International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395 -0056
Volume: 03 Issue: 10 | Oct-2016 www.irjet.net p-ISSN: 2395-0072

# A Survey on Image Super- Resolution Techniques for Image Reconstruction

**J.Josephin Nivetha[1], T.M.Babi Mol[2]**

*[1]PG Scholar, Communication Systems, PET Engineering College, Vallioor, Tamilnadu, India*
*[2]Assistant Professor,Electronics & Communication Engineering,PET Engineering College,Vallioor,Tamilnadu,India*

---------------------------------------------------------------------***---------------------------------------------------------------------

**Abstract -** Super Resolution (SR) is an image reconstruction process in which the resolution of an image is improved. It searches for creating a high quality image from combining one or more low quality images.

***Key Words***: Super resolution, Reconstruction, Interpolation, Regression, PSNR.

## 1.INTRODUCTION

Image reconstruction techniques are used to create a two dimensional and three dimensional images. For image reconstruction different methods are used such as back projection filters. Image reconstruction is commonly referd to as restoration of missing parts. Super-resolution technique aims to increase the resolution of the limits of the original image or video. It is used to extract the lost details of an image when it was up scaled. Interpolation based SR, Example based SR and Multi image based SR are the main techniques for reconstructing a super resolution image from LR image. Resolution refers to denote the number of pixels in an image and it is measured in pixel Per Inch (PPI). SR technique reduces the image's blurring and used in many image processing applications. SR technique applied in an improvement of test images, compressed video and image enhancement, medical imaging process and satellite and aerial imaging. SR is a badly postured issue on the grounds that every LR pixel must be mapped onto numerous HR pixels that are depending upon the desired up sampling variable. Generally well known single-picture SR techniques attempt to take care of this issue by upholding original image priors depend on either instinctive comprehension or many original images statistical analysis. In this paper the-state-of-art methods for super-resolution are discussed.

## 2. METHODOLOGY

### 2.1 Image Super-Resolution using ANR and GR

In this paper the fast Super-Resolution is performed by Global Regression (GR) and Anchored Neighborhood Regression (ANR). In Global Regression, sparse learned dictionaries that are Neighbor Embedding (NE) and Sparse Code (SC) approaches are used. To reduce the singularity problem, GR considers the whole LR dictionary as a starting point and computes the projected matrix. In GR high resolution patch output calculation includes multiplication of pre-computed projection matrix and LR input feature. ANR groups the local neighborhoods from dictionary atoms. Nearest Neighbor is found by the correlation between the dictionary atoms as opposed to Euclidean distance. If the neighborhoods are characterized then separate projection matrix for each dictionary atom is calculated. In ANR, stored projection matrix and input patch feature is multiplied to calculate the HR output patch[4].

### 2.2 Image Super-Resolution usingAdjusted Anchored Neighborhood Regression

In this paper super resolution is performed by combining the best characteristics of Anchored neighborhood regression (ANR) and Simple Functions (SF). Training sample neighborhood covers an anchoring atom's hyper cell and portion of its adjacent atoms. Euclidean distance is measured between the anchor atom and samples. Linear regression is used in the neighborhood of an atom. It accommodates all the nearby neighborhood samples and same samples shared among various atom focused neighborhoods. For encoding LR input patches to HR output patches, the time complexity of Adjusted Anchored Neighborhood Regression (A+) is linear in the number of anchoring atoms and in the number of input patches[6].

### 2.3 Image Super-Resolution Using Deep Convolutional Networks

In this method Conventional sparse-coding-based super resolution method is reformulated into a deep Convolutional Neural Network for Super Resolution (SRCNN). An end-to-end mapping between low resolution and high resolution images is learned directly. Representation of mapping is defined as a deep Convolutional Neural Network (CNN) that takes low resolution input image and gives high resolution output image. At first bicubic interpolation is used to upscale a single low resolution input image. This interpolated LR image extracts patches with high dimensional vector. Each high dimensional vector is mapped onto another high dimensional vector and this mapped vector represents HR patch. To generate the HR image, reconstruction is used to aggregate the high resolution patches. Super Resolution Convolutional Neural Network (SRCNN) robustness is applied to image deblurring and denoising low level vision problem[5].

## 2.4 Image Super-Resolution using Sparse-Representations

In this paper sparse-representation modeling and dictionary learning are used to recover an original image when maintaining edges and small details. It includes the operation on training phase and reconstruction phase. Using trained model from the previous phase the input image is up-scaled. Scale down operator is used to construct a Low Resolution (LR) images and matching patches are extracted. Preprocessing is applied to patches and is used to remove the low frequencies and patches are extracted. Trained dictionary is used to apply the sparse coding technique. High Resolution (HR) patches are recovered by multiplying sparse representation vector and patch from high resolution patch dictionary. For creating the resulting image, averaging is performed to recover high resolution patches. This SR technique is used to recover an original image from blurred or down scaled noisy image[1].

## 2.5 Image Super-Resolution using AISpH

In this paper Antipodally Invariant spherical Hashing (AISpH) and Iterative Back Projection (IBP) schemes are used to improve the resolution of the LR image. An input image undergoes Iterative Back Projection process in which back projecting error is used for improving the initial guess. IBP is used to improve the quality of up-scaled image that is filtered using 1-st and 2-nd order gradient filters. From each of the gradient images overlapped patches are extracted and Principle Component Analysis (PCA) compression is applied. To avoid zero solution normalization is processed for compressed patches. To avoid search complexity of patches AISpH is introduced. In this scheme feature vectors are compared with anchor points with calculation of Euclidean distance. Then the High Resolution (HR) patches are reconstructed to get a High Resolution image as an output. This SR technique is used to improve an image quality that is PSNR[5].

## 2.6 Image Super-resolution using Self-example based technique

In this paper redundancy properties are applied to reconstruct sharp edges using up-sampling and fractal-based gradient enhancement. An input Low Resolution image is up-scaled using magnification factor and self-similarity function. Fractal-based gradient enhancement is applied to that up-scaled image for smoothing an image. By using reconstruction the output High Resolution image is obtained. Fractal-based gradient is used for both detail enhancement and edge sharpening. It enhances reconstruction of fine-scale structures[3].

# 3. RESULTS AND DISCUSSION

## 3.1 Image Super-Resolution using ANR and GR

In this paper the PSNR and Execution time are calculated for different magnification factors as x2, x3, and x4[4].

**Table -1:** The result of PSNR & test time for different scale factors.

| Paper | Set 5 images | Scale | ANR | |
|---|---|---|---|---|
| | | | PSNR | Time |
| Anchored Neighborhood Regression for Fast Example-Based Super-Resolution | Baby | 2 | 38.4 | 1.8 |
| | Baby | 3 | 35.1 | 1.0 |
| | Baby | 4 | 33.0 | 0.8 |

## 3.2 Image Super-Resolution using Adjusted Anchored Neighborhood Regression

In this method time complexity is low and order of magnitude is less. When Anchored Neigh Boyhood Regression (ANR) or Simple Functions (SF) [6].

**Table -2:** The result of PSNR & test time for different scale factors.

| Paper | Set 5 images | Scale | ANR | |
|---|---|---|---|---|
| | | | PSNR | Time |
| A+: Adjusted Anchored Neighborhood Regression for Fast Super-Resolution | Baby | X2 | 38.5 | 1.3 |
| | Baby | X3 | 35.2 | 0.8 |
| | Baby | X4 | 33.3 | 0.6 |

## 3.3 Image Super-Resolution Using Deep Convolutional Networks

In this method input is a low resolution image and produces high resolution image as output. This method is used to optimize all layers. This method produced good restoration quality [5].

**Table -3:** The result of PSNR & test time for different scale factors.

| Paper | Set 5 images | Scale | ANR | |
|---|---|---|---|---|
| | | | PSNR | Time |
| Learning a Deep Convolutional Network for Image Super-Resolution | Baby | 2 | 38.30 | 0.38 |
| | Baby | 3 | 35.01 | 0.38 |
| | Baby | 4 | 32.98 | 0.38 |

### 3.4 Image Super-Resolution using Sparse-Representations

This proposed algorithm is highly efficient and much faster. This methods produce improvement better result than bicubic interpolation [1].

**Table -4:** The result of PSNR.

| paper | Images | PSNR |
|---|---|---|
| On Single Image Scale-Up using Sparse-Representations | Baboon | 23.5 |
| | Barbara | 26.7 |
| | Bridge | 25.0 |

### 3.5 Image Super-Resolution using AISpH

This method is to improve the quality. This method gives high PSNR value than A+[5].

**Table -5:** The result of PSNR & test time for different scale factors.

| Paper | Set 5 images | Scale | ANR | |
|---|---|---|---|---|
| | | | PSNR | Time |
| Antipodally Invariant Metrics For Fast Regression-Based Super-Resolution | Baby | 2 | 38.6 | 2.644 |
| | Baby | 3 | 41.7 | 0.887 |
| | Baby | 4 | 32.7 | 0.678 |

### 3.6 Image Super-resolution using Self-example based technique

This method improve the quality of an image interms of PSNR, IFC, SSIM[3].

**Table -6:** The result of RMS and SSIM.

| Paper | Method | RMS | SSIM |
|---|---|---|---|
| Self-Example Based Super-Resolution With Fractal-Based Gradient Enhancement | Bi-cubic | 15.847 | 0.705 |
| | fractal-based gradient enhancement | 21.119 | 0.602 |

## 4. CONCLUSIONS

From literature survey observed that execution time is high, does not give optimal results and nearest neighbor search is difficult. These problems can overcome by Antipodally Invariant spherical Hashing (AISpH) and improve the PSNR value.

## 5.REFERENCES

[1]. Roman Zeyde, Michael Elad and Matan Protter, “On Single Image Scale-Up using Sparse-Representations”, Lecture Notes in Computer Science: Curves & Surfaces 2010.
[2]. Aharon M. , M. Elad, and A. Bruckstein, “K-SVD: An algorithm for designing over complete dictionaries for sparse representation,” IEEE Trans. on Signal Processing, vol. 54, no. 11, 2006.
[3]. Licheng Yu, Yi Xu, Hongteng Xu, Xiaokang Yang, “Self-Example Based Super Resolution With Fractal-Based Gradient Enhancement”.
[4]. Timofte R. , V. D. Smet, and L. V. Gool, “Anchored neighborhood regression for fast example-based super-resolution,” in Proc. IEEE International Conf. on Computer Vision, 2013
[5]. Eduardo Perez-Pellitero, Jordi Salvador, Javier Ruiz-Hidalgo, and Bodo Rosenhahn, “Antipodally Invariant Metrics For Fast-Regression Based Super-Resolution”, IEEE Transaction on image processing, 2016.
[6]. Timofte R. , V. D. Smet, and L. V. Gool, “A+: Adjusted anchored neighborhood regression for fast super-resolution,” in Proc. Asian Conf. on Computer Vision, Lecture Notes in Computer Science, 2014.

[7]. Dong C. , C. Loy, K. He, and X. Tang, "Learning a deep convolutional network for image super-resolution," in Proc. European Conf. on Computer Vision, 2014.

[8]. Baker S. and Kanade T. , "Limits on super-resolution and how to break them," IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 24, no. 9, pp. 1167–1183, 2002.

[9]. Freeman W. , Jones T. , and Pasztor E. , "Example-based super- resolution," IEEE Trans. Computer Graphics and Applications, vol. 22, no. 2, 2002.