



INCREASING SINGLE IMAGE RESOLUTION AND DENOISING USING COMBINATION OF BICUBIC INTERPOLATION AND SPARSE REPRESENTATION

Anita Dangi
Department of EECE
Northcap University Gurgaon, India

Pankaj Rakheja
Department of EECE
Northcap University Gurgaon, India

Abstract - Today is the era of technical advancement. As the technology is advancing people want more and more of it. So is with images, people desire more information and details out of images. More information and details implies better image resolution. There are two possible ways for better image resolution (i) use expensive and complex camera components for image capturing or (ii) post processing of captured images to convert it into high resolution image. Method (ii) is computationally easy and relatively inexpensive. This thesis represents a new approach to generate a high resolution image from a low resolution image. Earlier various techniques were proposed to convert low resolution image into a high resolution image but we are utilizing a combination of bicubic interpolation and sparse representation for super resolution. In sparse image patches can be well represented as a combination of few atoms of an appropriately chosen over-complete dictionary. The sparse representation for each patch of the LR input is used to generate the HR output. Though bicubic interpolation is fast and easy to implement but usually yield overly smooth images, edge blurring and jagged artifacts. On the other hand super resolution using sparse representation yields better results in terms of finer details, sharper edges and visual effectiveness, but the only limitation of this method is the speed of recovering high-resolution images from low resolution one. So, we proposed a method in which both bicubic interpolation and sparse representation are used for super resolution to provide results better results and require less computation time.

Key words- *image resolution, bicubic interpolation, sparse representation and super resolution.*

I. INTRODUCTION

Today is the era of technical advancement. As the technology is advancing people want more and more of it. So is with images, people desire more information and details out of images. More information and details implies better image resolution. There are two possible ways for better image resolution (i) use expensive and complex camera components for image capturing or (ii) post processing of captured images to convert it into high resolution image. Method (ii) is computationally easy and relatively inexpensive these techniques are specially referred as super-resolution (SR) reconstruction. Before converting a LR image into HR image, de-noising is performed because any noise or artifact in the LR image will be kept magnified in the latter HR image.

Various algorithms for denoising the images were proposed [1] proposed Noise Reduction Through Spectral Unmixing ,Drawbacks of this method are (i) Require prior knowledge of scene and spectra (ii)It works well for natural scenes but not for man- made objects [14] proposed Image Denoising using Contourlet Transform, this method not only maintains the edges but also connects if there is any discontinuity. [2] Proposed Denoising Using Partial Differential Equations, major advantage of this method is it used noise free image for denoising a corrupted image. [16] Suggested Denoising Using Spatial Preprocessing This is an extended version of end-member extraction. Not only the abundant end-members but also the rare end-members are extracted



using this approach. [9] used Legendre Fenchel Transformation for denoising. It not only conserved the sharp edges and isolated noise very well but also reduced the run time significantly. [15] Proposed Denoising using Wavelet Packet Transform which used wavelet transform for denoising.

Super resolution produces the HR image and overcome the limitations of image capturing device The SR algorithms are first classified based on their number of input images (i) Super Resolution techniques using multi-image (ii) Super Resolution techniques using single-image.(i)requires many LR images as inputs to produce the HR output, while (ii) requires single low resolution image as inputs to produce the high resolution output. Classification on the basis of techniques used [7]: a). Interpolation techniques b). Methods based on Reconstruction, and c). Methods based on Example.

[21]Interpolation is a technique for achieving new unknown pixel values using known pixel values within certain range. Basically interpolation techniques classified into: (i) nearest neighbor, (ii)bilinear and (iii) bicubic interpolation .In nearest neighbor technique it fills the pixel with nearest neighboring pixel value. Result of generated image is smoother. Bilinear interpolation method, pixel value is estimated by the weighted average of nearest four pixel value. It generate better resolution image than the nearest neighbor method but it creates blurry image and poor preservation of high frequency components like edges and corner. Bicubic interpolation in which the pixel value determined by estimate weighted average of nearest 16 pixel value and produce the better resolution image than bilinear interpolation method. Drawback of interpolation based approach is it creates blurry image and poor preservation of high frequency components.

Methods based on Reconstruction include (i)Iterative Back Projection method and (ii) Regularization method. In (i), the error between the simulated and observed image is back projected. And this process is iteratively repeated so that this error is minimized in (ii) total regularization term is used to guide iterative back-projection process and minimize the SR reconstruction error. Although this approach can partly reduce the edge blurring and jagged artifacts caused by interpolation based methods. However, these methods are still limited to small increase in spatial resolution.

[18]Example based techniques aim at estimating the HR image by employing a dictionary of patch correspondences. The dictionary specifies the relationship between the HR image patch and its LR

patch. Patch can be built by either internal similarities or from the set of external training images. This type of algorithm consists of two steps: a training step and SR step. In the training step, LR image is partitioned into the overlapping patches. Then for LR patch, by using the LR-HR patch correspondences, HR image is estimated. In SR step, the final HR output is constructed by reassembling the all the estimated HR patches. This method further classified into the following categories (i). Learning based method[13] (ii). Regression based method [6] and (iii). Sparse coding method [11]. The only drawback of These Example based methods require enormous database and hence are computationally expensive.

However in this paper we are utilizing sparse representation for super resolution which can handle denoising and super resolution simultaneously [10]. Sparse representation approach is combined with bicubic interpolation to provide better and fast results.

The rest of this paper is categorized as follows. Section II is brief description of SR algorithm using sparse representation. Section III contains the details of our improved algorithm which is a combination of sparse representation and bicubic interpolation. Section IV, contains our experimental settings and results showing the effectiveness of the proposed algorithm. Section V concludes this paper along with its future scope.VI References.

II. SUPER-RESOLUTION BASED ON SPARSE REPRESENTATION

A LR patch can be expressed as

$$\text{Eq. } y=DI*\text{ALPHA} \quad (1)$$

where DI is dictionary formed by randomly reading patches from LR training database images and ALPHA are the sparse coefficients. Similarly, A high resolution patch can be expressed as

$$\text{Eq. } x=Dh*\text{ALPHA} \quad (2)$$

Where Dh is dictionary formed by reading different patches from HR training database images and ALPHA are the corresponding sparse coefficients.

As both LR patch and HR patches have same sparse representations following steps are utilized for producing HR output image.

(A)Prepare the database and Dictionaries

For preparing the database high resolution images of similar statistical nature are downloaded from internet. For LR database images are formed by down sampling the HR images. As Low resolution database is formed by down sampling the corresponding high



resolution database this can efficiently be used for the extraction of sparse coefficients.

These Dictionaries are trained[3], certain overlapping among the patches is done to allow local consistency.

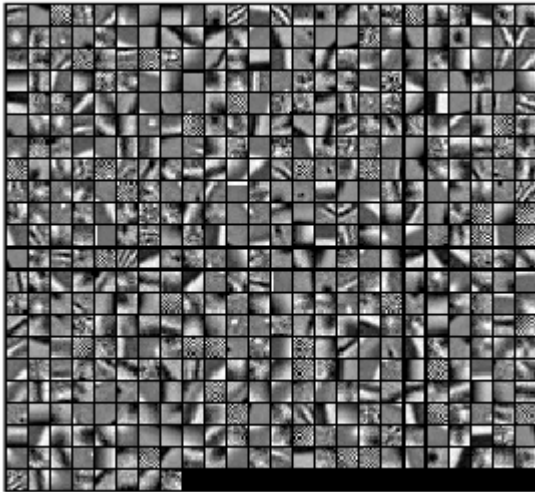


Fig 1: High resolution image patch dictionary having 512 atoms each of size 9x9

(B) Sparse Coding and output reconstruction

The LR dictionary and input low resolution patch is used to obtain the corresponding sparse coefficients. These extracted sparse coefficients and HR dictionary are used to form the HR patch. For this purpose the low resolution input images is divided and read in the form of patches resulting in HR patch generation. Above steps are repeated for all the patches of input image to obtain corresponding HR patch. Finally these patches are then recombined to form the final HR image and are displayed as output

III. EFFICIENT IMPROVED ALGORITHM

As super resolution can also be performed by interpolation techniques, here we are mainly focusing on bicubic interpolation as this method produces superior results than all interpolation techniques.

Algorithm for new approach -

1. Calculate the gradient of input low resolution image.

2. Divide the image into separate parts

(a). Containing the edges (b). Region having no edges

3. Apply super resolution techniques

To part (a) of input image sparse representation method is utilized for super resolution as this technique is known for its better performance and producing sharp edges with finer details.

To part (b) bicubic interpolation method is used for super resolution as it is simple and fast and these points do not represent edges, no blurring effect is observed in output.

4. Recombination of output images –

Finally the output from both the methods is combined to reconstruct the output high resolution image.

As we utilized Sparse representation method for points having high gradient value ie... edges and utilized bicubic interpolation method for points having low gradient ie... similar background

We are able to recover the sharp edges with finer details and the whole process took comparatively less computation time. Hence proposed algorithm represents a good compromise between the performance and the computational complexity.

IV. EXPERIMENTS

(A). Experimental Settings:

Number of training set images - 35,50 and 100. Dictionary size - 512, 1024 and 2048. Patch size - 3x3, 5x5 and 9x9. Magnification factor is 2. Evaluation parameter – PSNR, RMSE, Edges sharpness, Visual appearance and Computation time

(B) Experimental Results:

From the results we can conclude that the Sparse Representation algorithm creates high resolution images by sharpening the edges and textures despite of showing many jagged effects along the boundaries. Our method provides higher PSNR and lower RMSE than Bicubic interpolation method.

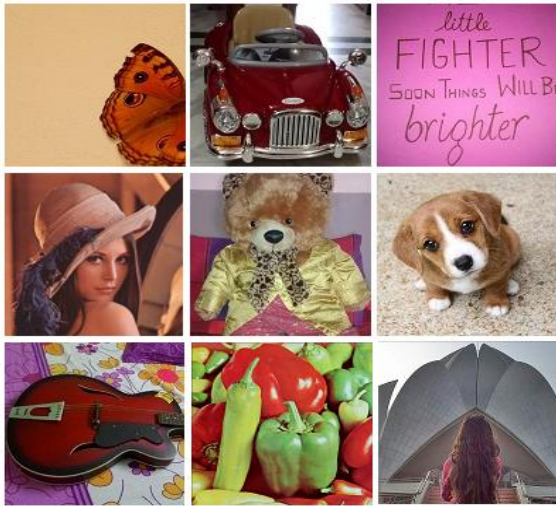


Fig 2 – Test Images

Table 1:PSNR and RMSE values for different images(a to g) using (i) bicubic interpolation (ii) our method

image	Bicubic PSNR	My PSNR	Bicubic RMSE	My RMSE
a	26.8077	27.1723	11.6455	11.1667
b	28.0177	28.0990	10.1311	10.0367
c	33.2998	33.8053	5.5150	5.2032
d	30.3123	30.6755	7.7790	7.4604
e	31.1515	32.0780	7.062	6.348
f	28.9515	29.2409	9.0984	8.8003
g	32.794	34.498	5.845	4.804
avg	30.1906	30.7958	8.1537	7.6884

Effects of Dictionary Size

Larger dictionaries possess more representation power as it contain more number of patches, and thus will produce more accurate approximation or results, but it also increases the computation cost. We train dictionaries of different size such as size 512, 1024, and 2048, and used these dictionaries on same input image. The results are evaluated both visually and quantitatively in terms of PSNR as well as computation time. Results showed that as the dictionary size is doubles it took almost double time for computation and the PSNR value was also increased but the improvement in PSNR value was not significantly high.

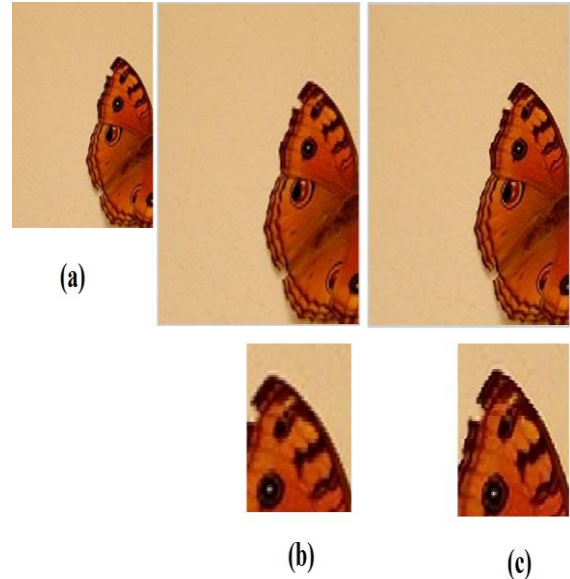


Figure 3: (a) shows input low resolution image, Figure (b) shows output resolution image obtained using bicubic interpolation , Figure (c) shows output resolution image obtained using our method.

V. CONCLUSION

Here we have used a combination of sparse representation and bicubic interpolation for image super resolution utilizing their properties of providing sharpening edges, textures and easy, fast implementation. From the experiment results we can conclude that proposed algorithm represents a good compromise between the performance and the computational complexity. For above butterfly image the computation time for our algorithm was half as compared to that of sparse representation method, producing similar results in terms of visual effects and statistics.

In future we can try to improve the resolution of videos.

VI. REFERENCE

- [1] .Daniele Cerra, Rupert Muller, and Peter Reinart,” Noise Reduction in hyperspectral Images Through Spectral Unmixing” IEEE geoscience and remote sensing letters, vol. 11, no. 1, january 2014.
- [2] Peng Liu, Fang Huang, Guoqing Li, and Zhiwen Liu “Remote-Sensing Image Denoising Using Partial Differential Equations and Auxiliary Images as Priors” IEEE geoscience and remote sensing letters, vol. . 9, no. 3,may 2012



- [3] M.Aharon, M.Elad, and A.M.Bruckstein, "The K-SVD: an algorithm for designing of overcomplete dictionaries for sparse representations", IEEE Trans. Image Process., vol. 54, no. 11, pp. 4311-4322, Nov. 2006.
- [4] Michal Irani and Shmuel Peleg, "Improving resolution by image registration", CVGIP: Graphical Models and Image Processing Vol.53, No.3, May, pp. 231-239, 1991.
- [5] J. Mairal, M. Elad, and G. Sapiro, "Sparse representation for color image restoration", IEEE Trans. on Image Processing, Vol. 17, No. 1, pages 53-69, January 2008.
- [6] R. Tishirani. "Regression shrinkage and selection via the Lasso", J. Royal Statist. Soc B., Vol. 58, No. 1, pages 267-288, 1996.
- [7] Jigar Dalvadi, "A Survey on Techniques of Image Super Resolution", International Journal of Innovative Research in Computer and Communication Engineering, Vol. 4, Issue 3, March 2016
- [8] Faezeh Yeganli, Mahmoud Nazzal, Murat Unal and Huseyin Ozkaramanli, "Image Super-Resolution via Sparse Representation over Coupled Dictionary Learning Based on Patch Sharpness," 2014 UKSim-AMSS 8th European Modelling Symposium.
- [9] Santhosh.S, Abinaya.N, Rashmi.G "A novel Approach for Denoising Coloured Remote Sensing Image using Legendre Fenchel Transformation" 2014 International Conference on Recent Trends in Information Technology
- [10] Jianchao Yang, John Wright, Thomas Huang and Yi Ma. "Image super resolution via sparse representation", Accepted To IEEE Transaction on Image Processing (TIP), 2010.
- [11] Jianchao Yang, John Wright, Thomas Huang and Yi Ma. "Image super resolution as sparse representation of raw image patches", Proc.CVPR, 2008.
- [12] H.Chang, D.-Y. Yeung, and Y. Xiong. "Super-resolution through neighbor embedding", CVPR, 2004.
- [13] LI Juan, WU Jin, YANG Shen, LIU Jin, "Dictionary Learning for Image Super-resolution", Proceedings of the 33rd Chinese Control Conference July 28-30, 2014, Nanjing, China.
- [14] R.Sivakumar, G.Balaji, R.S.J.Ravikiran, R.Karikalan, S.Saraswathi Janaki, "Image Denoising using Contourlet Transform," 2009 Second International Conference on Computer and Electrical Engineering
- [15] Jiayin Kang, Wenjuan Zhang, "Quickbird Remote Sensing Image Denoising using Wavelet Packet Transform," Second International Symposium on Intelligent Information Technology Application
- [16] Alp Ertürk, "Enhanced Unmixing-Based Hyperspectral Image Denoising Using Spatial Preprocessing," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing
- [17] Yizhou Ye, Yunze Cai "A Spatially Adaptive Denoising with Activity Level Estimation Based Method for Infrared Small Target Detection" proceeding of the 11th World Congress on Intelligent Control and Automation Shenyang, China, June 29 - July 4 2014
- [18] William T. Freeman, Thouis R. Jones, and Egon C. Pasztor, "Example-Based Super-Resolution" Comp. Graph. Appl., (2), 2002. March/April 2002.
- [19] Di Zhang, Minghui Du, "Super-Resolution Image Reconstruction via Adaptive Sparse Representation and Joint Dictionary Training", 2013 6th International Congress on Image and Signal Processing (CISP 2013).
- [20] Ron Rubinstein, Alfred M. Bruckstein and Michael Elad, "Dictionaries for Sparse Representation Modeling", IEEE PROCEEDINGS, VOL. 4, NO. 3, XX 2006.
- [21] Dianyuan Han, "Comparison of Commonly Used Image Interpolation Methods", Proceedings of the 2nd International Conference on Computer Science and Electronics Engineering (ICCSEE 2013).