Implementation Of Low Rank Matrix Method For Image Super Resolution

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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.

Keyword: *Low rank matrix technique; Bilinear technique; Super resolution.*

1. 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.

1.1 Low Rank 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. We therefore investigate the SISR problem under this condition by using the recently developed low-rank matrix recovery theory. When a low-resolution image is down sampled from the corresponding high-resolution image without blurring, i.e., the blurring kernel is the Dirac delta function, the reconstruction becomes an image interpolation problem. Hence, this is a way to define the linear relationship among side by pixels to reconstruct a high-resolution image from a low-resolution image.

2. 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.

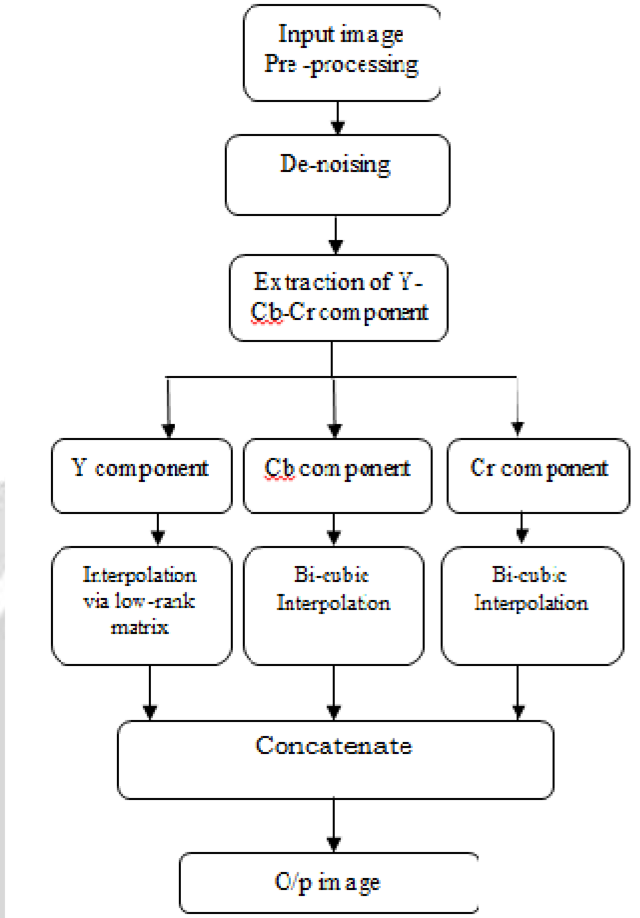

Fig-1: Block diagram

2.1 Input Image

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

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)

2.2 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 theimage we can use median filter. Median filter does the work of smoothening of image.

2.3 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.

2.4 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.

2.5 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.

3. 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.

4. 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. Low-rank matrix recovery theory is a new signal processing method which was proposed in the framework of compressed sensing theory . Here, the SISR problem is recast as that of recovering and completing a low-rank augmented matrix (MCR) in the presence of random perturbations and noise .This problem can be expressed as a rank minimization problem, which can be solved by the augmented Lagrange multiplier method (ALM).

EXPERIMENTAL RESULTS:IMAGEI

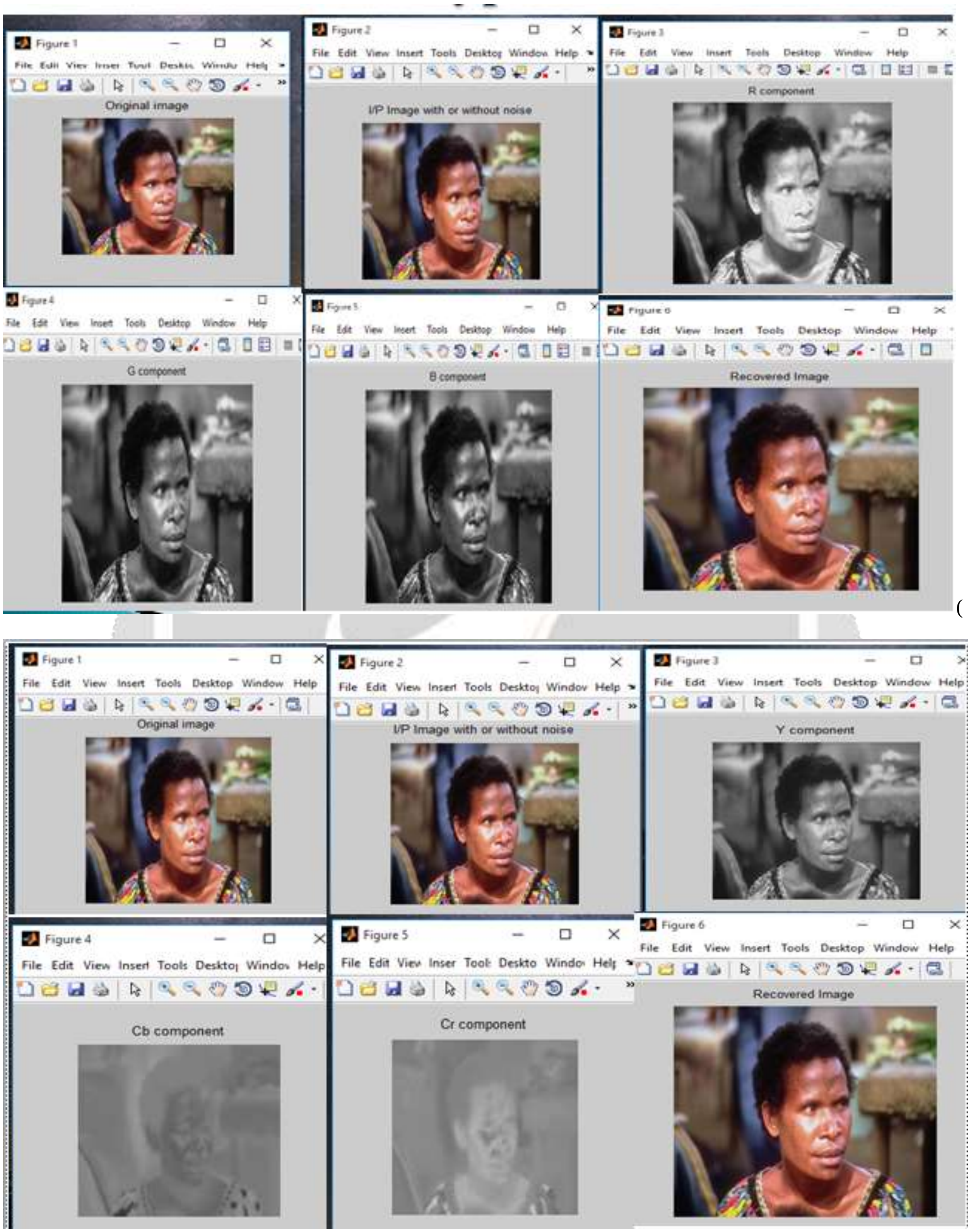

Fig-2: Compared the O/P (A) Bilinear Interpolation &(B) Interpolation Low rank Matrix Form Image I

Table -1: 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

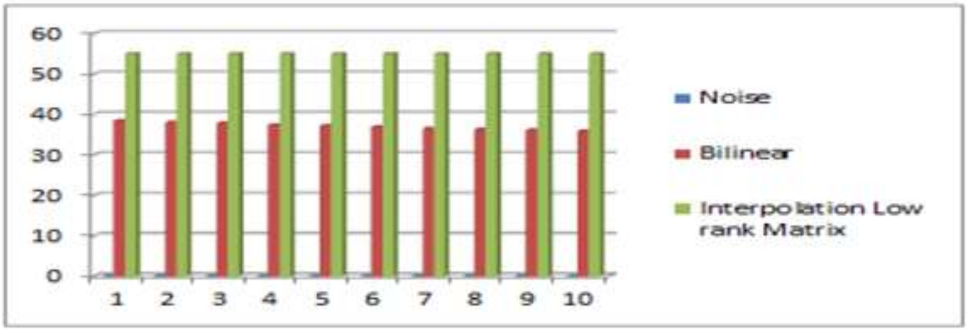

Chart -1:PSNR Vs Noise for Image Bilinear and Interpolation Low rank Matrix

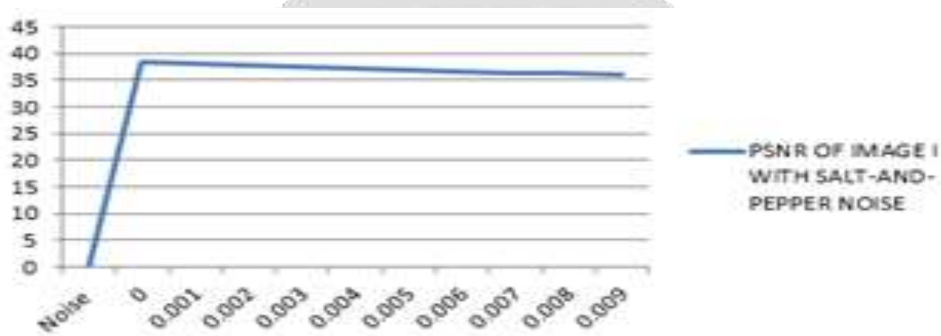

Chart -2: Bilinear Interpolation

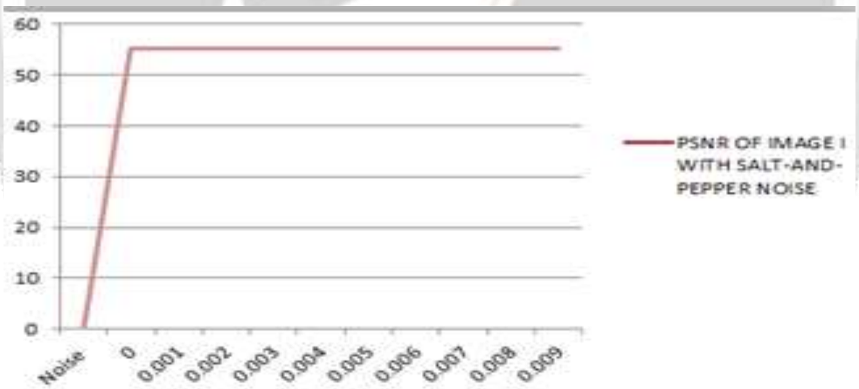

Chart -3: Low rank MatrixInterpolation

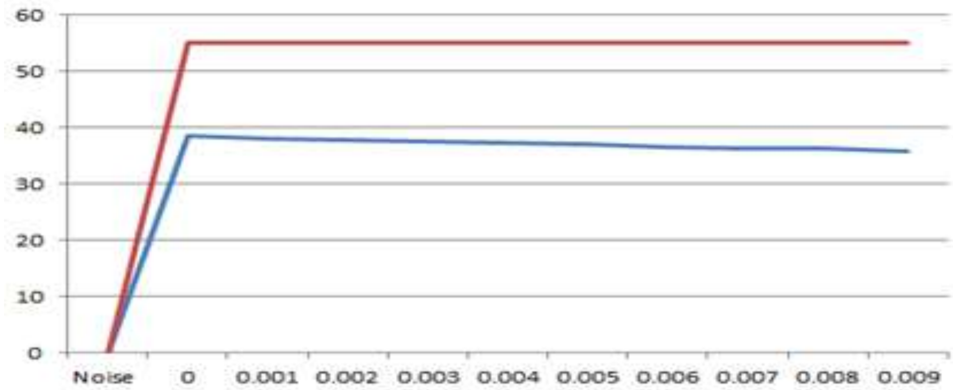

Chart -4: Compared the O/PBilinear Interpolation andLow rank MatrixInterpolation

5. 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.

6. 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"