Different Super Resolution Techniques-Merits And Demerits: A Systematic Review

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Abstract- *Super resolution (SR) plays a crucial role in enhancing the quality of an image. To better analysis of an image we need high resolution (HR) images which are often required in every field like face recognition, satellite images, medical diagnosis etc. In super resolution high resolution images are produced from single image or multiple low resolution images. At first LR images are sub sampled and after that shifted with sub pixel precision. By integer units if the LR images are shifted then each image will contain the same information, so there will be no new information that can be used to reconstruct an HR image. If the LR images have different sub pixel shifts from each other and if aliasing is present, then each image cannot be obtained from the others. In this case, the new information contained in each LR image can be used to obtain an HR image. It means if the pixel density of an image is high we can get more details from that image. The main aim of SR is to improve the resolution of an image. In this paper I discussed about various methods of super resolution techniques which enhance the quality of a low resolution image (LR) .Mainly the methods are divided into frequency domain and spatial domains. Here, I also discussed the comparison of different approaches, challenges and issues for SR and applications of SR.*

I. INTRODUCTION

In most electronic imaging processing application high resolution images are required .For better interpretation and analysis of an image high density pixel is needed so that the image can deliver more information. But when the number of pixel per unit area increases light on sensor decreases which generates shot noise. By increasing chip size the quality of a image can be enhanced but it increases the capacitance. This is not an effective approach as large capacitance difficult to speed up large transfer rate. Therefore a new approach is required to overcome such kind of limitation of sensor and optics manufacturing technology. One promising approach is to use signal processing techniques to obtain an HR image (or sequence) from observed multiple low-resolution (LR) images [1]. Recently, such a resolution enhancement approach has been one of the most active research areas, and it is called super resolution (SR) (or HR) image reconstruction or simply resolution enhancement. The method, super resolution takes more samples of the same scene so that to get some extra information which can be used, while merging the samples to get a high resolution image. These samples can be acquired by sub-pixel shifts, by changing scene illumination or, by changing the amount of blur [2].

II. IMAGE SUPER RESOLUTION

Super resolution is a technique through which we can extract more information from LR images. Super resolution can be acquired either by processing multiple low resolved images as input and generating a high detail containing a single super resolved image as output or enhancing the details in a single low resolved image and generating a high resolved image for analysis. [3]. In SR from multiple LR images, it is a construction of HR image from several LR images, thereby increasing the high frequency components. The main concept is that all the non repetitive information from the multiple LR images are combined together.

While in SR from single LR image, resolution of the image can be increased either by enhancing the edges of the objects present in an image or by patch redundancy technique, where each LR patch is replaced by its corresponding HR patch[3]. Enough shifting of LR images is required in viewing the same scene. If there is minor shifting in LR image then HR reconstruction image will not contain any new information. Let there are four images taken and out of four one image can be taken as reference and other be shifted horizontally, vertically or diagonally to a scale of half pixels. By taking that reference image, three other image pixels can be interleaved and from that a higher resolved image can be generated.

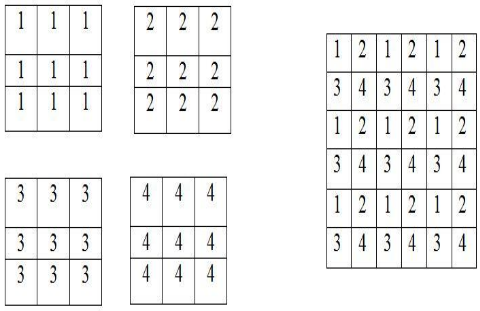


Figure 1. Ideal Super Resolution setup

(Out of the Four images are taken, first one can be taken as reference and other three images can be considered to be relative shifted to half a pixel in horizontal, vertical, and diagonal directions (left side-four images). These three image pixels can then be added to produce a high resolution image with increase in size of the image (right side-single image)) [1].

Most of the super-resolution image reconstruction methods consist of three basic components [1].

(i) Motion estimation (ii) interpolation and (iii) blur and noise removal.

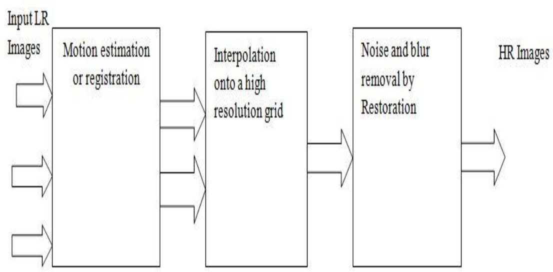
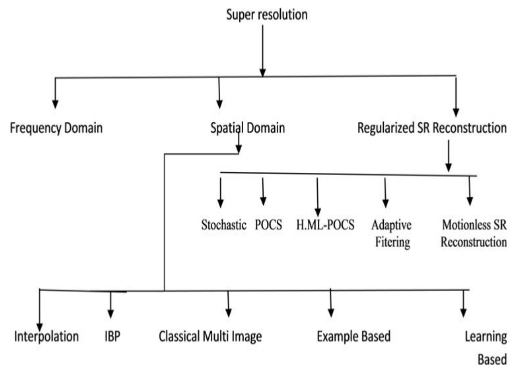


Figure 2 Basic SR reconstruction stages

In Image registration multiple images can be overlapped of the same scene, taken from the different angles by sensors.

Overlapping more than one images of the same scene which must be taken from different angles by the sensors is called image registration. Interpolation is to estimate the intermediate pixels between two pixel values. When any images are converted to HR images from LR images their present a gap which can be removed by interpolation process. Interpolation process introduces artifacts resultant images become blurry and noisy. By various filter noise can be removed and a super resolution image can be generated.



III. APPROACHES TO SR

Super-resolution techniques can be classified as (1) Frequency domain approach and (2) Spatial domain approach and (3) Regularized SR reconstruction

A. Frequency domain approach:

The frequency domain approach makes explicit use of the aliasing that exists in each LR image to reconstruct an HR image [6].Tsai and Huang proposed frequency based approach in which they stated to transform the LR image into Discrete Fourier Transform (DFT) domain and combined them according to the relationship between the aliased DFT coefficients of the observed LR images and that of the unknown high-resolution image [4]. After that that combined data are transformed back to spatial domain where a higher resolution image is generated. The principles of frequency domain approach areas follow: i) what is the shift property of the Fourier transform? ii) The aliasing association between the continuous Fourier transform (CFT) of an original HR image and the discrete Fourier transform (DFT) of observed LR images, iii) the supposition that an original HR image is band limited. Through these properties system equation is derived [5].

B. Spatial Domain Methods:

The frequency domain approach has certain drawbacks like it limits the inter-frame motion to be translational. As well it is very difficult in frequency domain to use the prior knowledge. As the main problem is ill-posed image in SR, prior knowledge is required to overcome this. The main benefit of spatial domain is the support for unbind motion between frames and prior knowledge availability for solving the problems. Some of the methods are interpolation, iterative back projection and projection onto convex. Drawbacks of frequency domain approach is that use of prior knowledge is difficult and inter frame motion is to be translational. The main cause of use of prior knowledge is to solve ill-posed image in SR. In spatial domain benefit is that support of unbind motion between prior knowledge availability to solve the problems and frames. Some of the methods are interpolation, iterative back projection and projection onto convex [7].

1. Interpolation Approach:

For doing Image enhancement, zooming and resizing interpolation plays very important role in image processing field. Interpolation is the technique of transferring image from one resolution to another without losing the image quality. Some interpolation techniques are nearest neighbour, bilinear and cubic convolution. Digital image is basically a signal which is spatially varying in two dimensions. This signal is sampled and quantized to get all values, called pixels of image. When we increase the resolution of image from low to high, it is called up-sampling or up-scaling while reverse is called down sampling or down scaling [8].

(i).Bilinear interpolation:

In Bilinear interpolation interpolated points are filled with four closest pixel's weighted average.

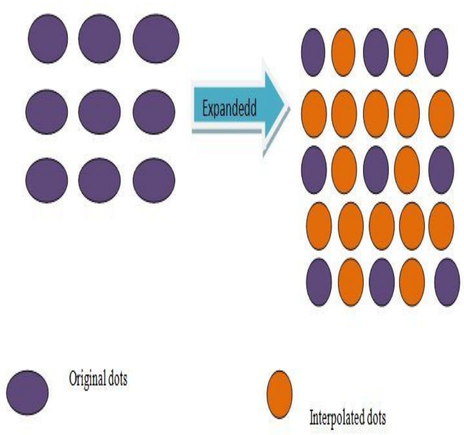


Figure 3- Basic Concept of Interpolation

Bilinear interpolation specially recommended for continuous data like elevation and raw slope values. The interpolation kernel for linear interpolation is:

$$v(p) = \begin{cases} 0 & |p| > 1 \\ 1-|p| & |p| < 1 \end{cases} \quad \text{-------------------- (1)}$$

Where p = distance between interpolated point and grid point.

(ii) Bicubic interpolation:

Looks at the sixteen nearest cells and fits a smooth curve through the points to find the output value. Bicubic interpolation is recommended for smoothing continuous data, but this incurs a processing performance overhead [4].

The interpolation kernel for cubic interpolation is:

$$v(p) = \begin{cases} \frac{3}{2}|p|^3 - \frac{5}{2}|p|^2 + 1 & 0 \le |p| < 1 \\ -\frac{1}{2}|p|^3 + \frac{5}{2}|p|^2 - 4|p| + 2 & 1 \le |p| < 2 \\ 0 & 2 < |p| \end{cases} \quad \text{---------- (2)}$$

Where p = distance between interpolated point and grid point.

(iii) Nearest Neighbour interpolation:

In this method, nearest value is copied for interpolation and this technique has less computational complexity. Nearest neighbour interpolation is recommended for categorical data such as land use classification [4].

The interpolation kernel for each direction for this method is:

$$v(p) = \begin{cases} 0 & |p| > 0.5 \\ 1 & |p| < 0.5 \end{cases} \quad \text{---------------------- (3)}$$

Where p= distance between interpolated point and grid point.

The main drawback is that resultant image produced by the various interpolation techniques generally suffers from artifacts.

2. Iterative Back Projection (IBP):

In IBP approach HR image is estimated by back projecting the difference between the simulated LR image and captured LR on interpolated image. This iterative process of SR does iterations until the minimization of the cost function is achieved. Mathematically the SR step to IBP is written as

$$p = p^{(0)} + p_e \qquad \text{----------------------- (4)}$$

Where, p - interpolated image; p_e - error correction

3. Classical Multi-Image SR:

In classical multi image SR technique reconstruction of a SR image is done. Here multiple LR images of same scene are taken. The assumption here is that the two or more LR images should contain distinguishable features. Because of these, practically it helps very less in improvement of image resolution, if distinguishable features in LR images are less [9].

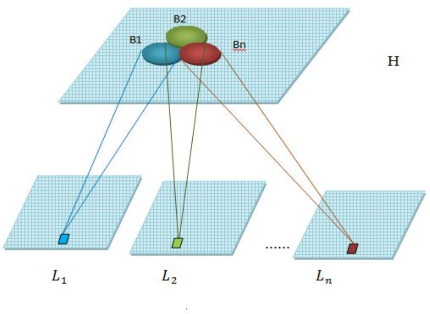


Figure 4-Multi Image SR

4. Example-Based SR:

In Example-Based approach, the image has small patches that redundantly reappear, both within the scale as well as across the scale [4]. Each LR patch in an image is replaced by its corresponding HR patch to generate the SR image [4]. Here assumption is that, the image should have enough HR patches for the correspondence LR patches [9].

5. Learning Based SR:

Here machine learning concept is used. Proper training is given to classify the LR and corresponding

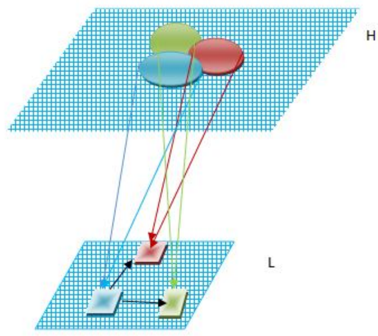


Figure 5-Single Image Multiple Patch

Its HR patches. In this approach, both LR and HR patches are divided into different classes [4].The comparison is done LR with its corresponding HR patches, by this number of comparison is reduced. For an image if it is an edge-area of the LR, the routine example-based image SR algorithm can be used to implement the local and fine SR. For the flat regions of the low-resolution, only interpolation algorithm is used for super-resolution [4]. The performance of learning based super-resolution depends on HR patch (es) retrieved from the training data for an input LR patch [10].

Table 1.Comparison of different SR approaches [11]

Categorization	**Description**	**Disadvantages**
Interpolation based	Different interpolation techniques are used	Over-smooth, jagged artifacts
Reconstruction based	Reconstruction constraint and image prior	Ringing artifacts, imposing additional prior

C. Regularized SR reconstruction approach:

1. Stochastic Approach:

Stochastic SR image reconstruction, typically a Bayesian approach, provides a flexible and convenient way to model a priori knowledge concerning the solution [1].

Bayesian estimation methods are used when the posterior probability density function (PDF) of the original image can be established [1].

The MAP estimator of p maximizes the a posterior PDF $P(p|q_n)$ with respect to p

$$p = \arg\max P(p \mid q_1, q_2, \ldots\ldots\ldots\ldots, q_n) \quad \ldots\ldots\ldots\ldots\ldots (5)$$

After taking logarithmic function and applying Bayes' theorem to the conditional probability, the MAP optimization problem can be expressed as

$$p = \arg\max \{\ln P(q_1, q_2, \ldots\ldots\ldots\ldots, q_n|p) + \ln P(p)\} \quad \ldots\ldots\ldots\ldots\ldots (6)$$

Here, both the a priori image model *P* (p) and the conditional density $P(q, q_2, \ldots\ldots\ldots\ldots, q_n|p)$ will be defined by a priori knowledge concerning the HR image p and the statistical information of noise. Since MAP optimization in (6) includes a priori constraints (prior knowledge represented by *P* (p)) essentially, it provides stable SR estimates effectively. Bayesian estimation differentiate between possible solutions by utilizing a priori image model, and Markov random field (MRF) priors that provides a powerful method for image prior models are often adopted. Maximum likelihood (ML) estimation is used in SR reconstruction. ML estimation is a special case of MAP estimation (no prior term is used).The inclusion of *a-priori* information is required for the solution of ill-posed inverse problems, The MAP estimation should be used in preference to ML.

Advantage of the Bayesian framework is the direct inclusion of *a-priori* constraints on the solution, often as MRF priors which provides an important method for image modeling using (possibly non-linear) local neighbour interaction.

MAP estimation with convex priors implies a globally convex optimization, ensuring solution existence and uniqueness allowing the application of efficient descent optimization methods. Simultaneous motion estimation and restoration is also possible .The rich area of statistical estimation theory is directly applicable to stochastic SR reconstruction methods.

2.Projection onto Convex Sets Approach (POCS):

The POCS method is an alternative iterative approach to incorporating the prior knowledge about the solution into the reconstruction process. With the estimation of registration parameters, this algorithm also solves the restoration and interpolation problem to estimate the SR image. This method is based on a linear model describing the relation of HR and LR images, a cost function is introduced and the HR image is obtained [1].

The POCS formulation of the SR reconstruction was first suggested by Stark and Oskoui [17]. According to the method of POCS incorporating a priori knowledge into the solution can be interpreted as restricting the solution to be a member of a closed convex set *Ci* that are defined as a set of vectors which satisfy a particular property[1]. If the constraint sets have a nonempty intersection, then a solution that belongs to the intersection set $C_s = \cap_{i=1}^{n} C_i$,which is also a convex set, can be found by alternating projections onto these convex sets[1]. Indeed, any solution in the intersection set is consistent with the a priori constraints and therefore it is a feasible solution [1]. The POCS method can be applied to find a vector which belongs in the intersection by the recursion

$$y^{m+1} = P_n P_{n-1} \ldots\ldots\ldots\ldots\ldots P_2 \quad \text{---------------------------} (7)$$

where y^0 is an arbitrary starting point, and P_i is the projection operator which projects an arbitrary signal *y* onto the closed, convex sets, C_i (i=1,2,.......,n). Although this may not be a trivial task, it is, in general, much easier than finding P_s , i.e., the projector that projects onto the solution set C_s in one step [17] .

POCS algorithm has several advantages like simplicity, it can be also applied to the occasion with any smooth movement, and can easily be joined in the prior information, so this method is widely used. POCS algorithm is very strict to the accuracy of movement estimation. So in order to improve the Stability and performance of the algorithm, the relaxation operator will be used to replace ordinary projector operator, at the same time it is not contributing to the resumption of the edge and details of images [1]. The advantage of POCS is that it is simple, and it utilizes the powerful spatial domain observation model [1]. It also allows a convenient inclusion of a priori knowledge.POCS methods have the disadvantages like non-uniqueness of solution, slow convergence, and a high computational cost.

3.H.ML-POCS Hybrid Reconstruction Approach:

The ML-POCS hybrid reconstruction approach finds SR estimates by minimizing the ML (or MAP) cost functional while constraining the solution within certain sets [1]. Earlier efforts for this formulation are found in the work by Schultz and Stevenson [18] where MAP optimization is performed while projections-based constraint is also utilized. The constraint set tells that the down-sampled version of the HR image matched the reference frame of the LR sequence. Elad and Feuer [19] proposed a general hybrid SR image reconstruction algorithm which combines the benefits of the stochastic approaches and the POCS approach. The simplicity of ML (or MAP) and non ellipsoid constraints used in POCS are simultaneously utilized by defining a new convex optimization problem as follows:

$$\min \epsilon^2 = \{[x_k - W_k\, y]^T R_n^{-1}[y_k - W_k\, y] + \alpha[S_y]^T V[S_y]\} \text{ -----------------(8)}$$

$$\{y \in C_k,\ 1 \le k \le N\}$$

Where R_n *is* the autocorrelation matrix of the noise, S is is the Laplacian operator, V is the weighting matrix to control the smoothing strength at each pixel, and C_k represents additional constraint. The advantage of the hybrid approach is that all priori knowledges are effectively combined, and it also ensures a single optimal solution in contrast to the POCS approach.

	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	Unique MAP estimate	Non Unique $\cap$ of constraints sets.
Optimization	Iterative	Iterative
Convergence	Good	Possibly slow
Computation req.	High	High
Complications	Optimization under non-convex priors	Definition of projection

4. Adaptive Filtering Approach:

Elad and Feuer [19] proposed an SR image reconstruction algorithm based on adaptive filtering theory applied in time axis. They modified notation in the observation model to accommodate for its dependence on time and suggested least squares (LS) estimators based on a pseudo-RLS or R-LMS algorithm[1]. At each time iteratively the steepest descent (SD) and normalized SD are applied to estimate the HR image, and the LMS algorithm is derived from the SD algorithm. As a result, at each time the HR image is calculated without computational complexity of a direct matrix inversion. This approach is shown to be capable of treating any chosen output resolution, linear time and space variant blur, and motion flow [19], which makes the progressive estimation of HR image sequence possible. Following this research, they rederive the R-SD and R-LMS algorithm as an approximation of the Kalman filter [19]. Here, computational complexity issues and convergence analysis of these algorithms were also discussed.

5. Motionless SR Reconstruction Approach:

Between the observed images the SR reconstruction algorithms presented so far require relative sub pixel motions. However, it is shown that SR reconstruction is also possible from differently blurred images without relative motion [19], [20]. Elad and Feuer [19] demonstrated that the motionless SR image reconstruction without a regularization term is possible if the following necessary condition is satisfied

$$L^2 \le \min\{(2n+1)^2 - 2, P\} \qquad \text{------------- (9)}$$

Where $(2n+1) \times (2n+1)$ is the size of the blurring kernel, and $L_1 = L_2 = L$ .Though more numbers of blurred observations of a scene do not provide any additional information, it is possible to achieve SR with these blurred samples, provided (eq.9) is satisfied. Recover of the HR image with much fewer LR images possible if regularization is incorporated to the reconstruction procedure. Rajan and Chaudhuri, [20, 22] proposed a similar motionless SR technique for intensity and depth maps using an MRF model of the image field. There have been other motionless attempts to SR imaging [20, 23]. Rajan and Chaudhuri [20, 22] presented the SR method using photometric cues, and the SR technique using zoom as a cue is proposed by Joshi and Chaudhuri [23].

IV. COMPARISON

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

V. CHALLENGES ISSUES FOR SR:

In practical building SR image, there are several challenges and issues regarding that. Some of them are as follows:

(i). Image Registration:

Ill-posed image is the main problem of image registration. The problem is more difficult in the SR setting, where the observations are low-resolution images with heavy aliasing artifacts [13].The error in the registration becomes more and more when resolution of the observed LR image. Degradations caused by these registration errors are visually more annoying than the blurring effect resulting from interpolation of a single image [13].

(ii). Computational Efficiency:

The inverse procedure in SR reconstruction obviously requires a very large computational load[1].In real time application it's important to develop an algorithm that reduces the computational cost.

Real time application is always requires good efficiency. As there are large numbers of unknowns in reconstructing SR images, matrix manipulation increases [12].

(iii). Robustness:

SR techniques are defenceless to the presence of outliers due to motion errors, inaccurate blur models, noise, moving objects, motion blur etc [4]. These effects are not easy to estimate which are not acceptable in many applications like video conversions, so robustness of SR is required [14]. Robustness of SR is of interest because the image degradation model parameters cannot be estimated perfectly, and sensitivity to deviations may result in visual degradations, which are unacceptable in many applications, e.g., video standard conversion [15], [13].

VI. APPLICATIONS[4]:

Several practical areas and applications of SR as follows:

i) **Biometrics** – Fingerprint Face and Character recognition, DNA analysis.
ii) **Medical Science** – MRI, CT, X-Ray, Ultrasound etc.
iii) **Satellite Imaging** – Planetary information, Weather forecasting, Target detection, Traffic detection etc.
iv)**Surveillance Video** – Zooming region of interest (ROI).e.g. license plate recognition of vehicle, target recognition etc.
v) **Entertainment** – HDTV and Photography
vi) **Commercial** – Barcode reading
vii) **Military** – Tracking and Detecting

VII. DIRECTIONS FOR FUTURE RESEARCH

Three research areas promise improved SR methods:

Motion Estimation: The main focus of SR research area is to enhance arbitrary scenes containing occlusions, transparency, global multiple independent motion etc. To achieve this need is robust, model based, sub-pixel accuracy motion estimation and segmentation techniques, all these are present research problem. Motion is estimated from observed under sampled data. Simultaneous multi frame motion estimation technique is reliable than other two frame techniques. Regularized motion estimation problem is used for the ill-pose problem of motion estimation problem. Simultaneous motion estimation and SR reconstruction approaches should yield improvements in both motion estimation and SR reconstruction. Sparse motion maps give accurate motion estimation.

Degradation Models: Accurate degradation or observation models promise improved SR reconstruction .Many SR application areas may benefit from improved degradation models. In colour SR reconstruction improved motion estimates and reconstructions are possible by utilizing correlated information in colour bands. Colour sub -sampling and quantization effects promise improved reconstruction of compressed video. Considering degradations inherent in magnetic media recording and playback are expected to improve SR reconstructions from low cost camcorder data. The response of commercial CCD arrays departs from the simple integrate and sample model prevalent in much of the literature. Models of sensor geometry, spatio-temporal integration characteristics, and noise and readout effects promise more realistic observation modeling which are expected to result in SR reconstruction performance improvements.

Restoration Algorithms: POCS and MAP based algorithms are very efficient. Hybrid MAP/POCS restoration techniques will combine the mathematical stiffness and uniqueness of solution of MAP estimation with the convenient a priori constraints of POCS [2], [15]. Restoration and simultaneous motion estimation is very important part for image reconstruction. Separate motion estimation and restoration, as is commonly done, is sub-optimal as a result of this interdependence [16].

VIII. CONCLUSION

I have explained the concept of SR technology in this article by providing an overview of existing SR algorithms and advanced issues currently under investigation. I specified frequency based, reconstruction based and spatial based approaches to achieve the goal. I also included applications and comparison of different SR approaches. SR image reconstruction is one of the most spotlighted research areas, because it can overcome the inherent resolution limitation of the imaging system and improve the performance of most digital image processing applications.

IX. ACKNOWLEDGEMENT

The author would like to acknowledge her project guide Mr. Pramit Ghosh, Asst. Prof. of Computer Science & Engineering of RCC Institute of Information Technology, for his immense support, and also to his college for providing the infrastructure to carry on her work. The author is also grateful to all the researchers for sharing their ideas through their different books, journals, papers, video lectures which had helped her very much in writing this review paper.

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