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Comparative Study on Super Resolution Image Reconstruction Techniques

KEYWORDS: Super Resolution (SR), High-resolution (HR), Low-resolution (LR), Super Resolution Reconstruction (SRR), Discrete Cosine Transform (DCT)

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ABSTRACT *Super-resolution (SR) is the process of combining a sequence of low resolution images in- order to produce a higher resolution images. The goal of super resolution, as its name suggests, is to increase the resolution of an image. Resolution is a measure of frequency content in an image: high-resolution (HR) images are band limited to a larger frequency range than low-resolution (LR) images. There are many algorithms and methods were developed to produce a super resolution imaging. In this technical paper provide a basis approach of super resolution, various methods for image reconstruction based on frequency and spatial domain. Finally, the comparison of frequency and spatial methods, based on various aspects such as degradation model, motion model and noise model etc.,*

1. Introduction

Super resolution refers to produce high quality (high resolution) images from a set of low quality images (low resolution images). Naturally there is always a demand for better quality images. However, the hardware for HR images is expensive and can be hard to obtain. The resolution of digital photographs is limited by the optics of the imaging device. In conventional cameras, the resolution depends on CCD sensor density, which may not be sufficiently high. As the image-capturing environment is not ideal, many distortions are also present in the low-resolution images [11]. They may have blurred, noisy, aliased low resolution captures of the scene. Therefore, a new approach is required to increase the resolution of the image. It is possible to obtain an HR image from multiple low-resolution (LR) images by using the signal processing technique called super resolution. Naturally, researchers cascade classifiers with SR modules are to improve the recognition rate of the classifiers on LR face images. However, the primary task of most SR algorithms is not to improve recognition performance significantly but to enhance the visual quality of images [35].

2. Basics of Super Resolution

There are several super resolution reconstruction methods are used to improve resolution of a images, Tsai and Huang were the first to consider the problem of obtaining a high-quality image from several lower quality and translation ally displaced images in 1984 [6].Their data set consisted of terrestrial photographs taken by Landsat satellites. Super resolution is a process of increase the quality of image. Now a day's Image restoration plays a major role. It is a well defined process of visually increase the quality of image and focus on clipping of unwanted effects which accomplished during the image capturing. For instance, de-blurring, de-noising methods are used to cancel or minimize those effects. Neither of these methods is able to increase the spatial resolution of the images [34, 10]. Nevertheless, without image restoration and interpolation one cannot understand the concept of super resolution.

Generally all super resolution has the following basis steps in Figure 1. based upon the scheme of research and include are exclude some of these steps [4]:

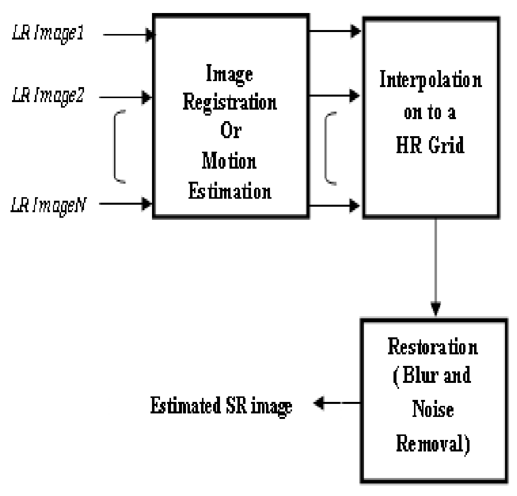

Figure 1. Basic Scheme of Super Resolution

Motion estimation is essential to enable motion compensated filtering. It determines the relative shift between LR images and registers the pixels from all available LR images into common reference grid.

Motion compensation and wrapping of the input LR images into reference grid. Note: the pixels of the LR images are usually non-uniformly distributed with respect to the reference grid.

Restoration of the LR images in order to reduce the artifacts due to blurring and sensor noise. The filtering is necessary to improve image quality.

Interpolation of the LR images with a predetermined zoom factor to obtain the desired HR image.

Fusion of the pixel values from the LR images. This operation is at the heart of all super resolution algorithms.

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Super resolution found in many applications areas, some of the first formulation areas are [3] Satellite imaging, Astronomical imaging, Video enhancement and restoration, Video standards conversion, Confocal Microscopy, Digital mosaicing, Aperture displacement cameras, Medical computed tomo graphic imaging, Diffraction tomography, Video freeze frame and hard copy and Restoration of MPEG-coded video streams etc.,

3. Approaches to Super Resolution

Super-resolution techniques can be classified into two categories [1, 2] they are Reconstruction based and recognition-based techniques.

Reconstruction based: Most super-resolution techniques are reconstruction-based [6]. These methods operate directly with the image pixel intensities and can super-resolve any image sequence provided the motion between observations can be modelled. Their useful magnification factors are usually low however, in that the super-resolved image becomes too smooth or blurred [9].

This reconstruction-based SRR algorithm doesn't require images for training therefore this algorithm doesn't depend on observed images but Reconstruction-based approach inherits its limitations when magnification factor increases.

Recognition-based: This method approaches the problem differently by learning features of the low-resolution input images and synthesizing the corresponding high resolution output [5, 9]. Training is performed by looking at high-resolution and down sampled versions of sample image patches. The reconstruction process involves looking at a patch of pixels in the low-resolution input and finding the closest matching low-resolution patch in the training set, then replacing that patch with the corresponding high-resolution patch. This recognition-based SRR algorithm require images for training therefore this algorithm depend on observed images but this algorithm have high performance when magnification factor increases[7,8].

4. Super-Resolution Reconstruction (SRR) Techniques :

SRR techniques may be divided into two main classes: frequency domain and spatial domain. All frequency domain methods are, to a greater or lesser extent, unable to accommodate general scene observation models including spatially varying degradations, non-global relative camera/scene motion, general a-priori constraints or general noise models [13]. Spatial domain formulations can accommodate all these and provide enormous flexibility in the range of degradations and observation models which may be represented and are thus the methods of choice.

4.1 Frequency domain methods:

The first frequency-domain SR method can be credited to Tsai and Huang [6], they considered the SR computation for the noise-free and low-resolution images. They proposed to the first transform of low-resolution image data into the Discrete Fourier transform (DFT) domain and combined them according to the relationship between the aliased DFT coefficients of the observed low-resolution images. The combined data are then transformed back to the spatial domain where the new image could have a higher resolution than that of the input images. In [12] they exploited the Discrete Cosine Transform (DCT) to perform fast image deconvolution for SR image computation. In following section gives some information about various methods under frequency domain approach.

4.1.1. Reconstruction via Alias Removal

The earliest formulation and proposed solution to the multi-frame super-resolution problem was undertaken by Tsai and Huang [6] in 1984, motivated by the need for improved resolution images from Landsat image data. Landsat acquires images of the same areas of the earth in the course of its orbits, thus producing a sequence of similar, but not identical images. Observed images are modeled as under-sampled versions of an unchanging scene undergoing global translational motion. Impulse sampling is assumed, but the sampling rate fails to meet the Nyquist criterion [16]. Neither the effects of blurring due to satellite motion during image acquisition nor observation noise are considered. The frequency domain formulation based on the shift and aliasing properties [17] of the continuous and discrete Fourier transforms for the reconstruction of a band-limited image from a set under-sampled, and therefore aliased, observation images. The shift and aliasing properties are used to formulate a system of equations which relate the aliased discrete Fourier transform (DFT) coefficients of the observed images to samples of the continuous Fourier transform (CFT) of the unknown original scene. Though this method is computationally attractive, have its own drawbacks and unrealistic assumption of ideal sampling. The possibility of an optical system Point Spread Function (PSF), or even that of spatially integrating sensors is not addressed. Observation noise, finite aperture time is not considered. Due to which we may get noise and blurred images.

4.1.2. Recursive Least Squares Techniques

An approach based on a least squares is implemented in a recursive fashion to improve computational efficiency. In [18] they utilize the frequency domain theoretical framework as well as the global translation observation model proposed [6], however extend the formulation to consider observation noise as well as the effects of spatial blurring. An excellent review of the frequency domain reconstruction method [6] precedes the authors' primary contribution - a recursive least-squares, and a weighted recursive least squares solution method. 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. Though this method addresses the problem of noise and blurring, there are several criticisms which can be leveled at the approach taken. Firstly, the stabilizing function (squared error) is unrealistic for images, tending to result in overly smoothed solutions. Secondly the use of an estimate of the unknown solution leaves unanswered questions as to the stability of the proposed recursive solution method.

4.1.3.Recursive Total Least Squares Methods:

A extensions of the recursive least squares work is that of recursive total least squares which is known to provide some degree of robustness to errors in the observation model, which are likely, in the case of super-resolution reconstruction, to result from errors in motion estimation[29]. Total least squares theory is well developed, Bose, Kim and Valenzuela [20, 21] extend the ideas to include a degree of robustness to errors which result from errors in the translational motion estimates required in the specification. Since it is well understood that motion estimates need be as accurate as possible to SR reconstruction, the justification for the TLS approach is clear. Though attention is directed to the problem of uncertainties in the global translation parameter estimates, this method does not address more fundamental issues such as the inherent limitations of the underlying frequency domain approach which cannot incorporate general scene or camera motion models.

4.1.4. Multichannel Sampling Theorem Based Techniques:

Although the implementation of this reconstruction method is achieved 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. Ur and Gross consider the linear degradation channels to include the effects of a blur PSF as well as global translation which may be modelled as a delay [40]. Observing that the operations of blurring and translation are commutative and assuming a single blur common to all the channels, it is show that the super-resolution problem may be separated into two distinct processes: "merging" the under-

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sampled signals into a single-band-limited function, followed by deblurring of the merged signal. Since the deblurring operation is independent of the merging process, it is possible to derive a closed form solution for computing the merged signal from the degraded and under sampled channel outputs. As mentioned in above, the Ur and Gross approach is a spatial domain analog of the Tsai-Huang frequency domain formulation, the only significant difference being the inclusion of a single PSF common to all the observations. Observation noise and motion blur is not considered. No attention is directed to the motion estimation problem. Since the Ur and Gross proposal is effectively a spatial domain implementation equivalent to the frequency domain methods, it suffers from the same limitations in range of feasible motion models.

Drawback of frequency domain

Despite their simplicity and ease of implementation, frequency-domain models have significant drawbacks. They can only accommodate a global translational model, due to the need for an equivalent transformation in the Fourier domain. For the same reason, the noise and degradation models can only be shift-invariant. Finally, since superresolution is inherently ill-posed, regularization is almost always required. The incorporation of a priori knowledge or constraints is often difficult or inconvenient in the frequency domain. Spatial domain methods, discussed next section.

4.2. Spatial Domain Methods

Most of the research done on super resolution today is done on spatial domain methods. Their advantages include a great flexibility in the choice of motion model, motion blur and optical blur, and the sampling process. Another important factor is that the constraints are much easier to formulate. Spatial domain reconstruction allows natural inclusion of (possibly nonlinear) spatial domain a-priori constraints (e.g. Markov random fields or convex sets) which result in bandwidth extrapolation in reconstruction.

4.2.1. Interpolation of Non-Uniformly Spaced Samples

In this approach the low-resolution observation image sequence are registered. As the relative shifts between the LR images are arbitrary, it is natural that the interpolation is non-uniform. This is the most intuitive method of SR. The first step is to estimate the shift. It is followed by a non-uniform interpolation to produce a HR image. The last step is a deblurring process .Though this approach may initially appear attractive, it is, however, overly simplistic as it does not take into consideration the fact that samples of the low resolution images do not result from ideal sampling but are, in fact, spatial averages. The result is that the reconstructed image does not contain the full range of frequency content that can be reconstructed given the available low-resolution observation data. Keren, Peleg and Brada describe a spatial domain approach to image registration using a global translation and rotation model, as well as a two stage approach to super-resolution reconstruction [23, 24]. Comparing to other techniques, this method is cheaper in computational costs. However, since the errors at the interpolation process is not accounted for during the de-convolution, it does not guarantee an optimal solution. Furthermore, this approach applies only to the case when the blur and the noise effects are constant over the lower resolution images. Hence, the use of degradation models is limited in this approach. The advantage of this approach is that it has low computational load, which is thus quite suitable for real-time applications. However, the optimality of the entire reconstruction process is not guaranteed, since the interpolation errors are not taken into an account.

4.2.2. Algebraic Filtered Backprojection

An early algebraic tomographic filtered back projection approach to super-resolution reconstruction is that of Frieden and Aumann, [19]. The authors do not consider the problem of super-resolution image reconstruction from an image sequence, but the related problem of super-resolution image reconstruction from multiple 1-D scans of a stationary scene by a linear imaging array. Noting that the PSF in the 1-D scan system represents a line integral and that of the multiple image super-resolution problems represents an integral area, it is clear that the problems differ only in the form of the imaging system PSF. The linear imaging array detectors are assumed to be larger than the limiting resolution of the optical system. Frieden and Aumann make no allowances for the presence of observation noise. This has serious consequences since inverse filtering is well known to be highly noise sensitive due to the increasing amplitude response of the inverse filter with increasing frequency.

4.2.3. Iterative Back-Projection Approach

Irani and Peleg [25] formulated the iterative back-projection (IBP) SR reconstruction approach is similar to the back projection used in tomography. In this approach, the HR image is estimated by back projecting the error (difference) between simulated LRimages via imaging blur and the observed LR images. This process is repeated iteratively to minimize the energy of the error. Mann and Picard [26] extended this approach by applying a perspective motion model in the image acquisition process. Later, Irani and Peleg [27] modified the IBP to consider a more general motion model. The advantage of IBP is that it is understood intuitively and easily. However, this method has no unique solution due to the ill-posed nature of the inverse problem, and it has some difficulty in choosing the back projection kernel error factor. In contrast to the POCS and regularized approach, it is difficult to apply a priori constraints.

4.2.4. Stochastic or Probabilistic Methods

Since superresolution involves estimating data or parameters that are unknown, it is natural to model images as probability distribution. Schultz and Stevenson [28] describe discontinuity-preserving prior image model that utilizes Huber Markov Randomelds within a Bayesian framework. Maximum A-Posteriori (MAP) estimation is done by the gradient projection algorithm, and independent object motion (estimated by hierarchical blocks) is assumed. Hardie, Barnard, and Armstrong present a super-resolution procedure which is similar to that of Schultz and Stevenson make a significant contribution in estimate the HR image and the motion parameters simultaneously.

A procedure is suggested where motion and the reconstructed image are estimated alternately, which offers the advantage of not estimating motion directly from LR images. Tom and Katsaggelos , on the other hand, use the ML (as opposed to MAP) approach for a degradation model that includes blur and additive noise[15].

Registration and restoration is performed simultaneously by the expectation maximization. Simultaneous motion estimation and restoration is also possible [14]. The rich area of statistical estimation theory is directly applicable to stochastic SR reconstruction methods.

4.2.5. Set Theoretic 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.

An alternate set theoretic SR reconstruction method uses an ellipsoid to bound the constraint sets [21, 39]. 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. These methods have the disadvantages of non-

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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 has no claim to optimality.

4.2.6. Optimal and Adaptive Filtering Methods

Several researchers have proposed inverse filtering approaches to super-resolution reconstruction. These techniques are considered primarily for completeness, as several are sub-optimal in terms of inclusion of a-priori constraints. In [30] a simple deconvolution restoration approach that assumes sub-pixel translational motion. A deconvolution filter suitable for restoration of merged observation images is determined. This approach is poorly suited to the incorporation of more general observation models and is limited in terms of inclusion of a-priori constraints. Techniques based on adaptive filtering, especially the Kalman filter, have also seen application in super-resolution reconstruction [32, 22].

In motion compensated model Kalman filter capable of super-resolution reconstruction under spatially varying blurs is proposed[31]. Though their Kalman filtering formulation is computationally efficient, it is, in effect, still a linear minimum mean square error estimator. Nonlinear image modeling constraints which provide bandwidth extrapolation cannot be easily incorporated into this method.

5. Comparison of super-resolution:

Spatial domain overcomes many of the short comings of the frequency domain constraints [33, 36 37, 38]. A comparison of frequency and spatial classification of super resolution reconstruction methods is listed in the tabular column (Table 1).

Table 1. Comparison for Frequency and Spatial Domain Methods

	Frequency Domain	Spatial Domain
Mode of Operation	Fourier transform of an image	Directly on Pixels
Domain for Observation	Frequency Domain	Spatial Domain
Simplicity	Theoretically simply, so Computationally	Complex in theory, so Computationally
Degradation Model	Limited	Almost unlimited
Noise model	Limited	Very flexible
Motion model	In flexibility	Almost unlimited
Computation	Flexible	More complex
A priori info.	Low flexibility	More flexible
Mechanism for SR	De-aliasing	De-aliasing with priori info.
Performance	Good for specific application	Good
Applicability	Limited	Wide
Extensibility	Poor	Excellent

6. Conclusion:

In this technical paper provided an overview approaches and methods of super resolution image reconstructions (SRR). And compared two methods of Super resolution images are frequency domain and spatial domain constraints. Among the two methods, frequency domain method has a significant drawback, because they can accommodate only global translation mode and lack of priori information. For these reason most of the researches choose spatial domain approach for SRR even though it is more expensive and more complex than frequency domain. Hybrid MAP/POCS approaches for spatial domain provides more suitable solution, when compare to other methods. Because, it combines the mathematical rigor and uniqueness of solution with a priori constraints. And also in restoration process it is capable to accommodate model based motion estimates.

REFERENCE

1. Vorapoj Patanavijit, "Super-Resolution Reconstruction and Its Future Research Direction"- AU J.T. 12(3): 149-163 (Jan. 2009) | 2. Yongjun Peng ,Jian He & Jun Sun,- "A Research of face Super-Resolution Technology In Low-Quality Environment" Journal of Theoretical and Applied Information Technology 20th March 2013. Vol. 49 No.2 -ISSN: 1992-8645. | 3. S. Borman and R.L. Stevenson, "Super-resolution from image sequences A review," in Proc. 1998 Midwest Symp. Circuits and Systems,1999, pp. 374-378. | 4. Meidi Trimche- "super resolution image reconstruction using non linear filtering techniques" in Tampere university of technology-publication 640. | 5. M. Elad and D. Datsenko. Example-based regularization deployed to super-resolution reconstruction of a single image. Published by Oxford University Press on behalf of The British Computer Society. The Computer Journal- 2007. | 6. R. Y. Tsai and T. S. Huang, "Multiframe image restoration and registration," in Advances in Computer Vision and Image Processing, T. S. Huang, Ed. JAI Press, 1984, vol. 1, pp. 317–339. | 7. Capel, D.P. 2001. Image mosaicing and super-resolution. Ph.D. Thesis, Robotics Research Group, Department of Engineering Science, University of Oxford, Oxford, England, UK. | 8. Capel, D.P.; and Zisserman, A. 2001. Super-resolution from multiple views using learnt image models. Proc. IEEE Computer Soc. Conf. on Computer Vision and Pattern Recognition (CVPR'01), Kauai, HI, USA, 8-14 December 2001, vol. 2, pp. 627-634. IEEE Computer Society, Washington, DC, USA. | 9. Baker, S., Kanade, T.: Limits on Super-Resolution and How to Break Them. 24(9),ieee Computer Society (1167–1183) (2002). | 10. R. Sudheer Babu and Dr.K.E.Sreenivasa Murthy, "A Survey on the methods of Super-resolution Image Reconstruction," in Proceedings of International Journal of Computer Applications (0975 – 8887) Volume 15– No.2, February 2011. | 11. S. Baker and T. Kanade, "Limits on super-resolution and how to break them," in Proceedings of the 2000 IEEE Conference on Computer Vision and Pattern Recognition, June 2000. | 12. S. H. Rhee and M. G. Kang, "Discrete cosine transform based regularized high-resolution image reconstruction algorithm," Opt. Eng., vol. 38, pp. 1348–1356, Aug. 1999 | 13. Jing Tian • Kai-Kuang Ma "A survey on super-resolution imaging", Springer-Verlag London Limited 2011, DOI 10.1007/s11760-010-0204-6 . | 14. Woods, N.A., Galatsanos, N.P., Katsaggelos, A.K.: Stochastic methods for joint registration, restoration, and interpolation of multiple undersampled images. IEEE Trans. Image Process, 201–213 (2006). | 15. Dempster, P., Laird, N.M., Rubin, D.B.: Maximum likelihood from incomplete data via the EM algorithm. Journal of the Royal Statistical Society. Series B (J. R. Stat. Soc. B 39(1), 1–38 (1977) | 16. A. K. Jain, Fundamentals of Digital Image Processing, Prentice-Hall, Englewood Cliffs, NJ, 1989. | 17. R. A. Roberts and C. T. Mullis, Digital Signal Processing, Addison-Wesley, 1987. | 18. S. P. Kim, N. K. Bose, H. M. Valenzuela,"Recursive total least squares algorithm for image reconstruction from noisy, undersampled multiframes". Multidimensional Systems and Signal Processing, vol. 4, no. 3, July 1993. | 19. B. R. Frieden and H. G. Aumann, "Image reconstruction from multiple 1-D scans using filtered localized projection," Applied Optics, vol. 26, no. 17, pp. 3615–3621, Sept. 1987. | 20. G. H. Golub and C. F. Van Loan, "An Analysis of the Total Least Squares Problem," SIAM Journal on Numerical Analysis, vol. 17, pp. 883–893, 1980. | 21. N. K. Bose, H. C. Kim, and H. M. Valenzuela, "Recursive Total Least Squares Algorithm for Image Reconstruction from Noisy, Undersampled Multiframes," Multidimensional Systems and Signal Processing, vol. 4, no. 3, pp. 253–268, July 1993. | 22. A. J. Patti, A. M. Tekalp, and M. I. Sezan. A New Motion Compensated Reduced Order Model Kalman Filter for Space-Varying Restoration of Progressive and Interlaced Video. IEEE Trans Image Process.7(4):543-54. doi: 10.1109/83.663499. Apr. 1998. | 23. J. L. Brown, "Multichannel sampling of low-pass signals," IEEE Transactions on Circuits and Systems, vol. 28, no. 2, pp. 101–106- 1981. | 24. D. Keren, S. Peleg, and R. Brada, "Image sequence enhancement using subpixel displacements," in Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, June 1988, pp. 742–746. | 25. M. Irani and S. Peleg, "Improving resolution by image registration,"CVGIP: Graphical Models and Image Proc., vol. 53, pp. 231-239, May 1991. | 26. S. Mann and R.W. Picard, "Virtual bellows: Constructing high quality stills from video," in Proc. IEEE Int. Conf. Image Processing, Austin, TX, Nov. 1994, pp. 13-16. | 27. M. Irani and S. Peleg, "Motion analysis for image enhancement resolution, occlusion, and transparency," J. Visual Commun. Image Represent., vol.4, pp. 324-335, Dec. 1993. | 28. R.R. Schulz and R.L. Stevenson, "Extraction of high-resolution frames from video sequences," IEEE Trans. Image Processing, vol. 5, pp. 996-1011, June 1996. | 29. N. K. Bose, H. C. Kim, and H. M. Valenzuela, "Recursive implementation of total least squares algorithm for image reconstruction from noisy, undersampled multiframes," in Proceedings of the IEEE conference on Acoustics, Speech and Signal Processing, Minneapolis, MN, Apr. 1993, vol. 5, pp. 269–272. | 30. G. Jacquemod, C. Odet, and R. Goutte, "Image resolution enhancement using subpixel camera displacement," Signal Processing, vol. 26, no. 1, pp. 139–146, 1992. | 31. A. J. Patti, A. M. Tekalp, and M. I. Sezan, "A New Motion Compensated Reduced Order Model Kalman Filter for Space-Varying Restoration of Progressive and Interlaced Video," IEEE Transactions on Image Processing, vol. 7, no. 4, pp. 543–554, Apr. 1998. | 32. Shi Ying Adaptive feature-spatial representation for mean-shift tracker. Proceedings - International Conference on Image Processing, ICIP. 2008, 2008, pp: 2012-2015. | 33. Netra M Lokhande,Dr. Dinkar M Yadav."Historical Overview: Techniques of Super-Resolution Image Reconstruction", International Journal Of Advances In Computing And Information Technology ISSN 2277–9140 December 2012. | 34. VorapojPatanavijit,"Super-Resolution Reconstruction and Its Future Research Direction," in Proceedings of International Journal of Computer Applications (0975– 8887) Volume 15– No.2, February 2011. | 35. Sean Borman, Robert Stevenson, "Spatial resolution enhancement of low- resolution image sequences: a comprehensive review with directions for future research". 1998. | 36. Dirck Schilling and Pamela C.Cosman, 'Preserving Step Edges in Low Bit Rate Progressive Image Compression', IEEE Transactions on Image Processing, December 2003. | 37. S.C.Park, M.K.Park, and M.G.Kang, 'Super-Resolution Image Reconstruction: A Technical Overview', IEEE Signal Processing Magazine, May 2003. | 38. V.Hemalatha* and Alok Ranjan,' Application of Super-Resolution Reconstruction of low-Resolution Image Sequences in Spatial Domain International Journal of Advanced Research in Computer Science, 3 (3), May –June, 2012,528-530. | 39. A. J. Patti, M. I. Sezan, and A. M. Tekalp. Superresolution Video Reconstruction with Arbitrary Sampling Lattices and Nonzero Aperture Time. IEEE Trans. IP, 6(8):1064–1076,Aug. 1997. | 40. A. Papoulis, "Generalized sampling expansion," IEEE Transactions on Circuits and Systems,vol. 24, no. 11, pp. 652–654, Nov. 1977. | |