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Edge Preserving Single Image Super Resolution Techniques– A Comprehensive Study

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ABSTRACT: High-Resolution (HR) images play vital role in almost every aspect of day-to-day life. The spatial resolution and the quality of the images can be improved with help of Super Resolution (SR) techniques. It rebuilds a HR image from one or multiple Low- Resolution (LR) images. During the application of these Super Resolution (SR) methods, some intricate details in the given low resolution image may be lost. Minute details preservation is essential in areas like medical imaging. This paper makes an attempt to review some of the state of the art single image edge preservation super resolution techniques. The current comprehensive survey classifies SR methods broadly into interpolation based, reconstruction based and learning based methods. Interpolation based methods are straight forward, but ends with producing blurred details and ringing artefacts. Reconstruction based methods are fast, but suffer with optimized parameters setting which are required for fine tuning of the output. Learning based methods involves construction of large image dictionaries. Though training these dictionaries consumes more time and complicated, learning based methods yield better quality images. Electing and designing a proper SR technique can be a real challenge for the researcher. However, assimilation of these methods are always proved to elicit better result.

KEYWORDS: Edge preserving, Interpolation, Learning based, Reconstruction, Single Image Super Resolution

1. Introduction

Human beings gain information from outdoor world by means of vision.In this vision process visual information is carried out through images. High resolution image offers a high pixel density and thereby more details about the original scene.It is very difficult to obtain high resolution images that meets real-world needs at all times. Since images are often deteriorated by noise and other data acquisition devices, illumination conditions, etc. the setup for high resolution imaging proves expensive and also it may not always be feasible due to the inherent limitations of the sensor and optics manufacturing technology. These problems can be overcome through the use of image processing algorithms, which are relatively inexpensive, giving rise to concept of super-resolution. It provides an advantage as it may cost less and the existing low resolution imaging systems can still be utilized.

Super Resolution is process of obtaining one or more high (HR) images from one or more low resolution(LR) images from the same scene. Since last two decades SR techniques have been a very attractive research topic and has found its applications in a wide range, which includes medical imaging, aerial and satellite imaging, facial image analysis, text image analysis, sign and number plates reading, biometrics recognition.

SR algorithms can be classified based on the domain employed [1] (spatial or frequency), the number of the LR images (single or multiple) involved and the actual reconstruction method. The current work mainly focuses on single image SR techniques irrespective of the domain. Most of the SR methods are basically image enhancement techniques. During the process of obtaining HR images through these techniques we may lose some intricate details like any other enhancement process. Preserving such minute details are very essential in medical imaging like applications. In the following section many of the interpolation based, reconstruction based and learning based SISR methods are summarized. Later an overview of the some of the state of the art edge preserving SR methods are given. Also response of these methods on standard image sets have been tabulated.

2. SINGLE IMAGE SUPER RESOLUTION TECHNIQUES

2.1 Interpolation based SR methods

Bilinear interpolation takes 2x2 pixels into account for up sampling an image. Bicubic interpolation is often chosen over bilinear interpolation which considers 16 pixels (4×4). Images resampled with bicubic interpolation are smoother and have fewer interpolation artefacts. Bicubic convolution interpolator requires several arithmetic operations per pixel for better result. Hence it is time consuming. In[2], [3], [4] simple interpolation methods such as Bilinear or Bicubic interpolation based on generic smoothness priors to produce more desired results, but indiscriminate smooth edges as well as regions. They have a tendency to produce overly smooth images with ringing and aliasing artefacts. Dai *et al.* [3] represented the local image patches using the background/foreground descriptors and reconstructed the sharp discontinuity between the two. Sun *et al.* [4] explored the gradient profile prior for local image structures and applied it to super-resolution. Such approaches are effective in preserving the edges in the zoomed image. However, they are limited in modeling the visual complexity of the real images. For natural images with fine textures or smooth shading, these approaches tend to produce watercolour-like artefacts.

To preserve details while synthesising SR output researchers proposed many new edge interpolation algorithms. Li*et al.* [5] proposed a new edge directed interpolation (NEDI) method using the covariance of HR image estimated from the covariance of LR image. To learn local structure, soft- decision interpolation (SAI) technique along with 2-D piecewise autoregressive model was used in [6]. SAI technique was able to calculate a patch of HR pixel values instead of a single pixel at a time. Based on NED Iand nonlocal means(NLM) filter, Zhang [7] proposed nonlocal edge directed interpolation (NLEDI) method with considering the difference of geometry structures of the samples in a local window, and the samples are assigned different weights according to the structure similarity with the pixel tobe interpolated. For the above interpolation algorithms, the shape of local analysis window is fixed usually, such as a square window centered at unknown pixel, but the statistics of the samples in a shape fixed window cannot adapt to local structure accurately. Wei *et al.* [9] designed a contrast-guided interpolation method by considering contrast, which provides information about edge strength. Combining the sparse representation model and non local self- similarity, two interpolation methods were developed in [10] and [11]. The main idea of [10] is that the sparse representation of each patch should be close to a linear combination of its similar patches sparse representations. The interpolation algorithm proposed in [11] is works in two stages: in the first stage the regions fitting non local self-similarity assumption are recovered and then in the second stage result is refined using non local sparsity model. Even though better out comes can be attained by these interpolation methods, interpolation algorithms are not popular SISR methods as the blur ring phase is neglected.

2.2 Reconstruction based SR methods

Reconstruction-based SISR approach uses a construction constraint, so that the blur red and down sampled SR image should be consistent with the observed LR image. Since the SISR problem is ill- posed, output image will have jagged and ringing arte facts. Image priors can be introduced to reduce these unwanted artefacts. The mathematical model of reconstruction-based SISR is given below:

$$X = \arg min \parallel Y - DHX \parallel_2^2 + \lambda . R(X) \qquad (1)$$

where $\parallel Y - DHX \parallel_2^2$is the L2 norm data-fidelity term, R(X) denotes regularization term and the regularization parameter λ is as calarto balance the data-fidelity term and regularization term. Data fidelity terms hows the consistency between the reconstructed HR image and observed LR image, while the regularization term represents image prior. The average length of lines in an intensity image and the edge smoothness prior can be in corporated in reconstruction model. Sparse representation and reconstruction-based methods were integrated by Yu *et al*. [12] to recover missing details and reduce the unwanted artefacts.

As harpness preserving interpolation technique was used in [13] to get a HR image with sharp edges. High frequency structures were recovered using gradient features of interpolation in reconstruction phase. By exploiting the directional sparsity of image gradients and the self-similarity with directional features, *Li et al*. [14] integrated total variation regularization and directional non local means regularization methods to obtain high resolution images. To preserve sharp details and reduce unwanted artefacts, the degradation model and the prior knowledge plays major role in reconstruction based methods.

Zhao *et al*. [15] proposed a generalized detail-preserving SR method based on a reasonable observation model and a new image prior model. The reasonable observation model is capable of describing the degradation process more fully and exactly. HR image is constructed by a non-local smoothness constraint through an adaptive non-local edge-preserving image prior.

Earlier image prior models were used to blur edges. Total Variation(TV) model was successful to preserve sharp details. Farsiu *et al*. [16] proposed the Bilateral TV(BTV) model by using the concept of bilateral filters and TV concept [16,17]. Bilateral Edge Preserving(BEP) [18] was proposed by Zeng andYang, called adaptive norm/Yang norm which is capable of minimizing the number of the artificial edges produced by the BTV model. Adaptive Non-Local Edge-Preserving (ANLEP) prior model was used by Zhao *et al.* It is based on the Yang norm proposed in [18] and the non-local self-similarity. ANLEP prior model can avoid artefacts along with preserving the edge. The ANLEP model can be written as follows:

$$\Re_{ANLP}(u) = \sum_{i=\Omega} \sum_{j=\varkappa(i)} \omega(i,j) \left(a\sqrt{a^2 + \| R_i u - R_j u \|_2^2} - a^2 \right) \quad (2)$$

where Ω represents the whole HR image, $\chi(i)$is neighbourhood of the pixel I, ω (i, j) is the weight of the j[th] neighbour pixel,R_i,R_j represent operators that extract a patch of a fixed and predetermined size from HR image u respectively. Image prior model used in the proposed method is as below:

$$p(\breve{u}|\lambda) = \lambda^{(dN+N)/2} exp \left(-\frac{\lambda}{2} \sum_{i=\Omega} \sum_{j=\varkappa(i)} \omega(i,j) \left(a\sqrt{a^2 + \| R_i u - R_j u \|_2^2} - a^2 \right) \right) \ (3)$$

λ represents hyper parameter and $\breve{u}$represents augmented image. GDP method has performed very well compared to TV methods with non-local similarity.

Surya narayana *et al.* [19] used stationary wavelet transform (SWT) to preserve the edges, is employed. Enhancement of the output image and noise reduction is achieved using complex diffusion based shock filter by operating in the dual dominant mode. These filtered sub bands are combined to generate a high resolution (HR) image. Artefacts are removed by back projecting onto a global image vector space. A blurred and down sampled observation of HR image is considered to be LR input image. Image observation model is given by the following:

$$\text{Y=DBZ+V} \quad (4)$$

where Z is the original HR image, B is the blurring operator and D is the down sampling operator. Additive noise V takes care of modelling error and observation noise. Initial estimation of HR image Z_0 is obtained by bicubic interpolation of the first input LR by a factor of s. The final HR image has to be computed by further processing the initial estimate Z_0, by adding additional high frequency details which are lost during down sampling and interpolations. This is done by sub band decomposition. Using SWT [20] the initial HR image $Z_0$is decomposed into four different sub bands namely, approximation ZA, horizontal ZH, vertical ZV, and diagonal ZD coefficients respectively. All these four sub bands will have same dimensions of the input image due to the inherent nature of SWT.ZA will possess poor edge evidence. Remaining three sub bands ZH, ZV and ZD would include high frequency details. Each sub band will undergo shock filter operation with appropriate λ value. Smaller the values of λ better will be edge enhancement. So we use it for sub band image ZA. Finally, the four processed sub bands are fused together to generate the pre-final HR image Z*using inverse SWT (ISWT). Then iterative back projection is applied on Z^* to get the output.

SR reconstruction error should be corrected, as Z^* lies in high dimensional space. It can be addressed by projecting Z*onto the solution space constrained by the LR observation model iteratively, using gradient descent method as shown below:

$$\text{Zi} + 1 = \text{Zi} + \mu[B^T D^T (Y - \text{DBZi}) + c\ (\text{Zi} - Z*)] \quad (6)$$

where Z iis the desired final HR image after i[th] iteration and μis the step size of gradient descent. The proposed method is simple with very less artefacts compared to learning based methods and has less computational complexity. But overall gain is slightly less compared to Sparse based method with 0.21dB less gain.

Nayak *et al*. [21] aims to enhance the performance of IBP based SR reconstruction(IBP-SRR) of image by using P-spline and MuCSO-QPSO algorithm. The P-spline interpolation scheme is used to make proper initial guess. The P-spline interpolation of the LR image is performed using a linear combination of a P-spline convolution kernel as given below:

$$\text{T (x, y)} = \sum_{s\epsilon\wedge} \eta(n_x, n_y)\, \phi^n \left(\frac{x-n_x, y-n_y}{\Delta}\right) + \text{P} \qquad (7)$$

ϕ^n is the 2-D B-spline of order n, $\eta(n_x, n_y)$ is the B-spline coefficient that uniquely determines ϕ^n and Λ represents a regularly sampled grid (Sx x Sy) of uniform spacing Δ andP=λp ⊗$I_{k.,}$ where λ is the smoothing parameter; *p* is the penalty for B-spline base; *Ik* is the identity matrix. An adaptive edge regularization technique is used in the constraint optimization of the reconstruction problem to minimize the effect of ringing artefacts.

Both noise and edge will be enhanced during the back projection process. The reconstruction error cumulates in the iterative process and should be minimized. Finally, the overall reconstruction error of the reconstruction system is optimized using a hybrid meta-heuristic optimization technique. The optimization algorithm hybridizes the notion of Cuckoo search optimization (CSO) algorithm with a mutation operator (MuCSO) and the quantum behaved particle swarm optimization (QPSO). The MuCSO-QPSO algorithm is compared with other significant optimization algorithms such as GA,PSO, QPSO, CSO, MuCSO and found to be out performing. Experimental results demonstrate the superiority of the proposed edge preserving IBP-SRR method in terms of enhanced spatial resolution, and more detail reconstruction. The proposed method uses fixed value of regularization parameter. Due to this the proposed method cannot take care of smooth edges separately as compared to adaptive regularization parameter algorithms. But the current method works at low cost and less computational overload.

Chen *et al*. [22] proposed non local, self-similarity based reconstruction SR method using the Split Bregman Iteration (SBI) optimization algorithm. In self-similarity, the patches would have tried to find similar patches in different locations within the same image.

The proposed algorithm is mathematically formulated as below:

$$\hat{X} = \arg min \parallel Y - DHX \parallel_2^2 + \lambda_1 . R_L(X) + \lambda_2 . R_{NL}(X) \quad (8)$$

where λ1 and λ2 are regularization parameters, R_L(X) and R_{NL}(X) denotes the local and non-local constraints respectively. The estimated HR image $\hat{X}$wouldcoincidewithLRimage Y after being degraded and satisfy the local and non-local priors at the same time. The objective function is different from the restoration model with respect to the down sampling operator D, which plays major role in SR method. Proposed algorithm is tested with 200 images in standard set of samples from BSDS500 and obtained better PSNR and SSIM values compared to already existing SR techniques. With varying values of up sample factor algorithm proved to obtain better gain over more number of iterations. However, like any other reconstruction algorithm setting up right tuning parameter and slow convergence rate are noticeable factors.

2.3 Learning based methods

In the past few years, learning based SR methods have gained more attention. Learning based SR methods uses the information learned/observed from training image data. This training image data comprises of low and high resolution image patch pairs. Learning-based methods focus on training the strategy between several HR and LR image patch pairs. The learning process is performed locally, by trying to infer the local HR details through the help of patches which are sub-windows of image. These trained set of image patch pairs generally known as dictionaries. High frequency details lost in the given input LR image can be recovered by learning the relationship between the LR-HR patch pairs from the dictionary. The nature of the dictionary, the number of candidates used as predictors which are taken from the dictionary and the way the patches are combined in order to generate the HR outputs determine the final output image. Further these methods can incorporate details preserving technique to get better HR images. Some of the state of the art edge preserving SR methods overview is given below.

Ram *et al. [*23] proposed a dictionary learning algorithm known as Graph Regularized Block Sparse Representation. The algorithm treats a signal as a block sparse in a given a basis and associates it with graph regularization to preserve the geometric structure. Block sparse representation assumes that the signal can be approximated by the union of a small number of sub spaces. Let G= {G1, G2, G3…Gg} be a partition of index set {1, 2, …m}, where g is the number of blocks. Let$D^h \in \mathbb{R}^{n \times m}$ be a HR dictionary built using the HR image; the dictionary is an n x m matrix whose m columns represents the m "atoms" of size n. Let $D_{G_i}^h$ denote the sub dictionary with columns identical to the corresponding columns of D^h. Then any patch x $\in \mathbb{R}^n$ can be represented as:

$$x \approx D^h \alpha = (D_{G_1}^h, D_{G_2}^h \dots D_{G_g}^h)(\alpha_{C_1}^T, \alpha_{C_2}^T \dots \alpha_{C_g}^T)^T \quad (9)$$

where$\alpha \in \mathbb{R}^m$is a sparse vector containing a few large coefficients grouped together in the presence of other, smaller coefficients. Such a sparse vector is called a group sparse vector, and T denotes the transpose of vector or matrix. Similarly, a y patch in the observed LR image can be represented using a corresponding LR dictionary $D^l$with thesame sparse coefficient vector α. This is ensured by co-trainingthe dictionary D^h with the HR patches and dictionary D^l with the corresponding LR patches. For a given input LR image patch y we determine the sparse solution vector:

$$\alpha^* = min \parallel \mathcal{F} D^l \alpha - \mathcal{F} y \parallel \tfrac{2}{2} + \lambda \sum_{i=1}^{g} \parallel \alpha_{c_i} \parallel_1 \quad (10)$$

where $\mathcal{F}$ is a feature extraction operator to emphasize highfrequencydetail. Also, the sparsity of the solution vector α^* iscontrolled by the weighting term λ. For the choice of featureextraction operator $\mathcal{F}$ and for finding the sparsest solutionvector α^*, we follow the same procedure as described in [24].The mapping gradient ∇f for a given y_0 is then obtained as$\nabla f(y_0) = D^h \alpha^*$. We repeat the procedure using overlappingpatches of image Y, and the final HR image X is generated byaggregating all the HR image patches x obtained. For largeupscaling factors, the algorithm is run iteratively, each timewith a manageable scaling factor r.

Patches are trained using joint dictionary which is constructed by HR and LR space from in-place and local self-similarity. GRBSR dictionary training uses bilateral filter to enhance the features while reducing the noise. Hence it can preserve more details compared to any Gaussian filter. By using a first order regression model LR and HR image patches are paired. But time complexity of the algorithm is more due to training of dictionary and usage of bilateral filter in that

Yang *et al.* [25]proposed a deep edge guided recurrent residual network to obtain SR images. In the current work, the edge information and image signals are separated to guide the recovery of the HR image. The extracted LR edge maps are used as parts of the input features and the HR edge maps are utilized to constrain the learning of parts of feature maps for image reconstruction. HR image x can be divided into low and high-frequency components, as shown below:

$$x = x_L + x_H \quad (11)$$

the high-frequency component x_H contains edge and texture details of the image. Usually x_H will be irregular and consists smaller magnitude compared to $x_{L.}$ Also the $x_H$component is more delicate and easier to be corrupted. In order to obtain better result for x_H, we need extra prior knowledge about x_H from the LR image y as a build-in component in the deep recurrent residual network to regularize the recovery process. Edges are extracted by using off the shelf edge detector on y and x to get its high- frequency component y_H and x_H. Then an edge prior model is trained to predict x by using both y and y_H.

The following major steps yields good result for DEGREE algorithm:

Step 1: LR Edge Extraction

An edge map of the input LR image is extracted by applying a hand-crafted edge detector and isfed into the network together with the raw LR image.

Step 2: Recurrent Residual Network

The recurrent residual network is used to map LR and HR images. DEGREE recovers the residual image at different frequency sub-bands progressively and combine them into the HR image. To provide a formal description, letf_{in}^k denote the input feature map for the recurrent sub-network at the k-th timestep. The output feature mapf_{out}^k of the recurrent sub-network is progressivelyupdated as follows:

$$f_{out}^k = \max(0, w_{mid}^k * f_{mid}^k + b_{mid}^k) + f_{in}^k, \text{with} f_{mid}^k = \max(0, w_{in}^k * f_{in}^k + b_{in}^k) (12)$$

where $f_{in}^k = f_{out}^{k-1}$is the output features by the recurrent sub-network at (k-1) th time step.

Step3: HR Edge Prediction

DEGREE produces convolutional feature maps in the penultimate layer, part of which are usedf_{edge} to reconstruct the edge maps of the HR images. Letf_{output} denote the features used to reconstruct HR images and let f_{edge} denote the edge feature computed by:

$$f_{edge} = \max(0, w_{edge} * f_{output} + b_{edge}) \quad (13)$$

where w_{edge} , b_{edge} are the filter and the bias of the convolution layer to predict the HR edge map. The featuresf_{rect} in the penultimate layer forreconstructing the HR image with the edge guidance are given as below:

$$f_{rect} = [f_{output}, f_{edge}] \quad (14)$$

Step 4: Sub-Bands Combination for Residue

The LR image comprises necessary low-frequency details. DEGREE emphases on recovering the high-frequency component. These high frequency components are obtained by several high-frequency sub-bands of the HR image. These high frequency sub bands are the differences or residue between the HR image and the input LR image. Combining the estimated residue with sub-band signals and the LR image gives an HR image.

Step 5: Training

Let F(.) represent the learned network for recovering the HR imagexbased on the input LR imageyand the LR edge mapy$_H$. Let$F_{edge}(.)$ denotethe learned HR edge predictor which outputsf*edge*. We useto collectively denote all the parameters of the network:

$$\Theta = \{W_{input}, b_{input}, W_{in}, b_{in}, W_{mid}, b_{mid}, W_{edge}, b_{edge}, W_{rect}, b_{rect}\} \ (15)$$

With the help of Sobel operator, the high-frequency components of LR and HR images,$\{y_{i,H}\}$ and $\{x_{i,H}\}$ are extracted by using npairs of HR and LR images$\{(x_i, y_i)\}_{i=1}^n$for training. The author has used following joint mean squared error (MSE) to train the network parameterized byΘsuch that it can jointly estimate the HR images and HR edge maps:

$$L(\Theta) = \frac{1}{n}\sum_{i=1}^n (\| F(y_{i,} y_{i,H}, x_{i,} x_{i,H}; \Theta) - x_i \|^2 + \lambda \| F_{edge}(y_{i,}, y_{i,H}, x_{i,} x_{i,H}; \Theta) - x_{i.H} \|^2) \ (16)$$

Here λ is a trade-of parameter that balances importance of the data fidelity term and the edge prior term. Initially $\lambda$is set to 1 and varied for r different values of λ in a largerange.The proposed work is capable of preserving sharp edges and textures. However, perform poorly for larger value of λ.

Si *et al*. [26] proposed a novel edge directed image SR method by learning based gradient estimation. In the current work the gradient of HR image was estimated by using the example based ridge regression model. The gradients of similar samples in one cluster are alike, so that it is easy to estimate gradient of a patch by HR gradient of samples in the same cluster with their feature regression coefficients. By using bicubic interpolated image patches with removing the mean value to perform clustering. The input LR image I_l, is up sampled to obtain bicubic interpolated image I_{bic}. The gradient estimation method is applied to patches whose variance is larger than a threshold TH1 in I_{bic}. The gradient is predicted using some coefficients on HR gradient of samples and are given below:

$$dx = DX_{ck^*}.\alpha = \sum_{j=1}^{N}(dx)_j x_j \qquad (17)$$

$$dy = DY_{ck^*}.\alpha = \sum_{j=1}^{N}(dy)_j x_j \qquad (18)$$

where dx and dy are estimated gradient in horizontal and vertical direction for the patch x, DX_{ck^*} and DY_{ck^*}.HR gradient matrix of all samples inthe two directions, $(dx)_j$ and $(dy)_j$ is gradient of the j[th] sample, which means that the estimated gradient is linear weighted sum of HR gradients of samples in the same cluster. Projection matrix is used to reduce the computational complexity of ridge regression. The projection matrix T is calculated offline and gets multiplied with the sparse feature f. The estimated gradient is the gradient constraint and guarantees that the output HR image preserves sharpness and induces very less artefacts.

Some of the standard datasets [1] which can be used in SR methods are given below:

Aerial imaging	Forward Looking Infrared (FLIR), IKONOS satellite, Moffett Field and Bear Fruit Gray for hyper-spectral imaging,Landsat7
Facial databases	Cohn-Kanade face database, NUST, Bio ID, Terrascope, Asian Face Database PF01, FG-NET Database, Korean Face Database, Max Planck Institute Face Database, IMM Face Database, PAL, USCSIPI, Georgia Tech, ViDTIMIT, FRI CVL, Face96, FEI face database, MBGC face and iris database, SOFTPIA Japan Face Database
Medical imaging	PROPELLER MRI Database, Alzheimer's Disease Neuro imaging Initiative (ADNI)database, DIR-lab 4D-CT dataset and3D MRI of the Brain Web Simulated Database
Natural images	Berkeley Segmentation Database

Table I: Standard datasets for super resolution method

The following TABLE gives PSNR(dB) values of few methods discussed in the current paper:

Method	Images						
	Lena	Peppers	Butterfly	Cameraman	Parthenon	House	Leaves
Bicubic [2]	31.09	32.35	27.46	26.33	26.33	32.76	26.13
NEDI [5]	30.93	31.96	27.14	26.39	28.69	32.28	25.51
SEPNMI [19]	33.12	34.07	30.58	26.61	31.09	34.25	28.89
GRBSR [23]		34.85			28.18		27.96
GDPSR [15]	33.56		26.10			32.77	
SI-LSN [22]		36.85	31.91		33.05	35.76	32.71

Table II: PSNR values of some common images used in few methods in the review

3. Conclusion

This survey paper reviews some of the papers published on super-resolution methods which can preserve edge information (up to 2016) and proposes a broad classification for these methods. Besides giving the details of most of the methods, it focuses on some of the state of art edge preserving methods in SR that belongs to any one of the three types, namely interpolation based, reconstruction based or learning based. The basic concepts and parameters used by the selected papers are given. Learning based methods are capable of producing more accurate results. However, they are time consuming and often produces dotted edges near the boundaries. There are plenty of approaches based on reconstruction. They are simple to implement and have less time complexity. Finding suitable tuning parameters, blurring operators, prior model is always a great challenge in these reconstruction based methods. Edge preserving interpolation methods are fast and simple. However, they often introduce jagged and false edges. Objective analysis of the some of the methods have been tabulated which are available in the reviewed papers. Even at the end of this review it is difficult to judge which methods are most efficient? The fact is, any edge preserving SR method is highly dependent on the application we choose. Any SR algorithm that suits for medical imaging need not be good for aerial or facial image processing. Different algorithms are leading in different applications. But generally speaking, comparing all the three category of edge preserving SR methods learning based methods are more promising.

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