ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 3, March 2016

A Survey on Techniques of Image Super Resolution

Jigar Dalvadi

M.E Student, Dept. of C.E., SVIT, Vasad, Anand, India

ABSTRACT: Objective behind Super-Resolution (SR) techniques is to generate one or more high resolution images from the one or more low resolution images. Aim behind super resolution techniques is to overcome the problems of physical image capturing device and recover image from the aliasing, blurring effects. In this paper super resolution techniques are classifying into different categories and presented the basic concepts for each category with their advantages and disadvantages. Furthermore i performed comparative analysis of these techniques.

KEYWORDS: Super resolution imaging, Regularization, Regression, Sparse coding, Resolution enhancement

I. Introduction

Super resolution is the process of generate or obtaining a High-Resolution (HR) form a single Low-Resolution (LR) image or a sequence of LR images taken at different viewpoints. Its aim produces the HR image and overcome the limitations of image capturing device. HR image not only for better visual appearance but also for the valuable in several applications of the computer vision areas such as satellite imaging, medical image processing, target recognition, video applications, automatic image mosaicing, fingerprint and face image enhancement. Another important application in surveillance where synthetic zooming of region of interest (ROI). [4] For surveillance or forensic purposes, a digital video recorder (DVR) is currently replacing the CCTV system, and it is usually needed to zooming objects in the scene such as the criminal's face or the licence plate. The SR technique is also useful in medical imaging such as computed tomography (CT) and magnetic resonance imaging (MRI) since the multiple images is possible to acquire while the quality of resolution is limited. In satellite imaging applications such as remote sensing and LANDSAT, several images of the same area are usually provided, and the SR technique to improve the resolution of target can be considered. Another application is conversion from an NTSC video signal to an HDTV signal since there is a clear and present need to display a SDTV signal on the HDTV without visual artifacts [4].

The sensor size and the density of detectors that form the sensor primarily determine the spatial resolution of the captured images. The larger size of the sensor and/or the higher density of the detector, better the spatial resolution of the acquired images. The most direct hardware-based approach of increasing the spatial resolution is to reduce the detector size or, equivalently, to increase the detector density. Alternatively, the sensor size can also be increased. However, smaller detectors have [10] lower dynamic range; less fill factor, worse low light sensitivity, higher dark signal, higher diffraction sensitivity, and higher similarity. Also, the hardware cost increases with both the increase of detector density and sensor size. Thus, the aforementioned hardware-based approach often restricts the maximum achievable resolution of the captured images. Besides the sensor-imposed restriction, there are several other factors that limit the capture of HR images, including lens and atmospheric blurs, finite shutter speed, finite aperture, movement of objects in the scene, sensor noise, and media turbulence.

The most direct solution to increase spatial resolution is to reduce the size of pixel (i.e., increase the number of pixels per unit area) by sensor manufacturing techniques [12]. As the size of pixel decreases, however, the amount of light available also decreases. It generates shot noise, which degrades the image quality severely. The high cost for high precision optics [4] and image sensors are also an important part in many applications regarding HR imaging. Therefore, a new approach against increasing spatial resolution is necessary to overwhelm these limitations of the sensors and optics manufacturing technology.

In this paper, we classify the past and newly emerging SR techniques into several categories. The criteria behind all the categories are discussed. Furthermore, improvements over the basic methods made by different researchers are also highlighted.

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 3, March 2016

The rest of the paper is organized as follows: Section 2 classifying the existing SR methods. Section 3 describes a general image observation model which is used by most of the SR methods. Section 4 presents the single-image SR methods. Section 5 discusses the research challenges which remain open for future investigation. Finally, conclusions are drawn in Section 6.

II. CLASSIFICATION OF SUPER RESOLUTION TECHNIQUES

In this present survey, the SR algorithms are first classified based on their number of input images, i.e. into multi-image and single-image SR techniques. Classification of the techniques based on domain of operation is only presented for the multi-image SR techniques. Single-image SR algorithms can be classified in terms of their operating principles. The detailed classification used in this survey is shown in Figure 1.

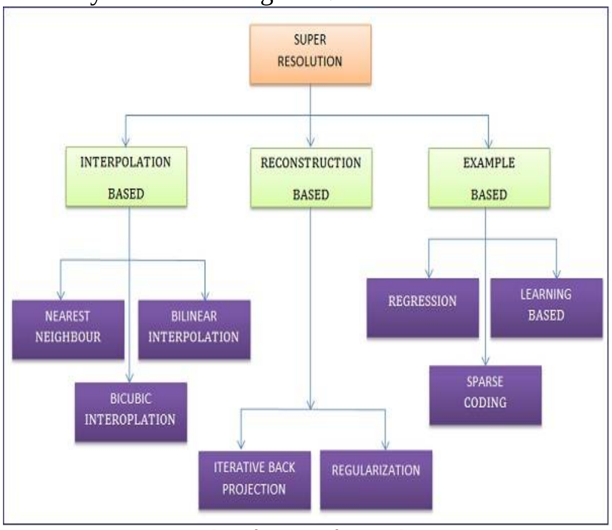

Fig 1. Classification of SR techniques

III. IMAGE OBSERVATION MODEL

The Super resolution enhancement is an ill posed inverse problem and solution to the problem is not unique. To understand the imaging process, the first step to understand the observation model that establishes the relation between original HR images to observed LR images. Observation model can be expressed in mathematical term as [1]:

$$Y = DHX + N \quad (1)$$

Where Y is the observed image,D represents the downsampling matrix,H represents the blurring operator,X is the unknown image to be estimated, and N represents the additive noise.

IV. SINGLE IMAGE SUPER RESOLUTION METHODS

As mentioned SR methods classified into the three categories: Interpolation based, Reconstruction based, Example based.

A. Interpolation based SR methods

Interpolation means to interpolate the missing pixels value into the image and create high resolution image for some specific application. In other words, Interpolation is a technique for achieving new unknown pixel values within the range of discrete known pixel values. Basically interpolation techniques classified into: nearest neighbour, bilinear and bicubic interpolation.

In nearest neighbour technique it fills the pixel with nearest neighboring pixel value; hence it called as nearest neighbour. Result of generated image is smoother. While in 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

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 3, March 2016

and produce the better resolution image than bilinear interpolation method. But it creates jaggy effect in the resulted image.

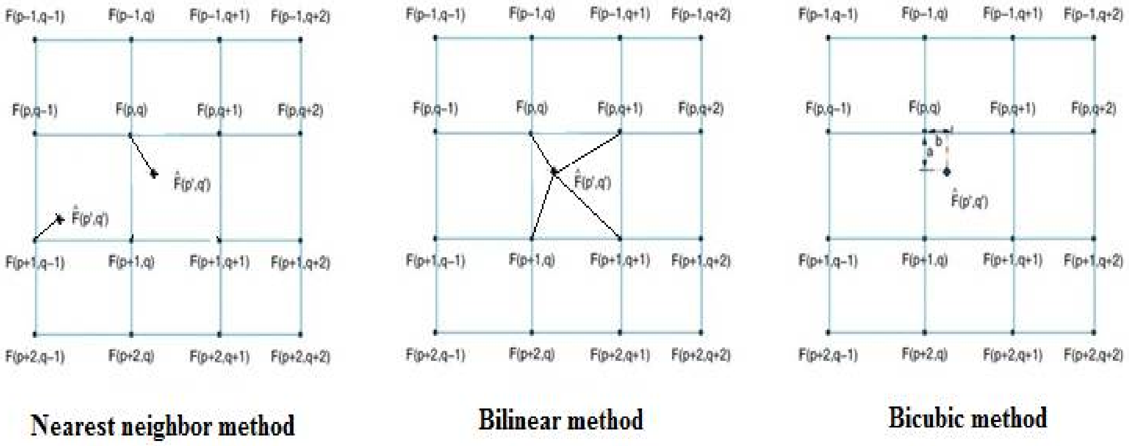

Fig 2. Interpolation Methods

B. Reconstruction based SR method

Generally, SR image reconstruction problem approach is ill-posed problem because of an insufficient number of LR images and ill-conditioned blur operators. Thus it classified into: Iterative Back Projection (IBP), regularization method.

1. Iterative Back Projection method

Irani and Peleg [14] formulated the iterative back-projection SR reconstruction approach is similar to the back projection used in tomography. In this approach, HR image is estimated by back projecting the error (difference) between simulated LR image via imaging blur and the observed LR image. And this process is iteratively repeated to minimize the error. Thus IBP method to estimate the HR image can be expressed by the following equation:

$$\hat{X}_k^{(n+1)} = \hat{X}_k^{(n)} + h^{BP} * (Y_k - \hat{Y}_k^{(n)}) \tag{2}$$

Where $\hat{X}_k^{(n)}$ is represents the estimated HR image of k^{th} image after n iteration process, $\hat{Y}_k^{(n)}$ represents the simulated degenerated LR image of X after n iteration, h^{BP} is the back-projecting operator.

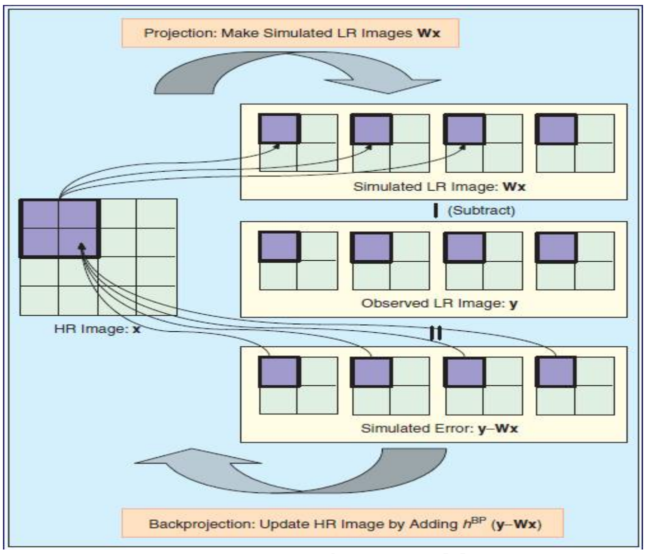

Fig 3.Iterative Back-Projection [4]

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 3, March 2016

This algorithm is simple and direct. However, $h^{BP}$is hard to choose and the resolution is not steady and unique.

2. Regularization method

By the motivation of SR problem is inverse and ill-posed nature, some regularized algorithms proposed including total variation, and sparsity. The basic idea of regularized SR approach is to incorporate some prior knowledge about the desired HR image to constrain the solution space. Li et al. propose an algorithm using two complementary regularization terms: steering kernel regression total variation (SKRT) and a non-local total variation (NLTV). Total regularization term is used to guide iterative back-projection process and minimize the SR reconstruction error.

In this method HR image is estimated using the observation model by minimizing the cost function which is as follow [2]:

$$\hat{X} = \arg\min_{X} \|DHX - Y\|^2 \qquad (3)$$

The fidelity term for penalizing the difference between the degraded HR image X and observed LR image$Y$. Since its ill-posed problem, regularization is added for stabilized solution and the cost function can re-write as [2]:

$$\hat{X} = \arg\min_{X} \|DHX - Y\|^2 + \lambda\Re(X) \qquad (4)$$

Where,$\Re(X)$ is the regularization term defined on prior knowledge and λ is used to balance the fidelity term and regularization term.

C. Example based SR method

Example-based single-frame SR, also referred to as the image hallucination method, aims 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: learning based, regression based and sparse coding method.

1. Learning based method

In this method, HR patches estimated by learning from dictionary. For each LR patch several LR patches are found by estimating the nearest neighbors in the dictionary. Later on HR patches are combined to generate the HR image. The figure 4 shows the flow diagram of learning based method. X_i , is the input image which is up-sampled by the linear interpolation to obtainY_i^L. The High frequency LR patches X_i^H is obtained from a high pass filter. X_i^H, is processed by the learning method. In learning process, LR training image X_r^H and HR training image Y_r^H are used. The desire HR image Y_o estimated from the training set comprising the LR image X_r^H and the corresponding HR training image set Y_r^H [7].

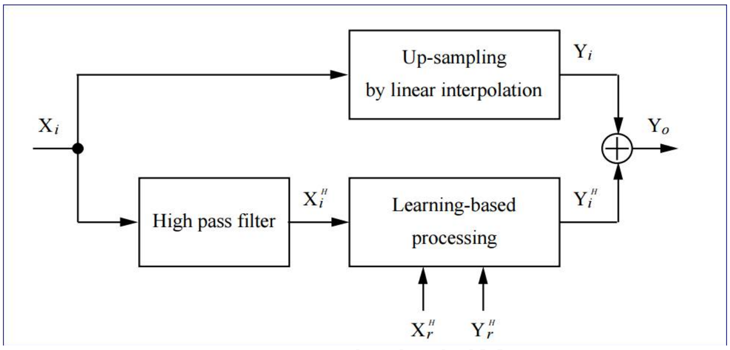

Fig 4.Learning based method [7]

The key issue in learning-based methods is the determination of the type and number of training images needed to form the patch dictionary.

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 3, March 2016

2. Regression based method

Regression method attempts to learn the relationship between the LR patches and the HR patches by regression function. This group of methods are not based on learning assumption. Similar to the Neighbor-Embedding method, LR training is chosen according to the similarity between LR patches and LR test patch. , HR training set identified corresponding to the LR training set. Then regression function is learned taking into account two training sets are l_{sample} and h_{sample}. After that the regression function can be obtained by minimizing a regularized cost function as below:

$$\mathcal{R}_f = argmin_{f\in\mathcal{H}} \left[\sum_{q=1}^{k} \left\| h_{sample}^{q} - f\left(l_{sample}^{q}\right)\right\|_2^2 + \lambda \|f\|_{\mathcal{H}}^2\right] (5)$$

Where, λ denotes regularization parameter, $\mathcal{H}$ is Hilbert function and $\|f\|_{\mathcal{H}}$ is the norm in $\mathcal{H}$. Finally the unique estimation of the desire HR patch is generated using the regression function.

3. Sparse coding method

Sparse representation for SR reconstruction uses sparse coding based on l_1 regularizationto learn two coupled dictionaries: D_h for HR patches and D_l for LR ones. The process of learning two coupled dictionaries adopts joint dictionary training method, which forces that the sparse representation of the HR patch is the same as that of the corresponding LR one. Given the sampled training image patch pairs $P = \{X^h, Y^l\}$, where $X^h = \{x_1, x_2, \dots, x_n\}$ are the set of sampled HR image features and $Y^l = \{y_1, y_2, \dots, y_n\}$ are the set of sampled HR image features [9].

The first- and second-order derivatives are exploited as features for the LR image patches. Similarly, the features of each HR image patches are extracted by subtracting the mean pixel value for each HR patch. The main contribution is to train two coupled dictionaries for HR and LR image patches so that the sparse representation of the LR patch can be suitable for recovering the corresponding HR patch [9].

V. DISCUSSION

This section providing the comparative analysis on methods of single image SR methods with their advantages and disadvantages. Since, single image SR methods classified into three categories. Following table shows the different SR methods with advantages and disadvantages.

Table 1. Comparative analysis of single image SR methods

Methods	Advantages	Disadvantages
Nearest Neighbor Interpolation	Simple and easy to implement	Doesn't have sub-pixel accuracy
Bilinear Interpolation	Provide better result than nearest neighbor method	Creates the artifacts and poor preservation image details
Bicubic Interpolation	Most popular and basic method used in SR methods, provide better smoothness, fast computation	It created jaggy effect because of the negative lobs of bicubic interpolation function
Iterative Back Projection(IBP)	Remove the noise and blurry effect from the image	Difficult to choose the h^{BP} which is back projecting operator and No unique solution
Regularization method	No need of large training dataset, image details preservation is high	Performance degraded with higher magnification factor and take more time for computation
Learning based method	Simple and remove artifices as well as provide better resolution image	One-to-multiple mapping of LR patch to HR patch results in image quality degradation
Regression method	Computationally faster than learning based method and provide better result	The regression function is expanded in the whole set of training data points and accordingly computationally demanding both in training and in testing
Sparse coding method	Highly compact dictionary size, low computation, no overlapping	Fail to consider the incoherence of dictionary entries, when consider the geometrical structure of data.

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 3, March 2016

VI. Conclusion and Future Work

Super resolution is the fundamental research area in image processing and overcome the resolution problems of imaging systems.in this paper I have analyse most of the published work on SR by categorizing into several groups. An interesting point finding from this survey is that, since different SR methods have been developed for different applications using different model parameters and assumptions, it is difficult to perform a fair comparison among them.

References

1. Li, Lin, et al. "Single image super-resolution using combined total variation regularization by split Bregman Iteration." Neurocomputing 142 (2014): 551-560.
2. Shi, Feng, et al. "LRTV: MR Image Super-Resolution with Low-Rank and Total Variation Regularizations." Medical Imaging, IEEE Transactions on34.12 (2015): 2459-2466.
3. Kim, Kwang In, and Younghee Kwon. "Example-based learning for single-image super-resolution." Pattern Recognition. Springer Berlin Heidelberg, 2008. 456-465.
4. Park, Sung Cheol, Min Kyu Park, and Moon Gi Kang. "Super-resolution image reconstruction: a technical overview." Signal Processing Magazine, IEEE 20.3 (2003): 21-36.
5. Kim, Kwang In, and Younghee Kwon. "Example-based learning for single-image super-resolution and jpeg artifact removal." (2008): 1-28.
6. Wang, Jong-Tzy, et al. "Super-resolution image with estimated high frequency compensated algorithm." Communications and Information Technology, 2009. ISCIT 2009. 9th International Symposium on. IEEE, 2009.
7. Goto, Tomio, et al. "Learning-based super-resolution image reconstruction on multi-core processor." Consumer Electronics, IEEE Transactions on 58.3 (2012): 941-946.
8. Freeman, William T., Thouis R. Jones, and Egon C. Pasztor. "Example-based super-resolution." Computer Graphics and Applications, IEEE 22.2 (2002): 56-65.
9. Lu, Xiaoqiang, Yuan Yuan, and Pingkun Yan. "Alternatively constrained dictionary learning for image superresolution." Cybernetics, IEEE Transactions on 44.3 (2014): 366-377.
10. Farrell, Joyce, Feng Xiao, and Sam Kavusi. "Resolution and light sensitivity trade off with pixel size." *Electronic Imaging 2006*. International Society for Optics and Photonics, 2006.
11. D. Lancaster , "A Review of Some Image Pixel Interpolation Algorithms" , 2012.
12. Tian, Jing, and Kai-Kuang Ma. "A survey on super-resolution imaging."*Signal, Image and Video Processing* 5.3 (2011): 329-342.
13. Wang, Jong-Tzy, et al. "Super-resolution image with estimated high frequency compensated algorithm." *Communications and Information Technology, 2009. ISCIT 2009. 9th International Symposium on*. IEEE, 2009.
14. Trimeche, Mejdi. *Super-Resolution Image Reconstruction Using Non-Linear Filtering Techniques*. 2006.
15. Ai, Na, et al. "Single image super-resolution by combining self-learning and example-based learning methods." *Multimedia Tools and Applications* (2015): 1-16.
16. Zhang, Kaibing, et al. "Learning multiple linear mappings for efficient single image super-resolution." *Image Processing, IEEE Transactions on* 24.3 (2015): 846-861.
17. Tang, Yi, et al. "Example-based super-resolution via social images."*Neurocomputing* 172 (2016): 38-47.

BIOGRAPHY

Jigar Dalvadiis a M.E student in the Computer Engineering Department, Sardar Vallabdhbhai Patel Institute of Technology, Vasad, Anand andPursuingMaster of Engineering (ME) degree in 2016 from SVIT, Vasad, Anand, India. Research interests are Image Processing (Super resolution), Image Restoration, and Image Denoising Algorithms etc.

