

Optimized Multi scale Similarity Approach for Images Based on Single Image Super Resolution Framework

Syeda Ayesha Farheen, A. Pugazhenti

(PG Student)¹

Department of ECE

G. Pulla Reddy Engineering College

Kurnool, Andhra Pradesh, India

ayeshafarheen455@gmail.com

M.Tech (Assistant Professor)²

Department of ECE

G. Pulla Reddy Engineering College

Kurnool, Andhra Pradesh, India

pugazh1989@gmail.com

Abstract— The aim of Super Resolution (SR) algorithms is to produce a High Resolution (HR) image with the help of one or more than one low resolution (LR) image(s) of some real scene. Existing SR algorithms are of 3 types – Interpolation based SR algorithms, reconstruction based and Example learning based SR algorithms. Example based image SR has been recognized as an effective way to produce a HR image using an external training set. However, the effectiveness of these example based SR methods highly depends upon the consistency between the training set and the LR image(s). Single image SR method by learning multi scale self-similarities from an LR image has been proposed for the reduction of the effect created by incompatible high frequency details that are present in the training set. This proposed method is based upon the observation that in the natural images, small patches tend to repeat themselves redundantly many times, both within the same scale and across different scales. And to synthesize the details that are missing, HR-LR patch pairs have to be established using the LR image input and its down sampled version in order to capture the similarities that are present across different scales. Then Neighbor Embedding (NE) algorithm is applied to estimate the relationship between HR and LR image pairs. To completely exploit the similarities across various scales of an LR image, we use the previous resultant images as training examples for subsequent reconstruction process and adopt a gradual magnification scheme to upscale the LR input to the desired size step by step. Further, in order to preserve the sharper edges, we apply non local means (NLM) method to learn the similarity within the same scale. This has also suppressed the aliasing artifacts which are not required in an image.

Keywords—*Image super-resolution (SR); multiscale self similarities; Bicubic Interpolation; neighbor embedding (NE); nonlocal means (NLM).*

I. INTRODUCTION

Super resolution is the method of generating a High resolution (HR) image by the help of one or more Low resolution (LR) image. An image is said to be in low resolution [1] when the pixel density in an image is small. The details offered by an LR image will be less. Low resolution image is visually blurred or jaggy. Higher pixel density yields a better quality image which is called as HR image. Thus the HR image quality is better than LR. But, even the HR images may be blurred due to optical limitations in hardware or due to movements while capturing an image. There are number of applications for super resolution such as Satellite imaging, Pattern recognition, Medical imaging for diagnosis, Biometrics, Surveillance and Forensic applications etc. Plenty of research has been done on single image super resolution.

L.Zhang and X.Wu [2006], proposed [2] the technique of novel edge-guided nonlinear interpolation by directional filtering and data fusion. The interpolation of missing sample is performed not in just one direction, but in both the directions that are mutually orthogonal. These two results of interpolation are taken as two estimates of the sample and adaptively fused by using statistics of the local window. Finally, the pixel is interpolated by the combination

of the two directional estimates in the principle of linear minimum mean square-error estimation (LMMSE). This method achieved observable reduction in visual artifacts by avoiding interpolation against the edge directions. But the drawback in this interpolation approach lies in its computational complexity which is relatively higher.

Y. W. Tai et al. [2010] proposed [3] a method for reconstructing the edges along with recovering of image details. Gradient profile prior is an edge-directed super-resolution technique used to reconstruct main edges. Later, these edges are added up with missing details which are taken from user's given example image or texture. This gives the user a better understanding in specifying the exemplar image that though the quality edges are not present in the example image, they can be achieved in the up-sampled image. But, when the large magnification ratio is done, this method not so efficient in generating the fine details present in an image.

J. Wright et al., [2010] presented [4] a new method based on sparse signal representation to single-image super-resolution. As per research on image statistics, from a suitably chosen over-complete dictionary of images, patches in an image can be represented very well as a sparse linear combination of pixels or elements. Considering this observation as a basis, a sparse representation for each and every patch of the low-resolution image's input is performed, and after that, the coefficients of this sparse representation are used in generating the high-resolution output. But, for the

image structures that are complicated, like the textural regions, this method does not perform well.

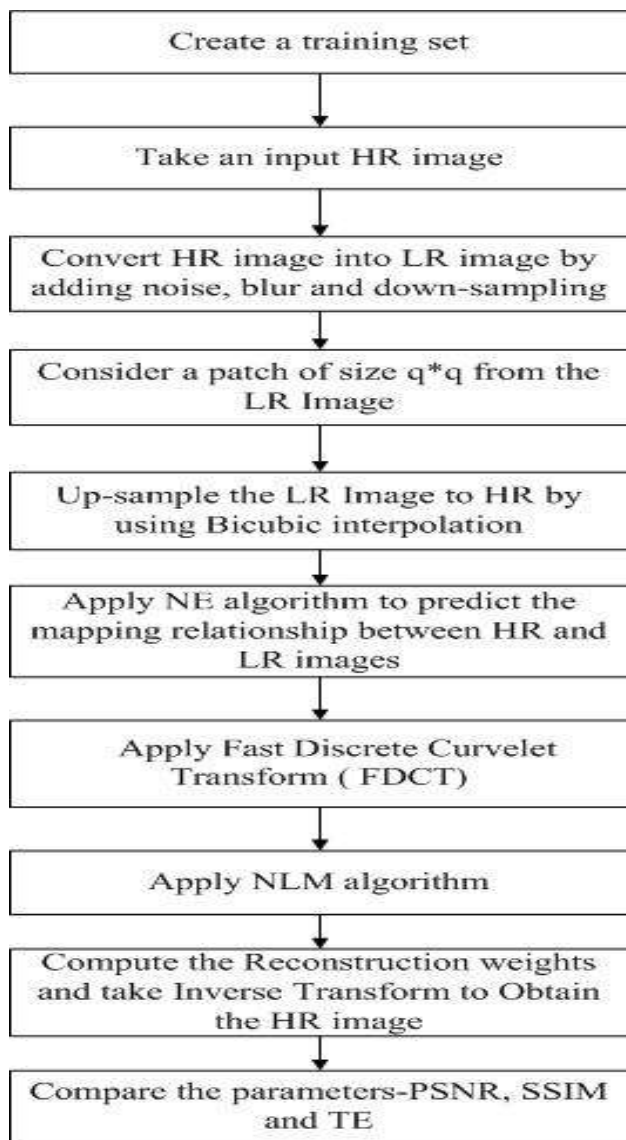
X. Gao, D. Tao et al. [2012] proposed [5] a sparse neighbor selection scheme for SR reconstruction. To perform clustering, we recognize the -nearest neighbor (-NN), a local statistical feature, namely histograms of oriented gradients (HoG) of low resolution image patches to characterize the local geometric structure of LR image patches. The synthesizing speed of HR image is enhanced while the quality of reconstruction has been preserved. But for complicated image structures, like textural regions, this presented approach is not so efficient.

II. PROPOSED ALGORITHM

STEP 1: Create a training set or dictionary.

STEP 2: Take an input HR image.

STEP 3: Convert HR image into LR image by adding noise, blur and down-sampling.



STEP 4: Consider a patch of size $q \times q$ from the LR image.

Step 5: Up-sample the LR image to HR image by using bicubic interpolation.

STEP 6: Apply Neighbor Embedding (NE) algorithm to predict the mapping between HR-LR images.

STEP 7: Apply Non Local Means (NLM) algorithm in order to reduce the artifacts introduced in above step.

STEP 8: Apply Fast Discrete Curvelet Transform (FDCT)

STEP 9: Compute the reconstruction weights and apply Inverse transform to reconstruct the HR image.

STEP 10: Compare the parameters – PSNR, SSIM, Correlation Coefficient and Time Elapsed.

III. RESULTS AND ANALYSIS

The algorithm is implemented in Matlab version R2009a on Windows7 Ultimate on Intel core(TM) i3 processor. The proposed Super Resolution algorithm is tested on set of five DIFFERENT images i.e. Baby, Butterfly, cat, Head High and Window.

A. QUALITATIVE ANALYSIS

In many super resolution applications that are concerned with digital imagery there is a real need for a digital metric that quantifies how distorted a super resolved image appears relative to the original version of the same image, as perceived by a human observer.

From the visual interpretation, by observing each set of outputs obtained, we can say that the image shown in (a) is a degraded image. Degraded image implies that the image is of less resolution. The image is pixelated. The image shown in (b) is the image obtained after the application of SR algorithm with the existing method. This image has higher pixel density than the previous image. Hence this image is of higher resolution and it is visually clear and better. We can say that image (b) is better by observing that the edges and fine details which can't be observed in image (a) have been preserved in image (b). Then the image shown in (c) is the image obtained after applying NLM filtering technique to the SR image. This image is free from noise and few jaggy effects which were present in image (b).

B. QUANTITATIVE ANALYSIS

Quantitative analysis is a numerically oriented procedure to figure out the performance of algorithms without any human error. The quantitative analysis of the experimental results obtained with developed algorithm is done by evaluating Mean Squared Error (MSE), Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM), Correlation Coefficient (CC) for set of 5 images.

1. MEAN SQUARED ERROR (MSE): Mean Squared Error [6] is the error between the original image and super resolved image. It is computed by averaging the squared intensity difference of original and segmented image pixels, and mathematically it can be defined as

$$MSE = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N [F_1(i, j) - F_2(i, j)]^2$$

As lower MSE shows the better resolution, desired value of MSE should be as low as possible.

2. PEAK SIGNAL-TO-NOISE RATIO (PSNR): The peak signal-to-noise ratio (PSNR) [7] is a measure of quality of super resolved image based on pixel difference between original and SR images. Mathematically PSNR is defined by

using the following formula in db:

$$PSNR = 10 \log_{10} \frac{(255)^2}{MSE}$$

As higher PSNR shows better resolution, desired value of PSNR is as high as possible.

3. STRUCTURAL SIMILARITY INDEX: The structural similarity (SSIM) index [8] is a method for measuring the similarity between two images. Structural information in an image is defined as those attributes that represent the structure of objects in the image. These dependencies carry important information about the structure of the objects in the visual scene. The SSIM is computed within a local $N \times N$ square window, which moves pixel-by-pixel over the entire image. At each step, the local statistics and SSIM index are calculated within the local window. Mathematically SSIM is defined by using the following formula

$$SSIM = \frac{(2\mu_x\mu_y + c_1)(2s_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(s_x^2 + s_y^2 + c_2)}$$

Where x is the original image and μ_x is the average of x , y is the SR image and μ_y is the average of y , s_x^2 is the variance of x , s_y^2 the variance of y , s_{xy} is the covariance of x and y , $c_1 = (k_1L)^2$, $c_2 = (k_2L)^2$, L is the dynamic range of the pixel values and $k_1=0.01$ and $k_2=0.03$. For good SR, SSIM index lies between -1 and 1, and the desired value of SSIM is closer to 1.

4. CORRELATION COEFFICIENT (CC): The Correlation Coefficient (CC) [9] measures how the super resolved image is correlated to the original image. Mathematically, CC is defined by using the following formula.

$$\rho_{x,y} = \frac{\text{cov}(x,y)}{\sigma_x \sigma_y} = \frac{E[(x-\mu_x)(y-\mu_y)]}{\sigma_x \sigma_y}$$

Where μ_x , μ_y and σ_x , σ_y represents the mean and standard deviation of original and SR images. The dynamic range of CC is [0, 1]. The maximal value occurs when both images are identical. The best value of CC is closer to 1.

TABLE I-COMPARISON OF PARAMETERS

Image	Parameter	Existing Method	Proposed Method
Butterfly	PSNR	7.5840	23.6538
	SSIM	0.7145	0.8501
	CC	0.8782	0.9817
	TE (in seconds)	262.014	98.006

Cat	PSNR	8.3454	31.5817
	SSIM	0.7864	0.9747
	CC	0.8752	0.9985
	TE (in seconds)	159.006	102.477
Window	PSNR	6.8686	23.7685
	SSIM	0.7717	0.9784
	CC	0.8266	0.9838
	TE (in seconds)	375.828	78.903
Head High	PSNR	8.2884	37.1076
	SSIM	0.6994	0.9923
	CC	0.9150	0.9992
	TE (in seconds)	187.265	90.229
Baby	PSNR	9.3208	34.9887
	SSIM	0.9070	0.9993
	CC	0.7337	0.9970
	TE (in seconds)	116.119	69.169

C. OUTPUT IMAGES



Fig 1:Output Images

The observed output images for the existing and proposed approaches are shown above. In each set of output images, first image represents the LR image. Second image is the representation of SR image obtained from existing approach. And third image is the SR image obtained from proposed method. This is the SR image obtained after filtering.

V. CONCLUSION

Using the modified single image SR approach, we can get a super resolved image without any database. Even if required, the database will be of very small size. The patches that we select in an image tend to repeat in a natural image within that scale or across different scales. The repetition of the patches within the same image scale produces classical SR. If the patches repeat themselves across different scales, then these methods produce example based SR. The advantage of example based single image SR method is that, it requires neither prior examples nor the large databases.

REFERENCES

- [1] Wan-Chi Siu and Kwok-Wai Hung, "Review of Image Interpolation and Super-resolution".
- [2] L. Zhang and X. Wu, "An edge-guided image interpolation algorithm via directional filtering and data fusion," *IEEE Trans. Image Process.*, vol. 15, no. 8, pp. 2226-2238, Aug.2006.
- [3] Y.W. Tai, S. Liu, M. S. Brown, and S. Lin, "Super resolution using edge prior and single image detail synthesis," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun 2010, pp. 2400-2407.
- [4] J. Yang, J. Wright, T. Huang, and Y. Ma, "Image super-resolution via sparse representation," *IEEE. Trans. Image Process.*, vol. 19, no. 11, pp. 2861-2873, Nov. 2010.
- [5] K. Zhang, X. Gao, D. Tao, and X. Li, "Single image super-resolution with sparse neighbor embedding," *IEEE Trans. Image Process.*, vol. 21, no. 7, pp. 3194-3205, Jul. 2012.
- [6] R. Kumar and M. Rattan, "Analysis of various Quality Metrics for Medical Image Processing," vol. 2, no. 11, November 2012.
- [7] Y. Sharma and P. Kaushik, "Comparison of Different Image Enhancement Techniques based upon PSNR and MSE," *International Journal of Applied Engineering Research*, vol. 7, no. 11, 2012.
- [8] Z. Wang, A.C. Bovik, R. Sheikh and E. P. Simoncelli, "Image Quality Assessment: From Error Visibility to Structural Similarity," vol. 13, no. 4, April 2004.
- [9] A. M. Neto, D. A. Lima, "Image Processing Using Pearson's Correlation Coefficient: Applications on Autonomous Robotics".
- [10] Jianchao Yang and Thomas Huang, "Image super-resolution: Historical overview and future challenges".