

Grid Analysis of MISO Image Super resolution Techniques

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Abstract— The selection of an appropriate super resolution technique for a specific application is a hard task in real scenario. This is true because of the availability of several super resolution approaches in both frequency and spatial processing domains. To make the task easier, we performed and present the well-known grid analysis for multi input single output (MISO) super resolution techniques by considering various valuable factors against several existing approaches. To further support our position, we also provide the quantitative as well as qualitative assessment for our performed work in this paper. It can be seen easily that the Projection Onto Convex Sets (POCS) based super resolution techniques provide potentially better choice for most of the real scenarios.

Keywords— Grid analysis, Iterative-Back Projection, MISO image super resolution, Projection Onto Convex Sets

I. INTRODUCTION

The physical and the economical limitations on Charged Coupled Device (CCD) and Complementary Metal Oxide Semiconductor (CMOS) sensors direct the people to find new solutions for obtaining high resolution (HR) images that are cheaper and easier. When creating an image of a scene, it is required that the information of the observed data is useful and has more details. As, the detail information of the scene is included in the high frequency components of the image. However, real imaging systems as well as imaging conditions are imperfect, due to which an observed image represents only a degraded version of the original scene. The degradation in the images may be caused due to various factors such as blur, noise and aliasing. A general model representing the various stages of degradation present in an imaging system can be found in [1]. Classical image restoration is a well-defined concept of visually improving the quality of a single image and finds application in many areas of multimedia and communications. For the classical restoration methods such as nearest neighbor, bilinear and bi-cubic interpolation, we have a single image and the available

pixels on this image are placed on the HR grid. Although, performing this re-sampling by using different kernels is easy and effective, but not optimal in terms of quality measurements. Moreover, none of the image restoration methods are able to increase the spatial resolution of the images. For the reason of additional information, multiple images are considered to resolve such problems. The field of image super resolution (so called second-generation of image restoration) arose from the need to overcome the physical limitations of low resolution (LR) imaging systems in order to generate higher resolution images than would be otherwise possible with the available hardware or by existing software techniques.

The rest of this paper is organized as follows: Section II deals with the motivation behind the research work presented in this paper. In section III, we briefly describe the core concept of MISO image super resolution. Section IV provides the overview of several important existing MISO super resolution techniques in both frequency and spatial processing domains. Next, section V summarizes the performed grid analysis for existing MISO super resolution techniques. To further support our position, section VI gives the analysis of our experimental results in terms of both quantitative as well as qualitative measurements carried out on different synthetic images. And, finally we conclude our work in section VII.

II. MOTIVATION

Digital imaging is taking a great part in our life day by day and constantly we require better image quality and higher resolution. Since, the recent development by the researcher in the field of MISO image super resolution introduces new approaches to generate a HR image or sequence of HR images by fusing a set of blurred, noisy and aliased LR images. On the positive side, a variety of new image super resolution techniques are available now, both in spatial as well as in frequency domain, covering a wide range of applications in different fields such as medical diagnosis (CT, MRI and ultrasound), satellite imaging (such

as remote sensing), microscopic imaging, radar imaging, video surveillance, image compression, computer vision, robotics, digital mosaicing, web cams and mobile camera images (having cheaper sensors). On the negative side, however it's become a little difficult to choose a proper technique to be adopt for a specific application. That is the motivation behind our work to make such task of decision making easier. We accomplished this job by performing well-known grid analysis for the MISO image super resolution techniques by considering various techniques against different valuable factors. It also helps in making a choice where many factors are under consideration.

III. CONCEPT OF MISO IMAGE SUPER RESOLUTION

The concept of MISO reconstruction-based super resolution is not a new one. In fact, MISO super resolution problem has been an active area of research for more than two decades now. Super resolution imaging is a process of fusing several LR images, related to each other primarily through random translations and rotations in the image plane, in order to reconstruct a single, HR image of the original scene. This process has been also referred as Multi Input Single Output (MISO) reconstruction-based super resolution. The core idea behind a MISO super resolution process is very simple. Basically the non-redundant information from the given LR images is used to generate a HR image. The whole process of MISO super resolution is summarized in figure (1) [1]. As seen, a general framework for MISO image super resolution for a given bunch of LR images typically involves two crucial steps. i.e. image registration and projecting LR image values onto HR grid. Thus, the key to a comprehensive analysis of the classical MISO super resolution problem is to formulate the problem and to model it as simply and as efficiently as possible. However, there are a few pitfalls that should be avoided when dealing with the super resolution problem, as they are potential risks for the super resolution algorithms. For example, although there are a lot of super resolution techniques available now-a-days, however every technique didn't provide the better results for every application. Therefore, an appropriate technique must be choose before it would apply to the given data. Similarly, if the objects in image are completely still or only move a little, the super resolution image could not be well reconstructed for the lack of sub-pixels shifts. Also, super resolution methods critically depend on the accuracy of image registration. The only way to improve the resolution is the correct utilization of sub-pixel shifts between images. Without sub-pixel accuracy, we only have shifted copies of the same image, which gives no extra information to recover the lost information. Moreover, if the original images were captured with much noise or overexposure, we could not reconstruct the good HR images for the error prone image registration.

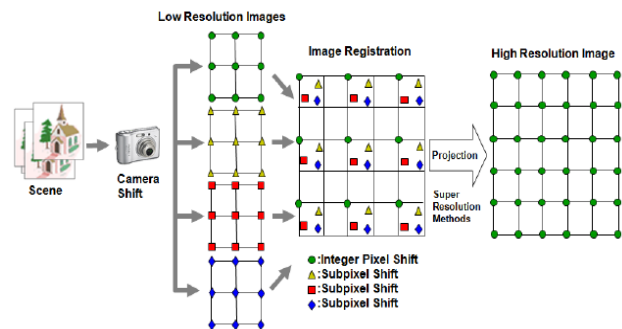


Figure 1. Basic concept of MISO image super resolution

IV. CLASSIFICATION OF MISO SUPER RESOLUTION TECHNIQUES

During the past twenty years, several algorithms for fusing LR images and producing a HR image have been proposed. The detail of those techniques can be found in [2]-[6]. According to the processing domain, the MISO super resolution methods may be categorized into two main classes; (i) Frequency domain Techniques, and (ii) Spatial domain Techniques. Approaching the super resolution problem in the frequency domain makes a lot of sense because it is relatively simple and computationally efficient. However, they are restricted to global translation motion model only as they relies on the shifting property of the Fourier Transform. They make explicit use of the aliasing that exists in each LR image to reconstruct a HR image by operating in the frequency domain. On the other hand, a variety of techniques exist for the super resolution problem in the spatial domain. However in this study, we restricted ourself only to four powerful approaches of spatial domain methods namely non-uniform interpolation, iterative back projection (IBP), projection onto convex sets (POCS) and maximum a-posteriori (MAP) reconstruction methods. The non-uniform interpolation technique of super resolution image reconstruction has advantage of less computational complexity and are thus suitable for real-time applications. However, it requires either a priori knowledge of sub-pixel shifts between frames or very accurate sub-pixel registration through a motion estimation algorithm. Moreover, optimality of the whole reconstruction algorithm using this technique is not guaranteed as the errors occurred during the interpolation step is ignored by restoration step. The main idea behind IBP technique is iteratively back-projecting the reconstruction error into the reconstructed image thus minimizing the reconstruction error. Initially, Irani and Peleg formulated the IPB algorithm for image super resolution based on computer-Aided Tomography (CAT). This technique is very easy to understand but provides no unique solution due to absence of a regularization parameter and ill-posed nature of inverse problem. MAP is a classical Bayesian approach, which allows inclusion of the priori constraints regarding the solution of the ill-posed inverse problem. That's why it is more suitable to the super resolution problem since super

TABLE 1. GRID ANALYSIS OF SUPER RESOLUTION TECHNIQUES CONSIDERING VARIOUS FACTORS

Factors Techniques	SR Solution (20%)	Computational Requirements (10%)	Time Consumption (10%)	Convergence Rate (10%)	A- priori Info (10%)	Applicability (30%)	Implementation (10%)	Total Score
Frequency domain methods	8	6	4	4	10	12	8	52
Non-uniform interpolation	12	6	6	6	6	24	10	70
IBP	12	8	4	4	6	24	10	68
POCS	12	6	6	6	8	24	10	72
MAP reconstruction methods	16	6	8	8	8	30	10	86

resolution is an ill-posed inverse problem. The Bayesian approach (is synonymous with MAP estimation) relies largely on the statistical knowledge that pixel-to-pixel differences are very small, and can be modeled with a probability distribution function. Thus, it seeks to find the solution having the maximum probability. Finally, POCS has attracted much attention in recent years in the field of image reconstruction and restoration applications because it is very intuitive and generally simple to implement and providing robust performance in the presence of missing or inconsistent data. This technique defines the feasible solution space as the region of intersection of a collection of convex constraint sets, which represent the space containing the possible HR images that can satisfy the image formation model. The idea to introduce the constraint set is to limit the feasible solution space of the super resolution reconstruction. However, this technique also suffers from slow convergence and high computational cost.

V. THE CENTRAL ROLE OF GRID ANALYSIS

The grid analysis (also known as Decision Matrix Analysis, Pugh Matrix Analysis or MAUT, stands for Multi-Attribute Utility Theory) is a useful technique used for making a rational decision. Grid analysis is the simplest form of Multiple Criteria Decision Analysis (MCDA), also known as Multiple Criteria Decision Aid or Multiple Criteria Decision Management (MCDM). Also, sophisticated MCDA is involved highly in complex modelling of different potential scenarios and advanced mathematics. A grid analysis is used in making a choice where many factors must be considered in almost any important decision where there isn't a clear and obvious preferred option. Grid analysis helps us to decide between several options, while taking many different factors into account. Moreover, being able to use grid analysis means that we can take decisions confidently and rationally, at a time when other people might be struggling to make a decision. Our research methodology

involves performing the grid analysis, as the procedure to perform grid analysis is very simple. We considered different performance limitation factors such as computational requirements, time consumption, convergence rate and implementation issues. The grid analysis for above discussed super resolution approaches is then performed and the result of which is summarized in Table (1).

VI. EXPERIMENTAL RESULTS

To demonstrate the usefulness of our analysis, extensive experiments on various synthetic image data are conducted to evaluate the performance of the various existing techniques for comparison. For this purpose, two results with different scenarios are provided in this section. In the first case, the LR images are assumed to be noiseless while in other, gaussian noise is introduced into the LR images. For both the cases, HR images are reconstructed using above mentioned spatial domain techniques. We used Matlab 7.6 (R2008a) and Image Processing Toolbox (IPT) 6.1, as development Tools for implementation of all the algorithms. We conducted our this study on Pentium IV, 2GB RAM with 2.0 GHz machine notebook. The numbers of randomly created LR images utilized in the reconstruction process are kept four. For this purpose, two test images Elaine and Mandrill of sizes 512 x 512 (8 bits gray-scale) and 256 x 256 (8 bits gray-scale) respectively were used in the simulations. The reconstructed images of Elaine and Mandrill images using above discussed approaches for both the cases are shown in figure (2)-(5) respectively. Also, Table (2)-(3) gives the quantitative comparison for both the test images in terms of PSNR and MSE.

VII. CONCLUSIONS

A grid analysis is performed for different existing MISO super resolution techniques against various factors in consideration. The result of which shown that among both the processing domains, spatial domain techniques are more superior than its frequency domain counterpart methods as

they deal the ill-posed nature of super resolution problem in better way. Further, within the class of spatial domain techniques POCS and MAP gives more promising results as compared to other approaches for different kind of applications.

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TABLE 2. PSNR AND MSE COMPARISON OF DIFFERENT METHODS FOR NOISELESS DATA

Test Image	Bicubic Interpolation		IBP		POCS		Robust SR	
	PSNR	MSE	PSNR	MSE	PSNR	MSE	PSNR	MSE
Elaine	21.34	477.61	21.54	456.12	24.38	237.18	21.52	458.22
Mandrill	20.97	520.09	17.29	1213.61	21.26	486.49	17.18	1244.74

TABLE 3. PSNR AND MSE COMPARISON OF DIFFERENT METHODS FOR NOISY DATA

Test Image	Bicubic Interpolation		IBP		POCS		Robust SR	
	PSNR	MSE	PSNR	MSE	PSNR	MSE	PSNR	MSE
Elaine	14.37	2377.28	10.68	5560.07	16.11	1592.5	10.95	5224.93
Mandrill	15.11	2004.84	11.87	4227.47	17.48	1161.66	11.78	4315.99

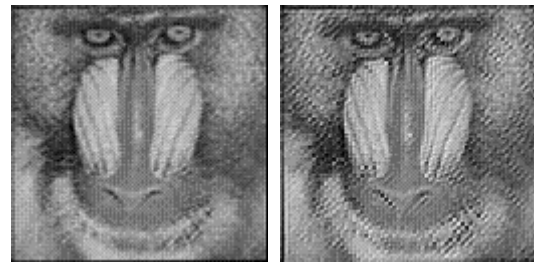


(a) (b)



(c) (d)

Figure 2. Experimental Results using noiseless data: (a) Bicubic Interpolation (b) IBP (c) POCS Method (d) Robust Super resolution

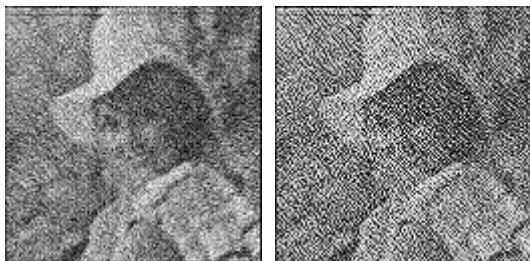


(a) (b)

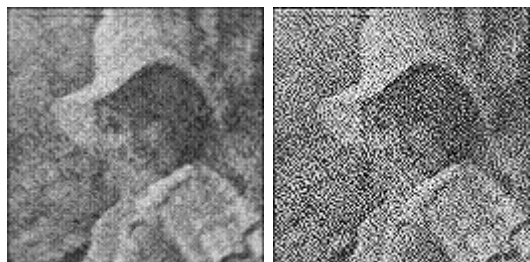


(c) (d)

Figure 3. Experimental Results using noiseless data: (a) Bicubic Interpolation (b) IBP (c) POCS Method (d) Robust Super resolution

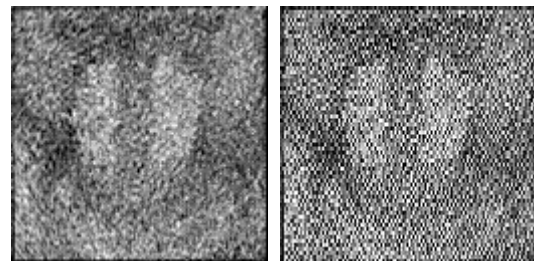


(a) (b)

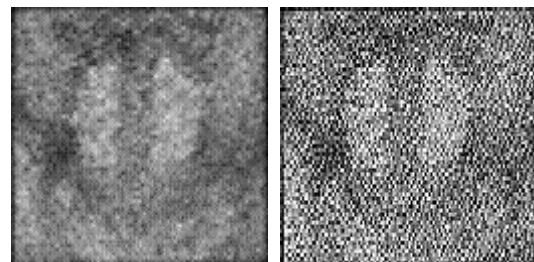


(c) (d)

Figure 4. Experimental Results using noise corrupted data: (a) Bicubic Interpolation (b) IBP (c) POCS Method (d) Robust Super resolution



(a) (b)



(c) (d)

Figure 5. Experimental Results using noise corrupted data: (a) Bicubic Interpolation (b) IBP (c) POCS Method (d) Robust Super resolution