A Survey: The Methods & Techniques of Super-Resolution Image Reconstruction

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Abstract— Super-resolution is the process of recovering a high-resolution image from multiple low-resolution images of the same scene. 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 provide a comprehensive review of existing super-resolution techniques and highlight the future research challenges. This includes the formulation of an observation model and coverage of the dominant algorithm – Iterative back projection .We critique these methods and identify areas which promise performance improvements. In this paper, future directions for super-resolution algorithms are discussed. Finally results of available methods are given.

Key words: Super-Resolution, POCS, IBP, Canny Edge Detection

I. Introduction

Super-resolution is a process in which a high-resolution image from one or more low-resolution image is produced. In the imaging process, it is possible to image detail or high frequency components lost for several reasons, including the low number of camera sensory cells, ambient light from different elements, camera movement and not adjust the camera's focal point. The super-resolution is an attempt to retrieve image details that are lost. In other words, super-resolution predicts or interpolates lost data from available evidences and minimizes the image's blurring and aliasing.

Super-resolution methods are used in many machine vision and image processing applications. Today, advances in computers with higher accuracy and processing power, has caused more attention to be software based super-resolution methods. super-resolution is used in monitoring systems such as the identification and recognition of license plates [1], face recognition [2], automatic target recognition [3] and [4], remote sensing [5], medical image processing such as CT and MRI [6] and [7], converting video to different standards (for example, converting NTSC to HDTV), image enhancing [8], processing of satellite images [9], astronomical image processing [10], microscopic image processing [11] and image mosaicking [12].A variety of approaches for solving the super-resolution problem have been proposed. 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 (typically with smoothness prior). 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.

II. Super Resolution Process

Given a set of low resolution images that result from the observation of the same scene from slightly different views, super resolution algorithm produce a single high resolution image by fusing the input LR images such that the final HR image reproduces the scene with a better fidelity than any of the LR images [13]. The central idea in super resolution processing is to convert the temporal resolution in to spatial resolution. In broad sense, this approach can be used to perform any combination of the following image processing tasks:

– Registration
– Interpolation
– De-bluriring

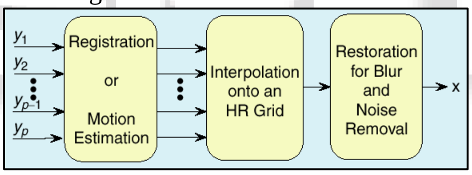

Fig. 1: Phases of Super-Resolution[3]

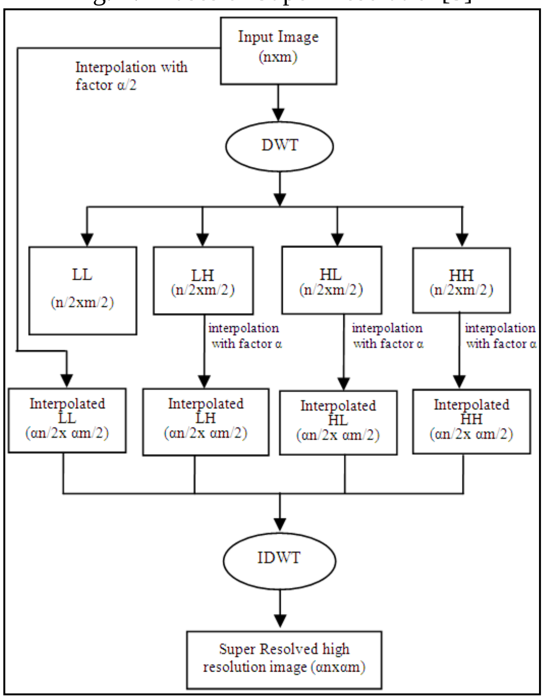

Fig. 2: Block diagram of Super resolution Technique

First, the SRR algorithm receive several low-resolution corrupted images as the inputs then the registration or Motion Estimation process estimate the relative shifts between LR images compared to the reference LR image with fractional pixel accuracy. Obviously, accurate sub-pixel motion estimation is a very important factor in the success of the SRR algorithm. Since the shifts between LR images are arbitrary, the registered HR image will not always match up to a uniformly spaced HR grid. Thus, non-uniform interpolation is necessary to obtain a uniformly spaced HR image from a composite of non-uniformly spaced LR images. Finally, image restoration(De-blurring) is applied to the up-sampled image to remove blurring and noise. Before presenting the review of existing SR algorithms, we first model the LR image acquisition process.

III. Principle of Super Resolution

Super-resolution image reconstruction is based on the theory of Analytic Continuation, which means reconstruction of the whole analytic function according to its values in certain area. Because of diffraction of lights, spectrum distribution of certain image is infinite in space and optical system truncates its frequency to obtain frequency-truncated image that is finite in space. Generally, truncation function cannot be bandlimited, but a diffraction limited optical system's truncation is band- limited, therefore, the reconstruction of whole spectrum function or just spectrum function above certain frequency is possible. Assume the imaging model:

$$\boxed{g(x,y)=h(x,y)*f(x,y)+n(x,y)} \quad (1)$$

Where, h(x, y) is the point spread function (PSF), ideal image, g (x, y) is the original image and n(x, y) is the noise. Its Fourier transformation is:

$$\boxed{G(u,v)=H(u,v).F(u,v)+N(u,v)} \quad (2)$$

Super-resolution reconstruction is to perform analytic continuation to F(u,v) to extend its support domain by using prior information of objects and posterior processing technologies, and then get a new PSF H '(u,v). H(u,v) also has the extended support domain, thus the resolution of image is improved.

IV. Literature Review of Image Super Resolution Techniques

Super-resolution techniques in terms of the nature are divided into linear and nonlinear methods, methods based on repeatable techniques (recursive) methods and single-frame or multi-frame methods. Super-resolution techniques are also classified according to the used domain which is the spatial domain, frequency-domain and wavelet domain. In this paper, we will investigate methods of super-resolution in these three domains.

A. *Frequency Domain Methods*

In this section, a review of the various super-resolution methods in the frequency-domain is presented. Super-resolution methods in the frequency-domain are related to the common feature of Fourier transforms particularly sampling theory and transport properties. Because these characteristics are completely known, frequency-domain perspectives are very easily understandable. Frequency-domain methods have advantages such as simplicity and low computational complexity, and they can be implemented in parallel. One major flaw in frequency-domain techniques is consideration a model based on the features that each transitional motion in the spatial domain has a dual feature in Fourier domain and it is equal to phase shift. However, any spatial variation in the spatial domain hasn't any duality in the Fourier domain and cannot be introduced in the considered model.

Denote the continuous scene by f (x, y). Global translations yield R shifted images, f_r(x y)= f(x+ dx_r, y+ $dy_{r)}$, r=1,2,3…. R. The CFT of the scene is given by F(u,v) and that of the translations by Fr(u, v). The shifted images are impulse sampled to yield observed images $y_r[m,n]=f(mT_x+\Delta x_r, nT_y+\Delta y_r)$ with m=0,1,2,3….M-1 and n=0,1,2….N-1. The R corresponding 2D DFT's are denoted by y_r [k l]. The CFT of the scene and the DFT's of the shifted and sampled images are related via aliasing,

$$\boxed{y_r[k,l]=\alpha\sum_{p=-\infty}^{\infty}\sum_{q=-\infty}^{\infty}F_r\left(\frac{k}{MT_x}+pf_{s_x},\frac{l}{NT_y}+qf_{s_y}\right)} \quad (3)$$

Where $f_a=1/T_a$ and $f_b=1/T_b$ are the sampling rates in the a=s_x and b=s_y dimensions respectively and $\alpha=1/(T_xT_y)$.. The shifting property of the CFT relates spatial domain translation to the frequency domain as phase shifting as,

$$F_r(u,v)=e^{j2\pi(\Delta x_r u+\Delta y_r v)}F(u,v) \quad (4)$$

If $f(x, y)$ is band-limited, $\exists L_u, L_v$ s.t. $F(u,v)\rightarrow 0$ for $|u| \geq L_u f_{s_x}$ and $|v| \geq L_u f_{s_y}$. Assuming $f(x; y)$ is band limited, we may use (4) to rewrite the alias relationship (3) in matrix form as,

$$Y=\phi F \quad (5)$$

Y is a R 1 column vector with the rth element being the DFT coefficients Yr[k, l] of the observed image Y_r[m,n] .Pie is a matrix which relates the DFT of the observation data to samples of the unknown CFT of f(x,y) contained in the 4 L_uL_v*l vector F.

1) *Restoration via Alias Removal*

First spatial image reconstruction using frequency-domain is presented by Tsai and Huang [13]. In this method, as mentioned earlier, Y=ΦF relation is obtained then Φ is estimated and by using the inverse Fourier transform, the high resolution image is obtained. Although the computationally attractive and simple method is introduced, it has many disadvantages. Assuming ideal sampling ignoring the effect of the imaging sensor and ignoring the effect of noise in the image is the most important of them, because the proposed method only considered the motion transition between images.

In [14] a method based on the model introduced by Tsai and Huang introduced. The Taylor series expansion is used to calculate the transition variables. This method has fewer computations than the Tsai and Huang frequency-domain method. In [15] the main approach problem expressed and a method based on frequency-domain was introduced in [16] is also extended. In this way blurring impact and noise is also considered. By using the least squares sense criterion and similar to Tsai and Huang method, a high resolution is reconstructed.

2) *Recursive Least Squares (RLS)*

In this approach Y=ΦF is solved based on the recursive least squares error equations and using of a recursive method. In these methods, blurring and noise are considered. A solution based on recursive least squares method of determining the F with regard to noise, is minimizing Eqn. (4) [17-19].

$$\|\Phi F - Y\|^2 + \gamma(\Phi) \quad (6)$$

Where y(.) is regularization functional. In [18, 19], the relation is considered as Eqn. (7), where is an approximate solution to the equation (not yet known).

$$\gamma(F) = \lambda\|F - c\|^2 \quad (7)$$

Replacement regularization function in equation (6) and minimizing it the Eqn. (8) is obtained.

$$\hat{F} = (\Phi^T\Phi + \lambda I)^{-1}(\Phi^T Y + \lambda c) \quad (8)$$

This equation is solved with a recursive relationship and without inversing matrixes. Initial value of the variable **c** is set to zero, then at each step, put **c** amount equal to the result of the previous step. One disadvantage of this method is the use of an estimate for the unknown **c** that does not guarantees the convergence and the stability of the recursive solution.

3) Recursive Total Least Squares (RTLS)

In [20] to provide a robust method for solving Y=ΦF the Recursive Total Least Squares method was used, where in addition to the noise, an error in Φ is also considered. The model used in this method is presented in Eqn. (9).

$$\boxed{Y = [\Phi + E]F + N} \quad (9)$$

Where E is the produced error in the Φ due to errors in the motion estimation and N denotes the noise that is proportional to the application. In this method is obtained based on the recursive method, Eqn. (7) and minimizing equation.

4) Multichannel Sampling Theorem Methods

In [22] a method based on multi-channel sampling theorem is introduced. However, this method is implemented in the spatial domain, but fundamentally, this method is a method in the frequency-domain, because transmission characteristics of the Fourier transform of the original image is used to model the translation. In this method, the band-limited function is passed through the number of "mutually independent" linear channels, the outputs of which are under-sampled at the rate below the Nyquist rate to produce discrete signals by a number equal to the number of channels. Using the theory of multichannel sampling the original signal can be fully reconstructed from these discrete signals. In this method, discrete signals that are actually sampled signals from the original signal are passed through R linear filters and then summing the resulting outputs and interpolating produced signals, the original signal can be reconstructed. Consider a function f(x) which is band-limited to $-\sigma < \omega < \sigma$ and is passed through R linear channels, the outputs of which are sampled at the rate $2\sigma / R$ ((under-sampled at 1/R of the Nyquist rate) to produce R discrete signals $y_r(mT)$, $T = R/2\sigma$, $m \in Z$ r={1,2,3,…R}.

In Multichannel Sampling Theorem, produced $y_r(mT)$ signals are passed throw R linear filters with impulse functions $h_r(.)$ and the total output of these filters is obtained according to Eqn. (10).

$$\boxed{\hat{f}(x) = \sum_{r=1}^{R} \hat{f}_r(x) = \sum_{r=1}^{R} \sum_{m=-\infty}^{\infty} y_r(mT)h_r(x - mT)} \quad (10)$$

B. Spatial Domain Methods

Approaching the super-resolution problem in the frequency domain makes a lot of sense because it is relatively simple and computationally efficient. However, there are some problems with a frequency domain formulation. For one, it restricts the inter-frame motion to be translational because the DFT assumes uniformly spaced samples. Another disadvantage is that prior knowledge that might be used to constrain or regularize the super-resolution problem is often difficult to express in the frequency domain. Since the super-resolution problem is fundamentally ill-posed4, incorporation of prior knowledge is essential to achieve good results. A variety of techniques exist for the super-resolution problem in the spatial domain. These solutions include interpolation, deterministic regularized techniques, stochastic methods, iterative back projection, and projection onto convex sets among others. The primary advantages to working in the spatial domain are support for unconstrained motion between frames and ease of incorporating prior knowledge into the solution.

1) Image Interpolation Algorithms

a) Bicubic Interpolation

Given a sampled signal, its continuous counterpart can be approximated using some suitable interpolation kernel. 2D interpolation is usually accomplished by applying successively 1D kernel interpolation on horizontal and vertical directions. For uniformly spaced data, the continuous-domain signal *Y(u,v)* can be written as,

$$\boxed{Y(u,v) = \sum_k \sum_l y(k,l) h\left(\frac{u-u_k}{\Delta u}\right) h\left(\frac{v-v_k}{\Delta v}\right)} \quad (11)$$

In this expression, (*u*, *v*) are sampling intervals, *h()* is the interpolation kernel and {y(k,l)} represent the pixel array in the Low rsolution(LR) grid. The SR signal is obtained by resampling (11) on a finer grid. In [10], the cubic convolution kernel is given as,

$$h(s) = \begin{cases} 1.5|s|^3 - 2.5|s|^2 + 1 & 0 \le |s| < 1 \\ -0.5|s|^3 + 2.5|s|^2 - 4|s| + 2 & 1 \le |s| < 2 \\ 0 & 2 \le |s| \end{cases} \quad (12)$$

b) Interpolation of Non-Uniformly Spaced Samples

Registering a set of LR images using motion compensation results in a single, dense composite image of non-uniformly spaced samples. A SR image may be reconstructed from this composite using techniques for reconstruction from non-uniformly spaced samples. Restoration techniques are sometimes applied to compensate for degradations [17].Iterative reconstruction techniques, based on the Land weber iteration, have also been applied [12]. Such interpolation methods are unfortunately overly simplistic. Since the observed data result from severely under sampled, spatially averaged areas, the reconstruction step (which typically assumes impulse sampling) is incapable of reconstructing significantly more frequency content than is present in a single LR frame.

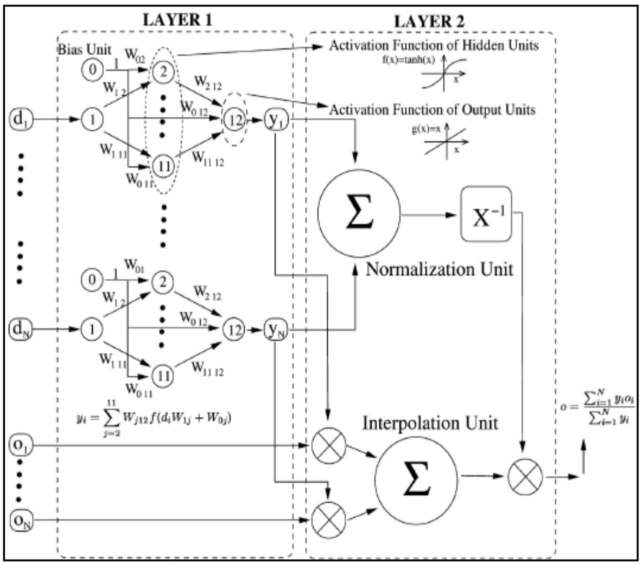

Fig. 3: Block diagram of neural network that is used in neural network

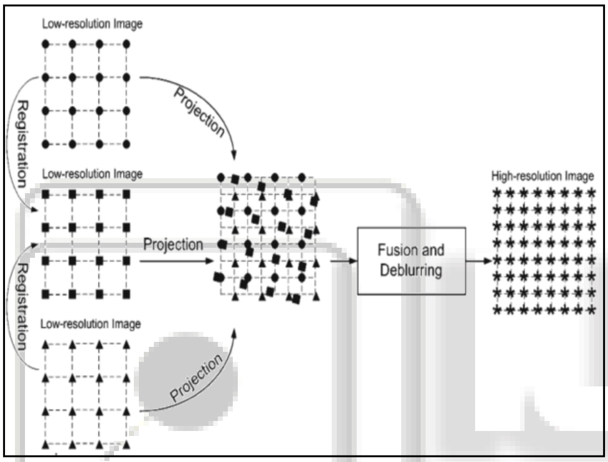

Fig. 4: Image registration before super-resolution

c) Wavelet-Based Image Interpolation

Wavelet-based image interpolation methods assume that the available image is the coarse approximation (LL0), that is,low-pass filtered subband of an HR image. The interpolation methods then first try to recover the missing horizontal (LH0), vertical (HL0) and diagonal (HH0) detail subbands, and then obtain the HR image by taking the inverse Discrete Wavelet Transform (DWT) of the expanded image. An important property of DWT is the persistence property. In fact several wavelet-based compression schemes, such as embedded zero tree wavelets, employ this property. Temizel and Vlachos [6] proposed a wavelet based image interpolation method. They used the idea of “persistence”, which implies that the magnitudes of wavelet coefficients corresponding to the same spatial location tend to propagate from lower scales to higher resolution scales. They extended the “persistence” idea to correlation coefficients. First, one goes one scale down, and estimates (HL1) by high pass filtering (LL1) horizontally. Then, correlation coefficients between (HL1) and its estimate are computed. Using these correlation coefficients and estimate of (HL0), exact value of (HL0) is computed. All these horizontal and vertical filtering operations are, however, implemented without decimation, in other words one stays at the resolution level of (LL0).

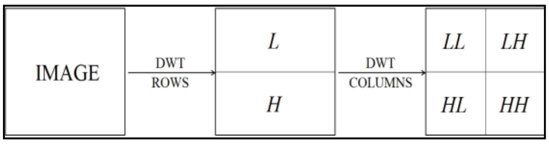

Fig. 5: DWT Multi-resolution decomposition

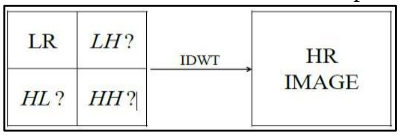

Fig. 6: Wavelet Super Resolution Concept

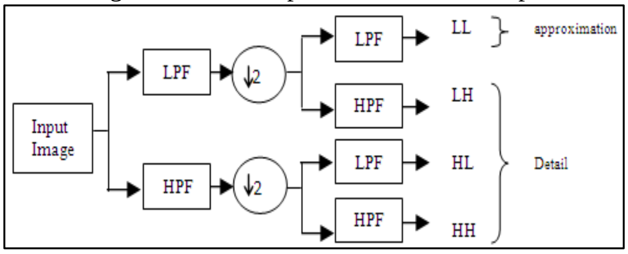

Fig. 7: Block Diagram of 1 level Discrete Wavelet Transform

d) Edge Adaptive Image Interpolation

The imaging process and the concomitant loss of resolution are modeled as low-pass filtering and decimation stages in [7]. The low-pass filtering operation modifies the values of the pixels near the edges proportionally to the distance between pixels and the edge. Therefore the analysis of the low resolution pixels should give an idea about the position of the edge at sub-pixel level. The one-dimensional case is illustrated in Fig.1

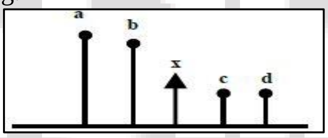

Fig. 8: The x pixel, astride an edge, is to be interpolated

The interpolated value x between the given a, b, c, d neighbors become [9]:

$$\boxed{\begin{aligned} x &= \mu b + (1-\mu)c \\ \mu &= \frac{k(c-d)^2+1}{k((a-b)^2+(c-d)^2)+2} \end{aligned}} \quad (13)$$

2) Iterated Back Projection

Given a SR estimate z and the imaging model H, it is possible to simulate the LR images Y as Y= Hz. Iterated back projection (IBP) procedures update the estimate of the SR reconstruction by back projecting the error between the jth simulated LR images Y j and the observed LR images Y via the back projection operator HBP which apportions “blame” to pixels in the SR estimate z j .Typically HBP approximates H^{-1}

$$\boxed{\begin{aligned} \hat{z}(j+1) &= \hat{z}(j) + H^{BP}(Y - \hat{Y}(j)) \\ &= \hat{z}(j) + H^{BP}(Y - H\hat{z}(j)) \end{aligned}} \quad (14)$$

Unfortunately the SR reconstruction is not unique since SR is an ill-posed inverse problem. Inclusion of a-priori constraints is not easily achieved in the IBP method.

3) Stochastic SR Reconstruction Methods

Stochastic methods (Bayesian in particular) which treat SR reconstruction as a statistical estimation problem have rapidly gained prominence since they provide a powerful theoretical framework for the inclusion of a-priori constraints necessary for satisfactory solution of the ill-posed SR inverse problem. The observed data *Y*, noise *N* and SR image z are assumed stochastic. Consider now the stochastic observation equation

$$Y = Hz + N.$$

Markov random field (MRF) image models as the prior term Pr fzg. Under typical assumptions of Gaussian noise the prior may be chosen to ensure a convex optimization in (5) enabling the use of descent optimization procedures. Examples of the application of Bayesian methods to SR reconstruction may be found in [15] using a Huber MRF and [3,7] with a Gaussian MRF. Maximum likelihood (ML) estimation has also been applied to SR reconstruction [18]. ML estimation is a special case of MAP estimation (no prior term). Since the inclusion of a-priori information is essential for the solution of ill-posed inverse problems, MAP estimation should be used in preference to ML.

4) Set Theoretic Reconstruction Methods

Set theoretic methods, especially the method of projection onto convex sets (POCS), are popular as they are simple, utilize the powerful spatial domain observation model, and allow convenient inclusion of a priori information. In set theoretic methods, the space of SR solution images is intersected with a set of (typically convex) constraint sets representing desirable SR image characteristics such as positivity, bounded energy, fidelity to data, smoothness etc., to yield a reduced solution space. POCS refers to an iterative procedure which, given any point in the space SR images, locates a point which satisfies all the convex constraint sets.

The centroid of this ellipsoid is taken as the SR estimate. Since direct computation of this point is infeasible, an iterative solution method is used. The advantages of set theoretic SR reconstruction techniques were discussed at the beginning of this section. These methods have the disadvantages of non-uniqueness of solution, dependence of the solution on the initial guess, slow convergence and high computational cost. Though the bounding ellipsoid method ensures a unique solution, this solution is has no claim to optimality.

5) Hybrid ML/MAP/POCS Methods

Work has been undertaken on combined ML/MAP/POCS based approaches to SR reconstruction [15, 5]. The desirable characteristics of stochastic estimation and POCS are combined in a hybrid optimization method. The a-posteriori density or likelihood function is maximized subject to containment of the solution in the intersection of the convex constraint sets.

6) Optimal and Adaptive Filtering

Inverse filtering approaches to SR reconstruction have been proposed, however these techniques are limited in terms of inclusion of a-priori constraints as compared with POCS or Bayesian methods and are mentioned only for completeness.

Techniques based on adaptive filtering, have also seen application in SR reconstruction [14, 4]. These methods are in effect LMMSE estimators and do not include non-linear a priori constraints.

7) Tikhonov Arsenin Regularization

Due the illposedness of SR reconstruction, Tikhonov-Arsen in regularized SR reconstruction methods have been examined[8]. The regularizing functional characteristic of this approach are typically special cases of MRF priors in the Bayesian framework.

C. Wavelet Domain Methods

Wavelet domain methods can include Regularity Preserving Interpolation, New Edge Direction Interpolation (NEDI), Wavelet domain Zero Padding and Cycle Spinning (WZP-CS), Dual Tree Complex Wavelet Transform (DT-CWT), Interpolation of wavelet domain high frequency subband and the spatial domain, Discrete Wavelet Transform (DWT) and Stationary Wavelet Transform (SWT)). These methods are described and compared with each other in [19]. Other methods based on wavelet domain individually or in combination with other methods are proposed in literature. For example, in [20] DASR and bicubic interpolation method are used in parallel.

D. Other Super-Resolution and Deblurring Methods

Other image super-resolution and deblurring methods are introduced in the literature. Nonnegative and Support Constraints Recursive Inverse Filtering (NAS_RIF), Iterative Blind Deconvolution (IDB) and Richardson Lucy are explained in [22]. In [23] some other methods like Poisson MAP, Wiener filter, Van-Cittert, Richardson Lucy, Scale space and some of the methods previously mentioned, such as Landweber, Tichonove Miller, Total variation and Expectation-Maximization Maximum Likelihood Estimator (EM-MLE) are discussed. Readers can get more details about these methods refer to the references cited.

E. Indexes used to compare SR methods

Because the various super-resolution methods are too high, it is not possible to compare these methods with each other with unique index and same condition. Usually the methods are compared to each domain or each group. For example, in [23] some wavelet domain methods and some interpolation methods are investigated and compared with Peak signal-to-noise ratio (PNSR) index. Root Mean Square Error (RMSR) and entropy are other indexes that used in literature. However, due to the great variety of methods, the comparison with these indexes is avoided. Usually the references that have been introduced in each category, two or more methods have been compared using these or other indexes.

V. CONCLUSION AND FUTURE WORK

A general comparison of frequency and spatial domain SR reconstructions methods is presented in Table 1.

	Freq. Domain	Spat. Domain
Observation model	Frequency domain	Spatial domain
Motion models	Global translation	Almost unlimited
SR Mechanism	Limited, LSI	LSI or LSV
Noise model	Limited, SI	Very Flexible
Degradation model	De-aliasing	De-aliasing A-priori info
SR Mechanism	Low	High
Computation req.	Limited	Good
A-priori info	Limited	Excellent
Regularization	Poor	Excellent
App. performance	Limited	Wide
Applicability	Good	Almost unlimited

Table 1: Frequency vs. spatial domain SR

	Bayesian (MAP)	POCS
Applicable theory	Vast	Limited
A-priori info	Prior PDF Easy to incorporate, No hard constraints	Convex sets Easy to incorporate Powerful yet simple
SR solution	MAP estimate Unique	Non-uniqueness of constraint sets
Computation req.	Iterative	High
Convergence	Good	Possibly slow
Optimization	High	Iterative
Complications	Non-convex priors Optimization under	Operators Defn. of projection

Table 2: MAP vs. POCS SR

Spatial domain SR reconstruction methods, though computationally more expensive, and more complex than their frequency domain counterparts, offer important advantages in terms of flexibility. Two powerful classes of spatial domain methods; the Bayesian (MAP) approach and the set theoretic POCS methods are compared in Table 2.

VI. CONCLUSION AND FUTURE WORK

In the literature, several image super-resolution methods have been introduced, which shows the importance of these methods in many applications. However, many methods have been introduced for image super-resolution still there are ongoing researches in this field and every day new articles are published on this subject which is indicates of its importance. So in this paper image super-resolution methods are classified and were introduced to an overview of them has been provided.

In this paper Super-resolution methods were examined for the frequency, spatial and wavelet domains and various methods have been introduced in each domain were studied and the characteristics of these methods were identified. Some type of indexes that are used to compare methods were introduced, but because comparison usually occurs between the methods in each domain or specific category was avoided.

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