A Review on Super Resolution Technique

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***Abstract*— In this paper, the different research papers applicable to topic of super resolution images are reviewed. Image super resolution is a most important subject of research in the area of image processing. The "super resolution image" refers as technique to produce the high resolution of the image from single or multiple low resolution images. Image resolution is described as information amount contained by images. The basic idea for Super-Resolution (SR) is that the fusion of a sequence of low-resolution (LR) images which are noisy and blurred that create a high resolution (HR) image. Super resolution is process of restoring and denoising of image.**

***Keywords*— Super resolution, high resolution, low resolution.**

I. Introduction

Super Resolution is a technique that creates the high resolution of image from single and several low resolution images. Image can get from the physical devices which are the capture digital images and camera, satellite, magnetic resonance imaging machine and microscope etc are use for that. There for demand is increase so performance of personal computing digital image processing is widely used in varies applications field.

The high resolution can get through applying the suitable transformations and the overlapped regions that warped the images, interpretation. It may be possible to generate a single image with high resolution. There for increasing the high frequency parameter and remove the degradations and some limitations part of low resolution imaging device as well as system. The requirement of high resolution is common and in computer vision application for better

performance in pattern recognition and analysis of images. High resolution is of importance in medical field. In many applications require for zoom the specific area in the image for interest where in high resolution essential.

II. LITERATURE REVIEW

Chao Dong, Chen Change Loy and Xiaoou Tang [1] presented a novel deep learning approach for single image Super-Resolution (SR). The Proposed approach, Super Resolution Convolutional Neural Network (SRCNN), learns an end-to-end mapping between low and high resolution images, with little extra pre/post processing beyond the optimization.

Zhaowen Wang, Ding Liu, Jianchao Yang, Wei Han, Thomas Huang [2] developed new model for image SR by combining the strength of sparse coding and deep network. Cascaded Sparse Coding Network (CSCN) method recovered all the structures of the characters without any distortion. A PSNR gain of 0.3 ~ 1.6 dB is achieved by CSCN.

Chao Dong, Chen Change Loy, Kaiming He and Xiaoou Tang [3] introduced SRCNN, learns an end-to –end mapping between low-and high resolution images with little extra pre /post-processing beyond the optimization. This achieved avg gains are 0.51 dB, 0.47 dB and 0.40 dB.

Ding Liu, Zhaowen Wang, Bihan Wen, Jianchao Yang and Thomas S. Huang[4] discussed a new model for image SR by combining the strength of sparse coding and deep network and make considerable improvement over existing deep and shallow SR models both quantitatively and qualitatively.

Radu Timofte, Vincent DE Smet and Luc Van Gool [5] put forward a new example based method for super resolution called Anchored Neighbor Regression (ANR) which focuses on fast execution.

Radu Timoftc,Vincent De Smet and Luc Van Gool [6] suggest Adjusted Anchored Neighbor hood Regression, or A+. It is shown on standard bench marks to improve 0.2 dB upto 0.7 dB in performance over state of the art methods such as ANR or SF.

Jia-Bin Huang, Abhishek Sing and Narendra Ahuja [7] submit a self-similarity based image SR algorithm. It uses a factored patch transformation representation for simultaneously accounting for both planar perspective distortion and affine shape deformation of image patches. In the absence of regular structures our algorithm reverts to searching affine transformed patches.

Yapeng Tian, Fei Zhou, Wenming Yang, Xuesen Shang and Qingmin Liao [8] recommend a novel anchored neighborhood regression based single image SR method, which generates training samples from an input image without using any external images.

Junjun Jiang, Xiang Ma, Chen Chen, Tao Lu, Zhongyuan Wang and Jiayi Ma [9] prefer Locally Regularized Anchored Neighborhood (LANR-NLM). It applies locality constraint to select similar dictionary atoms and assigns different freedom to each dictionary atom according to its correlation to the input LR patch.

Li-Wei Kang,Chih-chung Hsu, Boqi Zhuang, Chia-wen Lin and Chia-Hung Yeh [10] offer a learning-based SR frame work to achieve joint single- image SR and deblocking for image sparse representation for modeling the relationship between LR and HR image patches in terms of the learned dictionaries respectively, for image patches with and without blocking artifacts.

Li-Wei kang, Boqi Zhuang, Chih-chung Hsu, Chia-Wen Lin and Chia-Hung Yeh [11] prefer a learning-based SR frame work to achieve joint single-image SR and deblocking for image sparse representation for modeling the relationship between LR and HR image patches in terms of the learned dictionaries, respectively.

Naveed Akhtar,Faisal Shafait and Ajmal Mian [12] put up a Bayesian sparse representation based approach for hyper spectral image super resolution. Using the non-parametric Bayesian dictionary learning, the proposed approach learns distributions for the scene spectra and their proportions in the image.

Zahra Hashemi Nezhad, Azam Karami, Rob Heylen, Paul Scheunders [13] propound a new method for enhancing the spatial resolution enhancement using spectral unmixing and sparse coding (SUSC). The method combines the spectral mixing model to reduce spectral distortions from a dictionary of unrelated high spatial resolution images.

Jakub Bieniarz, Rupert Miiler, Xiao Xiang Zhu, Peter Reinartz [14] come up with multi-look joint sparsity fusion (MLJSF) method employs multi-source MSI and HSI remote sensing data and reconstructs high resolution HIS along with spectral abundance of end members for both low and high resolution HIS.

Weisheng Dong, Fazuo Fu, Guangming Shi,Xun Cao, Jinjian Wu, Guangyu Li and Xin Li [15] bring forward an effective sparsity-based hyper spectral image super-resolution method to reconstruct a HR hyper spectral image from a LR hyperspectral image and a HR RGB image of the same scene. An efficient non-negative dictionary learning algorithm is proposed using a block-coordinate decent algorithm.

TABLE I. THE RESULTS OF PSNR (DB) AND TEST TIME(SEC)

Title of the paper	**Method**	**Probable enhance ment**	**Metric**
Image Super-Resolution Using Deep Convolutional Networks.	SRCNN	Visual quality improvem ent	PSNR (44.35)
Deep Networks for Image Super-Resolution with Sparse Prior	CSCN	Visual quality improvem ent	PSNR (40.15)
Learning a Deep Convolutional Network for Image Super-Resolution	SRCNN	Visual quality improvem ent	PSNR (40.64) Execution time(0.10)
Robust Single Image Super-Resolution via Deep Networks With Sparse Prior	CSCN	Visual quality improvem ent	PSNR (37.00)
Anchored Neighborhood Regression for Fast Example Based Super-Resolution	ANR	Visual quality improvem ent and fast execution time	PSNR (35.83) Execution time(0.78)
A+: Adjusted Anchored Neighborhood Regression for Fast Super-Resolution	A+	Visual quality improvem ent and fast execution time	PSNR (36.55) Execution time(0.55)
Single Image Super-Resolution from Transformed Self-Exemplars	SR ALGORIT HMS	Visual quality improvem ent	PSNR (31.12) SSIM (0.88)
Anchored Neighborhood Regression Based Single Image Super-Resolution From Self Examples	SR ALGORIT HMS	Visual quality improvem ent	PSNR (36.89) SSIM (0.9629)
Single Image Super-Resolution via Locally Regularized Anchored Neighborhood Regression and Nonlocal Means	LANR-NLM	Visual quality improvem ent	PSNR (31.93) SSIM (0.8958)
Learning-Based Joint Super-Resolution and Deblocking for a Highly Compressed Image	Praposed Sparse coding super resolution (SCSR)	fast execution time	Execution time (121.9 s)
Learning-Based joint Super-Resolution and Deblocking for a Highly Compressed Image	Sparse representati on and MCA based image decomposit ion	Visual quality improvem ent	Time (153.74)
Bayesian Sparse Representation for Hyper spectral Image Super Resolution.	Bayesian sparse coding method	Visual quality improvem ent	Time(180)
Fusion of hyperspectral and multispectral images using spectral unmixing and sparse coding.	SUSC	Visual quality improvem ent and fast execution time	PSNR (32.3) TIME (551.36)
Hyperspectral Image resolution enhancement based on joint sparsity spectral unmixing.	MLJSF	Visual quality improvem ent	nRMSE (3.2%) NCC(0.98)
Hyper spectral image super-resolution via non-negative structured sparse representation	NSSR	fast execution time	PSNR (42.26) RMSE (2.21) SAM(4.33) ERGAS (0.30)

III. CONCLUSION

Several techniques are available to create super-resolution image from set of lower resolution images. All papers are studied thoroughly and concise table is made. From the table it is observed that SRCNN is better in comparison with other techniques against PSNR of 44.35 dB, the execution time is very small i.e. 0.10 sec.

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