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Enhancing the Still Image Using Super Resolution Techniques: A Review

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Abstract
Super Resolution (SR) refers to the reconstruction of images that are visually superior to the original low resolution (LR) images by bandwidth extrapolation beyond the pass band of the imaging system. Tsai and Hunag were the first to consider the problem of SR in 1984. Onwards over three decade various researchers contributed in the field of SR but all are intuitive SR mechanisms. This paper reviews the recent SR techniques. From the observations, the SR techniques are classified as; frequency domain or spatial domain techniques, but also need to classify SR techniques based on SR using multiple LR or single LR image(s). Survey carried by us revels that, the researches on SR reconstruction mainly considered the linear degraded model, results provided are mostly based on subjective measurements, and it is difficult to find an unbiased comparison. There must be considerations for number of available LR or HR image(s) for selection of appropriate SR technique. Hence, there is need to provide a clear method of comparing different implementations suitability, so one has to implement SR method based on problem model which can be generalized to all SR reconstruction problems.

Keywords: *Super Resolution, Registration, Reconstruction, Subpixel, Aliasing, Blurring*

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INTRODUCTION

Super Resolution (SR) is a technique to enhance the resolution of an image using multiple Low Resolution (LR) images, which extract the significant information from the images. SR often implies bandwidth extrapolation beyond the pass band of the imaging system, as additional spatio-temporal information available in the sequence of LR images enables reconstruction at resolutions higher than. Hence, there is a need to find a technique to enhance the current resolution level. It is desirable to have the High Resolution level close to that of an analog 35 mm film that has no visible artifacts when an image is magnified.

In conventional cameras, the resolution depends on CCD sensor density, which may not be sufficiently high [1]. For SR hardware solution is to reduce the pixel size by sensor technology. Reduction in pixel size leads to less availability of light to individual sensor, results in generation of shot noise that degrades the quality. Another way is to increase the chip size, which leads to an increase in capacitance, which limits the charge transfer rate and response time [2]. Hence signal processing approach is preferred for super-resolution.

In the super resolution technique, several LR images are considered to obtain HR image. LR images with some sub pixel variation between them are identified to recover lost information during capturing. The information contained about the object in multiple images and the knowledge of transformations between the images can enable to obtain a better image of the object. As single image interpolation cannot recover the high-frequency components loss. Multiple image SR technique utilizes multiple data sets in which additional data constraints from several observations of the same scene can be used. The combined information from various observations of the same image allows the SR reconstruction of the image.

SR reconstruction is an ill-posed inverse problem. Multiple possible solutions exist for given a set of images. The most probable solution is to constrain the solution space according to a-priori knowledge. This may include certain constraints. Inclusion of such constraints is critical to achieve high quality super-resolution reconstructions. Large emphasis will be placed on techniques which enable the inclusion of a-priori knowledge [3]. LR images are subsampled (aliased), shifted, rotated and scaled with subpixel precision. If the LR images are shifted by integer units, then there is repetition of same information which cannot be used to reconstruct HR image. If the LR images have different fractional pixel shifts from each other and aliasing is present, then each image cannot be obtained from the others.

In such cases, the new information contained in each LR image can be exploited to obtain HR image. Multiple LR images can be obtained from one camera with several captures or from multiple cameras located in different positions. If these LR images has shift and rotation motions and are known or can be estimated within subpixel accuracy, then SR image reconstruction is possible. The recorded image suffers from blur, noise, and aliasing effects. The aim of SR techniques is to restore HR image from many degraded and aliased LR images.

The image restoration is to recover a degraded image, but it does not increase the size of image. Also single image interpolation cannot recover the high-frequency components lost or degraded during sampling. So need to utilize multiple data sets in which additional data constraints from several observations of the same scene may be used. Before the review of various SR methodologies, let first model the LR image acquisition process, which provides input for processing the image through various steps to obtain SR image with more quality.

Rest of the paper is organized as follows: next section explains the generalized Observation model. Subsequent sections explore the Frequency Domain algorithms and Spatial Domain methods. Separate section summarizes the spatial domain methods. Last but one section classifies and explores SR methods by an alternative way, i.e., using single or multiple LR images (A-Using multiple LR images and B-Using single LR image) and last section summarizes the survey of all SR techniques.

OBSERVATION MODEL

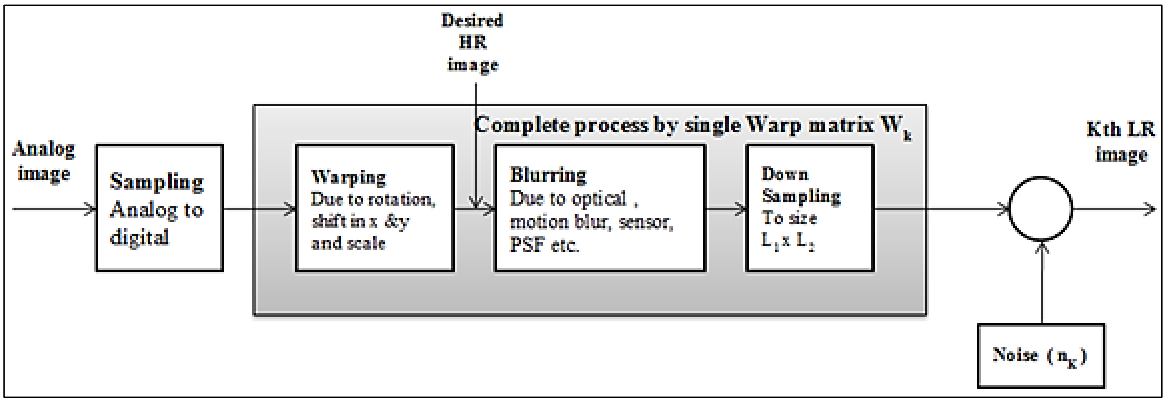

Fig. 1: *Observation Model (Relate LR images to HR Image).*

Observation model shown in Figure 1 provides a way to relate LR images to SR image which can be implemented with various ways of processing. The first step is, to formulate an observation model that relates the original HR image to the observed LR images. Several observation models have been proposed in the literature. The observation model for still images is considered here as it is easy to extend the still image model to the video sequence model. Consider the desired HR image of size L_1N_1 X L_2N_2 as the vector $x=[x_1, x_2, ... , x_N]^T$, where, $N= L_1N_1$ X L_2N_2. Namely, x is the ideal undegraded image that is sampled at or above the Nyquist rate from a Analog scene which is assumed to be bandlimited. The parameters $L_1$and L_2 represent the down-sampling factors for the horizontal and vertical directions, respectively. So, each observed LR image is of size N_1 X N_2. Let the k^{th} LR image be denoted as $y_k=[y_{k,1}, y_{k,2}, \ldots, y_{k,M}]^T$, for k =*1,2, , ... , p* and M = N_1 X N_2. Now, it is assumed that x remains constant during the acquisition of the multiple LR images, except for any motion and degradation allowed by the model. Therefore, the observed LR images result from warping, blurring, and subsampling operators performed on the HR image x. Assuming that each LR image is corrupted by additive noise,we can then represent the observation model as [1].

$$y_k = D B_k M_k x + n_k \quad \text{for } 1 \leq k \leq p \quad \ldots. \quad (1)$$

where, M_k is a warp matrix, B_k represents a blur matrix, D is a subsampling matrix, and n_k represents a noise vector. A block diagram for the observation model is described in Figure 1. The motion that occurs during the image acquisition is represented by warp matrix M_k. It may contain global or local translation, rotation, and scaling. As this information is unknown, there is need to estimate the scene motion for each LR frame with reference to one particular LR frame.

The warping process performed on HR image x is actually defined in terms of LR pixel spacing when we estimate it. The models can be unified in a simple matrix-vector form, as the LR pixels are expressed I terms of a weighted sum of the related HR pixels with additive noise. Hence express these models without loss of generality as:

$$y_k = W_k x + n_k, \; k = 1, \ldots, p, \quad \ldots.. \quad (2)$$

where, matrix W_k represents, via blurring, motion, and subsampling, the contribution of HR pixels in x to the LR pixels in y_k. Based on the observation model in Eq. (2), the SR image reconstruction is to estimate the HR image x from the LR images y_k for k =*1,.... , p*. The process of SR mainly consist of the stages as:

1) Registration- estimation of motion parameters like rotation, shift and scale factor.
2) Interpolation- places the subpixel information from LR images on HR Grid.
3) Reconstruction- estimation of high frequency information and removal of blur and noise.

Since, past three decades various algorithms are proposed to obtain HR image from LR image(s) using the various observation models. The subsequent sections explore the classification of SR algorithms. At highest level, super-resolution techniques can be divided into frequency domain or spatial domain algorithms. However, due to various algorithms proposed in last decade, there is another way to classify them, i.e., SR using single LR image or multiple LR images.

FREQUENCY DOMAIN ALGORITHMS

These algorithms mostly utilize the shifting property of the Fourier transform to model global translational scene motion, and take advantage of the sampling theory to enable effect restoration made possible by the availability of multiple observation images. Under the assumption of global translational motion, frequency domain methods are computationally efficient. Tsai and Hunag were the first to consider the problem of obtaining a high-quality image from several down sampled and translationally displaced images in 1984 [4]. Authors in [4] formulated a set of equations in the frequency domain, by using the shift property of the Fourier transform without considering Optical blur or noise. A finite object imaged by diffraction limited system can be perfectly resolved by extrapolation in the Fourier domain.

Extrapolation of the spectrum of an object beyond the diffraction limit of the imaging system is called SR [5]. This method, though computationally attractive, has significant disadvantages, as assumption of ideal sampling is unrealistic. The possibility of an optical system point spread function (PSF) or that of spatially integrating sensors is not considered. Observation noise, blurring due to finite aperture time are not addressed.

Tekalp *et al.* [6] extended Tsai-Huang formulation by including the PSF of the imaging system and observation noise. Formulation of the system of equations requires knowledge of the translational motion between frames to sub-pixel accuracy. Solution of the equations requires that each observation contribute independent equations, so places restrictions on the inter-frame motion that contributes useful data. Accuracy of the motion estimates is the limiting factor in SR reconstruction performance. A simultaneous multi-frame image registration algorithm is proposed which provides reliable registration parameters even under the conditions of severe under sampling, with a sufficiently large number of observation frames. The alias relationship in matrix form given as,

$$Y=\Phi F \quad \ldots\ldots \tag{3}$$

Here, Y is R x 1 each element is DFT coefficient of LR shifted images, Φ is a matrix which relates the DFT of the observation data to samples of the unknown Continuous Fourier Transform (CFT) of HR. SR reconstruction therefore is reduced to finding the DFT's of the observed images, determining Φ and then using the inverse DFT to obtain the reconstructed image. System matrix Φ requires knowledge of the translation, which is not typically known a-priori; these parameters must be estimated before reconstruction by registration.

An approach based on a least squares formulation for the solution of Eq. (3) which is implemented in a recursive fashion to improve computational efficiency. Recursive solution approach is computationally attractive, while the least squares formulation provides the advantage of a measure of robustness in the case of an under or over determined system. To overcome the inability to accommodate non-global motion models, observation images are decomposed into overlapping blocks; translational motion is estimated for these blocks in the observation sequence frames.

A extensions of the recursive least squares is that of recursive total least squares which provide some degree of robustness to errors in the observation model, which are likely, in the case of SR reconstruction, to result from errors in motion estimation. It includes a degree of robustness to errors in both the matrix Φ and the observation vector Y in Eq. (3). Also, multichannel sampling theorem based techniques of the reconstruction are implemented in the spatial domain; the technique is fundamentally a frequency domain technique relying on the shift property of the Fourier transform to model the translation of the source imagery.Various transforms are used by researchers to decompose the image in frequency domain. The discrete wavelet transform (DWT) is used by most of the authors to analyze or decompose the images, called as decomposition or analysis. DWT is applied in order to decompose an input image into different subbands. Then the high frequency subbands are manipulated to obtain HR image. Those components can be assembled back into the original image without loss of information. This process is called reconstruction.

Chappalli and Bose [7] used wavelet coefficients thresholding for reducing spatial domain noise in wavelet-based SR algorithms. However, the choice of optimal threshold is a tradeoff between noise filtering and blurring introduced by thresholding in second-generation wavelet SR (SGWSR) algorithm. Turgay Celik and Tardi Tjahjadi [8] proposed a complex wavelet-domain image resolution enhancement algorithm based on the estimation of wavelet coefficients. The HR image is reconstructed from the LR image, together with a set of wavelet coefficients, using the inverse Dual-Tree Complex Wavelet Transform (DT-CWT). The set of wavelet coefficients is estimated from the DT-CWT decomposition of the rough estimation of the HR image. Generate the initial estimate (Y) of the HR image; decompose Y using one-level DT-CWT to create a low- and high-pass matrix structure $[LP_Y\ HP_Y]$; formulate a matrix structure $[X_L\ HP_Y]$ using $[LP_Y\ HP_Y]$ and the input LR image X_L; and generate the HR image by employing the IDT-CWT on $[X_L\ HP_Y]$.

Gajjar and Joshi [9] proposed a learning-based approach as given in the schematic representation in Figure 2. Authors first obtained an initial HR estimate by learning the high frequency details from the available database. DWT based approach is proposed for learning that uses a set of LR images and their corresponding HR versions. The aliasing matrix entries are estimated using the test image and the initial HR estimate. The prior model for the super-resolved image is chosen as an Inhomogeneous Gaussian Markov random field (IGMRF) and the model parameters are estimated using the same initial HR estimate. A maximum a posteriori (MAP) estimation is used to arrive at the cost function which is minimized using a simple gradient descent approach. The missing high-frequency details are learned from a database consisting of LR images and their HR versions all captured by varying resolution settings of a MAP estimate. An inhomogeneous Gaussian MRF model is used as a prior. Both the model parameters as well as the decimation are estimated using the learned HR estimate. Authors have extended the algorithm to super-resolve the color images, where the luminance component is super-resolved using proposed technique and the chrominance components are interpolated using the wavelet transform.

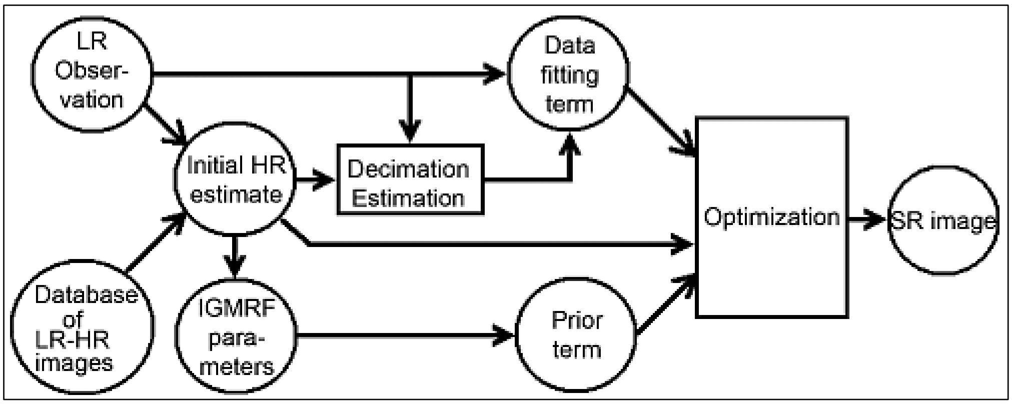

Fig. 2: *Schematic Representation of Proposed Approach for Image Super-resolution. Here LR, HR, and SR stand for LR, HR, and Super-resolution, Respectively. IGMRF Represents Inhomogeneous Gaussian Markov Random Field [9].*

Table 1: *PSNR (dB) Results for Resolution Enhancement From 128 X 128 To 512 X 512 of the Proposed Technique Compared with the Conventional and State-of-Art Image Resolution Enhancement Techniques [10].*

	PSNR (DB)			
Techniques \ images	**Lena**	**Elaine**	**Baboon**	**Peppers**
Bilinear	26.34	25.38	20.51	25.16
Bicubic	26.86	28.93	20.61	25.66
WZP (db.9\7)	28.84	30.44	21.47	29.57
Regularity-preserving image interpolation [7]	28.81	30.42	21.47	29.57
NEDI [10]	28.81	29.97	21.18	28.52
HMM [11]	28.86	30.46	21.47	29.58
HMM SR [12]	28.88	30.51	21.49	29.60
WZP-CS [13]	29.27	30.78	21.54	29.87
WZP-CS-ER [14]	29.36	30.89	21.56	30.05
DWT SR [15]	34.79	32.73	23.29	32.19
CWT SR [5]	33.74	33.05	23.12	31.03
SWT SR	32.01	31.25	22.74	29.46
Proposed Technique	**34.82**	**35.01**	**23.87**	**33.06**

Hasan Demirel and Gholamreza Anbarjafari [10] proposed an image resolution enhancement technique based on interpolation of the high frequency subband images obtained by DWT and the input image. The edges are enhanced by introducing an intermediate stage by using stationary wavelet transform (SWT). DWT is applied in order to decompose an input image into different subbands. Then the high frequency subbands as well as the input image are interpolated. The estimated high frequency subbands are being modified by using high frequency subband obtained through SWT. Then all these subbands are combined to generate a new SR image by using inverse DWT (IDWT).

The state-of-art techniques used for comparison purposes are:— regularity-preserving image interpolation; new edge-directed interpolation (NEDI); hidden Markov model (HMM); HMM-based image super resolution (HMM SR); WZP and cycle-spinning (WZP-CS); WZP, CS, and edge rectification (WZP-CS-ER); DWT based super resolution (DWT SR); complex wavelet transform based super resolution (CWT SR). Table 1 shows PSNR (dB) results compared with all above techniques.

Robinson et al. [11] presented an extension of the combined Fourier-wavelet deconvolution and denoising algorithm ForWardD to the multiframe SR application. In this work authors used a fast Fourier-based multiframe image restoration to produce a sharp, yet noisy estimate of the high-resolution image, then applies a space-variant nonlinear wavelet thresholding that addresses the nonstationarity inherent in resolution-enhanced fused images. For better performance ForWarD algorithm can be used with more sophisticated redundant wavelet techniques such as curvelets or ridgelets.

Hui Ji and Cornelia Fermuller [12] presented an analysis and algorithm for the problem of SR imaging for solutions to two problems; one is the alignment of image frames. The other, is the reconstruction of an HR image from multiple aligned LR images. Both are important for the performance of super-resolution imaging. Image alignment is addressed with a new batch algorithm, which simultaneously estimates the homographies between multiple image frames by enforcing the surface normal vectors to be the same.

Super-resolution reconstruction via the frequency domain approach discussed in this section has significant advantages: Simplicity, Computational complexity, Intuitive super-resolution mechanism. Significant disadvantages are Global translation motion model, Degradation models; difficult to include spatially varying degradation models in the frequency domain, Inflexibility regarding motion models; due to the inability to formulate Fourier domain transformations which are equivalent to spatially varying motion.

The frequency domain approaches published recently are mostly concentrated on the use of different types and components of the wavelet transform for obtaining the high frequency component of HR image from one or more LR images by inclusion of spatial domain a-priori knowledge for regularization. As most of researchers are concentrating on spatial domain techniques due to ability of local processing, however, frequency domain approaches still to explore to a further extent as it estimate the global registration parameters accurately.

SPATIAL DOMAIN METHODS

Formulate the SR reconstruction approach in the spatial domain has advantages such as General observation models, which may include:– Arbitrary motion models (global or non-global)– Motion blurring due to non-zero aperture time– Optical system degradations (spatially varying or invariant)– Effects of non-ideal sampling (spatially varying or invariant)– Ability to model complex degradations (such as compression blocking artifacts). Powerful methods for inclusion of a-priori constraints are – Spatial domain image models such as Markov Random Fields, set based constraints (POCS formulation) and nonlinear models capable of bandwidth extrapolation.

Interpolation of non-uniformly spaced samples is a simple approach for constructing SR images from an image sequence based on spatial domain interpolation. The LR observation image sequence is registered, resulting in a composite image composed of samples on a non-uniformly spaced sampling grid. These non-uniformly spaced sample points are interpolated and resampled on the HR sampling grid. However, it does not take into consideration the fact that samples of the LR images do not result from ideal sampling but are spatial averages. As a result, the reconstructed image does not contain the full range of frequency content that can be reconstructed with the available LR observation data.

Tekalp, Ozkan and Sezan [6] proposed a two steps procedure, where the up sampling of the LR images and the restoration are sequentially performed. The LR frames are registered and combined to form a non-uniformly sampled HR image which is then interpolated and resampled on a uniform grid to produce the reconstructed HR frame.

In the past two decades, a variety of SR methods have been proposed. These methods are usually very sensitive to their assumed model of data and noise, which limits their utility. Sina Farsiu, M. Dirk Robinson, Michael Elad, and Peyman Milanfar [13] investigated an alternate approach using L_1 norm minimization and robust regularization based on a bilateral prior to deal with different data and noise models. This computationally inexpensive method is robust to errors in motion and blurs estimation and results in images with sharp edges. In this method, resolution enhancement is broken into two consecutive steps: 1) noniterative data fusion; registration followed by the median operation. 2) iterative deblurring-interpolation; finding the deblurred HR frame by Wiener method. This method removes outliers efficiently, resulting in images with sharp edges but relatively high regularization factor which was chosen to reduce the motion artifact has resulted in a blurry image.

Sina Farsiu, Michael Elad, and Peyman Milanfar [14] proposed a fast and robust hybrid method of SR and demosaicing, based on a MAP estimation technique by minimizing a multiterm cost function. The L_1 norm is used for measuring the difference between the projected estimate of the HR image and each LR image, removing outliers in the data and errors due to possibly inaccurate motion estimation. Bilateral regularization is used for spatially regularizing the luminance component, resulting in sharp edges and forcing interpolation along the edges and not across them. Simultaneously, Tikhonov regularization is used to smooth the chrominance components. Finally, an additional regularization term is used to force similar edge location and orientation in different color channels. However, this approach cannot fully analyze subpixel motion estimation from colored filtered images.

Nathan A. Woods, Nikolas P. Galatsanos, and Aggelos K. Katsaggelos, [15] proposed two algorithms for SR using multiple noisy, blurred, and under sampled LR images. The first one is based on a Bayesian formulation that is implemented via the expectation maximization algorithm; Bayesian approach offers the advantage of more reliable parameter estimates as all the known information about the hidden variables is incorporated into the estimation process. The second is based on a MAP formulation. In both of formulations, the registration, noise and image statistics are treated as unknown parameters. These unknown parameters and the HR image are estimated jointly based on the available observations. Both of the proposed approaches produce superior registration estimates as compared to independent estimation of motion followed by restoration. The Bayesian method produces more accurate registration parameter estimates than the MAP approach. Still the sensitivity to errors in the blur is a disadvantage.

Giannis K. Chantas, Nikolaos P. Galatsanos, and Nathan A. Woods [16] proposed a MAP framework for the SR problem, with main two contributions are; first, the use of a new locally adaptive edge preserving prior for the SR problem. Second a two-step reconstruction methodology that includes first an initial registration using only the LR degraded observations. This is followed by a fast iterative algorithm implemented in the DFT domain in which the restoration, interpolation and the registration subtasks are preformed simultaneously. Images reconstructed using the proposed nonstationary prior, are visually more pleasant and display less ringing at the edges. It results into faster processing (4–5 sec) at cost of slight decrease in quality by estimating the registration parameter than real.
Russell Hardie, [17] proposed a computationally simple SR algorithm using a type of adaptive Wiener filter (AWF). Author used subpixel registration to position each LR

pixel value on a common spatial grid that is referenced to the average position of the input frames. The positions of the LR pixels are not quantized to a finite grid as with some previous techniques.

The output HR pixels are obtained using a weighted sum of LR pixels in a local moving window. Using a statistical model, the weights for each HR pixel are designed to minimize the mean squared error and it depends on the relative positions of the surrounding LR pixels. Thus, these weights adapt spatially and temporally to changing distributions of LR pixels due to varying motion. Both a global and spatially varying statistical model are considered here. Since, the weights adapt with distribution of LR pixels, it is quite robust. Advantages of the AWF SR algorithm are, it does not quantize the motion parameters and place the LR pixels on a discrete HR grid. Also, the filter weights for the AWF SR method are model-based and do not require empirical training images. Finally, no vector quantization is needed. Computational complexity of the method is quite low in comparison to iterative SR algorithms, but in the absence of translational motion, the complexity goes up drastically.

As most existing registration algorithms still experience various degrees of errors and the motion parameters among the LR images are unknown a priori. In view of this, Kim-Hui Yap, Li Chen, and Lap-Pui Cha [18], present a new framework that performs simultaneous image registration and HR image reconstruction to be estimated simultaneously and improved progressively. Motion model used in the algorithm includes translation as well as rotation motion.

Uma Mudenagudi, Subhashis Banerjee, and Prem Kumar Kalra [19] addressed the problem of SR by multiple LR inputs. The increased resolution can be in spatial or temporal dimensions, or even in both. Authors present a framework which uses a generative model of the imaging process and can address spatial SR, space-time SR, image deconvolution, single-image expansion, removal of noise, and image restoration. HR image is modeled as Markov random field and use MAP estimate as the final solution using graph-cut optimization technique. S. Derin Babacan, Rafael Molina, and Aggelos K. Katsaggelos, [20] proposed a method to estimate HR image and the motion parameters simultaneously. Authors utilized a Bayesian formulation to model the unknown HR image. The acquisition process, the motion parameters and the unknown model parameters are estimated in a stochastic sense. Variational Bayesian analysis is used to jointly estimate the distributions of all unknowns. The proposed framework has the following advantages: 1) With the uncertainty of the estimates, still the algorithms prevent the propagation of errors between the estimates of the various unknowns; 2) the algorithms are robust to errors in the estimation of the motion parameters; and 3) using a fully Bayesian formulation, simultaneously estimate all algorithmic parameters along with the HR image and motion parameters, and therefore they are fully-automated and do not require parameter tuning.

HR image is estimated with sharper edges and fewer ringing artifacts, effective in preserving sharp image features while suppressing noise and motion artifacts. The unknown HR image, motion parameters and algorithm parameters, including the noise variances are modeled within a hierarchical Bayesian framework. Estimate all unknowns and algorithm parameters from the observed LR images without prior knowledge or user intervention.

SUMMARY OF SPATIAL DOMAIN METHODS

SR reconstruction via the spatial domain approach has advantages as: 1) Motion models, using the linear observation model, it is just as simple to include a local motion model as a global model using the spatial domain formulation. 2) Degradation models, simple inclusion of linear degradations such as motion blurring resulting from a non-zero aperture time, spatially varying or invariant blurs, missing pixels and so on. 3) Inclusion of spatial domain a-priori knowledge for regularization, Markov random fields as well as the spatial domain POCS formulation provide simple, yet very powerful methods to incorporate a-priori constraints into the reconstruction process.

It is possible for spatial domain methods to powerfully extrapolate frequency information beyond the diffraction limitations of the optical system. Theoretical Framework, Probabilistic methods, especially the MAP estimation method, provides a solid mathematical framework within which further theoretical developments can be made.

Spatial domain methods are at some cost of: 1) Simplicity, the optimizations involved in spatial domain methods are more complex. 2) Computational complexity; the increased flexibility of spatial domain methods tend to come at the cost of much increased computational requirements. 3) All these are intuitive SR mechanisms.

Comparisons of above two techniques is given in Table 2, the table is divided into two sections, the upper portion deals with the formulation of the observation, motion and degradation models while the lower portion makes generalizations concerning the solution approaches. Within the spatial domain SR reconstruction methods, two most promising techniques are; the Bayesian (MAP) approach and the set theoretic Projection onto Convex Sets (POCS) methods, their comparison is shown in Table 3.

Table 2: *Comparison of Frequency Domain and Spatial Domain Techniques [3].*

Model	Frequency Domain Techniques	Spatial Domain Techniques
Observation model	Frequency domain	Spatial domain
Motion models	Global translation (Rotation and shift)	Almost unlimited, at any level
Degradation model	Limited	LSI or LSV
Noise model	Limited	Very flexible, even spatially varying
SR Mechanism	Dealiasing	Dealiasing and BW extrapolation using a-priori constraints
Simplicity	Very simple	Generally complex
Computational cost	Low	High
A-priori constraints	Limited	Almost unlimited
Regularization	Limited	Excellent
Extensibility	Poor	Excellent
Performance	Good for specific applications	Good

Table 3: *Comparison between Bayesian (MAP) and POCS Approaches of Spatial Techniques [3].*

	Bayesian (MAP)	POCS
Theoretical Framework	Rich	Limited
A-priori constraints	Prior PDF (typically convex) Easy to incorporate No “hard” constraints	Convex Sets Easy to incorporate Very powerful yet simple
SR solution	Unique MAP estimate	Non-unique Volume of intersection of sets
Optimization	Iterative, standard methods Good convergence	Iterative Often slow convergence
Computational Cost	High	High
Complications	Optimization difficult for non-convex priors	Projection operators can be difficult to define

SR METHOD BY USING SINGLE OR MULTIPLE LR IMAGES

Another way to classify the SR techniques is, SR using single LR image or multiple LR images. As SR is an ill posed problem so with multiple LR images, to find the sub pixel information correctly is difficult. So number of author tried to obtain the HR image by using single LR image with estimation of high frequency information from same image or by learning HR-LR relation from training sets. The correlation between LR images and corresponding HR images is learnt from a database of known LR and HR image pairs. This knowledge is then applied to a new LR image to obtain its most likely HR image.

Higher factors of SR have been obtained by repeated application of this process.

Using Multiple LR Images

Multiframe SR reconstruction aims to produce a HR image using a set of LR images, first used to set up a prior model for reconstructing super resolved images from a sequence of warped, blurred, subsampled, and noise-contaminated LR images. Although many SR algorithms have been proposed, most of them suffer from several impractical assumptions, e.g., the shift or rotation between LR images is global, the motion occurring between LR images is known exactly, or the LR images are noise free. However, the imaging procedure is generally much more complicated and may include local warping, blurring, decimation, and noise contamination. Some different methodologies are applied by many authors using multiple LR images which are discussed in this section.

Gao et al. [21] used fuzzy registration in the process of reconstruction, which is mainly focuses on the correlation between pixels of the candidate and the reference images to reconstruct each pixel by averaging all its neighboring pixels. However, if some objects appear or disappear among LR images or different angle rotations exist among them then the correlation between corresponding pixels becomes weak. If the LR images are noised, the reconstruction quality will be affected seriously. To reduce these problems, authors have used the Zernike moment, to make the most of possible details in each LR image for high-quality SR reconstruction.

For image registration, it is desirable to achieve the invariance to translation, rotation, or scaling changes. Moment is used as it is insensitive to noise and can accurately identify the target, whether it is closed or not. Zernike moments consist of a set of independent and invariant moments with an arbitrarily high order. The Zernike function consists of a set of orthogonal basis functions mapped onto a unit circle. It has three main properties with the orthogonality, rotation invariance, and information compaction.

$$\mathrm{M}_{pq} = \frac{p+1}{\pi} \sum_{\mathrm{x}} \sum_{\mathrm{y}} \mathrm{V}^{*}_{\mathrm{pq}}\ (\mathrm{x},\mathrm{y}) \mathrm{f}(\mathrm{x},\mathrm{y}) \ \ldots \qquad (4)$$

Subject to $x^2+y^2 \leq 1$ as higher order moments are more sensitive to noise authors have used first - third order moments M_{00}, M_{11}, M_{20}, M_{22}, M_{31} and M_{33}.

Esmaeil Faramarzi, Dinesh Rajan, and Marc P. Christensen [22] presented, a blind method for multi-image SR and multi-image blur deconvolution (MIBD) of LR images which are degraded by linear space-invariant (LSI) blur, aliasing, and additive white Gaussian noise (AWGN). The proposed approach is based on alternating minimization (AM) of a cost function with respect to the unknown HR image and blurs. The regularization term for the HR image is based upon the Huber-Markov random field (HMRF) model, which is a type of variational integral that exploits the piecewise smooth nature of the HR image. The blur estimation process is supported by an edge-emphasizing smoothing operation, which improves the quality of blur estimates. The blur estimation is done in the filter domain using the gradients of the LR and HR images.

Feng Li, Xiuping Jia, Donald Fraser, and Andrew Lambert [23] proposed a SR method called the MAP based on a universal Hidden Markov Tree (HMT) model for remote sensing images. The HMT theory is used to set up a prior model for reconstructing super resolved images from a sequence of warped, blurred, subsampled and noise-contaminated LR images. Because the wavelet coefficients of images can be well characterized as a mixed Gaussian distribution, an HMT model is better to capture the dependences between multiscale wavelet coefficients. Computational loads depend on the number of the LR images and the size of each image, which is large.

Some multiple image SR methods are already discussed in frequency domain approach are Dirk Robinson *et al.* [10] used combined Fourier-wavelet deconvolution and denoising algorithm ForWardD to the multiframe SR application. Hui Ji and Cornelia Fermuller [12] have addressed image alignment with a batch algorithm, which simultaneously estimates the homographies between multiple image frames by enforcing the surface normal vectors to be the same. Techniques discussed already in spatial domain approach based on multiple LR are, Tekalp, Ozkan and Sezan [6], Sina Farsiu, Hui Ji and Cornelia Fermuller [12], Michael Elad, and Peyman Milanfar [14], Nathan A. Woods, Nikolas P. Galatsanos, and Aggelos K. Katsaggelos, [15], Giannis K. Chantas, Nikolaos P. Galatsanos, and Nathan A. Woods [16], Kim-Hui Yap, Li Chen, and Lap-Pui Cha [18], Uma Mudenagudi, Subhashis Banerjee, and Prem Kumar Kalra [19], S. Derin Babacan, Rafael Molina, and Aggelos K. Katsaggelos [20].

The image registration is a basic image processing problem that is well known as ill-posed. Image registration is critical for the success of multi-frame SR reconstruction, where spatial samplings of the HR image are fused. The problem is more difficult in the SR setting, where the observations are LR images with heavy aliasing artifacts. 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.

The researches on SR image reconstruction mainly considered that degraded model is linear. As different methods of SR 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 which SR 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 SR approach and if one or more HR training images are available then use single image SR approach. If registration step is not required then single frame image resolution can be used. Also, if HR training is not available but different LR images are available for same scene than one must have to use multi frame SR.

This does not provide a clear method of comparing different implementations suitability for a desired application, so one have to implement SR method based on problem model which can be generalized to all SR reconstruction problems.

Using Single LR Image

As SR is an ill posed problem and with multiple LR images the obtained HR is not always a guaranteed solution and so number of author tried to obtain the HR image by using single LR image with estimation of high frequency information from same image or from training sets, generally multiple HR images that can be reduced to the same LR image. Accordingly, for this problem has to rely on strong prior information. While obtaining the HR image more attention is given for edge enhancement and sharpness.

Example-based SR algorithms can roughly be characterized as nearest neighbor (NN)-based estimation. It works in two phases, first during the training phase pairs of LR and corresponding HR image patches (sub windows of images) are collected. Then in second the SR phase, each patch of the given LR image is compared to the stored LR patches and the HR patch corresponding to the nearest LR patch and satisfying certain spatial neighborhood compatibility is selected as the output. NN-based estimation suffered from over fitting when the target function is highly complex or the data are high-dimensional. Few Single image SR techniques already discussed by Turgay Celik and Tardi Tjahjadi [8], Prakash P. Gajjar and Manjunath V. Joshi [9], Hasan Demirel and Gholamreza nbarjafari [10].

Some of the most recent work on single image SR has been done using texture hallucination patch based up sampling and example based SR. In edge-based algorithms, some edge priors are used to reconstruct sharp images but problem with these methods are they produce blurriness and over smoothness in some regions. Example-based SR, in which patch-based image model based on training database, is used. It generates good result but it does not produce consistent texture and also generates some noise.

Kwang In Kim and Younghee Kwon [24] proposed a framework with an idea is to learn a map from input LR images to target HR images based on example pairs of input and output images. Kernel ridge regression (KRR) is adopted for this purpose. KRR leads to a better generalization than simply storing the examples as done in pervious example-based algorithms so results in much less noisy images. However, this may introduce blurring and ringing artifacts around major edges as sharp changes are penalized severely. A prior model of a generic image class which takes into account the discontinuity property of images is adopted to resolve this problem.

Young Cheul Wee and Hyun Joon Shin [25], proposed to construct a HR image from a LR image using fractal coding. This SR method utilizes a type of orthogonal fractal coding method in which the fractal affine transform is determined by the range block mean and contrast scaling. The proposed non-adaptive fractal SR procedure uses a fixed domain block and a fixed contrast scaling factor. Drawbacks of the proposed method are: 1) Improvement of the visual quality does not match that of the numerical quality. 2) This method exaggerates the contrast around edges to increase numerical precision; which is not always visually pleasing.

Jianchao Yang, John Wright, Thomas S. Huang, and Yi Ma [26], given an approach, based upon sparse signal representation, as statistics suggests that image patches can be well represented as a sparse linear combination of elements from an appropriately chosen over-complete dictionary. Authors seek a sparse representation for each patch of the LR input and then use the coefficients of this representation to generate the HR output. Jointly training two dictionaries for the LR and HR image patches enforce the similarity of sparse representations between the LR and HR image patch pair with respect to their own dictionaries. However, need future investigation to determine the optimal dictionary size for natural image patches in terms of SR tasks. Connections to the theory of compressed sensing may provide conditions on the appropriate patch size, features to utilize and also approaches for training the coupled dictionaries.

Jian Sun, Zongben Xu, and Heung-Yeung Shum [27] proposed a gradient profile prior, which implies the prior knowledge of natural image gradients. In this prior, the image gradients are represented by gradient profiles, which are 1-D profiles of gradient magnitudes perpendicular to image structures. Using parametric gradient profile model, the prior knowledge of the gradient profiles is learned from a large collection of natural images, which are called gradient profile prior (GPP). Based on this prior, used a gradient field transformation to constrain the gradient fields of the HR image to preserve sharpness of discontinuities.

Feature spaces of LR and HR patches are not locally isometric because of one-to-many mappings between LR and HR patches. To reduce this problem for neighbor-embedding (NE)-based SR reconstruction Xinbo Gao, Kaibing Zhang, Dacheng Tao and Xuelong Li. [28], apply a joint learning technique to train two projection matrices simultaneously and to map the original LR and HR feature spaces onto a unified feature subspace. Subsequently, the nearest neighbor selection of the input LR image patches is conducted in the feature subspace to estimate the reconstruction weights. Refine further the initial SR estimate, impose a global reconstruction constraint on the SR outcome based on the MAP framework. Still there is a challenge for construction of optimal GPPs rather than a fixed neighborhood size.

Fei Zhou, Wenming Yang, and Qingmin Liao [29], investigated dictionary learning (DL) method using two-step procedure for DL. First partition the training samples into different subsets, and then learn an incoherent sub-dictionary for every subset. Finally, the input patches are super-resolved using their corresponding sub-dictionaries. Adopt an incoherent dictionary for sparse representation, as well as a coherent learning for learning-based SR. To satisfy the coherent property, assign the samples to different sub-sets based on their perceptual appearances. To achieve the incoherent property, learn a sub-dictionary for every subset by the concept of equiangular tight frame (ETF).

Kaibing Zhang, Xinbo Gao, Xuelong Li, and Dacheng Tao [30] believed that textures may be contained in multiple manifolds, corresponding to classes. Under this assumption, authors present an example-based image SR reconstruction algorithm with clustering and supervised neighbor embedding

(CSNE). First, a class predictor for LR patches is learnt by an unsupervised Gaussian mixture model. Then by utilizing class label information of each patch, a supervised neighbor embedding is used to estimate HR patches corresponding to LR patches. Disadvantages of the proposed algorithm are, first, the computation of clustering for huge training patches is a time-consuming so need to find a representative training set. Second, use more efficient methods for patch matching to speed up the SR process.

Zhang et al. [31], proposed an approach by learning multiscale self-similarities from an LR image itself. The approach is based upon an observation that small patches in natural images tend to redundantly repeat themselves many times both within the same scale and across different scales. To synthesize the missing details, establish the HR-LR patch pairs using the initial LR input and it's down sampled version to capture the similarities across different scales and utilize the NE algorithm to estimate the relationship between the LR and HR image pairs. Also, accumulate the previous resultant images as training examples for the subsequent reconstruction processes. A drawback of the method is that a fixed number of K-NN used in the example learning-based detail synthesis tends to result in blurring effects.

Min-Chun Yang and Yu-Chiang Frank Wang, [32] proposed framework, advance support vector regression (SVR) with image sparse representation, which offers excellent generalization in modeling the relationship between images and their associated SR versions. With theoretical supports of Bayes decision theory, SR framework learns and selects the optimal SVR model when producing an SR image. Method do not require training LR and HR image data also do not assume context, edge, etc. priors when synthesizing SR images and do not expect reoccurrence of image patches in images as many prior learning-based methods did.

Yang et al. [33], proposed a multiple-geometric-dictionaries-based clustered sparse coding scheme for SISR. First, a large number of HR image patches are randomly extracted from a set of example training images and clustered into several groups of "geometric patches" from which the corresponding "geometric dictionaries" are learned to further sparsely code each local patch in a LR image.

A clustering aggregation is performed on the HR patches recovered by different dictionaries, followed by a subsequent patch aggregation to estimate the HR image. Authors have added a self-similarity constraint on the recovered image in patch aggregation to reveal new features and details.

Most of single-image SR methods fail to consider the local geometrical structure in the space of the training data. To take this issue into account Xiaoqiang Lu, Yuan Yuan, and Pingkun Yan [34], proposes a method named double sparsity regularized manifold learning (DSRML). DSRML can preserve the properties of the aforementioned local geometrical structure by employing manifold learning.

Zhang et al. [35] proposed an algorithm via Bayesian modeling with a natural image prior modeled by a high-order Markov random field (MRF). The minimum mean square error (MMSE) criteria are used for estimating the HR image. A Markov chain Monte Carlo (MCMC) based sampling algorithm is presented for obtaining the MMSE solution, as it is less sensitive to the local minima problem. As the proposed method is an MCMC sampling-based generative approach, it is not as fast as the MAP solution.

Wang et al. [36], proposed an effective edge-directed SR method to handle preserving local edge structures. An adaptive self-interpolation algorithm is proposed to estimate a sharp HR gradient field directly from the input LR image. Then obtained HR gradient is regarded as a gradient constraint or an edge-preserving constraint to reconstruct the HR image.

Hongteng Xu, Guangtao Zhai, and Xiaokang Yang [37] proposed algorithm using local fractal analysis. Authors treat the pixels of a natural image as a fractal set, the image gradient as a measure of the fractal set. The fundamental of approach is the invariance of the bi-Lipschitz transform of fractal dimension, which suggests that the up-sampling processing does not change the fractal dimension of an image. According to the scale invariance feature of fractal dimension, estimate the gradient of a HR image from that of a LR.

HR image is further enhanced by preserving the local fractal length of gradient during the up-sampling process. But, in this method image gradient was used as a sole measure of fractal, which may be insufficient for some complicated image contents.

Single image method is effective in SR problem when insufficient observations are available. There are still a number of questions need to answer regarding this kind of approaches. First is how to choose the optimal patch size for the given target image? Perhaps a multi-resolution treatment is needed.

Second is how to choose the database? Different images have different statistics and thereby need different databases. An efficient method for dictionary adaptation to the current target image may suggest a way out. Third is how to use the example-based prior more efficiently? The computation issue could be a difficult for practical applications.

SUMMARY

SR refers to the reconstruction of images that are visually superior to the original LR observations. This often implies bandwidth extrapolation beyond the pass band of the imaging system, which is not possible by interpolation. Tsai and Hunag were the first to consider the problem of obtaining a high-quality image from several down sampled and translationally displaced images in 1984. Onwards over three decade various researchers contributed in the field of SR but all these are intuitive SR mechanisms.

SR reconstruction via the frequency domain approach has advantages: Simplicity, Computational complexity, Intuitive super-resolution mechanism and significant disadvantages are Global translation motion model, Degradation models, Inflexibility regarding motion models. The current frequency domain approaches are mostly concentrated using the wavelet transform. However, frequency domain approaches are still to explore to a further extent for single image SR.

SR reconstruction by spatial domain approach has advantage over frequency domain are: Motion models, Degradation models, Inclusion of spatial domain a-priori knowledge for regularization, Markov random fields as well as the spatial domain POCS formulation provide almost trivially simple, yet very powerful methods to incorporate a-priori constraints into the reconstruction process. It is possible to extrapolate frequency information beyond the diffraction limitations of the optical system. Theoretical Framework, Probabilistic methods, especially the MAP estimation method, provides a solid mathematical framework within which further theoretical developments can be made. Image registration is critical for the success of multi-frame SR reconstruction; it is more difficult when the LR observations are with heavy aliasing artifacts. As the resolution of the observations goes down, resulting in more registration errors, degradation by these errors is visually more annoying than the blurring effect by interpolation.

Multiframe SR reconstruction aims to produce a HR image using a set of LR images, which need to set up a prior model for reconstructing super resolved images from a sequence of warped, blurred, subsampled, and noise-contaminated LR images. Although many SR algorithms have been proposed, most of them suffer from several impractical assumptions, e.g., the shift or rotation between LR images is global, the motion occurring between LR images is known exactly, or the LR images are noise free.

However, the imaging procedure is generally much more complicated and may include local warping, blurring, decimation, and noise contamination. As SR is an ill posed problem and with multiple LR images, to find the sub pixel information correctly is difficult. So number of author tried to obtain the HR image by using single LR image with estimation of high frequency information from same image or by learning HR-LR relation from training sets. The correlation between LR-HR images is learnt from a database of known LR and HR image pairs which is utilized on new LR to obtain HR image.

Higher factors of SR have been obtained by repeated application of this process. The classical multi-image SR combining LR images obtained at subpixel misalignments and in Example-Based SR learning, correspondence between LR and HR image patches from a database is utilized. Combined approach can be applied to obtain SR from as little as a single image.

The researches on SR reconstruction mainly considered the situation that degraded model is linear, results provided are mostly based on subjective measurements, and it is difficult to find an unbiased comparison on which SR 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 SR approach and if one or more HR training images are available then use single image SR approach. If registration step is not required then single frame SR can be used. Also, if HR training is not available but different LR images are available for same scene than one must have to use multi frame SR. This does not provide a clear method of comparing different implementations suitability for a desired application, so one have to implement SR method based on problem model which can be generalized to all SR reconstruction problems.

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