SR Image Reconstruction Methods - A Survey

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Abstract: **The key objective of super-resolution (SR) imaging is to reconstruct a higher-resolution image based on a set of images, acquired from the same scene and denoted as 'low-resolution' images, to overcome the limitation and/or ill-posed conditions of the image acquisition process for facilitating better content visualization and scene recognition. In this paper we study and represent various techniques of image super resolution (SR), it is also called as super resolution reconstruction. The SR image approaches reconstruct a single higher-resolution image from a set of given lower-resolution images, reconstruct an image sequence with a higher-resolution from a group of adjacent lower-resolution image frames. We have represented various existing super resolution techniques, advantages and disadvantages of those techniques, recent work and recent methods of super resolution reconstruction method. Finally we have presented challenge issues and future research directions for super resolution.**

Keywords Super-resolution imaging · Regularization · Resolution enhancement

INTRODUCTION:

Super-resolution, loosely speaking, is the process of recovering a high-resolution image from a set of low resolution input images. Any given set of source low resolution (LR) images only captures a finite amount of information from a scene; the goal of SR is to extract the independent information from each image in that set and combine the information into a single high resolution (HR) image. For examples, a high resolution image is beneficial to achieve a better classification of regions in a multi-spectral remote sensing image or to assist radiologist for making diagnosis based on a medical image.

The most direct approach on obtaining higher-resolution images is to improve the image acquisition device (e.g., digital camera) by reducing the pixel size on the sensor (e.g., charge-coupled device). However, there is a limitation in reducing the sensor's pixel size in the sensor technology. When the sensor's pixel size becomes too small, the captured image quality will be inevitably degraded [10]. This is due to the fact that the noise power remains roughly the same, while the signal power decreases proportional to the sensor's pixel size reduction. Furthermore, higher cost is required to increase the chip size. SR techniques can prove useful in many different applications, and these applications can have different requirements in terms of both quality and computational complexity. The quality may also vary for different methods based on characteristics of the input image. The implementation complexity may be affected by implementation specifics, such as the availability of specific optimized libraries. Finally the artefacts caused by poor SR performance can be more visually distracting than blurring from interpolation. For these and other reasons choosing between SR methods is a complex task.

A variety of approaches have been proposed for solving the super-resolution problem. Initial attempts worked in the frequency domain, typically recovering higher frequency components by taking advantage of the shifting and aliasing properties of the Fourier transform. Deterministic regularization approaches, which work in the spatial domain, enable easier inclusion of a priori constraints on the solution space. Stochastic methods have received the most attention lately as they generalize the deterministic regularization approaches and enable more natural inclusion of prior knowledge. Other approaches include non-uniform interpolation, projection onto convex sets, iterative back projection, and adaptive filtering. With the increased emphasis on stochastic techniques has also come increased emphasis on learning priors from from example data rather than relying on more heuristically derived information.

To understand the SR imaging, several fundamental concepts are required to be clarified. First, it is important to note that an image's resolution is fundamentally different from its physical size. Fig 1 shows a framework of super-resolution imaging.

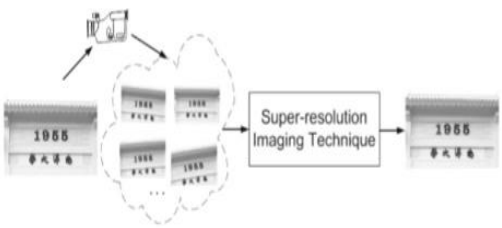

Fig. 1 A framework of super-resolution imaging

In our context, the objective of SR imaging is to produce an image with a clearer content from its low-resolution counterpart (e.g., producing Fig. 2f from Fig.2a–d), rather than simply achieving a larger size of image (e.g., Fig. 2e is produced by applying pixel duplication on Fig.2a). In other words, the main goal and the first priority of super-resolution imaging is to 'fuse' the contents of multiple input images in order to produce one output image containing with more clear and detailed contents.

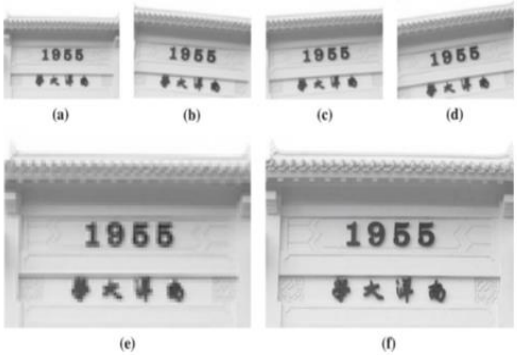

Fig. 2 a–d Four test images NTU (70×90, each); e An enlarged image (280×360) by applying pixel duplication method on the image (a); f An enlarged image (280×360) by applying a SR algorithm based on the images (a)–(d)

The physical size of the output image (in terms of total number of pixels) could be the same as any one of the input images or subject to further enlargement using an image interpolation method. Second, in our context, the term resolution of super-resolution is referred to the spatial resolution of the image, not the temporal resolution of the image sequence. The latter is commonly expressed in terms of the number of frames captured per second (i.e., frame rate). Third, it is worth while to note that the term super resolution has been used in other research areas as well.

The paper is organized as follows. Section 2 presents a description of the general model of imaging systems (observation model) that provides the SR image computation. Section 3 presents the SR image reconstruction approaches that reconstruct a single high-resolution image from a set of given low-resolution images acquired from the same scene. Section 4 presents the comparison of various SR techniques. Each section begins with some introductory remarks, followed by an extensive survey of existing approaches. Section 5 discusses several research challenges that remain open in this area for future investigation. More specifically, we discuss the SR computations for multi-view images. Finally, Sect. 6 concludes this paper.

OBSERVATION MODEL FOR SUPER-RESOLUTION IMAGE

In this section, observation models of the imaging system are presented to formulate the SR image reconstruction problem.

As depicted in Fig. 3, the image acquisition process is modelled by the following four operations: (i) geometric transformation, (ii) blurring, (iii) down-sampling by a factor of q1 ×q2, and (iv) adding with white Gaussian. Note that the geometric transformation includes translation, rotation, and scaling. Various blurs (such as motion blur and out-of-focus blur) are usually modelled by convolving the image with a low-pass filter, which is modelled by a point spread function (PSF)[3].

The given image (say, with a size of M1×M2) is considered as the high-resolution ground

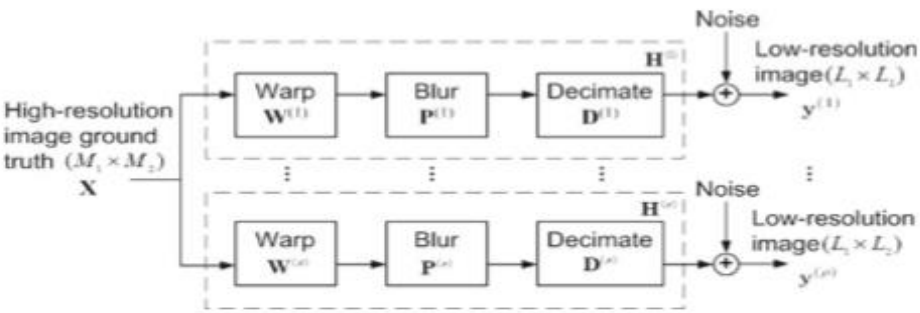

Fig. 3 The observation model, establishing the relationship between the original high-resolution image and the observed low-resolution images. The observed low-resolution images are the warped, blurred, down-sampled and noisy version of the original high-resolution image[3]

truth, which is to be compared with the high-resolution image reconstructed from a set of low-resolution images (say, with a size of L1 × L2 each; that is, L1 = M1/q1 and L2 = M2/q2) for conducting performance evaluation. To summarize mathematically,

$$y^{(k)} = D^{(k)}P^{(k)}W^{(k)}X + V^{(k)}, \quad (1)$$

$$= H^{(k)}X + V^{(k)}, \quad (2)$$

Where $y^{(k)}$ and X denote the k th L1×L2 low-resolution image and the original M1×M2 high-resolution image, respectively, and k =1,2,...,ρ. Furthermore, both $y^{(k)}$ and X are represented in the lexicographic-ordered vector form, with a size of L1L2×1 and M1M2×1, respectively, and each L1×L2 image can be transformed (i.e., lexicographic ordered) in to a L1L2×1 column vector, obtained by ordering the image row by row. = $D^{(k)}$is the decimation matrix with a size of L1L2× M1M2, $P^{(k)}$is the blurring matrix of size M1M2 × M1M2, and $W^{(k)}$is the warping matrix of size M1M2×M1M2. Consequently, three operations can be combined into one transform matrix $H^{(k)} = D^{(k)} P^{(k)} W^{(k)}$with a size of L1L2 × M1M2. Lastly, $V^{(k)}$ is a L1L2 ×1 vector, representing the white Gaussian noise encountered during the image acquisition process. Note that $V^{(k)}$is assumed to be independent with X. Over a period of time, one can capture a set of (say, ρ) observations $y^{(1)}, y^{(2)},\ldots\ldots y^{(p)}$

With such establishment, the goal of the SR image reconstruction is to produce one high-resolution image X based on $y^{(1)}, y^{(2)},\ldots\ldots y^{(p)}$

It is important to note that there is another observation model commonly used in the literature (e.g., [34–37]). The only difference is that the order of warping and blurring operations is reversed; that is, $y^{(k)} = D^{(k)} W^{(k)}P^{(k)} X = V^{(k)}$. When the imaging blur is spatio-temporally invariant and only global translational motion is involved among multiple observed low-resolution images, the blur matrix $P^{(k)}$ and the motion matrix $W^{(k)}$ are commutable[3]. Consequently, these two models coincide. However, when the imaging blur is spatio-temporally variant, it is more appropriate to use the second model. The determination of the mathematical model for formulating the SR computation should coincide with the imaging physics (i.e., the physical process to capture low resolution images from the original high-resolution ones)[7].

SUPER RESOLUTION IMAGE RECONSTRUCTION:

At present there are various super resolution reconstruction algorithms are available we will discuss some of them here.

1. Non-uniform Interpolation

The basis of non-uniform interpolation super-resolution techniques is the non-uniform sampling theory which allows for the reconstruction of functions from samples taken at non-uniformly distributed locations [18]. Early super-resolution applications used detailed camera placement to allow for accurate interpolation, because this method requires very accurate registration between images.

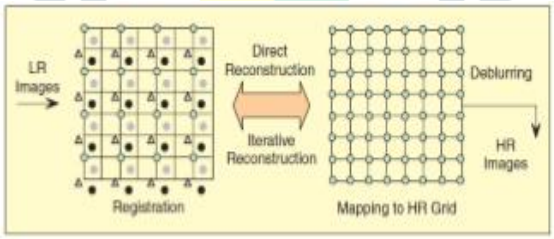

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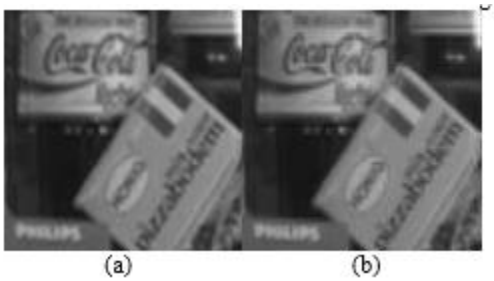
Figure 4.1: Registration-interpolation-based reconstruction [18].

A new method was developed to overcome the limitations of insufficient registration accuracy by applying multiple digital sensors with different pixel sizes [18], [19], [20]. This ensures that pixels of multiple images will not coincide regardless of camera placement. Non-uniform interpolation is a basic and intuitive method of super-resolution and has relatively low computational complexity, but it assumes that the blur and noise characteristics are identical across all low-resolution images as shown in figure 4.1 [18]. Figure 4.2 [18] shows results obtained by various interpolation methods for super resolution of image. The advantage of this approach is that it takes relatively low computational load and makes real-time applications possible [18], [19]. However, in this approach, degradation models are limited they are only applicable when the blur and the noise characteristics are the same for all LR images [18], [20].



2. Projection onto Convex Sets

This method is based on a linear model describing the relation of HR and LR images, a cost function is introduced and the HR image is obtained [18]. POCS algorithm has many

Figure 4.2: Nonuniform interpolation SR reconstruction results by (a)nearest neighbour interpolation, (b) bilinear interpolation, (c) nonuniform interpolation using four LR images, and (d) debluring part (c) [18].

advantages like simplicity; it can be applied to the occasion with any smooth movement, and can easily join in the prior information, so this method is widely used. But POCS algorithm is strict to the accuracy of movement estimation [18]. So in order to improve the stability and performance of the algorithm, the relaxation operator will be used to replace ordinary projector operator, at the same time it is not contributing to the resumption of the edge and details of images. This method is based on a linear model describing the relation of HR and LR images, a cost function is introduced and the HR image is obtained. POCS algorithm has many advantages like simplicity, it can be applied to the occasion with any smooth movement, and can easily join in the prior information, so this method is widely used [18]. But POCS algorithm is strict to the accuracy of movement estimation. So in order to improve the stability and performance of the algorithm, the relaxation operator will be used to replace ordinary projector operator, at the same time it is not contributing to the resumption of the edge and details of images [18]. However, the linear model used in this method is an ill-posed problem in the sense that its transformation matrix may be singular and so a unique solution cannot be obtained. The advantage of POCS is that it is simple, and it utilizes the powerful spatial domain observation model [18]. These methods have the disadvantages like non-uniqueness of solution, slow convergence, and a high computational cost. Figure 4.3 shows various results of this method.

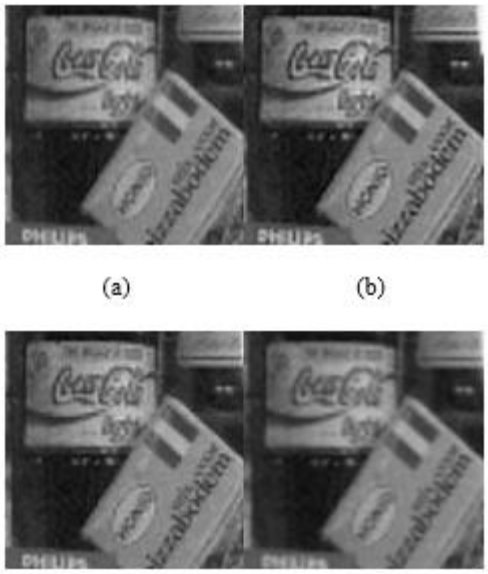


Figure 4.3: POCS SR results (a) by bilinear interpolation and by POCS after (b) 10 iterations, (c) 30 iterations, and (d) 50 iterations [18].

3. Frequency Domain Method

The frequency domain approach makes explicit use of the aliasing that exists in each LR image to reconstruct an HR image [3]. Tsai and Huang first derived a system equation that describes the relationship between LR images and a desired HR image by using the relative motion between LR images. The frequency domain approach is based on the following three principles [18]. (1) the shifting property of the Fourier transform, (2) the aliasing relationship between the continuous Fourier transform (CFT) of an original HR image and the discrete Fourier transform (DFT) of observed LR images, (3) and the assumption that an original HR image is band limited. These properties make it possible to design the system equation relating the aliased DFT coefficients of the observed LR images to a sample of the CFT of an unknown input image [19]. For example, let us assume that there are two 1-D LR signals that are sampled below the Nyquist sampling rate. From the above stated principles, the aliased LR signals can be decomposed into the unaliased HR signal as shown in Figure 4.4.

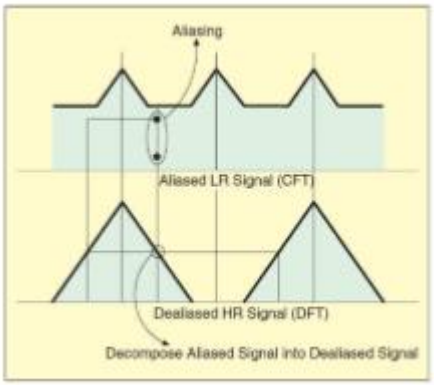


Figure 4.4: Aliasing relationship between LR image and HR image [2].

4. Sparse Representation Method

This method is based on single-image super resolution, which is based on sparse signal representation. Researchers in imaging field suggest that image patches can be well represented as a sparse linear combination of elements from an appropriately chosen over-complete dictionary [2], [18]. Learning an over-complete dictionary capable of optimally representing broad classes of image patches is a difficult problem. It is difficult to learn such a dictionary or using a generic set of basis vectors (e.g., Fourier), so for simplicity one can generate dictionaries by simply randomly sampling raw patches from training images of similar statistical nature [2]. Researchers suggest that simple prepared dictionaries are already capable of generating high-quality reconstructions, when used together with the sparse representation prior. Figure 4.5shows several training images and the patches sampled from them.

Figure 4.5: Left: three training images which are used in experiments. Right: the training patches extracted from them.

By jointly training two dictionaries for the low- and high-resolution image patches, one can enforce the similarity of sparse representations between the low-resolution and high resolution image patch pair with respect to particular dictionaries [22], [23]. So, the sparse representation of a low-resolution image patch can be applied with the high-resolution image patch dictionary to generate a high-resolution image patch [22], [23]. The learned dictionary pair is a more compact representation of the patch pairs. The effectiveness of such approach is demonstrated for both general image super-resolution (SR) and the special case of face hallucination [22]. Figure 4.6 shows some results obtained by this method.

Figure 4.6: The flower and girl image magnified by a factor of 3. Left to right: input, bicubic interpolation, neighbour embedding, sparse representation, and the original image [22].

5. Super Resolution through Neighbour Embedding

This method is used for solving single-image super-resolution problems [23]. Given a low resolution image as input, objective is to recover its high-resolution counterpart using a set of training examples [23], [24]. In a recent neighbor embedding method based on Semi-nonnegative Matrix Factorization (SNMF) only nonnegative weighs are considered [24]. In LLE the weights are constrained to sum up to one, but no constraints are specified for their sign [23]. This might explain the unstable results observed in [9], since possible negative weights can lead to having subtractive combinations of patches, which is counterintuitive. This method is based on assumption that small patches in the low- and high-resolution images form manifolds with similar local geometry in two distinct spaces. In this method each low- or high-resolution image is represented as a set of small overlapping image patches [24],. Each patch is represented by a feature vector. The feature may be contrast, correlation, entropy, variance, sum of average, sum of variance, homogeneity, variance of difference, sum of entropy, difference of entropy, change of luminance, [9] etc. Figure 4.7 shows one example of such a patch generation.

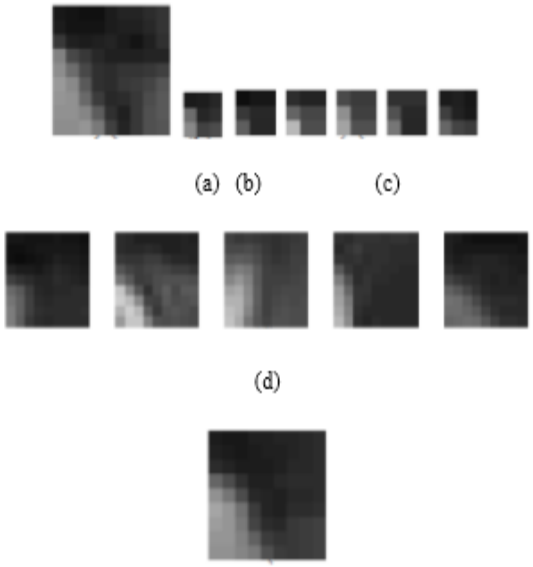


Figure 4.7:Neighbor embedding procedure applied to a low-resolution patch for 3X magnification: (a) true high-resolution patch; (b) input low-resolution patch down sampled from (a); (c) five nearest neighbour low-resolution patches from the training images; (d) high-resolution patches from the training images corresponding to the low-resolution patches in (c); (e) target high-resolution patch constructed from (d). [9]

This method is also called as learning based method for super resolution; this method has been inspired by recent manifold learning methods, particularly locally linear embedding (LLE) [8], [23]. In that method small image patches in the low and high resolution images form manifolds with similar local geometry in two distinct feature spaces. As in LLE, local geometry is characterized by how a feature vector corresponding to a patch can be reconstructed by its neighbours in the feature space [9].

Also using the training image pairs to estimate the high-resolution embedding, some researchers have enforced local compatibility and smoothness constraints between patches in the target high-resolution image through overlapping. Experiments show that this method is very flexible and gives good empirical results [8], [9], [10].Figure 4.8 shows some results of this method with available high resolution training image and input low resolution image.

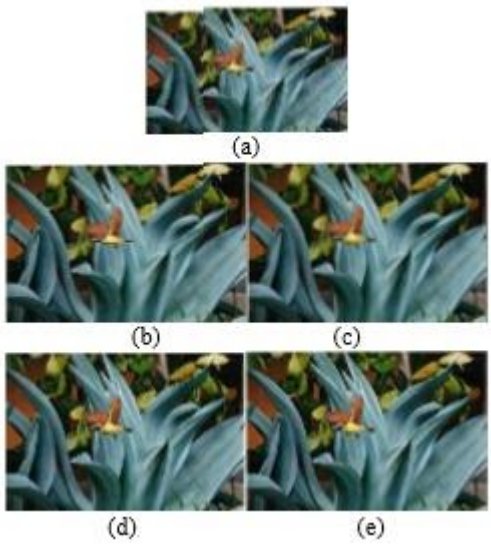


Figure 4.8: 3X magnification of the bird image: (a) input low-resolution image; (b) true high-resolution image; (c) median filtering; (d) cubic spline interpolation; (e) Neighbour Embedding method [9].

COMPARISON OF VARIOUS SUPER RESOLUTION TECHNIQUES

Comparisons of super-resolution techniques have been mainly concerned with what assumptions are made in the modelling of the super-resolution problem. The blurring process to be known or those regions of interest among multiple frames are related through global parametric transformations, these are the assumptions one has to make. Other models take into account arbitrary sampling lattices, physical dimension of sensor, a non-zero aperture time, focus blurring, and more advanced additive noise models. To simplify a model many times these assumptions are chosen and are usually used in a specific method [2], [12].

In addition, methods that do not make these assumptions have not demonstrated objectively that removing these assumptions gains better super-resolution reconstruction performance. Signal-to-noise ratio (SNR), Peak signal-to noise ratio (PSNR), Root mean square error (RMSE), mean absolute error (MAE), and mean square error (MSE) have all been used as objective measures of super-resolution accuracy; however, the outstanding method of presenting results is clearly subjective to visual quality [12], [13].

CHALLENGE ISSUES FOR SUPER RESOLUTION

Image registration

Image registration is critical for the success of multi-frame SR reconstruction, where spatial samplings of the HR image are fused. The image registration is a basic image processing problem that is well known as ill-posed. The problem is more difficult in the SR setting, where the observations are low-resolution images with heavy aliasing artefacts [12]. The performance of the standard image registration algorithms decreases as the resolution of the observations goes down, resulting in more registration errors. Degradations caused by these registration errors are visually more annoying than the blurring effect resulting from interpolation of a single image [12].

Computation Efficiency

Another difficulty limiting practical application of SR reconstruction is its intensive computation due to large number of unknown samples, which require expensive matrix manipulations [12]. Real applications always demand efficiency of the SR reconstruction to be of practical utility.

Robustness Prospects

Traditional SR techniques are vulnerable to the presence of deviation due to motion errors, inaccurate blur models, noise, moving objects, motion blur, moving scene etc. Robustness of SR is of interest because the image degradation model parameters cannot be estimated perfectly, and sensitivity to deviations may result in visual degradations, which are unacceptable in many applications, e.g., video standard conversion [12], [13].

FUTURE RESEARCH DIRECTIONS

Degradation Models

Accurate degradation/observation models promise improved SR reconstructions. Several SR application areas may benefit from improved degradation models. For improved reconstruction of compressed video, degradation models for lossy compression schemes are most promising one to use [12].

Motion Estimation

SR enhancement of random scenes containing global, multiple independent and individual motion, occlusions, transparency etc. is a main focus of SR research. Obtaining this is critically dependent on robust, model based, sub-pixel accuracy motion estimation and segmentation techniques is a crucial research problem [13]. Motion is typically estimated from the observed under-sampled data.

Restoration Algorithms

MAP and POCS based algorithms are very successful. Hybrid MAP/POCS restoration techniques will combine the mathematical stiffness and uniqueness of solution of MAP estimation with the convenient a priori constraints of POCS [2], [13]. Simultaneous motion estimation and restoration gains improved reconstructions since motion estimation and reconstruction are correlated. Separate motion estimation and restoration, as is commonly done, is sub-optimal as a result of this interdependence. Simultaneous multi-frame SR restoration is expected to achieve higher performance since additional spatio-temporal constraints on the SR image ensemble may be included. In SR reconstruction this technique has limited application.

CONCLUSION

The researches on super-resolution image reconstruction mainly consider the situation that degraded model is linear. Noise is not much concerned and systemic analysing method and filter designing method have not been formed yet [25], [26]. As different methods of super-resolution have been developed using models with unequal assumptions of the existing problem, and because the results provided have been primarily based on subjective measurements, it is difficult to find an unbiased comparison on what super-resolution methods are more appropriate for a given task. There must be considerations like if more than one input images are present then use multi frame super resolution approach and if one or more high resolution training images are available then use single image super resolution approach. If we do not want registration step then we can use single frame image resolution. Also if high resolution training is not available but different low resolution images are available for same scene than one must have to use multi frame super resolution. This does not provide a clear method of comparing different implementations suitability for a desired application, so one have to implement super resolution method based on problem model which can be generalized to all SR reconstruction problems.

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