Implementation of Low Rank Matrix Method For Image Super Resolution

Miss.Mhaske Gayatri.1,Mr. Srivastava Atul 2

1Electronics and Telecommunication, Vishwabharti Academy's College of Engineering, Ahmednagar, India

2Electronics and Telecommunication,Vishwabharti Academy's College of Engineering, Ahmednagar, India

Abstract- Now a day's immense work is going on image super resolution. In order to improve image resolution different techniques have been propounded. Improving image resolution has its importance in different image processing applications. At commercial background especially in photography it has become important part as well as on research background in biomedical engineering, satellite communication image resolution improvement has its own significance. This paper is supposed to implement an Innovative and highly effective method to analyze the local order of the linear model depending on theory of low-rank matrix completion and recovery; it is a technique for performing single-image super resolution that is initiated by generating the reconstruction as the recovery of a low-rank matrix. Besides that the proposed method can be utilized to process noisy data and random perturbations effectively. The proposed method is compared with bilinear method.

Keywords- Bilinear technique, Low rank matrix technique, Super resolution.

I. INTRODUCTION

Image super resolution is a research topic that is fetching many researchers to work for improving image resolutions with versatile algorithms. These research approaches are extended towards having an optimized super level of resolution without even damaging original image. In earlier years, number of interpolation algorithms has propounded for single image super-resolution (SISR), such as the new classical bilinear, new bi-cubic interpolation and Innovative edge-guided interpolation methods. Nevertheless, almost no single traditional interpolation methods can fully satisfy correlations in image edge pixels, and therefore these resolution improving methods may cause some ringing artifacts and blurring effect at the edge of the reconstructed input image. Therefore, as the linear correlations are fixed and predefined in these resolution techniques, these techniques cannot efficiently model the textures in input application images. In this paper we proposed a new method to solve the SISR problem based on the recently developed technique of low-rank matrix completion, which determines the order of the linear model adaptively and implicitly. The linear relationship among neighboring pixels was determined implicitly and adaptively by exploring the low-rank properties of theaugmented matrix. The low rank of the augmented matrix is due to the local structural similarity of the images. In this technique, the center pixels can be effectively represented by the local 8-connected neighboring pixels or a local subset of the 8-connected neighboring pixels. However, due to the presence of noise and random perturbations, some entries in the augmented matrix are corrupted.

II. LITERATURE SURVEY

In the paper 'Image interpolation via low-rank matrix completion and recovery' by Feilong Cao, Miaomiao Cai, and Yuanpeng Tan . It states that "this paper seeks an efficient method to determine the local order of the linear model implicitly. According to the theory of low-rank matrix completion and recovery, a method for performing single-image super resolution is proposed by formulating the reconstruction as the recovery of a low-rank matrix, which can be solved by the augmented Lagrange multiplier method. In addition, the proposed method can be used to handle noisy data and random perturbations robustly. The proposed method aims to explore the local linear relationship among neighboring pixels. Unlike previous interpolation-based SISR methods which use fixed-order linear models, the proposed method can implicitly determine the optimum order of the linear model. By considering the low-rank property of the augmented matrix, the super-resolution problem has beenreformulated as the recovery of a low-rank matrix from missing and corrupted observations, which can be solved efficiently using the ALM method. Experimental results have demonstrated that the proposed method can achieve better recovery effects than the other methods in terms of PSNR. The biggest advantage of the proposed method is its ability to handle noisy data and random perturbations. The feasibility and effectiveness of the proposed method can also be demonstrated using real images with noisy data. Existing interpolation-based methods still generate serrated and blurred edges as recovery effects."[1]

In the paper 'Bilateral filtering for gray and color images' by C. Tomasi and R. Manduchi .it states that "In this paper we have introduced the concept of bilateral filtering for edge-preserving smoothing. The generality of bilateral filtering is analogous to that of traditional filtering, which they called domain filtering in this paper. The explicit enforcement of a photometric distance in the range component of a bilateral filter makes it possible to process color images in a perceptually appropriate fashion. The parameters used for bilateral filtering in our illustrative examples were to some extent arbitrary. This is however a consequence of the generality of this technique. In fact, just as the parameters of domain filters depend on image properties and on the intended result, so do those of bilateral filters. Given a specific application, techniques for the automatic design of filter profiles and parameter values may be possibleAlso, analogously to what happens for domain filtering, similarity metrics different from Gaussian can be defined for bilateral filtering as well. In addition, range filters can be combined with different types of domain filters, including oriented filters. Perhaps even a new scale space can be defined in which the range filter parameter _r corresponds to scale. In such a space, detail is lost for increasing _r, but edges are preserved at all range scales that are below the maximum image intensity value. Although bilateral filters are harder to analyze than domain filters, because of their nonlinear nature."[2]

In the paper named as 'Cubic convolution interpolation for digital image processing' by Robert G. keys. It states that "A one-dimensional interpolation function is derived in this paper. A separable extension of this algorithm to two dimensions is applied to image data. The cubic convolution interpolation function is derived from a set of conditions imposed on the interpolation kernel. The kernel is required to be symmetric, continuous, and have a continuous first derivative. It is further required for the interpolation kernel to be zero for all nonzero integers and one when its arguments zero. Finally, the cubic convolution interpolation function must agree with the Taylor series expansion of the function being interpolated for as many terms as possible. The interpolation kernel derived from these conditions is unique and results in a third-order approximation."[3]

In the paper "Advances and challenges in super-resolution" SinaFarsiu,Dirk Robinson, Michael Elad, Peyman Milanfar. It states that "Although several articles have surveyed the different classical Super-Resolution methods and compared their performances, the intention of this article is to pinpoint the various difficulties inherent to the Super-Resolution problem for a variety of application settings often ignored in the past. We review many of the most recent and popular methods, and outline some of our recent work addressing these issues."[4]

In the paper 'Directional Bicubic Interpolation — A New Method of Image Super-Resolution' by Liu Jing ,Gan Zongliang and Zhu Xiuchang, it states that "Bicubic interpolation is a standard method in image interpolation field because of its low complexity and relatively good results. But as it only interpolates in horizontal and vertical directions, edges easily suffer from artifacts such as blocking, blurring and ringing. This paper proposed a new method of image super-resolution which is named directional bicubic interpolation. According to local strength and directions, different ways are used to interpolate missing pixels. Compared with bicubic interpolation, the proposed method can preserve sharp edges and details better. Experiment results show that the proposed method is better than existing edge-directed interpolations in terms of subjective and objective measures, and its computation complexity is low."[5]

In the paper 'High Accuracy Bicubic Interpolation Using Image Local Features' by shuai yuan, masahide abe, akira taguchi and masayuki kawamata, it states that "In this paper, we propose a novel bicubic method for digital image interpolation. Since the conventional bicubic method does not consider image local features, the interpolated images obtained by the conventional bicubic method often have a blurring problem. In this paper, the proposed bicubic method adopts both the local asymmetry features and the local gradient features of an image in the interpolation processing. Experimental results show that the proposed method can obtain high accuracy interpolated images." [6]

III. SYSTEM DEVELOPMENT

The proposed system development showing detailed block diagram in Figure.1. This detailed block diagram system is based on low rank matrix method for image super resolution.

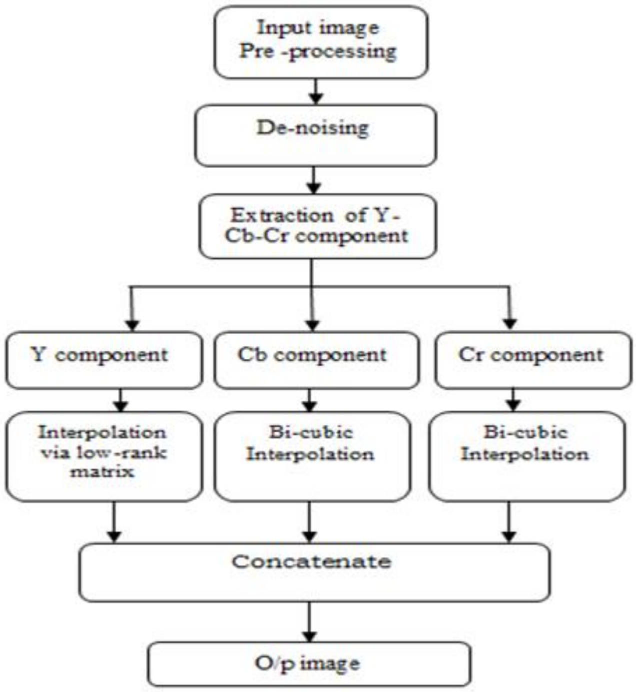


Fig.1: Block diagram

A. Input image

Input image is taken from database of images. This database includes random colored images of different size and types.

B. Pre-processing of an image

Pre-processing of an image includes resizing of an image. The basic condition for any image processing algorithm is that images must be of same size for processing purpose. Hence in order to process out any image with respective algorithm we resize the image. The size can be fixed like (256*256) or (512*512)

C. De-noising of an image

It's necessary to have quality images without any noise to get accurate result. Noisy image may lead your algorithm towards in accurate result. Hence it becomes necessary to de-noise the image. Image de noising is an important image processing task, both as a process itself, and as a component in other processes. Very many ways to de noise an image or a set of data exists. The main property of a good image de noising model is that it will remove noise while preserving edges. Traditionally, linear models have been used. To de-noise the image we can use median filter. Median filter does the work of smoothening of image.

D. RGB to YCbCr

Given a color image must first be transformed from RGB color space to YCbCr color space. The proposed method will be applied to the Y channel only. As for the color channels (Cb,Cr), the bicubic interpolation method is used to up-sample them. In the Y channel, the proposed low-rank matrix recovery method is used.

E. Interpolation via low-rank matrix

Low matrix is concerned with missing pixels around the central pixel due to random noise. The center pixels can be sufficiently represented by the 8-connected neighboring pixels or a subset of the 8-connected neighboring pixels. However, due to the presence of noise and random perturbations, some entries in the augmented matrix are corrupted. In this low matrix we are interpolating the missing pixels with central pixel.

F. Bi-cubic interpolation

Bi-cubic interpolation is an extension of cubic Interpolation for interpolating data points. Interpolation data points on a two dimensional regular grid. The interpolated surface is smoother than corresponding surfaces obtained by bilinear interpolation or nearest-neighbour interpolation. Bi-cubic interpolation can be accomplished using either Lagrange polynomials, cubic splines, or cubic convolution algorithm.

In image processing, bi-cubic interpolation is often chosen over bilinear interpolation or nearest neighbour in image re-sampling, when speed is not an issue. In contrast to bilinear interpolation, which only takes 4 pixels (2×2) into account, bi-cubic interpolation considers 16 pixels (4×4). Images re-sampled with bi-cubic interpolation are smoother and have fewer interpolation artifacts.

Concatenate: All three components of images are concatenated together to form high resolution output image.

IV. OBJECTIVES

- To de-noise the image.
- To implement Image Interpolation via Low-rank Matrix Completion and Recovery.
- To implement Image Interpolation Bilinear Interpolation Method.
- To reconstruct the image in both algorithms.

Advantages

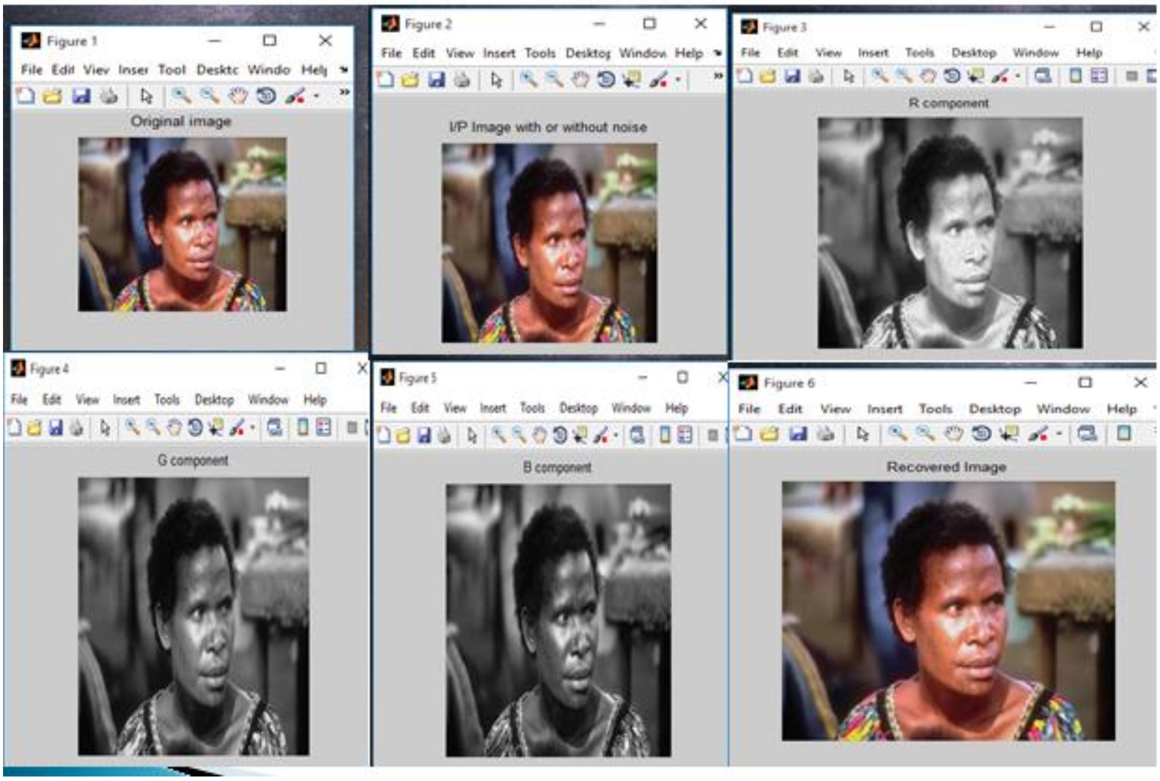
- Its ability to handle noisy data and random perturbations.
- De noised output images.
- The proposed method can achieve better recovery effects than the other methods
- Applicable for color images also.
- Accurate and efficient way for image interpolation.

Disadvantages

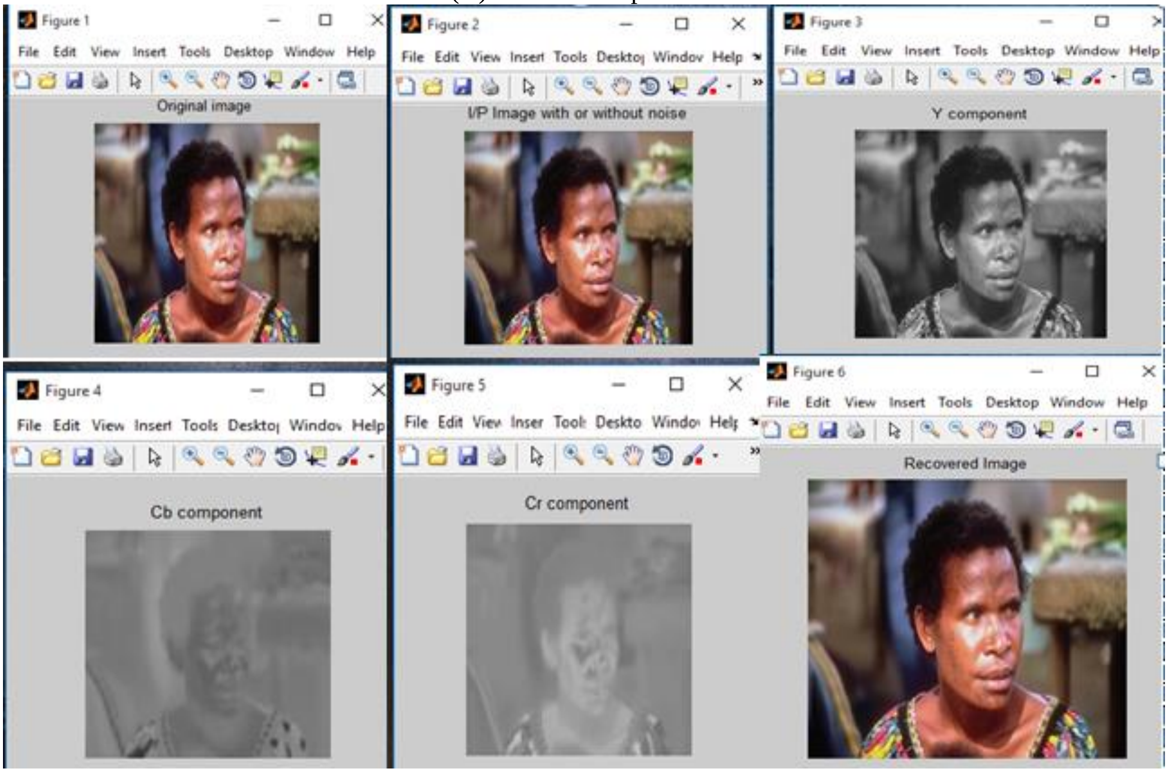
- This system is dependent on camera quality. This is only disadvantage of this system.

V. EXPERIMENTAL RESULTS

Now in this chapter we will see the simulated result and intermediate output of each stage and compare with Bilinear Interpolation Method.



(A)Bilinear Interpolation



B)Interpolation Low rank Matrix

Fig.2: Compared the O/P(A)Bilinear &(B)Low rank matrix Interpolation

Table1 Bilinear Interpolation

Image	Noise	MSE	PSNR	Entropy	Standard Deviation	variance
Image 1	0	9.3005	38.4797	7.6801	55.3102	3.0592e+03
	0.001	10.0974	38.1227	7.6844	55.2953	3.0576e+03
	0.002	10.6660	37.8848	7.6870	55.3180	3.0601e+03
	0.003	11.6508	37.5013	7.6888	55.2603	3.0537e+03
	0.004	12.3316	37.2546	7.6880	55.1982	3.0468e+03
	0.005	13.1902	36.9623	7.6891	55.2385	3.0513e+03
	0.006	14.3194	36.6055	7.6936	55.1786	3.0447e+03
	0.007	15.0905	36.3778	7.6958	55.2175	3.0490e+03
	0.008	15.7557	36.1904	7.6954	55.1546	3.0420e+03
	0.009	16.7843	35.9158	7.6987	55.1133	3.0375e+03

Table 2 Interpolation Low rank Matrix

Image	Noise	MSE	PSNR	Entropy	Standard Deviation	variance
Image 1	0	247.2802	55.1052	0.8242	0.4377	0.1916
	0.001	247.1957	55.1018	0.8248	0.4379	0.1918
	0.002	247.0595	55.0963	0.8255	0.4382	0.1920
	0.003	246.9387	55.0914	0.8251	0.4381	0.1919
	0.004	246.8165	55.0865	0.8257	0.4383	0.1921
	0.005	246.6281	55.0788	0.8260	0.4384	0.1922
	0.006	246.5164	55.0743	0.8266	0.4386	0.1924
	0.007	246.4441	55.0714	0.8276	0.4390	0.1927
	0.008	246.3325	55.0668	0.8278	0.4390	0.1927
	0.009	246.2318	55.0627	0.8282	0.4392	0.1929

Table 3 PSNR Of Image with SALT-AND-PEPPER Noise

Image	Noise	Bilinear	Interpolation Low rank Matrix
Image I	0	38.4797	55.1052
	0.001	38.1227	55.1018
	0.002	37.8848	55.0963
	0.003	37.5013	55.0914
	0.004	37.2546	55.0865
	0.005	36.9623	55.0788
	0.006	36.6055	55.0743
	0.007	36.3778	55.0714
	0.008	36.1904	55.0668
	0.009	35.9158	55.0627

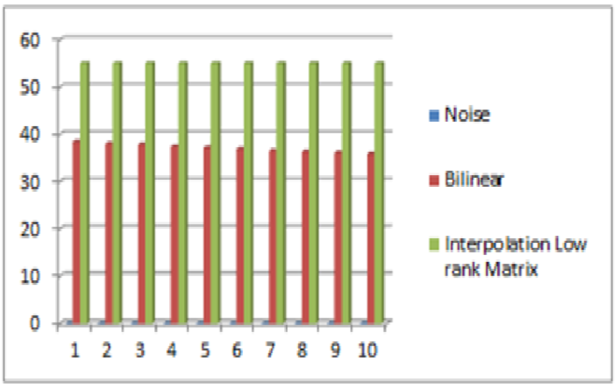


Chart 1 PSNR Vs Noise for Image Bilinear and Interpolation Low rank Matrix

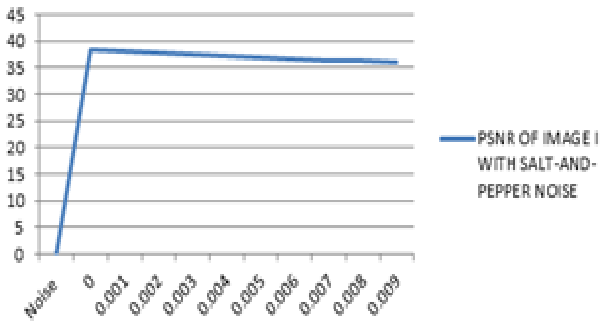


Chart 2 Bilinear Interpolation

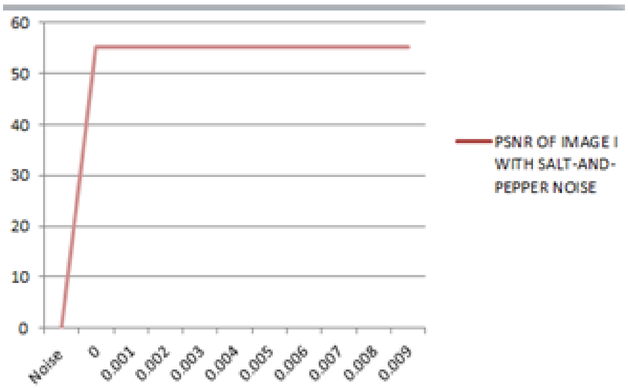


Chart 3 Low rank Matrix Interpolation

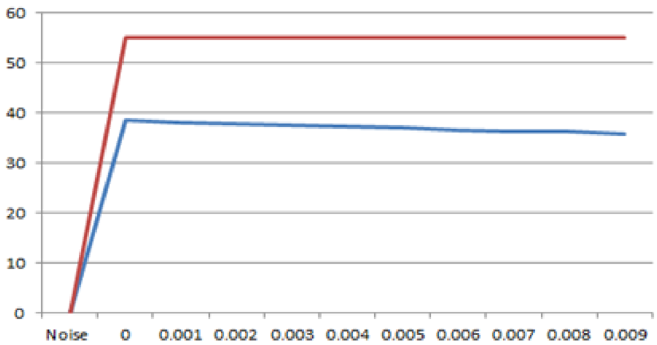


Chart 4 Compared the O/P Bilinear Interpolation andLow rank Matrix Interpolation

VI. CONCLUSIONS

- The proposed algorithm has been successfully implemented. The algorithm is applied against multiple different kinds of resolution images. On variety of low resolution images it is showing good results. The proposed system is comparatively analyzed against bilinear interpolation method as well.
- For comparative analysis purpose objective quality analysis method is used. In objective analysis mainly PSNR and mean square error parameters are calculated.

On the background of these parameters, the proposed system is out performing over bilinear method.

- The proposed method can implicitly determine the optimum order of the linear model. By considering the low-rank property of the augmented matrix, the super-resolution problem has been reformulated as the recovery of a low-rank matrix from missing and corrupted observations.

VII. ACKNOWLEDGMENT

I am taking this opportunity to thank my guide Mr. Atul Srivastava, Assistant Professor, E&TC Department, Vishwabharati Academys College of Engineering, Ahmednagar to have his creative support to implement this proposed system successfully, without him it was not possible to do this work. Finally I would like to thank non-teaching staff of Vishwabharati Academys College of Engineering, Ahmednagar for providing me software support to perform my task.

VIII. REFERENCES

[1]. Feilong Cao, Miaomiao Cai, and Yuanpeng Tan a "Image interpolation via low-rank matrix completion and recovery"*IEEE* Trans, 2015.

[2]. C. Tomasi and R. Manduchi, "Bilateral filtering for gray and color images" IEEE transactions on image processing.

[3]. Robert G. keys "Cubic convolution interpolation for digital image processing,"IEEE International Conference on Acoustics,2013 .

[4]. Sina Farsiu,Dirk Robinson, Michael Elad, Peyman Milanfar"Advances and challenges in super-resolution"

[5]. Liu Jing ,Gan Zongliang and Zhu,"Directional Bicubic Interpolation — A New Method of Image Super-Resolution" 3rd International Conference on Multimedia Technology（ICMT 2013)

[6]. shuai yuan, masahide abe, akira taguchi* and masayuki kawamata ,"High Accuracy Bicubic Interpolation Using Image Local Features"