing some one textural detail. For reconstruction-based algorithms, super-resolution is cast as an inverse problem of recovering the original high-resolution image by fusing multiple low-resolution images, based on certain assumed prior knowledge of an observation model that maps the high-resolution image to the low resolution images [36, 37]. Each low-resolution image imposes a set of linear constraints on the un-known high-resolution pixel values. When a sufficient number of low-resolution images are available, the inverse problem becomes over-determined and can be solved to recover the high-resolution image. However, it has been shown that the reconstruction-based approaches are numerically limited to a scaling factor of two [37]. For example-based methods, the mapping between low-resolution and high-resolution image patches is learned from a representative set of image pairs, and then the learned mapping is applied to super resolution. The underlying assumption is that the missing high-resolution details can be learned and inferred from the low-resolution image and a representative training set. Numerous methods have been proposed for learning the mapping between low-resolution and high-resolution image pairs [38-40, 35, 41-43] with demonstrated promising results. The success of example-based super-resolution methods hinge on two major factors: collecting a large and representative database of low-resolution and high-resolution image pairs, and learning their mapping. Example-based super-resolution methods often entail the need of a large dataset to encompass as much image variation as possible [38-40, 35, 41-43] with ensuing computational load in the learning process. Moreover, the mapping learned from a general database may not be able to recover the true missing high-frequency details from the low-resolution image if the input frame contains textures that do not appear in the database. For example, the mapping function learned from low-resolution/high-resolution image pairs containing man-made objects (e.g., buildings or cars) is expected to perform poorly on natural scenes. Furthermore, the rich image structural information contained in an image is not exploited. In light of this, Glasner et al. [44] propose a method that exploits patch redundancy among in-scale and cross-scale images in an image pyramid to enforce constraints for reconstructing the unknown high-resolution image.

In [42], Yang et al. present a super-resolution algorithm by employing sparse dictionary learning on high-resolution and low-resolution images. In this algorithm, the low-resolution images are considered as a downsampled version of high-resolution ones with the same sparse codes. Using a representative set of image patches, a dictionary (or bases) is learned for sparse coding using both high-resolution and low-resolution images. Their approach performs well under the assumption that image patches of the input image are similar to the ones in the training data, e.g., similar types of images. Existing dictionary learning algorithms often operate on individual data samples without taking their self-similarity into account in searching for the sparsest solutions [45].

Conclusion:

After reviewing for both multiframe and single frame Super Resolution using Wavelet domain and Spatial Domain, We need to conclude that the current SR approaches are effective at some extent, and these approaches are conceptually efficient for getting the result. By Total least Squares method is used for minimize the errors in SR Approaches.

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