IMAGE SUPER RESOLUTION RECONSTRUCTION TECHNIQUES-A SURVEY

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ABSTRACT

In this paper, we study and represent various techniques of image super resolution (SR). Super resolution reconstruction produces high resolution image from sequence of low resolution images. Super-resolution (SR) aims to increase the spatial resolution of images from a single low resolution (LR) images. Super resolution is a technique where there is a availability of multiple LR images captured from the same scene. It is an algorithm to reconstruct HR images from the under sampled LR images. The main aim of super resolution is to improve visual quality of available low resolution image. This paper focuses on interpolation based; reconstruction based and learning based super-resolution methods. We presented various existing super resolution techniques, advantages, disadvantages and the recent works and methods of SR reconstruction.

Key Terms: - Low Resolution; High Resolution; Reconstruction based super resolution; learning based super resolution; interpolation based.

INTRODUCTION

Super resolution is a method for reconstructing a high resolution image from several overlapping low-resolution images. The low resolution input images are the result of re-sampling a high resolution image. The goal is to find the high resolution image which, when re-sampled in the lattice of the input images according to the imaging model, predicts the low resolution input images [1].

The super resolution method is to take more samples of the scene so as to get some extra information which can be used to merge the samples and to get a high resoluted image as output . These samples can be acquired by sub-pixel shifts, by changing the amount of blur or changing scene illumination. Images with high resolution (HR) are desired and often required in most electronic imaging applications. HR means that pixel concentration within an image is high, therefore an HR image can offer more details that are important in many applications[2]. For example, HR medical images are very helpful for a doctor to make diagnosis. There are various ways to increase resolutionof an image. The most direct method [2] to increase spatial resolution is to reduce the pixel size by sensor manufacturing techniques. It generates shot noise that degrades the image quality seriously. Another method for enhancing the spatial resolution which leads to an increase in capacitance is to increase the chip size [2]. The method considered here is not too much effective because large capacitance makes it difficult to speed up a charge transfer rate. So, an effective method towards increasing spatial resolution is required to overcome these limitations of the sensors and optics manufacturing technology. One approach is to use signal processing techniques to obtain an HR image (or sequence) from observed multiple low resolution (LR) images [2].

In recent times, such a resolution enhancement approach has been one of the most active research areas, and it is called super resolution (SR) or High resolution image reconstruction or simply resolution enhancement. The advantage of the super resolution approach is that it may cost less and theexisting LR imaging systems can be still utilized [2]. The SR image reconstruction is proved to be useful in many practical cases where multiple frames of the same scene can be obtained. It includes medical imaging, satellite imaging and video applications. The SR technique is also useful in medical imaging such as computed tomography (CT) and magnetic resonance imaging [1], [2](MRI). Insatellite, applications such as remote sensing and LANDSAT during which several images of the same area are usually provided and the SR technique used to improve the resolution of target. The basic quandary is to obtain an HR image from multiple LR images. The basic theory for increasing the spatial resolution in SR techniques is the availability of multiple LR images captured from the same scene. In Super resolution, the LR images represent different "views" at the same scene [1], [2], [5]. In that, LR images are sub-sampled as well as shifted with sub-pixel precision. If the Low Resoluted images are shifted by integer units, then information in each image will be same, and there is no new information that can be used to reconstruct an HR image. If the LR images have diverse sub-pixel shifts from each other and if aliasing is present and then each image cannot be obtained from the others[2], [3]. In this case, the new information contained in each LR image can be exploited to obtain an HRimage.

To obtain different looks at the same scene, some relative scene motion must exist from frame to frame through multiple scenes or video sequences. Numerous scenes can be obtained from one camera with several captures or from multiple cameras situated in different positions [3]. These scene motions can occur due to the controlled motions in imaging systems, e.g., image acquired from orbiting satellites. It is also true for uncontrolled motions, e.g., movement of local object. Super resolution method assumes that there are small differences between the input images [2], [3]. These differences are caused by small camera movements. In an ideal situation, one can assume that of four images takenthe second to fourth image have a horizontal, vertical, diagonal shift of half a pixel compared to the first image. The pixels from the first image can then be interleaved with pixels from the other three images, and a double resolution image is obtained [3], [5]. This setup is shown in figure 1.1.

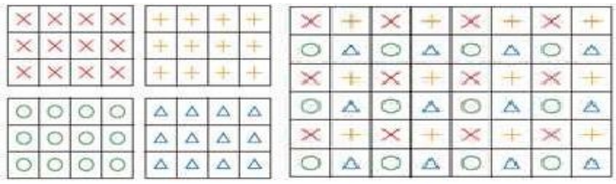

Figure-1.1:-Ideal super-resolution setup. Four images are taken with relative shifts of half a pixel in horizontal, vertical, and diagonal directions (left). Their pixels can then be interleaved to generate a double resolution image (right) [3].

SR IMAGE RECONSTRUCTION ALGORITHMS:

The various super resolution reconstruction algorithms at present are discussed. Letz see them in detail below.

A. Non- uniform interpolation:

The foundation of non-uniform interpolation in super-resolution technique is the non-uniform sampling theory which allows for the reconstruction of functions from samples taken at non-uniformly dispersed locations. Early super-resolution applications used detailed placement of camera to allow for accurate interpolation, because this method requires very accurate registration between images.

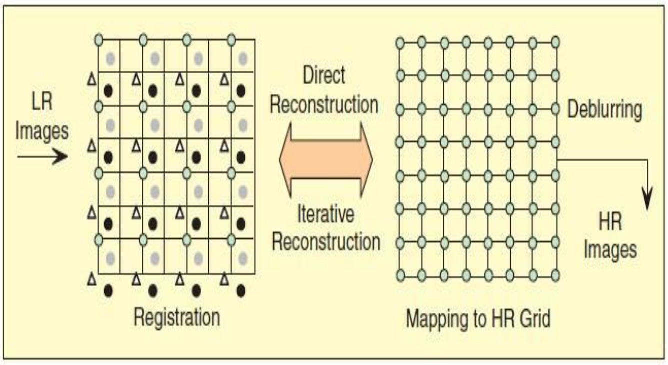

Figure 2.1:Registration-interpolation-based reconstruction [2].

A new method was developed to overcome the limitations of insufficient registration accuracy by applying multiple digital sensors with different pixel sizes [2],[4].This ensures that pixels of multiple images will not coincide regardless of placement of camera. Non-uniform interpolation is a basic and intuitive method of super-resolution and has relatively low computational complexity, but it assumes that the characteristics of noise and blur are identical across all low-resolution images as shown in figure 2.1

B. Projection onto Convex Sets

This method is based on a linear model describing the relationship between the HR and LR images and a cost function is introduced and then the HR image is obtained [2]. POCS algorithm has many advantages like simplicity, as it can be applied to the occasion with any smooth movement, and can join easily in the prior information, so this method is widely used. POCS algorithm is strict to the accuracy of estimating the movement [2]. So in order to improve the stability and performance of the algorithm, instead of using the ordinary projector operator the relaxation operator will be used, at the same time it is not contributing to the resumption of the edge and details of images available.However, the linear model used in this method is an ill-posed problem in the sense that its transformation matrix may be singular and so a unique solution cannot be obtained. The advantage of POCS is it is simple and it utilizes the spatial domain observation model as it is powerful [2]. It also allows a convenient inclusion of a priori information. These methods are also having the disadvantageslike non-uniqueness of solution, slow convergence, and a high computational cost.

Figure 2.3: POCS SR results (a) by bilinear interpolation and by POCS after (b) 10 iterations, (c) 30 iterations,
(d) 50 iterations [2].

C. Frequency Domain Method

The frequency domain approach makes explicit use of the aliasing that exists in each LR image to reconstruct an HR image [3]. Tsai and Huang first derived a system equation that describes the relationship between LR images and a desired HR image is obtained by using the relative motion between LR images. The frequency domain approach is based on the following three principles [2], [3].

1. The shifting property of the Fourier transforms.

2. The aliasing relationship between the continuous Fourier transform (CFT) of an original HR image and the discrete Fourier transform (DFT) of observed LR images,

3. The assumption that an original HR image is band limited.

These properties make it possible to design the system equation relating the aliased DFT coefficients of the observed LR images to a sample of the CFT of an unknown input image [3]. For example, let us assume that there are two 1-D LR signals that are sampled below the Nyquist sampling rate. From the principles stated above, the aliased LR signals can be decayed into the unaliased HR signal as shown in Figure 2.4.

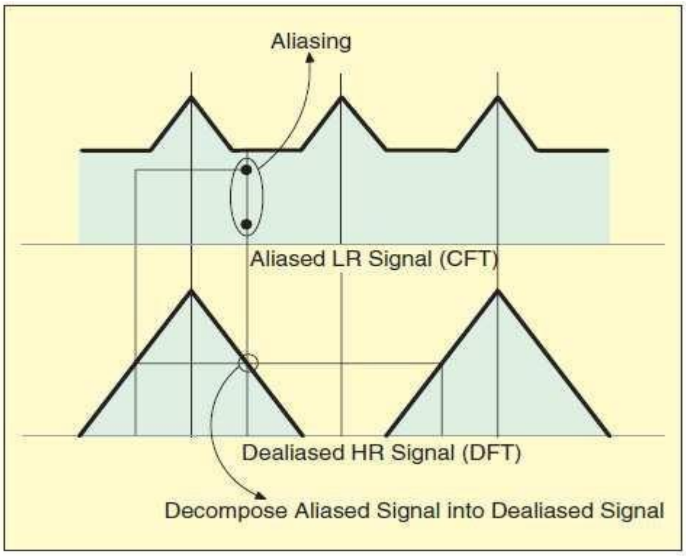

Figure 2.4: Aliasing relationship between LR image and HR image [2].

D. Sparse Representation Method

This method is based on single-image super resolution, which represents the sparse signal coefficients. Researchers in imaging field suggest that image patches can be well represented as a sparse linear combination of elements from an appropriately chosen over-complete dictionary [2], [7]. Learning an over-complete dictionary capable of optimally representing broad classes of image patches is a hard problem. It is hard to learn such a dictionary or using a generic set of basis vectors (e.g., Fourier), in order to simplify, one can generate dictionaries by randomly sampling raw patches from training images of similar statistical nature [2]. Researchers suggest that simple prepared dictionaries are already capable of generating high-quality reconstructions when used together with the sparse representation prior. Figure 2.5 shows several training images and the patches sampled from them.

Figure 2.5: Left: three training images which are used in experiments. Right: the training patches extracted

From them

By jointly training two dictionaries for the low- and high-resolution image patches, one can make obligatory on the likeness of sparse representations between the low-resolution and high resolution image patch pair with respect to particular dictionaries [7], [8]. So, the sparse representation of a low-resolution image patch can be applied with the high-resolution image patch dictionary to generate a high-resolution image patch [7], [8]. The learned dictionary pair is a more compact representation of the patch pairs. The success of such approach is demonstrated for both general image super-resolution (SR) and the special case of face hallucination [7]. Figure2.6 shows some results obtained by this method

Figure 2.6: The flower and girl image magnified by a factor of 3. Left to right: input, bi-cubic interpolation, Neighbor embedding, sparse representation, and the original image [7].

E. Super Resolution through Neighbor Embedding

This method is used for solving single-image super-resolution problems [8]. Given a low resolution image as input and the objective is to recover its high-resolution counterpart using a set of training examples [8], [9], [10].In a recent neighbor embedding method, which is based on Semi-nonnegative Matrix Factorization (SNMF) in which only the nonnegative weights are considered [10]. In LLE, the weights are constrained to amount up to one, but no constraints are specified for their sign [10], [15]. This might explain the unstable results observed in [9], since possible negative weights can lead to having subtractive combinations of patches, which is counter intuitive. This method is based on assumption that small patches in the low- and high-resolution images form manifolds with similar local geometry in two distinct spaces. In this method, all low or high-resolution image is represented asa set of small overlapping image patches [8], [9]. Each patch is represented by a feature vector. The features are correlation, entropy, sum of variance. Figure 2.7 show some example of such a patch generation.

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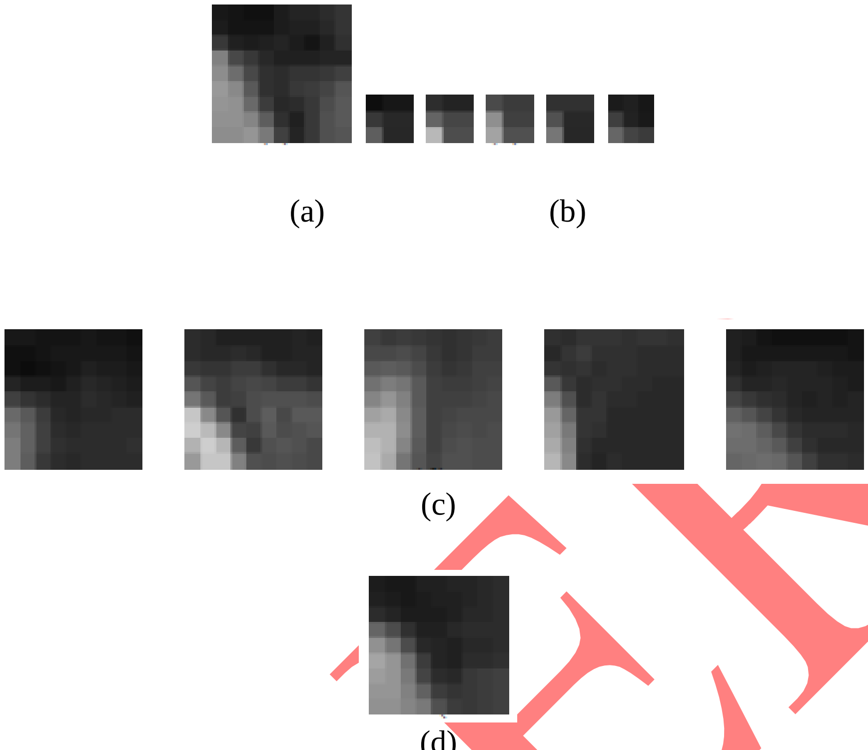

Figure 2.7: Neighbor embedding procedure applied to a low resolution patch for 3X magnification: (a) true high-resolution patch; (b) five nearest neighbor low resolution patches from the training images; (c) high-resolution patches from the training images corresponding to the low-resolution patches in (b); (d) target high-resolution patch constructed from (c). [9]

This method is also called as learning based method for super resolution; this method has been inspired by recent manifold learning methods, particularly locally linear embedding (LLE) [8], [9]. In that method small image patches in the low and high resolution images form manifolds with similar local geometry in two distinct feature spaces. As in LLE, local geometry is characterize by feature vector corresponding to a patch and it can be reconstructed by its neighbor in the feature space [9].Also using the training image pairs to estimate the high-resolution embedding, various researchers have enforced local compatibility and efficiency constraints between patches in the target high-resolution image through overlapping. Experiment show that this method is very lithe and gives good empirical results [8], [9],[10]**.**Figure 2.8 shows some results of this method with available high resolutiontraining image and input low resolution image.

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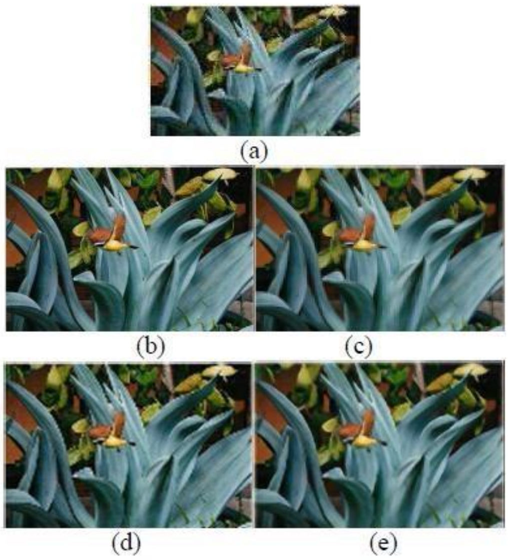

Figure 2.8: 3X magnification of the bird image: (a) input low resolution image; (b) true high-resolution image; (c) median filtering; (d) cubic spline interpolation; (e) Neighbor embedding method [9].

F) Super resolution based on compressive sensing*:*

CS is a signal processing technique for efficiently acquiring and reconstructing a signal.It is a new method of reducing the sampling rate without signal loss through a description of a signal in the transforming space[12].

It uses interpolation based technique such as bi-cubic interpolation.The pre-HR image can be formed from the LR image by using an interpolation method.then the image is divided in to patches and they are trained by dictionary and the corresponding HR image patches are obtained[11].then,finally HR image patches are assembled to reconstruct the final HR image.

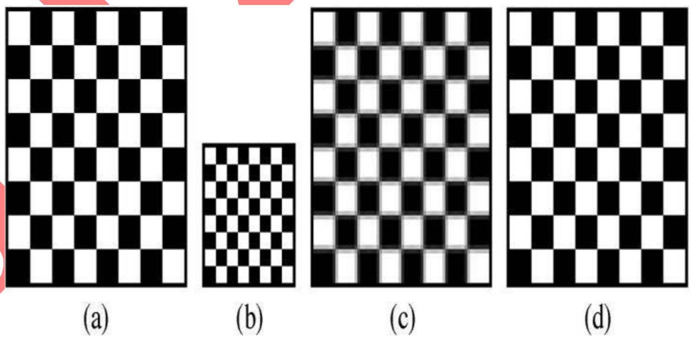

Figure 2.9 Experimental results for the simulation image with sharp edges. (a) Original HR image. (b) Degraded LR image. (c) Bi-cubic interpolation method. (d) Our method [11]

COMPARISON OF VARIOUS SUPER RESOLUTION TECHNIQUES

Comparisons of super-resolution techniques have been mainly concerned with what assumptions are made in the modeling of the super-resolution problem. The process of blurring to be known or those regions of interest among multiple frames. They are related through global parametric transformations and these are the assumptions to be made. Other models take into account arbitrary lattices for sampling, sensor physical dimension, a non-zero aperture time, focus blurring, and more advanced additive noise models. To simplify a model these assumptions are chosen and are usually used in a specific method [2] [13] [14].

In addition, methods that do not make these assumptions have not demonstrated objectively that removing these assumptions gains better super-resolution reconstruction performance. Signal-to-noise ratio (SNR), Peak-signal-to noise ratio (PSNR), Root mean square error (RMSE), mean absolute error (MAE), and mean square error (MSE) have all been used as objective measures of super-resolution accuracy; however, the outstanding method of presenting results is clearly subjective to visual quality[13][14].

ISSUES CHALLENGING IN SUPER RESOLUTION

Computation Efficiency:

Practical application of SR reconstruction that limits it is its intensive computation, due to large number of unknown samples, which require expensive matrix manipulations. Real applications always demand efficiency of the SR reconstruction to be of practical utility [13].

Robustness:

Traditional SR techniques are vulnerable to the presence of deviation due to motion errors, inaccurate blur models, noise, moving objects, motion blur, moving scene etc. Robustness of SR is of interest because the image degradation model parameters cannot be estimated perfectly, and deviationstowards sensitivity may result in visual degradations, which are unacceptable in many applications, e.g., video standard conversion [13] [14].

Image registration*:*

Image registration is critical for the success of multi-frame SR reconstruction, where spatial samplings of the HR image are fused. The image registration is a basic image processing problem that is known as ill-posed [13].The problem is more difficult in the SR setting, where the observations are low-resolution images with heavy aliasing artifacts. The performance of the standard imageregistration algorithms decreases as the resolution of the observations goes down, resulting in more registration errors. Degradations caused by these registration errors are visually more annoying than the blurring effect resulting from interpolation of a single image [13].

Future work:

We can propose a method developing an objective measurement for comparison of super-resolution techniques. One possible objective measurement is a universal image quality measures for computer vision systems and human vision systems. An alternative method would be to use the high-resolution images as the input to some other image processing system, such as a face-recognition algorithm, and we can examine how different super-resolution techniques affect the accuracy. Two research areas promise improved

Super resolution methods:

Degradation Models:

Accurate degradation and observation models promise improved SR reconstructions. Several SR application areas may benefit from improved degradation models. For improved reconstruction of compressed video, degradation models for lossy compression schemes are most promising one.

Restoration Algorithms:

MAP and POCS based algorithms are very successful. Hybrid MAP/POCS restoration techniques will combine the mathematical stiffness and uniqueness of solution of MAP estimation with the convenient a priori constraints of POCS [2], [13]. Simultaneous motion estimation andrestoration gains improved reconstructions since motion estimation and reconstruction are correlated. Separate motion estimation and restoration, as is commonly done, is sub-optimal as a result of this interdependence. Simultaneous multi-frame SR restoration is expected to achieve higher performance since additional spatial temporal constraints on the SR image ensemble may be included. In SR reconstruction this technique has limited application.

CONCLUSION

In this paper, we discussed the various super resolution techniques that is used to enhance the resolution from the under sampled LR images. The researches on super-resolution image reconstruction mainly consider that the degraded model is linear. Different methods of super- resolution techniques have been developed using models with unequal assumptions of the existing problem, because the results provided have been primarily based on subjective measurements, it is difficult to find an comparison on what basis super-resolution methods are more appropriate for agiven task. So, there must be considerations like if more than one input images are present then use multi frame super resolution approach and if one or more high resolution training images are available then use single image super resolution approach. we can use single frame image resolution when we avoid the registration step. If high resolution training is not available but different low resolution images are available for same scene then we can choose multi frame super resolution. But this does notprovide a clear method for comparing super resolution techniques. Hence, we propose super resolution based on compressive sensing for solving the problem.

The extra information for SR reconstruction is found in similar patches that commonly exist in natural images. The LR image is first interpolated to construct a pre-HR image. From them HR image is obtained. The comparative experimental results show that our method outperforms the other approaches because it can adequately use information hidden in the image itself. In addition, our method runs faster than do the other methods, which is also an important issue for consideration.

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