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Survey on Single Image based Super-resolution — *Implementation Challenges and Solutions*

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Abstract
Super-resolution includes the techniques which deal with the methods of converting the low-resolution image into the high-resolution image. In this paper, various challenges affecting the implementation of Super-Resolution (SR) along with the detailed survey of SR implementation methods have been presented. Different issues related to the SR have been explored from literature which are limiting the SR implementations. Besides, there are also various techniques to implement the SR, detailed survey of these techniques along with comparison, have been included in this paper. In this work main focus has been given to a single image based super-resolution as it is the more practical type of super-resolution. The basic purpose of the paper is exploring the various possibilities of SR along with practical constraints.

Keywords Super-resolution · Low-resolution (LR) · High-resolution(HR)

1 Introduction

In today's time, almost every digital imaging application demands high-resolution images. It is mainly required for efficient processing and analysis of image details. Image resolution basically describes the details contained in an image, i.e. the higher the resolution, higher the number of pixels and more is the image detail [78]. There are a number of examples where

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high-resolution images are desirable like in human interpretation, surveillance, HDTV, medical imaging, satellite imaging etc. In addition to that improved resolution is also helpful in automated system perception (ASP) based applications. Therefore, improvement of pictorial information is always desirable. Super-resolution (SR) area is mainly inspired by these type of requirements. Technically, Super-resolution (SR) term is used for the class of techniques which work in up-scaling of video or images. Image SR techniques take a low-resolution (LR) image as an input and generate a corresponding high-resolution (HR) image. The terms like zooming, HR image reconstruction, digital image magnification etc. are used interchangeably for the same process [97]. In the same way terms such as up-convert, upscale, upsize also describe an increase of resolution by SR image processing [97]. Image SR schemes try to preserve the high-frequency information, geometrical regularities and smoothness of the original input image in the process of generating HR image from the source input image. Image SR has many applications in various areas e.g. high-definition television (HDTV) [], medical imaging [112], satellite-imaging [57], surveillance systems, and entertainment etc. [104, 147].

In literature, there are various methods which are available to create super-resolution (SR) from low-resolution (LR) images by maintaining the image details. Early methods of producing an SR image generally include multiple LR images as a contribution to calculate the details [9, 35, 124]. There are also multiple methods which works with single LR image and having the capability of LR to HR image conversion. In the category of multiple images based SR, there are also some multi-view based approaches [28, 29, 40, 41, 49]. The approach listed in [40] is designed for curved and multi-view surfaces. It requires the multiple images for super resolution. In [28], the method is useful in mixing the different photographs; It provides the artifact free blending and requires multiple unordered images for super resolution. The method listed in [49], is used for up sampling in real time with good GPU systems. It requires the high end GPU for geometrical up-sampling of images. Edge-Constrained Image Compositing is listed in [29]. It includes the image overlapping and stitching for Super resolution, based on multiple input images. Similarly, [41] has proposed multi-view 3D reconstruction from multiple images. On the other side, single Image based Super Resolution. Single image based methods use only one single image for super resolution and proved to be more practical in today's time. These algorithms of SR can be categorized in different categories like Interpolation-based methods, learning based methods, Soft Computing based methods etc. which have been discussed in detail in further sections. Algorithms based on interpolations are comparatively faster in response [70, 91, 114]. In real time systems along with many practical applications, some standard interpolation based methods are being used. There are some methods of reconstruction [52, 54, 80, 90, 101, 106, 119] which applies the various smoothness priors [5, 20, 108] for SR imaging. Another approach is based on learning based methods [16, 37, 75, 129], there is a training a set of LR/HR images or blocks and detailed HR image is constructed based on learning from these pairs. Selection of training set is crucial for these methods of SR; wrong selection could lead to undesired results [21]. Recently, deep learning based methods are also becoming more popular due to their state of art performance [23, 24, 45, 59, 63, 64, 71, 103, 136, 138, 142].

1.1 Motivation and contribution

There are a number of possible approaches which could be used to address the problem of super-resolution. However, for in depth study and solution oriented approach of this problem, there is always a requirement of proper classification and systematic study of the previous approaches. Therefore, there should firstly identification of challenges related to image super resolution and then there should a systematic approach towards the solutions. In the proposed work, the main focus is concerned on Single Image Super-Resolution based solutions. In this paper, the proposed solution is threefold i.e. (a) Image Super Resolution based challenges have been identified and presented, these challenges are acting as limiting factor for the implementation of Super resolution; (b) Survey on Single Image based Super-Resolution has been presented for different type of SR methods along with their year-wise progress, (c) The comparison of different existing state of art methods of Super-Resolution is also presented in the work.

In this paper, Section 2 is presenting the basic details of Super Resolution (SR) as an inverse problem, Section 3 is presenting the identified challenges which are limiting the implementation of SR, Section 4 is giving the detailed review and survey of different methods usually used in the single image based SR including simulation based different comparisons and in the Section 5 conclusion has been presented.

2 Super resolution of images

Super-Resolution **(**SR) is the process of converting the low resolution image into high resolution image. In the process, the number of pixels in the input low resolution (LR) image are increased as per required scaling factor, therefore high resolution image is achieved at the output (Fig. 1).

The main aim of SR (Super-resolution) is to estimate a high-resolution (HR) Image from one or a set of low-resolution images. The process of reconstruction of the HR image from the input source image by adding one or more LR images is considered as an inverse problem [97]. In order to implement the super-resolution of images, proper reconstruction schemes are required. It is a very ill-posed problem since many HR images can produce the same LR image. The reconstruction of super-resolution image is centered on available prior information or rational deduction of the supposed model that builds the exaggerated image from the available LR images. Therefore, the reconstruction is reflected as the problem in the inverse route to calculate the original particulars around the geometrical symmetries of the SR image by merging one or more LR images [78]. However, due to the less prior information and ill-conditioned registration difficulties, there is always a scope to improve the quality of the reconstructed image [7]. During the literature survey, it has been comprehended that there are several methods that had been proposed to fix above-mentioned problems.

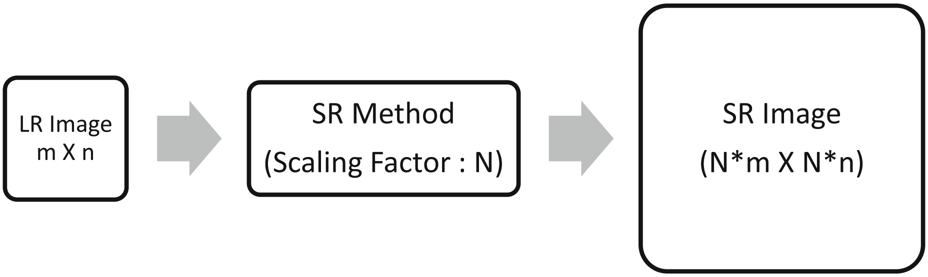


Fig. 1 A basic block diagram of Image Super Resolution

2.1 Super-resolution as an Inverse Problem

Super-resolution is an inverse problem where target information is estimated from the observed data i.e. high-resolution image from low-resolution image or images. In order to unravel the inverse problem, it requires to understand the basic down sampling model as shown in Fig. 2. Basically, Super-resolution algorithms attempt to extract the high-resolution image degraded by the limitations of the optical imaging system [7].

Let low-resolution image is denoted by Y_k, for k = 1,2,3…. K and a high-resolution image are denoted by X. Assume X is Linearly Spatial Invariant (LSI) and is the same for all K frames. Suppose M_k considers only simple motion parameter such as translation and rotation, D_k is a sub-sampling matrix (compression) and N_k represents the noise, then the low-resolution image can be denoted as below:

$$\begin{gathered} Y_k = D_k M_k X + N_k \\ where\ k = 1, 2, 3\ldots, K \end{gathered} \tag{1}$$

With reference to the model in Fig. 2, the approach for the solution should be inverse of it i.e. It may include stages like interpolation and restoration and noise removal to get original high resolution image X in Fig. 2 [32, 35].

3 Factors limiting the implementation of SR

There are various factors which are limiting the implementation quality of SR imaging. These factors are related to many methods used to convert the low-resolution image to the high-resolution image. With reference to literature study, it has been observed that there are various types of practical challenges which are faced during the implementation of super-resolution of images and acting as limiting factors for the implementation of SR. Taking everything into account some major challenges related to super-resolution are further explained (Fig. 3):

3.1 Registration of Multi-frame images

Image registration one of the very crucial factors for the implementation of multi-frame SR reconstruction. It includes the spatial fusion of images and it is also a well-known ill-posed problem. The problem gets more severe when low-resolution images also contain aliasing artifacts. These artifacts are more annoying than the blurring effect which may come due to interpolation of the single image. The SR performance deteriorates as the resolution of observational images decreases. The recovery of high-resolution (HR) image depends upon the image

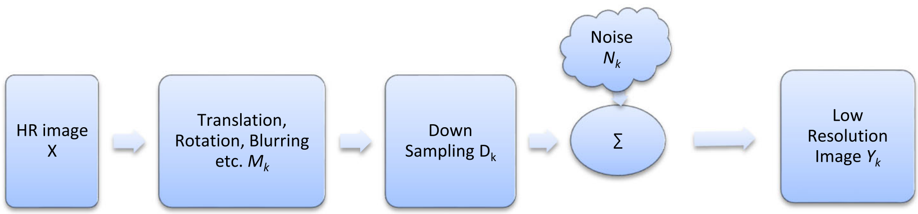


Fig. 2 Model for Down Sampling

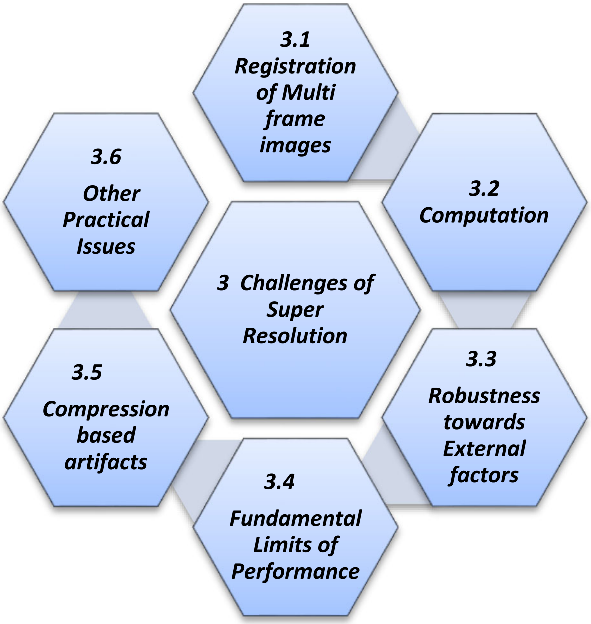


Fig. 3 Challenges of Super-resolution

registration accuracy. There are many image registration methods which have been proposed in the literature [12, 3, 87, 102, 123, 146]. Some of registration based performance limits have been mentioned in reference [92].HR image estimation crucially depends upon the accuracy of registration of LR images [93]. In order to converge towards the practical applicability of SR, improvements are desirable in this area. Due to the challenges in registration of multiple LR images, single image based super resolution (SISR) is becoming more practical solution.

3.2 Computation

Other major limiting factor for the practical applications of Super Resolution is the high computation of a large number of unknowns, which results in extreme matrix manipulations and calculations. Practical applications always require a high speed computation in SR reconstructions, like surveillance systems which demands real-time alarms and active identifications etc. The desired Algorithms should be superior in terms of computational efficiency. One of the recent solutions is parallel computing. Parallel computing can improve the further efficiency of the system. However, its practical implementation in small power devices is a challenge. Many algorithms have been proposed until now to speed up the SR image reconstruction problem but still many are waiting to become practical on smaller devices. There is a class of algorithms which is focused upon computational efficiency known as Interpolation based approaches, however the quality of these methods is not very accurate. In reference [11] Authors have proposed a real-time based SR system which has been improved from [9, 32] in order to make SR more practical. However, despite that these algorithms are limited by precise image registration which again requires very high computation if multiple images are used. Many algorithms can also handle only simple motion models but real-world data of images/videos involves more complexity. Hardware and GPU improvements involving parallel computation can help in improving the computational efficiency but that is again limited by other cost factors of the hardware systems.

3.3 Robustness towards external factors

Robustness of SR method towards external factors is also one of the restraining factors of SR. Many of the SR techniques are affected by the motion errors, inaccurate blur models, noise, moving objects, motion blur, etc. This inaccuracy leading to a basic model error that cannot be treated as common Gaussian noise [105]. Furthermore, the basic model error will lead to visually annoying artifacts creating disturbance in applications based on image and video standards. Meanwhile, as per literature, there is not enough work has been devoted to such an important aspect of robustness towards external factors. Yet in some references [19, 14, 30, 98, 110, 128, 145, 148], authors have worked on a robust aspect of Super-resolution of images. Pham et al. [86] have proposed a bilateral filtering similar scheme for robust certainty. It has been seen that with the proper improvements in estimations of outliers or external factors, results of SR can be improved. On the other hand, for this purpose proper experimental data is required and by including that into the modeling, it can improve the robustness of real-time SR.

3.4 Fundamental limits of performance

There are always some fundamental limits of SR performance that may limit the performance or efficiency of the SR reconstruction algorithms. SR reconstruction is a complex task which involves many interdependent components. In the reference [7], authors have analyzed the limits for SR and have given analysis for Zooming factor. In addition, reference [73] has worked on fundamental limits on reconstruction-based super-resolution algorithms under local translation. Robinson et al. in reference [92] have analyzed the registration performance limit with a simple translation model and the work was further extended with analysis of factors such as motion estimation, decimation factor, number of frames, and prior information. Moreover, their understanding could lead to the better SR camera design, better understanding of model errors, zooming factors limits and number of frames required etc. Eekeren et al. [127] have given performance evaluation of super-resolution reconstruction methods on real-world data by exploring many influential factors limits empirically. Based on above mentioned literature, it is very difficult to conclude that performance limits of SR. therefore no method can be called a best SR method in terms of performance as it varies with environment and image conditions. However, based on studies, a fair benchmark can be defined for particular conditions and real-time based database may be used to give a good performance evaluation of SR methods along with their performance limits.

3.5 Compression based artifacts

Recently it has been observed that multimedia data is increasing day by day continuously and handling or storage of such a huge amount of data is in itself a big challenge. There are many limitations on transmission and storage of such data with limited resources including other cost factors. Therefore, transmission of multimedia data like images, videos are usually done in the compressed forms. It may also include the various lossy types of compression. It has been seen that due to compression quality of images goes down or may contain artifacts like blocking artifacts in jpeg based compressed images. Removal of these artifacts is very necessary if doing the super-resolution. Consequently, it makes the process more complex. In today's time, every transmission standard contains the compression encoder /decoder. Clearly, this challenge needs to be handled suitably in every system of Super Resolution.

3.6 Other practical issues

There are various other practical issues which lead to the complexity and the quality trade-off in the SR implementations. In the practical infrastructure, there is always a probability of noise from external resources that can decrease the SNR of that channel. Therefore, it is also a practical challenge which could be seen in various transmission channels which are susceptible to noise, like wireless channels etc. Furthermore, in many applications, there are some application based local challenges which may decrease the efficiency of SR methods or might leads to errors in results.

4 Single image based super-resolution literature survey and comparison

The Previous section has listed the main challenges which affect the implementation of image Super Resolution (SR). Clearly, there is a need for work to handle these issues to get the acceptable quality of SR images. Meanwhile, there are various methods reported in the literature that have already been proposed to implement the SR. A survey of SR methods for single image based SR has been presented in this section, as single image-based methods are more realistic and practically required methods. Further with reference to Fig. 4 details of each method along with its literature survey has been discussed in subsections.

4.1 Interpolation based methods

Image interpolation focuses on creating the high resolution image from its lower resolution version of the image (Fig. 5). Image interpolation is basically a method of artificially increasing the number of pixels in an area inside an image. Image interpolation is also one of the traditional methods used in the Super Resolution. Conventional systems include the bilinear and bi-cubic interpolation which are having good real time computational simplicity. These require very limited arithmetic operations. Video interpolation or inter frame interpolation can also be achieved by these methods. Interpolation based approach is one of the fastest

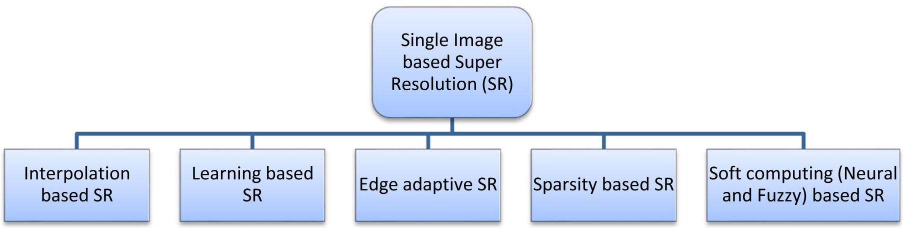


Fig. 4 Single Image based SR techniques

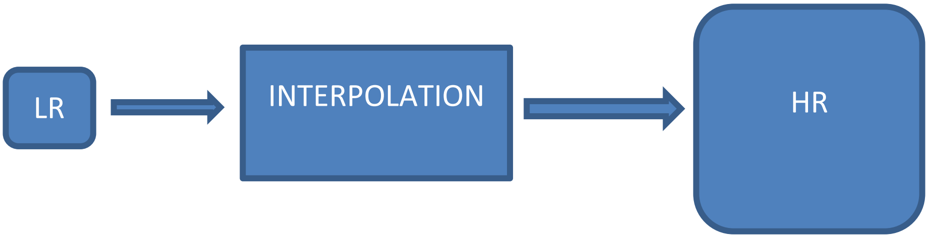


Fig. 5 Interpolation based SR Model

methods for image Super Resolution. Interpolation based SR schemes are often used when working with the real practical environment having a single LR image as input [50, 74]. Nearest neighbor (NN), bilinear (BL)and bi-cubic (BC) are the regularly used interpolation techniques [2, 6, 53]. However, these techniques are non-adaptive so they are computationally efficient but undergo with problems of aliasing, blurring etc. Even Though, these are used in numerous applications due to their simplicity of implementation. There are several adaptive non-linear schemes which have been advanced to minimalize the glitches faced by non-adaptive interpolation schemes [58, 60, 74]. In these techniques, re-sampling info is determined according to the geometrical symmetries. There is always a tradeoff among image quality, time and computational complexity, for this category of methods. In some advanced methods adaptive and interpolation based on higher order derivatives of polynomials have been suggested in literature [96, 133]. Detailed work in the field of Interpolation based SR has been presented in Table 1.

4.2 learning based Super-resolution

There is another approach of SR which is based upon example-based learning (Fig. 6). There are multiple methods of SR which are based on example-based learning approach as suggested in references [38, 39, 42, 48, 61, 115, 116, 121, 141]. These methods of this category are creating high-frequency details from a low-resolution image by process of example based learning. The quality of output HR images created by this method good but consumes more time due to learning process. Multiple Low-resolution images besides their corresponding high quality/high-resolution image patches are stored in the database. The SR algorithm got its training from the database of stored patches i.e. low-resolution and high-resolution image patch pairs. These techniques have certain restrictions due to the dependency on numerous factors like numbers and kind of the images present in training dataset, size of the patches etc. With a variation of these parameters the running time along with the quality of images may change i.e. there is a trade-off between these parameters. These techniques do have high time complexities so rarely used in real-time applications. Table 2 gives the survey of various method included in this category.

4.3 Edge directed Super-resolution

In literature, there are some methods which produces the HR images based on edge directed calculations [20, 31, 36, 56, 67, 76, 108, 109, 113, 130]. These methods are based on edge knowledge of objects in an image which is included in the calculation of HR image from LR

Table 1 Interpolation based SR Methods

Year /reference	Title	Description	Constraints
1978 [50]	Cubic splines for image interpolation and digital filtering	The authors have introduced the theory of B-splines and presented the B-splines as a tool for digital processing applications. This paper has introduced the basics for the B-splines based interpolation.	B-splines based basic interpolation method.
1981 [91]	Cubic Convolution Interpolation for Digital Image Processing	The paper has presented the cubic convolution interpolation as a technique for re-sampling discrete data. [91] has presented the cubic convolution as a useful technique for digital image processing when used on a digital computer. It is also one of the classic paper in the field of image interpolation.	Fundamental work based on Cubic Convolution.
1991 [125]	Fast B-spline transforms for continuous image representation and interpolation	This paper is an extension of previous work of B-spline. It has given the efficient algorithm for continuous representation for interpolative signal reconstruction.	B-spline transform based classical work .
2004 [53]	Adaptive image interpolation based on local gradient features	In this research work, a new adaptive method is proposed for interpolation based on local gradient features which are better than bilinear and bi-cubic methods.	Local gradient calculation is required .
2007 [2]	Computational Foundations of Image Interpolation Algorithms	Presented work gives a review of the progress of both non-adaptive and adaptive image interpolation techniques. Moreover, it has also proposed a new algorithm for image interpolation in the discrete wavelet transform domain.	Review work suggested method requires the wavelet transformation
2010 [58]	Nonlinear image up-sampling method based on radial basis function interpolation	The research paper has proposed a novel method of edge directed sampling. It is based on the radial basis function (RPF). In order to remove blocking artifacts and blurred edges, it is a nonlinear method which considers the edge information of images.	The nonlinear method requires a radial basis function .
2011 [60]	Curvature interpolation method for image zooming	The presented work has proposed an interpolation method which determines the re-sampling information based on geometrical regularities.	Complexity has increased, detection of geometrical regularities is required .
2014 [96]	Multi-kernel based adaptive interpolation for image super-resolution	This research paper has given a novel method for super-resolution which is based on adaptive interpolation with	An adaptive technique requires more computation as

Table 1 (continued)

Year /reference	Title	Description	Constraints
		Gaussian kernel variations. Here Gaussian kernel varies its value depending upon local image area.	compared basic interpolation.
2016 [144]	Image Interpolation Based on Non-local Geometric Similarities and Directional Gradients	The proposed work is based interpolation however it is also combining the directional information to interpolate the required pixel values.	The directional gradient is required to be calculated.
2016 [133]	Image super-resolution reconstruction using the high-order derivative interpolation associated with fractional filter functions	This work is using the interpolation in the very advance form using higher order derivative.	Complexity has increased due to the calculation of higher order derivative.

image (Fig. 7). This category of methods are mainly an extension of the interpolation techniques. The fundamental work was done in NEDI [70] and afterwards many methods based on edge detection were published. In many extended publications it has been observed that multiple techniques are combined for edge calculations and in obtaining of HR resolution images. Furthermore, some techniques are based on the gradient profile prior (GPP) techniques [108, 109, 113]. In GPP (gradient profile prior) it is based on image data set, so HR image result relies on the accuracy of the learning process, so partially including the learning based methods. The edge knowledge in the base image helps in reproducing the HR image with sharp edges and lower artifacts. Another approaches of Super-resolution [67, 76, 130] algorithms also require to locate edges in images and work in combination of other methods. Some edge directed reconstruction models use the iteration based methods where good initialization by edge detection could lead to a reduction of iteration time and lead to good quality of HR images. Table 3 contains the major work of Edge directed SR methods that are included in this category.

4.4 Sparsity based Super-resolution

In this class of methods, the approach is based on a sparsity based SR model (Fig. 8). It is having the sparsity based dictionaries, image details of HR are calculated from sparse

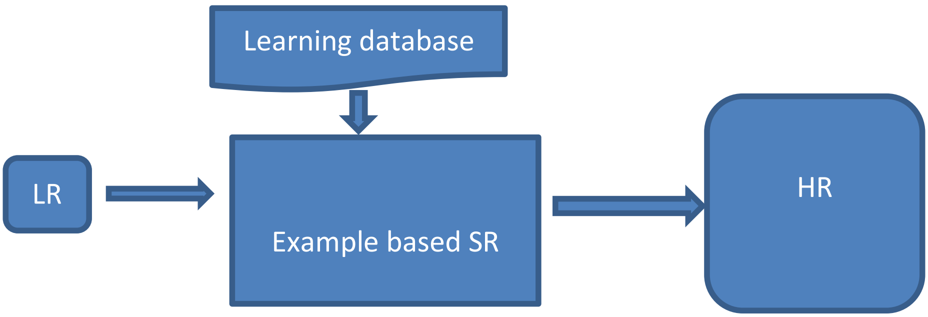


Fig. 6 Learning-based SR Model

Table 2 Learning /Example based SR Methods

Year /reference	Title	Description	Constraints
2000 [38]	Learning low level vision	The proposed methodology is the basic approach of SR which is based on learning oriented methods. The method generates the some synthetic scene for low-level vision problems.	Fundamental work related to learning based methods.
2001 [48]	Image analogies	The research paper has given a training based method. It has two phases one is design phase and other is the application phase. So pairing based data is developed where one target image is created based on training data.	The database is required for SR. Its performance depends upon the data set used for training.
2008 [61]	Example-based learning for single image super-resolution and jpeg artifact removal	The work is based on the single image super-resolution. The main idea is to map the low-resolution image with a high-resolution image which is based on example pairs. It is involving the kernel ridge regression (KRR) for its implementation.	Training data set required and Time consumption is high.
2011 [39]	New learning based super-resolution: use of DWT and IGMRF prior	The presented work is an addition to the previously learning based approaches which is using the DWT and IGMRF prior techniques for super-resolution of images.	Work is using DWT and IGMRF prior techniques includes high complexity.
2013 [141]	Single Image Super-Resolution with Multiscale Similarity Learning	The paper is based on the work of patch level learning as these may exist in images in multiscale. Based on nonlocal prior regularization SR algorithm has been proposed .	The method requires the non-local prior regularization with high computation.
2013 [140]	Landmark Image Super-Resolution by Retrieving Web Images	worked on example based method landmarked from internet correlated images for upscaling	requires database from internet
2014 [116]	Learning from Errors in Super-Resolution	This proposed approach is a method based on learning from the errors in estimations. It includes a low-rank decomposition technique for the estimation and obtaining the high-resolution images.	It includes the long term computation and low rank decomposition for the learning process.
2016 [42]	Image super-resolution based on the pairwise dictionary selected learning and improved bilateral regularization	A pairwise dictionary selected learning (PDSL) is based on external learning. This method uses the bilateral regularization for edge reservation and avoids the fictitious information.	This method requires long computation including bilateral regularization calculations for edge preserving.
2016 [121]	Anchored Neighborhood Regression based Single Image Super-Resolution from Self-Examples	This method is based on self-image based learning. It uses the sampled image patches from same image as the anchor points. The anchored points learns the LR-HR relation from self-image examples by using Anchored Neighborhood Regression and do not require external training images.	The method requires the Anchored Neighborhood Regression for LR-HR patch learning from self-image, so computational time is high.
2017 [115]	Pairwise Operator Learning for Patch-Based Single-Image Super--Resolution	In this work regression operator has been used to map the low-resolution patches to high-resolution along with left and right multiplication operators	Although includes fewer storage data still requires high computations.

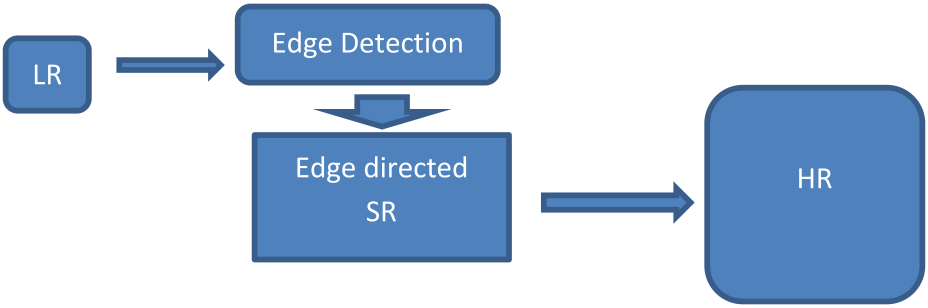


Fig. 7 Edge directed SR Model

properties of an image, like the model shown in Fig. 8. The image super-resolution by sparse representation has been suggested in references [1, 26, 62, 66, 77, 81, 132]. These methods include the sparse image patch prior calculations from the dictionaries. The researchers had worked on mixed estimators for l1 and l2 norms for the dictionary coefficient blocks calculations [77]. In the methods based on patch prior, it is presumed that LR and equivalent HR patches are on the same manifold in L1 space. The HR patch can be estimated from same convex combination which is present for LR patches i.e. sparse convex combinations in a dictionary. The approach is based on learning of coupled dictionary from LR-HR patch feature space. As per literature, there are various extensions for these sparse estimators [25, 88, 131]. Multiple dictionaries could also be included in spite of a single dictionary [88]. Semi coupled dictionary concept has been used for LR to HR conversion in reference [131]. This category of methods also produces the good quality of results and comparable to other methods. Table 4 represents the detailed survey of this category of methods.

4.5 Soft Computing (Neural and fuzzy) based Super-resolution

In recent time, it has been observed that there is a good evolution of methods for image processing based on soft computing like neural networks and fuzzy systems (Fig. 9). Fuzzy system based image processing deals with the various approaches of fuzzy systems that are useful in image processing and includes the fuzzification / defuzzzification of data. These methods also include their applications in the areas like image up-scaling, image filtering, removal of image noise, image segmentation and image interpretation [10, 15, 22, 33, 34, 51, 68, 69, 72, 82, 85, 95, 99, 100, 107, 126, 135]. Some Image upscaling related methods have been developed using the fuzzy sets which are useful for Super Resolution [8, 17, 18, 83, 89, 122]. The fuzzy based methods can be combined with interpolation based SR approaches as well as with learning based SR approaches in order to provide the improvements in SR results [18, 83]. Fuzzy rule based systems are based on imprecision which is the practical situation of every event in reality. It manages the imprecision along with the expert knowledge of the field. Fuzzy based methods are very useful for the development of learning algorithms useful in computer vision. As these are the knowledge based methods and work in a nonlinear way, so these methods deal with the artifacts in a very robust way. Table 5 lists the work of SR done with the fuzzy based methods.

In the More recent literature for the Single Image based Super resolution, Neural network based Deep learning related methods has been suggested [23, 24, 45, 63, 64, 71, 103, 136, 138, 142]. In the last 10 years, the Super Resolution approaches developed on neural networks with

Table 3 Edge directed SR based Methods

Year /reference	Title	Description	Constraints
2001 [70]	New edge directed interpolation	The proposed work is an advancement of previous work done in the interpolation. This paper is based on the estimation of the co-variance of a high-resolution image by estimating the local co-variance of low-resolution which is based on the low-resolution covariance and the high-resolution covariance geometric duality.	Edge detection is required with co-variance calculations.
2007 [36]	Image upsampling via imposed edge statistics	The research paper proposed a method based on the statistical dependency of edge features of different resolution of images. Moreover, it makes the resultant images sharper.	Feature extraction is required for edge detection.
2007 [20]	Soft edge smoothness prior for alpha channel super-resolution	This work has proposed an effective method for super-resolution which is based on the effective image prior. It has proposed a soft edge smoothness prior which is especially for soft edges that reveal gradual intensity transitions.	Image prior calculations are required for the soft edge smoothness.
2008 [108]	Image super-resolution using gradient profile prior	In this approach, super-resolution of the image is achieved based on the gradient profile prior. Gradient Profile prior (GPP) is a parametric prior relating the shape and the sharpness of the image gradients. Here learning of GPP from natural image data set is used to construct the high-resolution image.	Gradient profile prior is required from image data set.
2011 [109]	Gradient profile prior and its applications in image super-resolution and enhancement	The proposed methodology is related to the work presented in [108]. This paper has proposed a generic image prior-gradient profile prior to super-resolution image construction.	Pre-Gradient profile learning is required.
2013 [130]	Edge-Directed Single-Image Super-Resolution Via Adaptive Gradient Magnitude Self-Interpolation	In this research work, an adaptive gradient combined with the interpolation has been used to implement the edge directed single image super-resolution .	Adaptive gradient magnitude self- interpolation needs to be implemented .
2015 [76]	Image super-resolution via hybrid NEDI and wavelet-based scheme	In this work low frequency information is obtained with wavelet based processing and the new edge directed method (NEDI) is combined to obtain better results.	Complexity has increased as it is a hybrid method leading to more computation.
2016 [67]	An edge-guided image interpolation method using Taylor series approximation	The presented work is a new method which includes the calculations of edges by using the 1st and 2nd derivatives of the image and then Taylor series is used for interpolation in 4 directions.	Performance depends upon the geometric calculation of edges.

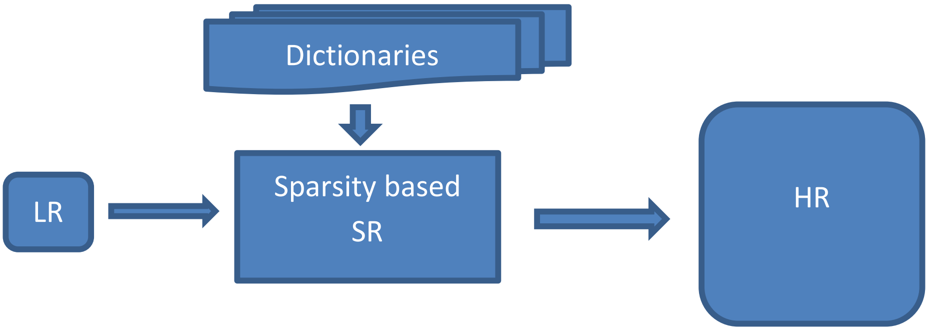


Fig. 8 Sparsity based SR Model

deep convolutional Network have sharply increased. These approaches have shown good performance as compared to other SR methods. The main reason behind these developments is the advancements in hardware for fast computation with which efficiency of these methods have evolved [13, 23, 24, 45, 46, 63–65, 71, 103, 136, 138, 142, 143]. This category based approaches uses the neural networks which requires the training in the initial stage. That training of the network crucially decides the quality of output from these kind of methods. The performance of these systems also depends upon the quality of training database and mostly provides the state of art results with good training. The initial time to train the network might be high but once the network is trained, afterwards it produces the required results with acceptable time. The training time of network can also be further reduced with the advancement of GPU and other related hardware. Table 6 shows the main publications related to this category.

4.6 Miscellaneous methods

In literature, there are also some methods which are present in addition to previous categories, like Maximum aposteriori (MAP) framework, wavelet based methods, regularization based SR approaches [44, 43, 84, 111]. These methods are similar to previous methods however the approach used in these methods is some different from defined categories. Maximum aposteriori (MAP) framework can be used for motion estimation and segmentation along with Super resolution of images [44,]. In the presence of noise, the wavelet transform based approach can also be useful for super-resolution and it can be combined with other approaches to achieve the SR [84, 111]. Based on the combination of different approaches, some methods are also developed for the specific robust environments like web images/videos transmissions [134]. Table 7 includes miscellaneous type of methods of SR as below.

4.7 Comparison of Single image based SR methods

In order to bring the study to a single platform the performance of various existing single image based SR methods from literature review have been observed. Based on above mentioned study this has been found that Interpolation based SR methods are traditional and fastest Super Resolution methods. Algorithms based on interpolations perform faster in comparison to other methods, but sometimes lacks fine details [50, 53, 96, 125, 133, 144]. Therefore, there is still scope of improvement in their performances. Edge adaptive methods

Table 4 Sparsity based SR Methods

Year /Reference	Title	Description	Constraints
2010 [132]	Resolution enhancement based on learning the sparse association of image patches	Learning based approach has been implemented with the usage of patches including the sparse association.	Sparsity transformation required, computational time is high .
2010 [137]	Image super-resolution via sparse representation	The work is focused upon the usage of sparsity and dictionary based learning for image super-resolution. Accuracy of HR images depends upon the level of dictionary learning.	Sparsity transformation required which is increasing the complexity and time consumption.
2010 [62]	Single-image super-resolution using sparse regression and natural image prior	Regression based approach which is using the natural image priors.	Database with the natural image prior required .
2011 [26]	Image deblurring and super-resolution by adaptive sparse domain selection and adaptive regularization	Adaptive regularization approach with adaptive sparse domain selection used in deblurring and image super-resolution.	Improved results, however, complexity increasing.
2010 [77]	Super-resolution with sparse mixing estimators	Mixing estimators in the sparse domain used for Super-resolution .	Mixing estimators required
2012 [88]	Image upscaling using multiple dictionaries of natural image patches	Multiple dictionaries used for upscaling of images from natural image based patches.	Database required for the dictionaries.
2012 [131]	Semi-coupled dictionary learning with applications to image super-resolution and photo-sketch synthesis	Dictionary learning concept modified with semi coupling for achieving the Super-resolution .	Database dictionaries required.
2013 [25]	Sparse representation based image interpolation with nonlocal autoregressive modeling	Auto regressive modeling used with interpolation for sparse representation.	Faster than previous methods but autoregressive modeling required to application area.
2016 [1]	A modified dictionary learning method for sparsity based single image super-resolution	In this presented work local variance based method has been used to speed up the dictionary learning based methods for obtaining the single image based super-resolution.	The method requires the data base again based on conventional methods.
2017 [81]	Sparsity-based Color Image Super-resolution via Exploiting Cross Channel Constraints	Sparsity based method is further modified by including colored channels based dictionaries to obtain a good super-resolution of colored images.	Constraints related to optimizations are present, leading to increase in complexity of the method.

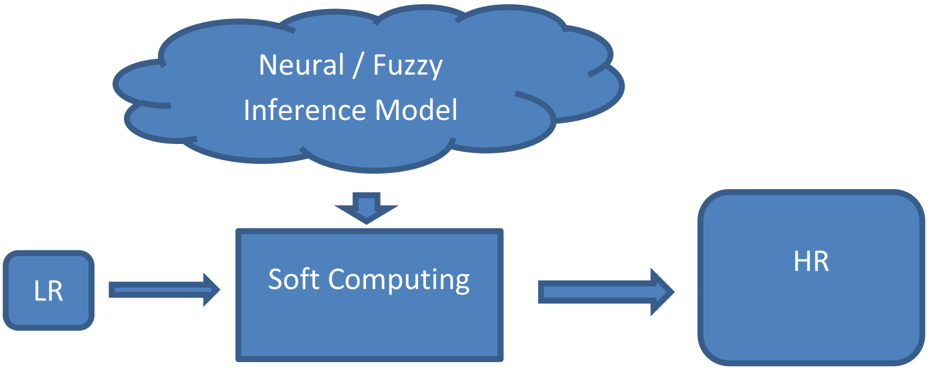


Fig. 9 Soft Computing based SR model

basically work on reconstruction models which are edge directive. These methods use various edge directive reconstruction models to get sharp edges for SR imaging [20, 36, 67, 76, 108, 109, 130], thus are more complex as compared to interpolations based methods. Learning or training based methods use learning based approaches [38, 39, 48, 61] using a training database with a set of LR/HR images pairs. A detailed HR image is re-constructed based on Learning from these pairs. The output image quality depends upon the training dataset and wrong selection could lead to different results [36]. Learning based methods requires training

Table 5 Fuzzy based SR Methods

Year /Reference	Title	Description	Constraints
1997 [122]	Edge preserving interpolation of digital images using fuzzy inference	The presented work is a very basic approach of fuzzy inference for edge preservation.	Fuzzy inference modeling required
2000 [17]	2-D discrete signal interpolation and its image resampling application using fuzzy rule-based inference	Fuzzy inference based concept further enhanced for image interpolation approach.	Image resampling and fuzzy rule based inference required
2010 [18]	Locally edge-adapted distance for image interpolation based on genetic fuzzy system	Edge adaptive interpolation has been used with genetic algorithm for giving better results in image interpolation.	Genetic algorithm required along with the fuzzy system
2013 [83]	Example based super-resolution using fuzzy clustering and sparse neighbor embedding	Learning based approach has been combined with sparse neighbor embedding and for fuzzy clustering in order to achieve the Super-resolution.	A hybrid method using sparsity and example database with fuzzy logic. Complexity is high .
2013 [89]	Fuzzy-rule based approach for single frame super-resolution	Single image frame based super-resolution using fuzzy rule based system has been explained under this paper .	Single frame based approach more practical, however, the complexity involved in the fuzzy based system.
2015 [8]	Fuzzy based super-resolution multispectral image compression with improved SPIHT	Multi spectral image compression with improved SPIHT has been implemented with Fuzzy based modeling.	Requires to change the compression technique.

Table 6 Neural Network/ Deep Learning Based SR Methods

2001 [117]	Super-resolution target identification from remotely sensed images using a Hopfield neural network	Neural network based approach has been used for the target detection for remotely sensed images.	Hopfield network required to be implemented.
2009 [13]	A modular neural network for super-resolution of human faces	Modular neural network and its versatile architecture have been used for Super-resolution and human face detection.	The modular neural network requires the database.
2010 [143]	Super-resolution image reconstruction based on three-step-training neural networks	Train based approach having 3 steps, has been used for the Super-resolution of images .	Three step training network required
2012 [65]	Neural network based single image super-resolution	Single image based approach for enhancing the quality of the image has been used for the image super-resolution .	Simple, however time consuming
2014 [24]	Learning a deep convolutional network for image super-resolution	The presented work was first to introduce CNN to solve single image super-resolution; It has presented the state-of-the-art restoration quality with CNN based Method, and has shown the faster performance than previous Neural based methods.	Performance is database dependent and training of convolutional neural network.
2016 [118]	Image Super-Resolution Using Image Registration and Neural Network Based Interpolation	Image interpolation concept has been clubbed neural network for image super-resolution .	Neural based interpolation required
2016 [103]	Real-time single image and video super-resolution using an efficient sub-pixel convolutional neural network	Sub-pixel convolution layer has been proposed to learn the upscaling operation for image and video super-resolution. Method super-resolve HR data from LR feature maps.	Sub pixel based convolutional network required to be implemented .
2016 [23]	Image Super-Resolution Using Deep Convolutional Networks	Convolutional neural network for image super-resolution has been presented. Mapping of low and high resolution images has been established with the convolutional network directly with some pre/ post-processing. Network Structure is motivated by traditional sparse-coding based SR methods.	It uses more training data to achieve better SR performance
2016 [63]	Accurate Image Super-Resolution Using Very Deep Convolutional Networks	An effort to achieve High learning rates based on residuals with adjustable gradient clipping have been presented. It is based on deep convolutional network.	Quality depends upon the adjustable gradient clipping.
2016 [64]	Deeply-Recursive Convolutional Network for Image Super-Resolution	Super resolution method based on Deep Recursive Convolutional Network (CN) has been presented.	Deep recursive CN is required for better results.

Table 6 (continued)

		The traditional recursive network has been improved with recursive supervision and skips connections.	
2017 [138]	Single Image Super-Resolution with a Parameter Economic Residual-Like Convolutional Neural Network	In the proposed method, filter size and number for each layer in the convolutional network has been explored to reduce the number of parameters.	Performance depends on the feature map size of the network
2017 [139]	Light-Field Image Super-Resolution Using Convolutional Neural Network	Extension of previous concepts of a convolutional neural network for light field image super-resolution .	Applicable to light field Image super-resolution .
2017 [71]	Enhanced Deep Residual Networks for Single Image Super-Resolution	Multiscale deep super resolution method has been presented. Different upscaling factors for high resolution images has been implemented in a single model. It is one of the state of art method.	It requires good training for the model to give better results.
2017 [136]	Fast and Accurate Image Super Resolution by Deep CNN with Skip Connection and Network in Network	They have proposed a parallelized CNN structure with the network in network approach. The network is having lesser computation compared to other deep learning based methods.	Network in network approach needs to be implemented for better performance.
2018 [45]	Deep Back-Projection Networks For Super-Resolution	Deep back projection networks based on iterative up and down sampling layers have been implemented. It works on error feedback mechanism for projection errors at every stage. A further method is extended with dense DBPN by allowing concatenation of features across up/down sampling .	Feature concatenation is required for better performance.
2018 [142]	Image Super-Resolution Using Very Deep Residual Channel Attention Networks	Deep Residual channel attention has been proposed with residual in residual (RIR) structure which leads to the trainable very deep network. The method has also proposed channel attention to adaptively rescale the features.	Channel attention is required for better performance.

Table 7 Miscellaneous SR Methods

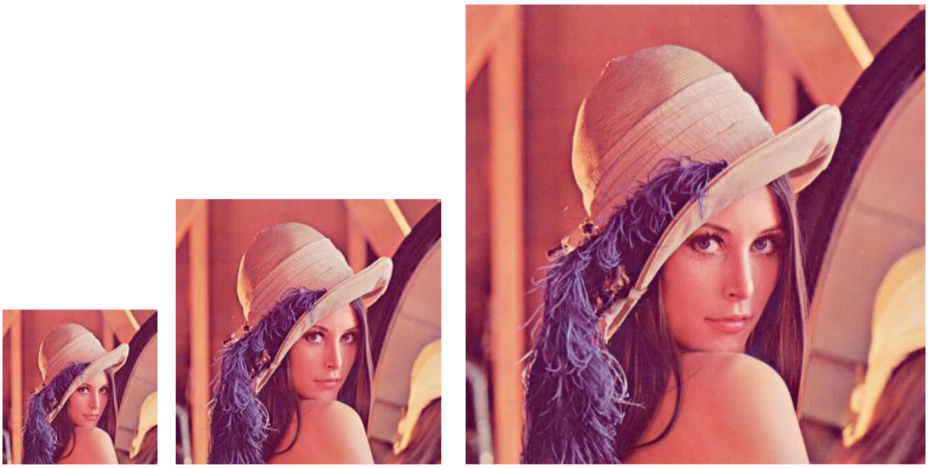
Year /reference	Title	Description	Constraints
1997 [44]	Joint MAP registration and high-resolution image estimation using a sequence of under-sampled images	The research paper has proposed a method for estimating the high-resolution image from under sampled low-resolution images. This method jointly estimates image registration parameters and the high-resolution image with a maximum a posteriori (MAP) framework.	Maximum aposteriori (MAP) framework pre requirement
2007 [120]	Edge-adaptive super-resolution image reconstruction using a Markov chain Monte Carlo approach	In this work, for implementing the super-resolution of images the Markov chain Monte Carlo (MCMC) technique has been used. In order to further enhance the performance an edge-adaptive MCMC framework has been proposed which enhances the edges information of images.	A reconstructed high-resolution image is too smooth may lose much detailed information
2000 [84]	A wavelet-based interpolation--restoration method for superresolution,	This paper has proposed a wavelet based interpolation restoration approach for super-resolution. This approach has less computation burden due to the advantage of the regularity as well as structure inherent in interlaced data used in the interpolation.	Wavelet based approach has been used in the work.
2007 []	A MAP approach for joint motion estimation, segmentation, and super-resolution	The presented work has proposed a method which sensibly combines motion estimation, segmentation, and super-resolution together. It is done by maximum a posteriori (MAP) framework. This paper proposes a joint formulation for a complex super-resolution problem.	A hybrid method leading to much consumption.
2010 [134]	Robust Web Image/Video Super--Resolution	The research paper combines adaptive regularization and learning-based super-resolution for obtaining the practical solution of super-resolution .	The work is focused on web images/videos.
2016 [111]	Single picture super-resolution of natural images using N-Neighbor Adaptive Bilinear Interpolation and absolute asymmetry based wavelet hard thresholding.	The work is based on single image super-resolution of images with N- neighbor adaptive bilinear interpolation combined with the wavelet hard thresholding for better visual results.	This method is again a hybrid method based on wavelet and adaptive thresholding.

of data, which is very crucial for these methods, but the process is very time consuming although giving satisfactory performances [42, 115, 116, 121, 141]. Sparsity based methods require dictionary based models [25, 26, 62, 77, 88, 131, 137] and patch based dictionary learning is there, which is similar to example learning based methods. Sparsity based SR methods are also giving good comparable results. Recently deep learning based methods derived from neural networks are also becoming more popular [23, 24, 45, 63, 64, 71, 103, 136, 138, 142]. Moreover, convolutional neural network based models are becoming more famous because of their good performance. Once the network is trained these methods perform faster than learning based methods, giving better results, but require huge amount of data for trainings and high end GPUs for processing of trainings.

4.7.1 Qualitative analysis

In order to explore the qualitative comparison of the SR methods, a qualitative analysis of the performance of high resolution images has been performed. Simulations have been performed for each class of methods, at least one recent state of the art method from each category of SR has been taken for the performance analysis. Well known qualitative matrices like PSNR, SSIM along with the computational time have been used to compare different existing SR methods for multiple scaling factors. The high resolution image results obtained from state of art SR methods for multiple scaling factors (SF) using 'Lena' test image shown in Fig. 10a have been presented in, Figs. 11 and 12. Fig. 11 demonstrates the super resolved images with scaling factor of '2' and Fig. 12 shows the super resolution image results for the scaling factor of '4'.

The comparison of visual quality of High resolution images has been shown in Fig. 11 and in Fig. 12. Tables 8, 9 and 10 demonstrates the simulations results in terms of well-known quality matrices PSNR and SSIM along with the computational time for different SR methods. Table 8 and Table 9 are for scaling factor of '2' with different size of input images and in Table 10 results have been given for the scaling factor '4'. Results presented in Tables 8, 9 and 10 demonstrates that computational time is least in case of fundamental interpolation based methods, however the quality of the output image is average as shown in Figs. 11 (b), (c) and 12 (b), (c). Bicubic interpolation performs better in terms of PSNR and SSIM than the bilinear interpolation at different scaling factors of '2' and '4'. An edge oriented method proposed in

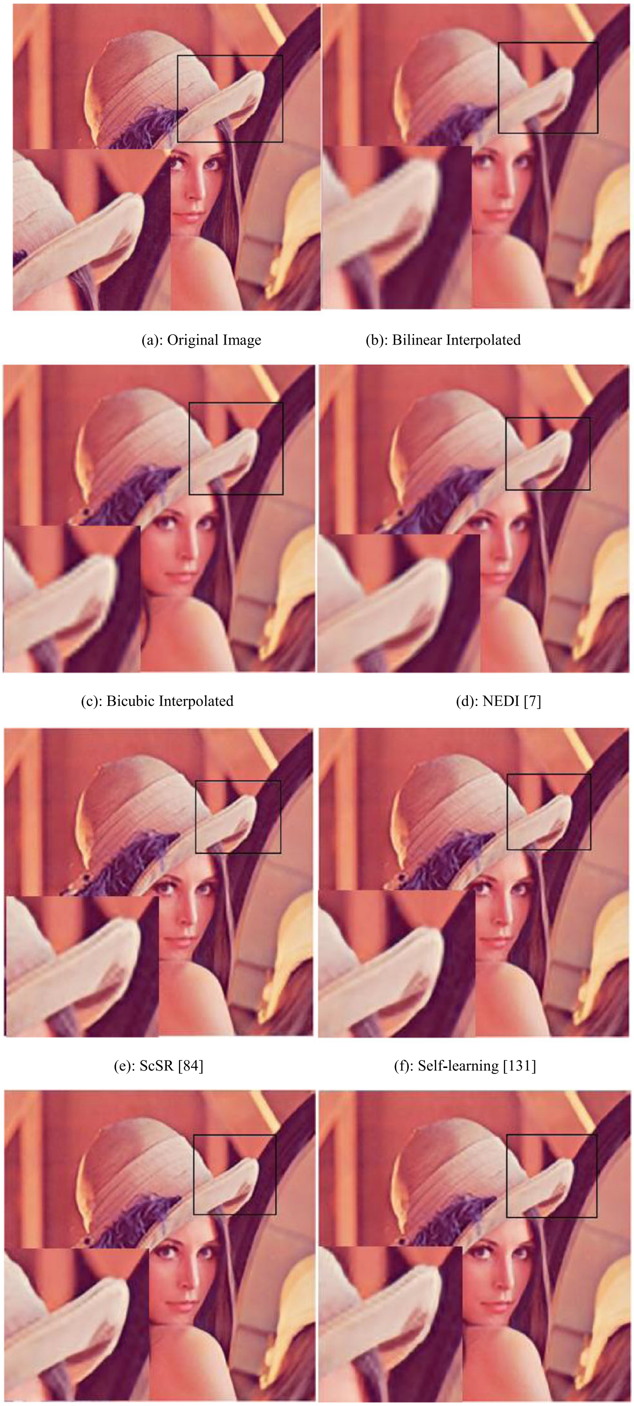


(a): 128 x 128 (b): 256 x 256 (c): 512 x 512

Fig. 10 Test Image 'Lena' of different sizes

Fig. 11 (a) –(h) High resolution Images obtained using various existing SR methods with scaling factor of ‘2’ for input ‘Lena’ image (128 × 128)

NEDI [70] switches among bilinear and covariance based adaptive interpolation for the reconstruction of high resolution image that gives good visual quality for both scaling factors as shown in Figs. 11 (d) and 12(d). With reference to the Tables 8, 9 and 10, the computational complexity and time for this method has been increased with moderate PSNR with better visual quality than the interpolation based methods at different scaling factors of ‘2’ and ‘4’. In the next method [137] (ScSR), it is a Sparsity based method which works on dictionary based usage. The performance time of ScSR may vary depending upon the level of dictionary used. In simulations results as given Tables 8, 9 and 10, it has been observed that ScSR [137] has given good PSNR and SSIM value, however at the same time it takes the higher computational



(a): Original Image (b): Bilinear Interpolated

(c): Bicubic Interpolated (d): NEDI [7]

(e): ScSR [84] (f): Self-learning [131]

(g): SRCNN [141] (h): VDSR [144]

Fig. 12 (a) – (h) High resolution Images obtained using various existing SR methods with scaling factor of '4' for input 'Lena' image (128 × 128)

Table 8 Comparison of different SR Methods using PSNR, SSIM indices along with the computational time for Scaling factor of '2' for input 'Lena' image (128 × 128)

Input Image Size [Pixels]	SR Method	Scaling Factor	PSNR	SSIM	Computational Time (Sec)	Output Image Size [Pixels]
128 × 128	Bilinear Interpolation	2	30.1098	0.9778	0.0722	256 × 256
128 × 128	Bicubic Interpolation	2	31.4441	0.9832	0.0908	256 × 256
128 × 128	NEDI [70]	2	31.0722	0.9804	9.7178	256 × 256
128 × 128	ScSR [137]	2	33.1741	0.9883	50.8581	256 × 256
128 X 128	Self-learning [121]	2	33.3919	0.9887	1105.5649	256 X 256
128 X 128	SRCNN [24]	2	33.5772	0.9892	5.1280	256 X 256
128 X 128	VDSR [63]	2	32.0081	0.986	2.8581	256 X 256

time. The visual results shown in Figs. 11e and 12e for scaling factor of '2' and '4' are also good. In case of self-example based method [121], it is a learning based method which uses the anchored neighborhood regression for the LR to HR mapping. This method has given the good results in terms of PSNR and SSIM but computational time is higher than all other considered methods. The visual quality of method shown in Figs. 11f and 12f is sharper than ScSR [137].SRCNN [24] is based on convolutional neural network, the performance of the method depends upon the training of neural network. VDSR [63] is based on very deep learning where residual learning based network has been used and its performance is faster than SRCNN. SRCNN and VDSR have given the good results in terms of visual quality as given Figs. 11(g-h) and 12(g-h). In Tables 8, 9 and 10, both PSNR and SSIM values for SRCNN and VDSR are comparable to the other state of art methods like ScSR and self-learning based methods. However, these methods required to pre-train their network in order to get good results. The residual training concept was used in VDSR which was not used in SRCNN and has taken lesser computational time than SRCNN. Neural network based method specially based on Deep neural networks, take much time to train the network i.e. from hours to days, but once network model is trained, in future that network may result in good performance for SR. It is to mention that the performance of all these methods may vary depending upon the hardware and other parameters used for the execution of these methods, however the comparative performance almost remains same and can be generalized. In order to generalize and to summarize the

Table 9 Comparison of different SR Methods using PSNR, SSIM indices along with the computational time for Scaling factor of '2' for input 'Lena' image (256 x 256)

Input Image Size [Pixels]	SR Method	Scaling Factor	PSNR	SSIM	Computational Time (Sec)	Output Image Size [Pixels]
256 X 256	Bilinear Interpolation	2	31.8635	0.9826	0.0844	512 X 512
256 X 256	Bicubic Interpolation	2	32.9749	0.9862	0.1069	512 X 512
256 X 256	NEDI [70]	2	32.0461	0.9850	43.5115	512 X 512
256 X 256	ScSR [137]	2	34.0972	0.9891	223.5925	512 X 512
256 X 256	Self-learning [121]	2	34.2671	0.9894	1233.4121	512 X 512
256 X 256	SRCNN [24]	2	34.3555	0.9897	32.7591	512 X 512
256 X 256	VDSR [63]	2	33.1496	0.9874	11.6180	512 X 512

Table 10 Comparison of different SR Methods using PSNR, SSIM indices along with the computational time for Scaling factor of '4' for input 'Lena' image (128 x 128)

Input Image Size [Pixels]	SR Method	Scaling Factor	PSNR	SSIM	Computational Time (Sec)	Output Image Size [Pixels]
128 X 128	Bilinear Interpolation	4	27.9215	0.9617	0.0740	512 X 512
128 X 128	Bicubic Interpolation	4	28.6162	0.9655	0.0923	512 X 512
128 X 128	NEDI [70]	4	28.0534	0.9619	44.6136	512 X 512
128 X 128	ScSR [137]	4	29.6868	0.9713	305.5819	512 X 512
128 X 128	Self-learning [121]	4	29.6698	0.9712	1071.6568	512 X 512
128 X 128	SRCNN [24]	4	29.7881	0.972	26.6579	512 X 512
128 X 128	VDSR [63]	4	29.6537	0.9713	11.7791	512 X 512

comparison based on the study of literature and analysis, a comparison between different SR techniques has been presented in tabular form in Table 11.

4.8 Survey Comparison

Super resolution is a very important and classic problem in the image process. It is still an active area of research and many researchers have given their valuable contribution in this area. There are some other survey papers published in the literature [4, 27, 47, 55, 79, 94] which have discussed the various Super Resolution methods. The brief comparative details of year wise surveys are presented in Table 12.

In the proposed survey, an effort has been made to cover all types of the single image based SR techniques. In the presented work firstly challenges of Super Resolution have been stated and then as possible solutions based on different techniques from literature have been presented. In comparison to previous surveys, identified challenges of SR methods along with their year wise progress in different techniques has been explained. In the presented work, each

Table 11 Comparison of single image based super resolution (SISR) Methods

Super Category	Method's Working Model	Training data Set	Output Results Quality	Computation Requirements	Time consumption
Interpolation based SR	Mainly new pixels are calculated based on original neighbor pixels.	No	Average	Lesser	Least compared to other methods
Learning based SR	Based on HR and LR pair based learning	Yes	Good	Very high	Very high
Edge adaptive based SR	Reconstruction based on edge information	No	Average sharp	Average	Average
Sparsity based SR	Dictionary based learning Model	Yes	Good	High	High
Deep Learning/ Neural Network based Methods	Deep learning for Convolutional Neural Network based models	Yes	Highest	High	Firstly high for training afterwards lesser
Fuzzy Network based Methods	Fuzzy inference Models are involved	Yes	Good	Complex	High

Table 12 Year wise surveys comparison on Super Resolution

Year/ Reference	Title	Content/Classification	Scope	Constraints
2013 [94]	Survey on Single image Super Resolution Techniques	In the presented survey Different Techniques on the single image based SR has discussed.	The work includes the Single image based techniques upto year of publication	Recent methods of Deep learning based SISR methods not included; The presented survey is upto 2013.
2016 [55]	A Survey on Single Image Super Resolution Techniques	Various Methods of Single Image Super Resolution are briefly presented.	The study is based on Single Image Super Resolution	limited number of papers are covered.
2017 [4]	Single Image Super Resolution Algorithms: A Survey and Evaluation	Based on algorithms categorization has been presented with evaluations.	Work is including only Single Image based Super Resolution with numerical evaluation.	Some conventional Algorithms are not included in the survey.
2017 [79]	Single-Image Super-Resolution Techniques: A Review	Work is presenting the Single image super resolution (SISR) Based on methods	Work is only including the Single image based Super Resolution.	limited number of papers discussed.
2017 [47]	Multimedia super-resolution via deep learning: a survey	Deep learning based Image Super Resolution has been explained	Presented work is based on Multi image based Deep learning based methods.	Only deep earning based methods have been included in the survey.
2018 [27]	Literature Review on Single Image Super Resolution	Super resolution Technique based division has been briefly presented.	Only a single image based SR covered	The survey covers the limited research in the related field.
Proposed Survey	Survey on Single Image based Super-resolution —Implementation Challenges and Solutions	In the proposed work, challenges and detailed survey of all SISR method are listed with comparison.	Single image based survey covering all published techniques including deep learning based recent methods.	Focused on single image based methods.

method's literature review has been included. In order to summarize the proposed study, Figs. 13 and 14 represents the diagrammatic approach of complete work. In Fig. 13, Distribution of Research Papers selected by publication year has been presented. Fig. 14 represents the distribution of Research Papers selected as per methods for Single image based Super-resolution.

5 Conclusions

In the proposed work various issues related to the implementation of Super Resolution (SR) along with Single Image based Super Resolution implementation methods published in literature have been presented. Basically, super-resolution is an inverse problem, considerably there are various challenges to achieve it. It is one of the classic problems where various researchers have given their contribution by proposing various methods in order to implement the Super-resolution. Details of various techniques for Single image based Super resolution

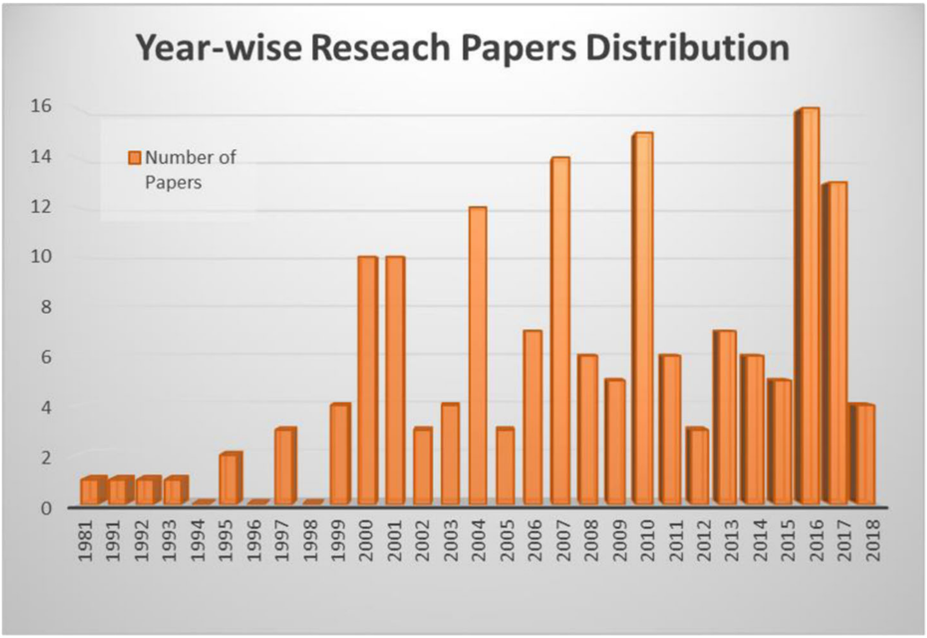


Fig. 13 Distribution of Research Papers selected by publication year

from beginning to current methods have been discussed in the paper. The comparison based on simulations is also presented for various state of art methods. However, depending upon the particular application, suitable SR technique could be selected. Moreover, in today's time, everything is digital and need for data transportation is increasing which may also contain

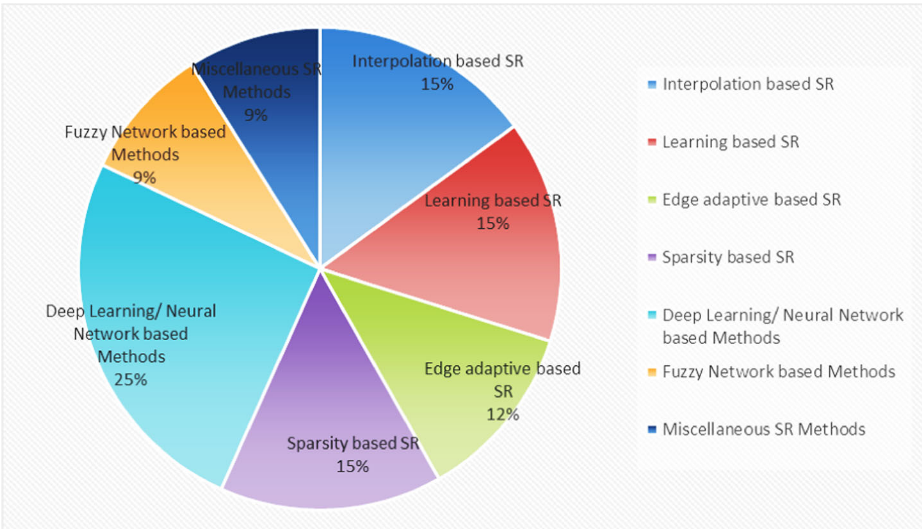


Fig. 14 Distribution of Research Papers selected as per methods for Single image based SR

multimedia data i.e. images and videos. Therefore, many times images are compressed or converted to low resolution with various standards and clearly there is always a need for the reverse process of compression like Super-resolution. As a conclusive remark, it could be stated that there is a basic need of low computational fast SR methods which could be implemented for real time applications with acceptable quality of resultant images.

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