A Short Survey of Image Super Resolution Algorithms

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Abstract: Image super resolution is to estimate a high resolution image from a low resolution image or a sequence of low resolution images using image processing and machine learning technology. So far, there have emerged lots of super resolution algorithms. According to the input number of image, these algorithms can usually be divided as single image based algorithm and multiple images based algorithm. And according to technique principle, these algorithms can also be divided into three categories - interpolation based algorithm, reconstruction based algorithm and learning based one. This work mainly addresses the basic principle and different strategy of super resolution algorithms in detail. Then, the evaluation criteria and its application issues of super resolution are also discussed in the end.

Keywords: Image super resolution, Interpolation based super resolution, Reconstruction based super resolution, Learning based super resolution.

1. INTRODUCTION

More than 80% information [51] acquired by people is coming from human visual system (HVS), which mostly is in the form of image or video. Video and image are the main carriers of perceived data contain huge and rich information. With the rapid development of smart mobile phone, image and video acquisition become more and more convenient. Although the requirement for HD display quality is increasing much, due to the limitation of bandwidth and storage capacity, most videos and images have to be stored and displayed at low resolution. To address the demand of low resolution images clearly played back in HD screen, we need to achieve high resolution display based on low resolution images.

Traditional ways to get high resolution images are to improve image acquisition system sensors and optical devices, namely to reduce the size of the imaging unit by adopting high precision imaging chip and other related equipment [1]. However, due to the high cost of high precision equipments, people have to choose a low cost lower resolution imaging device. In addition, there are usually lots of limitations for such hardware based methods in practice. Therefore, at this context, image super resolution technology naturally appears. Image super resolution is a technique that obtains a high resolution image from a single or multiple low resolution images. It combines signal processing, computer vision and machine vision, whose core idea is to make good use of relevant and high complementary useful information from multiple images. It exploits software based method to improve image resolution under existing low resolution imaging scenario without hardware change. And it is proved that this technology can provide a better observation effect with overcoming inherent limitations of low resolution imaging system. In addition, it can also recover some details which are lost in observation. Currently, image super resolution has shown a powerful potential and good effect in many areas, such as medical images processing, remote sensing images, high-definition digital television, video surveillance and other fields.

So far, some important progress has been made and good reconstruction effect can be achieved by utilizing some super resolution algorithms in some cases. But in general, the details of super resolution images reconstructed by most current algorithms are not enough clear and consistent, and the overall reconstruction effect is still limited. At the same time, most reconstruction algorithms spend huge time and cannot be implementing in real time [37]. Therefore, there is further space for super resolution improvement. In a word, with the increasing demands for HD video display and the gradually wide application to all levels of image processing society, super resolution not only can present important theoretical significance but also can lead to practical application value.

According to technique principle and input and output data form, current super resolution algorithms can be divided into various types [1, 2, 3]. The division standards also include transformation domain, the number of input image, color space and so on. Based on these division factors, we get the following taxonomy for image super resolution (Figure **1**).

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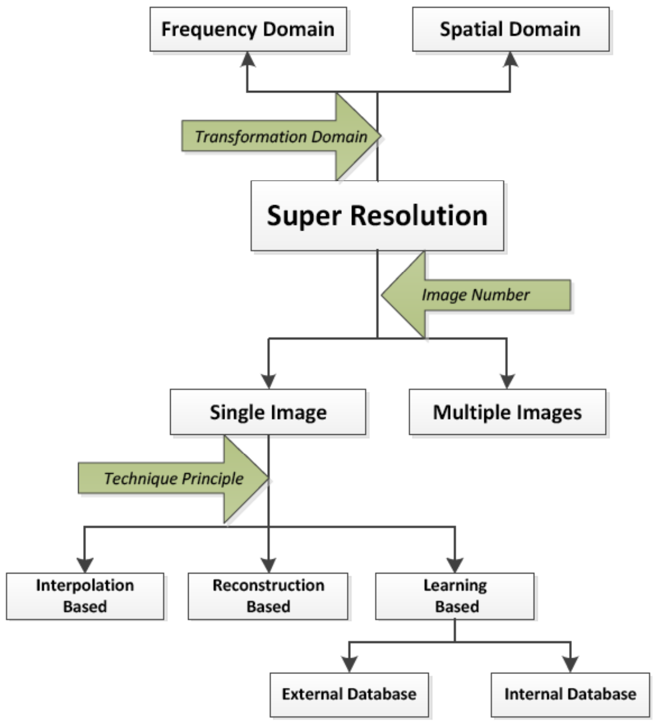

Figure 1: The taxonomy for super resolution algorithms.

As shown in Figure **1**, frequency domain and spatial domain are divided from the perspective of signal transformation domain. Based on input number of image, we can obtain single image based super resolution and multiple images based super resolution. According to technique principle, super resolution can be divided into three types, namely, interpolation based, reconstruction based and learning based. And among existing super resolution methods, reconstruction based method and learning based method are the most popular ones.

Most multiple images based super resolution algorithms are reconstruction based methods. These algorithms assume that there is a target high resolution image and the low resolution observations have some relative geometric displacements from the target high resolution image. They usually exploit these differences between low resolution observations and the targeted high resolution image, and hence are referred to as reconstruction based super resolution algorithms [1]. In this paper, we also focus on learning based super resolution algorithms from the point of technique principle. Based on above taxonomy, we will firstly review the degradation model based image super resolution principles and discuss the characteristics of different algorithms. On this basis, we further give the discussions on evaluation criteria and application challenges.

The rest of this paper is organized as follows. Section 2 presents image super resolution principle. Section 3 introduces image super resolution algorithms from the perspective of technique principle. Then, we discussed the evaluation criteria and the application hardship of super resolution in Section 4. Finally, a short conclusion is given in Section 5.

2. IMAGE SUPER RESOLUTION PRINCIPLE

2.1. Imaging Degradation Model

For image super resolution, imaging degradation model is an important basis, for which image motion, optical blur and sampling are three essential factors. Understanding the procedure of image degradation will be a key hint for image super resolution. Figure **2** shows a sketch map of degradation procedure [52] for high resolution (HR) image degenerating to low resolution (LR) image.

Above degradation procedure can be represented as the following equation [53].

$$Y_k = DF_k NX + V_k \tag{1}$$

where X represents a HR image, Y_k denotes K-th LR image. Actually, super resolution is the inverse processing of above procedure - estimating a HR image through the input LR observation.

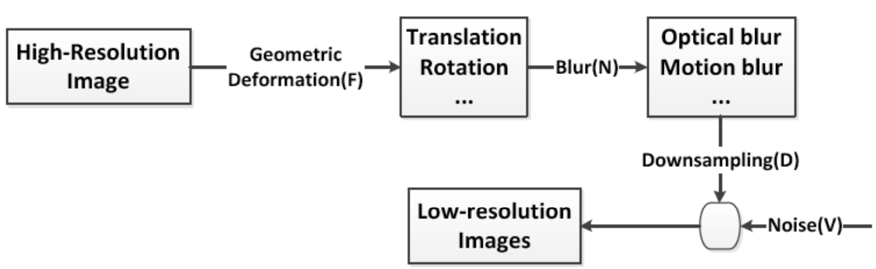

Figure 2: Image degradation model.

2.2. Basic Strategy for Image Super Resolution

It is clear that image super resolution and image degradation are the inverse process. Naturally, we can draw basic strategy of super resolution according to inverse process of degradation model. The basic strategy contains three steps as following:

1. First, calculating the relative motion between image sequences, which is called image registration. This step should be considered especially in multiple images based super resolution when there are multiple LR images.

2. Secondly, identifying image prior knowledge and the noise model.

3. Finally, reconstructing the super resolution image with the most suitable algorithm.

3. IMAGE SUPER RESOLUTION ALGORITHMS

In many practical application scenarios, to obtain image sequence of same scene is quite difficult. Moreover, most multiple images based super resolution algorithms are the extension of single image based one. Therefore, in the following we will focus on single image based super resolution algorithms there. And according to technique principle, as stated in the above, current image super resolution algorithms can be categorized as interpolation based method, reconstruction based method and learning based method. They will be investigated in detail in the following.

3.1. Interpolation Based Image Super Resolution

Image interpolation is the process that estimating new pixels by interpolating given pixels, which is the easiest way to improve image resolution. Compared with other approaches, interpolation base method keeps the most simple calculation procedure and the minimum computation complexity. Actually, image interpolation is an essential operation technique in most image processing field, which is mainly utilized for image resizing. Classical interpolation based methods have the following three ways:

1). Nearest Neighbor Interpolation

In this method, the value of the point to be interpolated is determined by the gray value of its closest neighbor [4], so the method is operated simple and computed fast. However, the simple interpolation rule leads the reconstructed high resolution image to contain block effect and the image edge will produce jagged effects with different levels.

2). Bilinear Interpolation

The main idea of bilinear interpolation is implementing linear interpolation both in horizontal and vertical directions [5]. This method will estimate the value of the pixel to be interpolated through interpolating the value of its surrounding pixels bilinearly. Compared with nearest neighbor interpolation, bilinear interpolation can not only overcome the blocking effect and jagged artifacts, but also be able to smooth the edges of reconstructed image. The schematic of proposed algorithm is as follow.

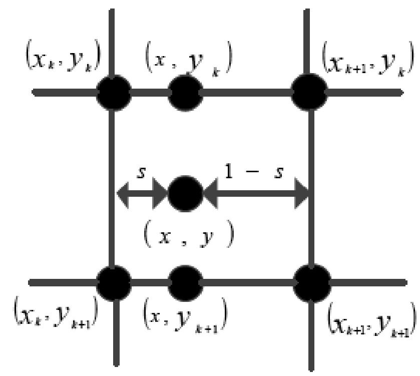

Figure 3: Bilinear interpolation

3). Bicubic Interpolation

Contrast to above two methods, bicubic interpolation is more complex. This method utilizes 16 neighborhood pixels of the point to be interpolated to do cubic interpolation respectively [6]. In terms of calculation, this method requires a large amount of computation and a longer processing time, resulting in poor performance in real time. Despite this, bicubic interpolation holds many obvious advantages that it is able to eliminate jagged edges and blockiness and the reconstructed effect will be significantly better than previous two algorithms.

Above interpolation based methods are simple, but their reconstructed effect is not good enough [19] relatively. In recent interpolated works [7], it introduces an edge forming rule which can partially solves blur and chessboard effect in reconstructed image. And wok in [8] combines interpolation based method and wavelet transforms to obtain a better visual effect and can get a higher PSNR. In addition, due to the poor effect of image edges acquired by bilinear interpolation, work in [9] propose an edge detection based reconstruction algorithm, where canny operator is implemented to get edge position information of low resolution image.

3.2. Reconstruction Based Image Super Resolution

Reconstruction based Image super resolution receives most widespread attention over the past years. The main idea is to impose a linear constraint on reconstructed HR image, which was observed by low resolution images. The processing producer actually is a modeling process of image degradation, where motion estimation and prior knowledge extraction are two key steps. Reconstruction based method mainly focuses on how to get the forward observation model and try to solve the problem by utilizing above image degradation model. The degradation model [52] can be rewritten as following.

$$g_k = DBM_k z + n_k \tag{2}$$

where g_k and z denotes a LR image and a HR image separately, M_k, B, and D represents geometry motion matrix, blur matrix and down-sampling matrix respectively. n_k is the additive noise. And reconstruction based methods mainly include the following categories.

1). Iterative Back Projection

Iterative back projection (IBP) was proposed by Irani *et al* [10]. First, an initial estimate of HR image is regarded as an intermediate result. And then the result can be mapped onto LR observation image by the degradation model to acquire LR simulation image. Then the difference between LR simulation image and actual observed LR image is calculated and it can be called simulation error. Finally the estimated HR image is updated based on simulation error. The processing procedure is looped to get the final result. They can be expressed as following equations:

$$y^o = W_k x^o + n_k \tag{3}$$

$$x^1 = x^o + H^{BP}\left(y - y^0\right) \tag{4}$$

where x^0 denotes HR image of initial estimation, y^0 represents LR simulation image calculated by degradation model, y is the LR observation image, x^1 denotes first improved HR image. H^{BP} represents back projection operator. It is difficult to choose H^{BP} for IBP algorithm, because the solution is not unique with different initial value. Moreover, the algorithm cannot combine the prior knowledge of HR image and in iterative procedure, back projection error is uniformly accumulated on the reconstructed image, which can lead the edges of reconstructed HR image to be jagged.

Future, in work [11], Song *et al*. proposed a combining wavelet transform and iterative back projection algorithm. The algorithm firstly decomposes image by wavelet transform, then minimize reconstruction error by iterative back projection algorithm.

2). Projection on to Convex Sets

Projection onto convex sets (POCS) was first raised by Stark *et al* [12]. The idea of POCS is that the feasible solution of image super resolution should satisfy a plurality of constraints, and each constraint can be defined a convex set C_i ,thus the solution for super solution is the intersection C_s of such convex sets.

Supposing that for one image f the projection operator onto convex set C_i is p_i, denoted as $p_i f$, then projection onto m continuous convex sets can be written as $p_m p_{m-1} \cdots p_1 f$. Given the initial value $f^{(0)}$, we can obtain reconstructed HR image with following equation:

$$f^{(n+1)} = P_m P_{m-1} \ldots P_1 f^n \tag{5}$$

The advantage of POCS algorithm is it is easy to introduce prior knowledge, which can keep edge detail of HR image. But the obtained solution is unstable and not unique, whose convergence process is sensitive to initial value.

In [13], Patti *et al*. describe how to use POCS method to remove image edge ringing artifacts. And Yu *et al*. [14] eliminate color inconsistency of image edges with modified POCS method.

3). Maximum a Posterior

Maximum a posterior (MAP) was first used by Schultz R and Stevenson R [15, 16]. The algorithm firstly takes Markov Random Field as a prior model of image, and then tries to achieve a final HR image by maximum its posterior after given a sequence of LR images. The algorithm has been widely used in the field of super resolution reconstruction. The algorithm can be represented as the following.

$$Y = \arg\max_Y \left[P\left(Y / X\right)\right] \tag{6}$$

$$Y = \arg\max_Y \left[\frac{P(Y/X)P(Y)}{P(X)} \right] \quad (7)$$

$$Y = \arg\max_Y \left[-\log\left(P(Y/X)\right) - \log\left(P(Y)\right) \right] \quad (8)$$

where $P(Y|X)$ denotes conditional probability of the input LR images to the known HR image, $P(Y)$ and $P(X)$ refer to the prior probability of desired HR image and the posterior probability of input LR image respectively.

MAP algorithm may introduce constraints directly, which is able to ensure the solution is convergent. While if lacking experience data and prior knowledge, it will lead the solution to be uncertain and random.

Currently, researchers have combined MAP with POCS methods and then proposed a hybrid MAP-POCS algorithm [17, 18], which integrates both merits of the two methods.

In general, when the resolution ratio increases or the number of low resolution images is insufficient, reconstruction based method can only provide less useful information and will get poor image quality that emerges excessive smoothing phenomenon and lacks high frequency details. At this time, even if increasing the number of LR images will produce more high frequency detail, the reconstructed effect is not enough good.

3.3. Learning Based Image Super Resolution

Recently, learning based super resolution becomes a hot research point, which was first proposed by Freeman *et al* [20]. The basic idea of the method is to study the mapping relationship between the LR image and the HR image, and then reconstruct the result image by using the relationship. In general, learning based method firstly divide image into blocks, and construct the samples library of LR and HR respectively. Then it manages to learn the relationship between corresponding LR blocks and HR blocks. Finally, the method utilizes the relationship to reconstruct HR image based on input LR image. The processing flow can be illustrated as Figure **4** [2].

According to source types of training patches, existing learning based super resolution algorithms can be divided into two main categories - external and internal methods.

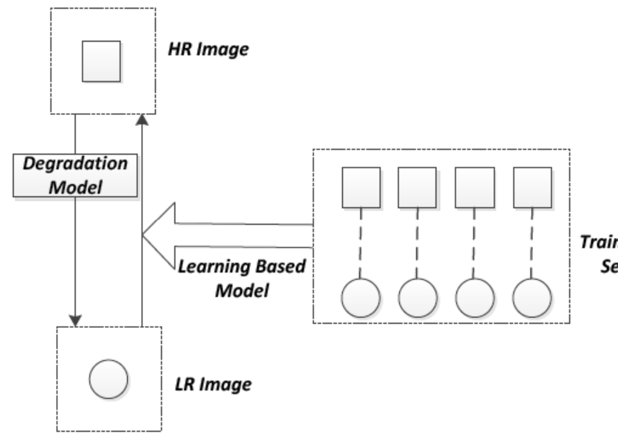

Figure 4: Learning based algorithm.

3.3.1. External Database

External database methods focus on learning the relationship between LR and HR images. Existing methods employ various learning algorithms to acquire LR to HR mapping, such as manifold learning, sparse representation and deep learning.

A. Manifold Learning

The main idea of manifold learning is to map a high dimensional data to low dimension, which can reflect the essence of high dimension data. Manifold learning methods can be classified as linear manifold learning and nonlinear one. In [21], Chang *et al*. realize image super resolution using neighbor embedding algorithm in manifold learning.

Neighbor embedding assumes that HR images and LR images hold the similar local manifold in the feature space. Neighbor embedding image super resolution can be detailed described as follows.

First, among a sample set of LR patches, we seek k nearest neighbor image patches to the input LR patch x which keep closest features. Then, we can calculate local geometry structure of x based on following equation:

$$W_i = \arg\min_{W_i} ||x - \sum_{i=1}^{k} W_i x_i||_2^2 \quad (9)$$

Then among sample set of HR patches, we continue to find corresponding HR patches $y_1, y_2, \dots, y_k$ to $x_1, x_2, \dots, x_k$. And we map the obtained local geometry features onto HR patches $y_1, y_2, \dots, y_k$ to finally reconstruct the HR image y by the following equation:

$$y = \sum_{i=1}^{k} W_i y_i \tag{10}$$

For HR image reconstructing, neighbor embedding method reduces the dependency on samples set. But due to the fixed number of neighbors, over fitting or under fitting phenomena may appear and result in image blur. To address this problem, Some improvements are implemented in [22, 23]. And since the neighborhood relationship using such method cannot be keep well, Gao *et al*. [24] provide an edge detection and feature selection based method to improve neighborhood preserving characteristic, which make image details well recovered.

B. Sparse Representation

Traditional learning based super resolution algorithm do not consider the prior knowledge of other sample blocks in sample set, the reconstruction performance is depended on the quality of selected samples. Yang *et al*. [25, 26, 27] introduce compress sensing theory into super resolution, and proposed a sparse representation based reconstruction model. The basic idea of sparse representation based reconstruction algorithm is firstly learning to obtain HR and LR over complete dictionary basis, then based on LR over complete dictionary basis calculating the sparse representation coefficients of input LR image blocks, finally, reconstructing HR image based on HR dictionary basis.

In [25], such sparse representation based algorithm can be formatted as follow equations:

$$\min \left|\left|\alpha\right|\right|_0 \quad \text{s.t.} \quad ||FD_l\alpha - Fy||_2^2 \ll \epsilon \tag{11}$$

where F is a feature operator, y denotes LR patches, α is sparse coefficient, D_l is LR over complete basis.. Due to NP hard problem of Eq. (11), usually we approximate it to the following one:

$$\min ||\alpha||_1 \quad \text{s.t.} \quad ||FD_l\alpha - Fy||_2^2 \ll \epsilon \tag{12}$$

Lagrange multipliers offer an equivalent formulation

$$\min_\alpha ||FD_l\alpha - Fy||_2^2 + \lambda||\alpha||_1 \tag{13}$$

where λ balances sparsity of the solution and fidelity of the approximation to y. Then if we introduce HR dictionary D_h, the super resolution optimization problem is converted into

$$\min \left|\left|\alpha\right|\right|_1 \quad \text{s.t.} \quad ||FD_l\alpha - Fy||_2^2 \ll \epsilon_1 \quad ||PD_h\alpha - \omega||_2^2 \ll \epsilon_2 \tag{14}$$

where P extracts the overlap region between the current target patch and previous reconstructed HR image, and ω represents the pixels' value of the previous reconstructed HR image in the overlap part. Once acquiring the optimal coefficient α, the HR image patch can be reconstructed as $x = D_h\alpha$, and all these patches can be integrated to get result HR image.

In a sense, sparse representation based method is an extension of neighbor embedding method, which overcomes the problem of fixed neighbor numbers and of which the sparse description has a better adaptive in reconstruction process. Therefore, it has become a research hotspot [28, 29, 30].

C. Deep Learning

Deep learning, especially convolutional neural network (CNN), has recently shown an explosive popularity due to its success in computer vision. CNN combines local receptive field, time or spatial sub sampling with sharing weights to obtain the invariance to displacement, scale and deformation. Deep learning method has been successfully applied to other fields, such as image classification, speech recognition.

Dong *et al*. [32, 33] first apply CNN for image super resolution in 2014. They directly learned the mapping function between LR images and corresponding HR images by CNN large data training. Then given an input image, a HR image can be reconstructed by the learned model. This method can also be applied to color images, and better reconstruction effect can be expected.

Following Figure **5** gives the sketch map of Dong's proposed model [33] - super resolution convolutional neural network (SRCNN).

This SRCNN model contains three dominant function operations through three layers structure:

1). Patch Extraction and Representation

$$F_1(Y) = \max(0, W_1 * Y + B_1) \tag{15}$$

where W_1 and B_1 represent the filters and biases respectively. Y denotes the LR image. Rectified Linear Unit (ReLU) was chosen as the activation function.

2). Non-Linear Mapping

$$F_2(Y) = \max(0, W_2 * F_1(Y) + B_2) \tag{16}$$

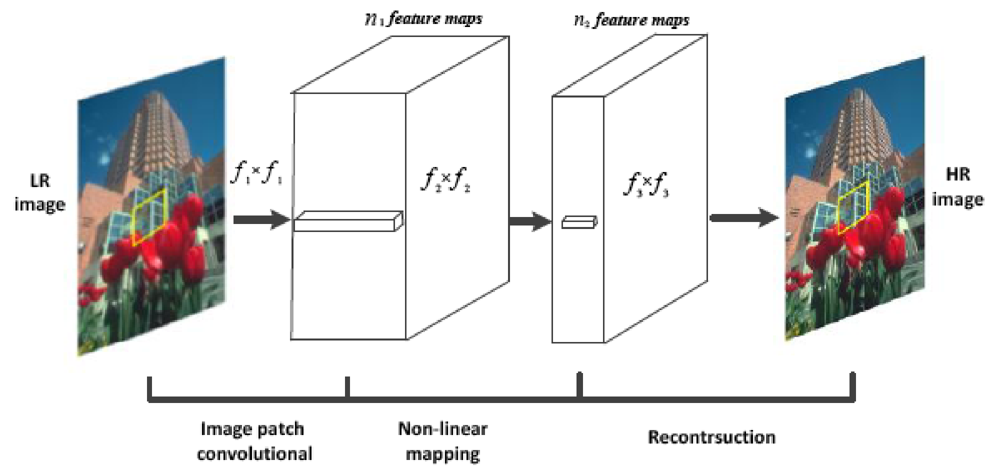

Figure 5: Sketch map of SRCNN.

where W_2 and B_2 denotes the filters and biases respectively.

3). Image Reconstruction

The operation aggregates the HR patch wise representations to generate the final HR image through the following equation.

$$F(Y) = W_3 * F_2(Y) + B_3 \tag{17}$$

where W_3 and B_3 refer to the filters and biases respectively in the third layer. $F(Y)$ is the reconstructed image. Our goal is to learn the mapping F by minimizing the loss between the reconstructed HR image and the true one. Mean Square Error (MSE) can be treated as the loss function by

$$L(\Theta) = \frac{1}{n}\sum_{i=1}^{n} ||F(Y_i;\Theta) - X_i||^2 \tag{18}$$

CNN uses stochastic gradient descent for optimization. Here, the weight matrices of convolution kernel are updated as:

$$\Delta_{i+1} = 0.9 * \Delta_i - \eta * \frac{\partial L}{\partial w_i^l} \quad W_{i+1}^l = W_i^l + \Delta_{i+1} \tag{19}$$

where l and i are the indices of layers and iterations, η is the learning rate, and $\frac{\partial L}{\partial w_i^l}$ is the derivative.

In addition, Wang *et al*. [34] combined sparse coding and the merits of deep learning to achieve better super resolution performance with faster training and smaller model size. And Osendorfer *et al*. [35] use deconvolutional networks with sparse coding to learn the non-linear mapping from LR image to HR image.

External database based approach have attracted most attention, and there appears many work [32, 33, 36, 38, 41] that have better performance. All these methods learn mapping relationship between LR images and HR images using an external database. However, all these methods have common shortcomings. For example, the number and the type of training images required for satisfactory reconstruction performance are not clear. And large scale training sets are often required learning a sufficiently expressive dictionary at the cost of much time. In addition, for every new scale factor by which the resolution has to be increased, these methods need to retrain the learning model on large external datasets again.

3.3.2. Internal Database

Internal database methods utilize image self-similarity [31], which indicates that patches content of a natural image recur within and across scales of the same image. Singh *et al*. [24] utilize self-similarity principle for super-resolving noisy images. And Michaeli and Irani [46] show that recurrence of small patches can be used for estimating the blur kernel. Yang *et al*. [37] refine the local self-similarity and performed first-order regression on them. Yang *et al*. [39] also exploited patch self-similarity within image and introduced the group sparsity for better regularization in the reconstruction process. Work in [44] propose a deformable patches based method for single image super-resolution, and utilize multiple deformed patches combination for the final reconstruction. In [45], Zhu *et al*. extend the deformable patches based model to the gradient domain and raise a deformable compositional model to decompose the non-singular structures into singular structures. Huang *et al*. [40] propose a decomposition of geometric patch transformation model into perspective distortion for handling structured scenes, and they take additional affine transformation for modeling local shape deformation.

4. RELATED TECHNOLOGY DISCUSSION

4.1. Dataset

Super resolution algorithms have been most employed in many fields. In experiment of super resolution, the selection of dataset is an important step, especially for some learning based algorithms. The following shows some common databases that super resolution algorithms have used.

4.1.1. Dataset for Training

1). 91-images

An image dataset consist of 91 natural images, which are usually divided into image patches for dictionary learning or model training [26, 27].

2). Image Net

An image database organized according to the WordNet hierarchy, in which each node of the hierarchy is depicted by hundreds and thousands of images [49]. Currently we have an average of over five hundred images per node.

3). Urban100

Contains 100 HR images with a variety of real-world structures. Huang *et al*. [40] constructed this dataset using images from Flickr using keywords such as urban, city, architecture and structure.

4.1.2. Dataset for Testing

1). Set5 and Set14

Made up of 5 images and 14 images separately, which are exploited most often.

2). BSD 200

Contains 200 images from the Berkeley segmentation dataset, whose all images are of 321x481 pixels covering diverse contents acquired in a professional photographic style [42].

3). LIVE 1

Consists of 29 undistorted high-quality images, which resolution ranges from 480x720 to 512x768 pixels [42].

4.2. Evaluation Criteria

The image quality of super resolution reconstruction can be evaluated by image evaluation measures. Image evaluation measures include subjective evaluation method and objective evaluation method.

Subjective evaluation refers to evaluate the image quality using subjective factors such as visually distinguishing, including subject feeling and scoring system. This kind of method mainly depends on the participators' feeling, so there are many complex constraints not only on participators but also on the test environment.

Objective evaluation uses quantitative assessment index, which is calculated by specific formula. Following are commonly used objective evaluation standards for image super resolution.

1). Peak Signal Noise Ratio (PSNR)

PSNR estimates the image quality by the error of pixels. It is very accurate for a noise image, which is simple and easy to operate. The greater the value of PSNR, the higher the image quality is. PSNR is calculated as follows [1, 47]:

$$\mathrm{PSNR} = 10 \times \log_{10}\left(\frac{(2^n-1)^2}{\mathrm{MSE}}\right) \tag{20}$$

where MSE denotes mean square error, and can be defined as

$$\mathrm{MSE} = \frac{\sum_{i=1}^{N_1}\sum_{j=1}^{N_2}(F(i,j)-f(i,j))^2}{N_1 \times N_2} \tag{21}$$

Figure **6** shows a comparison with different super resolution algorithms by PSNR objective evaluation measure.

2). Structure Similarity (SSIM)

SSIM considers the homogeny and phase coherence of the gradient magnitude of original image and the reconstructed image, which is based on the similarity in three aspects (structure, brightness and contrast) [48, 50]. Compared with other methods, it will be more in line with the human visual system. SSIM can be calculated as following formula.

Figure 6: Comparison of different algorithms.

$$\mathrm{SSIM} = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (22)$$

where μ_x and μ_y represent the mean value of the original image and reconstructed image, C_1 and C_2 denote the brightness of two images, σ_1 and σ_2 are variances of two images.

4.3. Application Field

With increasing demand for high resolution images and the development imaging techniques, super resolution technology has been applied in more and more industry fields.

1). Medical Image

Super resolution can improve the diagnosis of disease by increasing the resolution of medical images to make the location and size of the lesion part more exactly and clearly.

2). Digital High Definition

Currently, 4K display becomes a mainstream display technology in TV. However, since most source video is not 4K, it becomes a problem to obtain and display high resolution video in 4K screen. Using super resolution can improve the compatibility of TV display, which can transforms the standard low resolution signal into high definition signal to get 4K or higher resolution video.

3). Video Surveillance

Video surveillance has played an important role in security against terrorism. However, the images in surveillance video are usually low resolution, which are bad quality and cannot be easily used to deal with emergency matter. However, we can get HR images through super resolution reconstruction based on low resolution surveillance video.

4). Image Compression

Super resolution can be used for image compression. LR images can be stored or transmitted in general. When necessary, different resolution images can be acquired by super resolution technique according to LR compressive images.

4.4. Technical Bottleneck

Here, some practical problems or hardship are to be addressed when considering industrial application. For example, when applied super resolution to digital high definition, the two problems will be encountered - how to improve reconstruction performance and how to speed up its reconstruction procedure.

1). Improve Performance

In recent years, super resolution technique has made great progress and some of them achieved better results. But in general, the details in HR images are not clear and consistent enough. As a whole, the reconstruction is still specific and limited. Therefore, it is still a challenge to design a better algorithm to get better performance.

2). Speed up Reconstruction

Most super resolution algorithms cost much time when reconstructing HR images, which cannot meet the requirement of real time application. However, real time processing is a basic demand in many practical applications. Therefore, for super resolution, the difficult of real time reconstruction is another major bottleneck.

The following Table **1** is a comparison of performance and speed for different super resolution algorithms.

Table 1: Comparison of Different Super Resolution Algorithms

Super-Resolution Algorithms		Performance	Speed
Interpolation based		bad	fast
Reconstruction based		better	slower
Learning based	External database	good	slow for training
	Internal database	good	slow for testing

5. CONCLUSION

This paper shortly and systematically introduces different super resolution algorithms, and discusses some potential problems when processing. In general, learning based algorithm achieves better effect compared with other methods. Research on super resolution is still expanding, and a few of such algorithms has been applied to practical life and application software. However, image super resolution technology is far from mature and there is much room for further research.

1. The edge and texture are still smooth and fuzzy in some algorithms, and real time processing should be managed to satisfy.

2. With the development and wide use of smart device, transplanting super resolution technology to smart device can stimulate more application needs.

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REFERENCES

[1] Kamal Nasrollahi, Thomas B. Moeslund. Super-resolution: a comprehensive survey. Machine Vision and Applications 2014; 25: 1423-1468. http://dx.doi.org/10.1007/s00138-014-0623-4

[2] Su H, Zhou J, Zhang ZH. Survey of Super-resolution Image Reconstruction Methods. Acta Automatica Sinica 2013; 39: 1202-1213. http://dx.doi.org/10.3724/SP.J.1004.2013.01202

[3] Xiao S, Han GQ, Wo Y. Survey of Digital Image Super Resolution Reconstruction Technology. Scientific Journal of Computer Science, 2009; 36.

[4] Schultz RR, Stevenson RL. A Bayesian approach to image expansion for improved definition. IEEE Trans. on Image Processing 1994; 3(3): 233-242. http://dx.doi.org/10.1109/83.287017

[5] Hou HS, Andrews HC. Cubic splines for image interpolation and digital filtering. IEEE Trans. on Acoustics, Speech and Signal Processing 1987; 26(6): 508-517.

[6] Li X, Orchard MT. New edge-directed interpolation. IEEE Trans. on Image Processing 2001; 10(10): 1521-1527. http://dx.doi.org/10.1109/83.951537

[7] Cha Y, Kim S. Edge forming methods for color image zooming. IEEE Trans. on Image Processing 2006; 15(8): 2315-2323. http://dx.doi.org/10.1109/TIP.2006.875182

[8] Lin H. Research on the Algorithms of Super resolution Image Reconstruction with Wavelet and Interpolation. Xidian University (Chinese) 2005; p. 7-14.

[9] Wang ZS. Research on Super-resolution Image Processing Algorithm Based on Interpolation and Worked Examples. Zhejiang Normal University (Chinese) 2014; p. 10-22.

[10] Irani M, Peleg S. Improving resolution by image registration. Graphical Models and Image Processing 1991; 53(1): 231-239.

[11] Song JW, Xu YM, Xiao XJ. A Super Resolution Algorithm Based on Wavelet Transform and Iterative Back Projection. Computer Technology and Development 2015.

[12] Stark H, Oskoui P. High resolution image recovery from image-plane arrays, using convex projections. J. Opt. Soc. Am 1989; 6: 1715-1726. http://dx.doi.org/10.1364/JOSAA.6.001715

[13] Patti AJ, Altunbasak Y. Artifact reduction for set theoretic super resolution image reconstruction with edge adaptive constraints and higher-order interpolants. IEEE Trans. on Image Processing 2001; 10(1): 179-186. http://dx.doi.org/10.1109/83.892456

[14] Yu J, Xiao CB, Su KN. A method of gibbs artifact reduction for pocs super-resolution image reconstruction. In: Proceedings of the 8th International Conference on Signal Processing; Beijing; 2006.

[15] Schultz RR, Stevenson RL. Improved definition video frame enhancement. IEEE Trans. on Acoustics, Speech and Signal Processing 1995; 4: 2169-2172.

[16] Schultz RR, Stevenson RL. Extraction of High-resolution frames from video sequences. IEEE Trans. on Image Processing 1996; 5(6): 996-1011. http://dx.doi.org/10.1109/83.503915

[17] Raj A, Thakur K. Fast and stable Bayesian image expansion using sparse edge priors. IEEE Trans. on Image Processing 2007.

[18] Chantas GK, Galatsanos GP, Woods NA. Super-resolution based on fast registration and maximum a posteriori reconstruction. IEEE Trans. on Image Processing 2007.

[19] Maeland E. On the comparision of interpolation methods. IEEE Trans. on Medical Imaging 1988; 1: 213-217.

[20] Freeman WT, Pazstor EC. Learning low-level vision. Springer Intertional Journal Computer Vision 2000.

[21] Chang H, Yeung DY, Xiong Y. Super-resolutoin through neighbor embedding. In: Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition; Washington, DC, USA; 2004: p. I-I.

[22] Gao XB, Zhang KB, Tao DC, Li XL. Image super-resolution with sparse neighbor embedding. IEEE Trans. on Image Processing 2012; 21(7): 3194-3205. http://dx.doi.org/10.1109/TIP.2012.2190080

[23] Zhang KB, Gao XB, Li XL. Partially supervised neighbor embedding for example-based image super-resolution. IEEE Joyrnal of Selected Topics in Signal Processing 2011; 5(2): 230-239. http://dx.doi.org/10.1109/JSTSP.2010.2048606

[24] Singh A, Porikli F, Ahuja N. Super-resolving noisy images. In: IEEE Conference on Computer Vision and Pattern Recognition; Columbus, OH; 2014; p. 2846-2853.

[25] Yang JC, Wright J, Lin Z, Cohen S, Huang T. Coupled dictionary training for image super-resolution. IEEE Trans. on Image Processing 2012; 21(8): 3467-3478. http://dx.doi.org/10.1109/TIP.2012.2192127

[26] Yang JC, Wright J, Huang T, Ma Y. Image super-resolution as sparse representation of raw image patches. In: IEEE conference on Computer Vision and Pattern Recognition; Anchorage, AK; 2008; p. 1-8.

[27] Yang JC, Wright J, Huang T, Ma Y. Image super-resolution via sparse representation. IEEE Trans. on Image Processing, 2010; 19(11): 2861-2873. http://dx.doi.org/10.1109/TIP.2010.2050625

[28] Li M, Cheng J, Le X, Luo HM. Super-resolution Based on Sparse Dictionary Coding. Journal of Software (Chinese) 2012; 23(5): 1315-1324.

[29] Liao XX. Research on Learning-based Image Super-Resolution Reconstruction Algorithms. South China University of Technology (Chinese) 2013; p. 29-32.

[30] Mairal J, Elad M, Sapiro G. Sparse representation for color image restoration. IEEE Trans. on Image Processing 2008; 17(1): 53-69. http://dx.doi.org/10.1109/TIP.2007.911828

[31] Glasner D, Bagon S, Irani M. Super-resolution from a single image. In: IEEE 12th International Conference on Computer Vision; Kyoto; 2009; p. 349-356.

[32] Dong C, Loy CC, He KM, Tang XO. Learning a deep convolutional network for image super-resolution. In: Proceedings of 13th European Conference on Computer Vision; Zurich, Switzerland; 2014; p.184-199.

[33] Dong C, Loy CC, He KM, Tang XO. Image super-resolution using deep concolutional networks. IEEE Trans. on Pattern Analysis and Machine Intelligence 2015; (99): 1.

[34] Wang ZW, Liu D, Yang JC, Huang T. Deep Networks for Image Super-Resolution with Sparse Prior. In: Conference on Computer Vision and Pattern Recognition; 2015.

[35] Osendorfer C, Soyer H, P van der Smagt. Image super-resolution with fast approximate convolutional sparse coding. In: 21st International Conference on Neural Information Processing; Kuching, Malaysia; 2014; p. 250-257.

[36] Timofte R, De V, Gool LV. A+: Adjusted anchored neighborhood regression for fast super-resolution. In: 12th Asian Conference on Computer Vision; Singapore; 2014; p. 111-126.

[37] Yang JC, Lin Z, Cohen S. Fast image image super-resolution based on in-place example regression. In: IEEE Conference on Computer Vision and Pattern Recognition; Porland, OR; 2013; p. 1059-1066.

[38] Zeyde R, Elad M, Protter M. On single image scale-up using sparse representations. In: 7th International Conference on Curves and Surfaces; Avignon, France; 2010; p. 711-730.

[39] Yang CY, Huang JB, Yang MH. Exploiting self-similarities for single frame super-resolution. In: 10th Asian Conference on Computer Vision; Queenstown, New Zealand; 2010; p. 497-510.

[40] JB. Huang, A. Singh, N. Ahuja. Single image super-resolution from transformed self-examplars. In: IEEE Conference on Computer Vision and Pattern Recognition; Boston, MA; 2015; p. 5197-5206.

[41] Schulter S, Leistner C, Bischof H. Fast and accurate image upscaling with super-resolution forest. In: IEEE Conference on Computer Vision and Pattern Recognition; Boston, MA; 2015; p. 3791-3799.

[42] Yang CY, Ma C, Yang MH. Single image super-resolution: A benchmark. In: Proceedings of 13th European Conference on Computer Vision; 2014; p.372-386.

[43] Timofte R, De V, Gool LV. Anchored neighborhood regression for fast example-based super-resolution. In: IEEE International Conference on Computer Vision; Sydney; 2013; p. 1920-1927.

[44] Zhu Y, Zhang YN, Yuille YN. Single image super-resolution using deformable patches. In: IEEE Conference on Computer Vision and Pattern Recogition; Columbus, OH; 2014; p. 2917-2924.

[45] Zhu Y, Zhang YN, Bonev B, Yuille AL. Modeling deformable gradient compositions for single-image super-resolution. In: IEEE Conference on Computer Vision and Pattern Recognition; Boston, MA; 2015; p. 5417-5425.

[46] Michaeli T, Irani M. Nonparametric blind super-resolution. In: IEEE International Conference on Computer Vision; Sydney; 2013; p. 945-952.

[47] Tian L, Suzuki A, Koike H. Task-oriented evaluation of super-resolution techniques. In: Proceesings of 20th International Conference on Pattern Recognition, Istanbul; 2010; p. 493-498.

[48] Begin I, Ferrie FP. Comparision of super-resolution algorithms using image quality measures. In: The 3rd Canadian Conference on Computer and Robot Vision, Canada; 2006; p. 72.

[49] Krizhevsky A, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. Advances in Neural Information Processing Systems 2012; 1097-1105.

[50] Reibman, AR, Bell, RM, Gray, S. Quality assessment for super-resolution image enhancement. In: proceedings of IEEE International Conference on Image Processing, USA; 2006; p. 2017-2020.

[51] Zhang JP, Wang RB, Zhang ZK. Time and space integration model of primary visual cortex based on motion vision. In: proceedings of the 8th Biennial Conference of the Chinese Society for Neuroscience, China; 2009.

[52] Rehanullah K, Robert S, Abdul B, Yahya MK. Comparison of reconstruction and example-based super-resolution. In: Proceedings of 7th International Conference on Emerging Technologies, Islamabad; 2011; p. 1-6.

[53] Irani M, Peleg S. Super-resolution from image sequences. In: Proceedings of IEEE International Conference on Pattern Recognition, USA; 1990; p. 115-120.

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