Comparative Study of Various Methods of Super Resolution For Image Reconstruction

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Abstract—In most areas we are using High-resolution images Which provide more clarity and Information such as in medical imaging, satellite imaging, industrial inspection, surveillance etc. so in order to produce a higher resolution images Super resolution is the Best method. This method increase the resolution of an image i.e. is the process of combining a sequence of low resolution images to produce a higher resolution images. Various approaches are used to improve the resolution of image. In this paper we have explained various existing methods to produce high resolution images. We summarized the comparative study of existing methods that may be useful for selection of appropriate method according to resources and applications. At last, several aspects of super-resolution image reconstruction that should be studied further more were put forward.

Keywords— Aliasing, blurring, Discrete Cosine Transform (DCT), High-resolution (HR), Low-resolution (LR), Super Resolution Reconstruction (SRR),

1. INTRODUCTION

Super resolution is used to produce high quality (high resolution) images from a set of low quality images (low resolution images). Naturally there is always a Requirement for better quality images. However, the hardware for HR images is expensive and can be difficult to obtain. The resolution in conventional cameras depends on CCD sensor density, which may not be sufficiently high. As the image-capturing environment is not ideal, many distortions, noise are also present in the low-resolution images. They may have noisy, blurred, aliased low resolution captures. Therefore, a new approach is required to enhance the resolution of the image. It is possible to obtain an HR image from multiple low-resolution (LR) images by using the signal processing technique called super resolution. The primary task of the SR algorithms is not to improve recognition performance significantly but to enhance the visual quality of images. Another class of SR reconstruction methods to generate an HR image from a single LR image. These methods are called “example-based SR”. These algorithms are in generally based on natural image edge or gradient profile prior. Glasner et al[9]. Merge the concepts of both single-frame SR and multiframe SR for HR image reconstruction from a single frame. In previous years, SR image reconstruction algorithms with sparse image prior have been receiving more attention due to advancement of sparse coding techniques. Those algorithms are based on dual dictionary learning techniques on the pairs of HR and LR image patches. The approach mentioned in this paper is based on the regularization framework, where the HR image is estimated based on some prior knowledge about the image (e.g., degree of smoothness) in the form of regularization. The probability based MAP approach mentioned previously is equivalent to the concept of regularization; only in this case it gives a probabilistic meaning to the regularization expression. One of the popular regularization methods is Tikhonov regularization based on bounded variation is for SR reconstruction. It imposes smoothness in reconstructed image, but at the same time loses some edge details present in the image. The first successful edge
preserving regularization method for Removing noise and blurring is the total variance (TV) method. Another interesting algorithm, proposed by Farsiu et al. [10], employs bilateral total variation (BTV) regularization. To achieve further development, Li et al. [11] used a locally adaptive BTV (LABTV) operator for the regularization. Recently, two other regularization types were proposed for SR image reconstruction, i.e. “nonlocal means regularization” and “steering kernel regression”. Usually, iterative SR image reconstruction methods based on differentiable regularization terms with Lp norm (1 < p ≤ 2) use the gradient descent approach to obtain optimal solution. On the other hand, a few techniques are available in the literature to efficiently handle nondifferentiable regularization terms with L1 norm (e.g., TV regularization). A group of solvers, evolved from Bregman iteration, recently developed best methods for such nondifferentiable constraint optimization problems. Marquina and Osher were first to use the Bregman iteration for fast SR image reconstruction with TV regularization.

However, even though all these regularization terms for SR image reconstruction lead to a stable solution, their performance depends on optimization technique as well as regularization term. For example, with gradient descent optimization technique, the LABTV regularization outperforms BTV which gives better result than TV regularization. On the other side, based on TV regularization, Marquina and Osher obtained superior result by employing Bregman iteration. So we consider that even better results would be obtained by adding Bregman iteration and a more sophisticated regularization method that can suppress noise in LR images and ringing artifacts occurred during capturing the details of the HR image. We propose a new regularization method based on multiscale morphologic filters which are nonlinear in nature. Morphological operators and filters are well-known tools that can extract structures from images. They are used in image denoising image segmentation and image fusion successfully.

2. METHODOLOGY

S. Lertrattanapanich and N. K. Bose, et al. [1] propose an algorithm based on spatial tessellation and approximation of each triangle patch in the Delaunay triangulation (with smoothness constraints) by a bivariate polynomial is advanced to build a high resolution (HR) high quality image from a set of low resolution (LR) images. The high resolution algorithm is accompanied by a site-insertion algorithm for update of the initial HR image with the availability of more LR frames till the desired image quality is attained. This algorithm, followed by post filtering, is suitable for real-time image sequence processing because of the fast expected (average) time construction of Delaunay triangulation and the local update feature. N. Nguyen and P. Milanfar, et al. [2] proposed the algorithm is a combination of interpolation and restoration processes. Unlike previous work, the method exploits the interlaced sampling structure in the low resolution data. Numerical experiments and analysis will demonstrate the effectiveness of our approach and illustrate why computational complexity only doubles for 2-D superresolution versus 1-D case. Superresolution produces high quality, high resolution images from a set of degraded, low resolution frames. We present a new and efficient wavelet-based algorithm for superresolution image.

H. Stark and P. Oskoui, et al. [3] propose the problem of reconstructing remotely obtained images from image-plane detector arrays. Although the individual detectors may be larger than the blur spot of the imaging optics, high-resolution reconstructions can be obtained by scanning or rotating the image with respect to the detector. As an alternative to matrix inversion or least-squares estimation [Appl. Opt. 26, 3615 (1987)], the method of convex projections is proposed. We show that readily obtained prior knowledge can be used to get
good-quality imagery with reduced data. The effect of noise on the reconstruction process is considered. Andrew J. Patti and YucelAltunbasak et al. [4] propose to improve the POCS-based super-resolution reconstruction (SRR) methods in two ways. First, the discretization of the continuous image formation model is developed to explicitly allow for higher order interpolation methods to be used. Second, the constraint sets are modified to decrease the amount of edge ringing present in the high resolution image estimate. This effectively regularizes the inversion process. SRR algorithms all attempt to create a single higher resolution image from a number of reduced resolution images.

M. Irani and S. Peleg et al. [5] propose an iterative algorithm to enhance image resolution together with a method for image registration with subpixel accuracy. Image Resolution can be improved when the relative displacements in image sequences are known accurately and some knowledge of the imaging process is available. The proposed approach is similar to back projection used in tomography. Example of improved image resolution are given for gray level and color images, When the unknown image displacements are damaged from the image sequence. M. Elad and A. Feuer et al. [6] propose Three main tools in the single image restoration theory are the maximum likelihood (ML) estimator, the maximum a posteriori probability (MAP) estimator and the set theoretic approach using projection onto convex sets (POCS). This paper utilizes the above three tools to propose a unified methodology toward the more complicated problem of super resolution restoration. In the super resolution restoration problem, an improved resolution image is restored from several geometrically warped, blurred, noisy and down sampled measured images. The super resolution restoration problem is modeled and analyzed from the ML, the MAP, and POCS points of view, yielding a generalization of the known super resolution restoration methods. The proposed approach is general but assumes explicit knowledge of the linear space- and time-variant blur, the (additive Gaussian) noise, the different measured resolutions, and the (smooth) motion characteristics. A hybrid method combining the simplicity of the ML and the incorporation of non-ellipsoid constraints is presented, giving improved restoration performance, compared with the ML and the POCS approaches.

L. Xiao and Z. Wei et al. [7] propose the issue of solving the image super-resolution reconstruction from the single or multi-frame low-resolution (LR) image to the required high resolution (HR) image. According to the degradation model of LR image, we present a maximum a posteriori estimation (MAP) framework and find out that the problem of the image super-resolution reconstruction can be regarded as the inverse problem considering the minimization of the variational energy functional. Three different energy functional including total variation integrals, Huber integrals and improved entropic integrals are considered to resolve this problem. However, the above defined models have not local, contextual information, and thus the mosaic phenomena along image edges can not be effectively decreased. To overcome the bad phenomena, we first present a new contextual magnitude of spatial gradient definition, then propose a new class of local and contextual information driven PDE for super-resolution reconstruction. Finally, a numerical scheme and corresponding iterative algorithm is presented in this method. The performance of all the above mentioned algorithms is examined from the PSNR and edge preservation ability points of view. Super resolution image reconstruction allows the recovery of a high-resolution (HR) image from several low-resolution images that are noisy, blurred.

3. Super-Resolution Reconstruction (SRR) Techniques

Super-Resolution Reconstruction techniques may be classified into two types: frequency domain and spatial
domain. All frequency domain techniques are, to a greater or lesser extent, unable to accommodate general scene observation and noise models including spatially varying degradations, non-global relative camera/scene motion. Spatial domain formulations can accommodate all above these and provide enormous flexibility in the range of degradations and observation models which may be presented.

**Frequency domain methods**

This frequency-domain SR method can be credited to Tsai and Huang [8], they considered the SR computation for the noise-free and low-resolution images. They proposed to the first transform of low-resolution image data into the Discrete Fourier transform (DFT) domain and add them according to the relationship between the aliased DFT coefficients of the observed low-resolution images. The combined data are then transformed returned to the spatial domain where the new image could have a higher resolution than that of the input images. In [14] they exploited the Discrete Cosine Transform (DCT) to perform fast image de-convolution for SR image computation.

**A. Reconstruction via Alias Removal**

In the earliest formulation and proposed solution to the multiframe super-resolution problem was motivated by the need for improved resolution images from Landsat image data. Landsat acquires images of the same areas of the earth in the course of its orbits, thus producing a sequence of similar, but not identical images. Observed images are modeled as under-sampled versions of an unchanging scene undergoing global translational motion. Impulse sampling is assumed, but the sampling rate fails to get the Nyquist criterion. The effects of blurring due to satellite motion during image acquisition and observation noise are not considered. The frequency domain formulation based on the shift and aliasing properties of the continuous and discrete Fourier transforms for the reconstruction of a band-limited image from a set under-sampled, and therefore aliased, observation images. The shift and aliasing properties are used to formulate a system of equations which relate the aliased discrete Fourier transform (DFT) coefficients of the observed images to samples of the continuous Fourier transform (CFT) of the unknown original scene. Though this method is computationally attractive, have its own drawbacks and unrealistic assumption of ideal sampling. The possibility of an optical system Point Spread Function (PSF), or even that of spatially integrating sensors is not defined. Observation noise, finite aperture time is not defined. Due to which we may get noise and blurred images.

**B. Recursive Least Squares Techniques**

The least squares is implemented in a recursive fashion to improve computational efficiency. It utilizes the frequency domain theoretical framework and the global translation observation model proposed, however extend the formulation to consider observation noise as well as the effects of spatial blurring. Two methods a recursive least-squares, and a weighted recursive least squares solution method. Recursive solution approach is computationally attractive, while the least squares formulation provides the benefits of a measure of robustness in the case of an under or over determined system. This method defines the problem of noise and blurring, there are several criticisms which can be removed at the approach taken. Firstly, the stabilizing function (squared error) is unrealistic for images, tending to result in overly smoothed solutions. And the other is the use of an estimate of the unknown solution leaves unanswered questions as to the stability of the proposed recursive solution method.

**C. Recursive Total Least Squares Methods:**

It is the extensions of the recursive least squares work is similar that of recursive total least squares which is known to provide some degree of robustness to errors in the observation model, which are similarly, in the case
of super-resolution reconstruction, to result from errors in motion estimation. Total least squares theory is well developed. Bose, Kim and Valenzuela to extend the ideas to include a degree of robustness to errors which result from errors in the translational motion estimates required in the specification. Since it is well understood that motion estimates need be as correct as possible to SR reconstruction

Spatial Domain Methods
Most of the research done on super resolution is done on spatial domain methods. Its advantages is great flexibility in the choice of motion model, motion blur and optical blur, and the sampling process. Another important factor is that the constraints are easier to formulate. Spatial domain reconstruction allows natural inclusion of (possibly nonlinear) spatial domain a-priori constraints which result in bandwidth extrapolation in reconstruction.

A. Interpolation of Non-Uniformly Spaced Samples
In this method the low-resolution observation image sequence are registered. As the relative shifts between the LR images are arbitrary, it is natural that the interpolation is non uniform. The first step is to estimate the shift. It is followed by a non-uniform interpolation method to produce a HR image. The last step is a de-blurring process. Though this method appear attractive, it is, however, simplistic as it does not take into consideration the fact that samples of the low resolution images do not result from ideal sampling. The result is that the reconstructed image does not contain the full range of frequency content that can be reconstructed given the available low-resolution observation data.

B. Algebraic Filtered Backprojection
An early algebraic filtered back projection method to super-resolution image reconstruction is that of Frieden and Aumann, [12]. The authors do not consider the problem of super-resolution image reconstruction from an image sequence, but the related problem of super-resolution image reconstruction from multiple 1-D scans of a stationary scene by a linear imaging array. Noting that the PSF in the 1-D scan system represents a line integral and that of the multiple image super-resolution problems represents an integral area, it is clear that the problems differ only in the form of the imaging system PSF. The linear imaging array detectors are assumed to be larger than the limiting resolution of the optical system.

C. Iterative Back-Projection Approach
Irani and Peleg [5] formulated the iterative back-projection (IBP) SR reconstruction approach is similar to the back projection. In this approach, the HR image is estimated by back projecting the error difference between simulated LR images via imaging blur and the observed LR images. This process is repeated iteratively to reduce the energy of the error. Mann and Picard [13] extended this approach by applying a perspective motion model in the image acquisition process. Later, Irani and Peleg modified the IBP to consider a more general motion model. The advantage of IBP is easily understood. However, this method has no unique solution due to the ill-posed nature of the inverse problem, and it has some difficulty in choosing the back projection kernel error factor.

4. CONCLUSION
This paper presents the comparative study of Various Methods of Super Resolution for Image Reconstruction. This paper provided an overview approaches and methods of super resolution image reconstructions (SRR). And compared two methods of Super resolution images are frequency domain and spatial domain. In this two methods, frequency domain method has a significant drawback, because they can accommodate only global translation mode and lack of priori information. For these reason most of the researches choose spatial domain approach for SRR even though it is more expensive and more complex than frequency domain. Hybrid MAP/POCS approaches for spatial domain provides more suitable solution, when compare
to other methods. Because, it adds the mathematical rigor and uniqueness of solution with a priori constraints. And it is capable to accommodate model based motion estimates in restoration process.

REFERENCES


