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High Resolution Image Reconstruction with Compressed Sensing based on Iterations

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Abstract

This paper proposes a new method of efficient image reconstruction based on the Modified Frame Reconstruction Iterative Thresholding Algorithm (MFR ITA) developed under the compressed sensing (CS) domain by using total variation algorithm. The new framework is consisted of three phases. Firstly, the input images are processed by the multilook processing with their sparse coefficients using the Discrete Wavelet Transform (DWT) method. Secondly, the measurements are obtained from sparse coefficient by using the proposed fusion method to achieve the balance resolution of the pixels. Finally, the fast CS method based on the MFR ITA is proposed to reconstruct the high resolution image. The proposed method achieved superior results on real images, and demonstrate qualitative improvements in terms of PSNR and SSIM values. Furthermore, achieved good reconstruction SNR in the presence of noise.

***Keywords**: Compressed Sensing, Image Reconstruction, Multilook, MFRITA, Thresholding*

1. Introduction

High Resolution image is consider to be a major component in digital imaging, and achieving a good contrast and better resolution remain a critical issues. Therefore to overcome this problem several methods have been proposed. In general a possible way to achieve this goal is by using image fusion methods. If we considering about image compression methodology in image processing, the new techniques which embark the great result and received great deal of attention of the researcher called compressed sensing [1-2], and requires the less amount of linear projections from the required samples comparatively with the Nyquist rate and this method would drastically reduce computational cost and storage space without obtaining the whole image information. The image fusion method has been used based on the compressed sensing (CS) method [4-6], this method cannot recover the image. The same idea has applied by using the fused measurement through maximum selection (MS) [7]. Lately the CS has been most valuable method that can recovers the signals which are sparse or compressible based on some linear measurement matrix other than the traditional Nyquist method. The CS has been used to achieve exact signal reconstruction while sampling a signal at low sampling rate, and it was much smaller than the traditional Nyquist theorem [4].

Recently the new methodology using the dual pulse coupled neural network (DPCCN), using multi focus scheme based on the CS concept has been incorporated into the fusion measurement by defining weighting factor produced good efficiency of reconstruction of image, but it has required large space and processing time to get this conversion [6]. Several methods fused the measurement of the sparse signal and then processed based on the CS,

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this method was required long computational processing time [8]. Many traditional image reconstruction algorithms based on the fusion method to reconstruct an image have been applied to section of the images recently. These methods included the pyramid based method and discrete wavelet transforms [9-10] *etc*. In practice the DWT methodology is the robust method than the pyramid method, but there is some disadvantages if we applied the DWT method directly, it would not provide the optimal solution such as, reduced the brightness, contrast and noise.

In this paper, we proposes an image reconstruction by using the CS based on the modified frame reconstruction iterative thresholding algorithm (MFR ITA). The input images are process by using multi look processing to minimize the noise present in image prior to discretize by the DWT to achieve the better contrast of the image, then the measurement are obtained by defining measurement matrix and fused by proposed method to recover the sparse coefficients from the fused measurements. The last contribution of this paper lies by applying measurement in the CS domain based on MFR ITA by updating and thresholding to achieve the optimum solution of the recovery of sparse signal, and to reconstruct the high resolution image by applying the total variation (TV). The simulation results have shown good improvements by comparing PNSR and SSIM values of proposed method with other traditional methods namely as, OMP, Min TV. In addition, the proposed method achieved better SNR values in the presence of noise by comparing with the iterative hard thresholding (IHT).

2. Problem Formulation and Modeling

As illustrated in the introduction section, the most significant issue which is associated with HR imaging for reconstruction of high resolution image is poor contrast and, blurriness at output when the resolution of input image is low. The structure of the proposed method is shown in Figure 1 in the form of block diagram to clarify the above statement. This method consists of three parts sampling of image, then measurement approximations and finally image reconstruction. Firstly, the input image X_i is divided into $n \times n$ segments. Then these segments are processed by the look formation and its output is sampled by measurement matrix $[\theta]$ with the size of $M \times N$, and assuming that $M < N$. Secondly, the sampled result is fused to construct Y by using the fusion scheme under measurement domain. Finally, this complete measurements Y is processed by MFR ITA to achieve high resolution image by defining the updating and thresolding under CS domain.

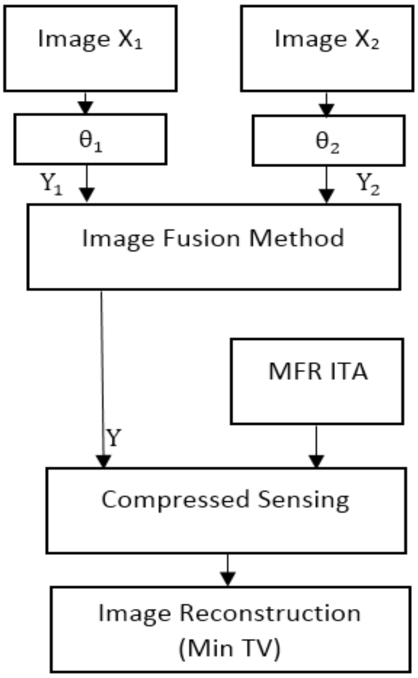


Figure 1. Problem Formulation Block Diagram

2.1. Multilook and Compressed Sensing

Compressed sensing has shown that the sparse or compressible can be done by using low rate acquisition process [11]. The multilook processing is widely used to reduce speckle method in the image processing and the SAR imaging [12], and it is summing of the input images such as sub images.

$$[Y] = [\theta][X] \tag{1}$$

where the matrix $[X]$ stands for the input images, $[Y]$ is output image, and $[\theta]$ is the sampling coefficient matrix of the measurement.

Sampled results need to convert into the complete measurement based on fusion method. The proposed image reconstruction based on the CS with one dimensional length finite length signal $x_i \in R^N$ can be expressed as vector forms.

$$x_i = c_i\, \varphi_i \tag{2}$$

$$X = \sum_{i=1}^{K} x_i = \sum_{i=1}^{K} c_i \varphi_i \tag{3}$$

where φ_i is expressed the orthonormal basis matrix and c_i is the sparse coefficients.

The input image X is with K sparse representation, K < N. We define that $Y \in R^M$ is the measurement and θ is the M×N sampling matrix then,

$$y_i = \theta_i x_i \tag{4}$$

$$Y = \sum_{i=1}^{k} y_i = \sum_{i=1}^{k} \theta_i x_i = \sum_{i=1}^{k} (\theta_i c_i) \varphi_i \tag{5}$$

The matrix form can be expressed as,

$$[Y] = [\Theta][\Phi] \tag{6}$$

where the matrix $[\Theta]$ size is M×N.

The measurement process is not adaptive, it means that if θ_i is fixed and it does not depend on the reconstructed signal x_i. When M < N, recovering X from the measurement Y becomes the linear problem [13-14], yet the original signal is reconstructed it can be recovered perfectly by using optimization procedures.

2.2. Modified Frame Reconstruction (MFR ITA)

The iterative threshold is very simple iterative procedure with some general definition. For a signal x_i, the iterative of the starting signal can be expressed as follows [15-16],

$$x_i^0 = 0$$
$$x_i^n = H\ (b_i^n) \tag{7}$$

where H is the nonlinear operator that set the largest we adopt MFR ITA technology, which is the frame reconstruction algorithm and is dependent on the steps length. b_i^{n+1} is a variable determined by signal, and residual and thresholding.

The MFR ITA has shown great modifications both of increases of convergence and success rate to recover the original sparse signal to from the general definition. It involved in two steps, update and thresholding respectively. The iteration used to extract the useful information from residual and thresholding will suppress the alias effect and gives the sparsity of the signal.

$$b_i^{n+1} = x_i^n + \mu\theta_i^T(y_i - \theta_i x_i^n) \tag{8}$$

where y_i is the vector of the measurement and θ_i is the measurement matrix parameters which controls the rate of convergence of the iteration, as we need to recover the sparse signal.

The MFR ITA algorithm is very efficient and simple method which provides intuitive solution and it is based on the operator θ_i in each iteration. Eq. (8) is the updating form, variable b_i^{n+1} is the updating parameter of each frame, we introduce an adjustable factor $\mu_i = {}^{2}/_{(a+b)}$, where a and b are the image frame bounds for s sparse vectors. So from (7), the sparse vectors can be recovered.

$$x_i^{n+1} = H\left[b_i^{n+1}\right] = H\left[x_i^n + \mu_i\theta_i^T(y_i - \theta_i x_i^n)\right] \tag{9}$$

Eq. (9) is the thresholding form in each step of frame based on i^{th}iteration and it selects the largest of the magnitudes and preserves all components.

3. HR Image Reconstruction

Image reconstruction plays a very vital role in biomedical imaging, digital image processing and many others applications. Compressed Sensing (CS) is an efficient method which is fast and highly reliable recovery algorithm [4]. In this section, we discussed the image fusion based on the CS concept.

3.1. Compressive Image Fusion

In past, the wavelet based method is used as an effective fusion way for fusion images there were still some problems exist because the using of the high and low frequency have quite different in certain aspects. In the CS domain, it only needs to consider compressive measurement [4]. The fusion scheme have maximum of absolute values (MAV) which is used widely in the wavelet domain and the standard deviation (SD) of the measurement sampling in the CS domain is used to balance the contrast and minimizes the blurriness of the output image [17]. The SD is commonly method is used to evaluate the amount information contained in the different form of the signal and the SD of the image pixel information is given by below under the CS domain.

$$\sigma_x = \sqrt{\frac{1}{n\times n}\sum_{i=0}^{n-1}\sum_{j=0}^{n-1}\left(x_{ij} - x\right)} \tag{10}$$

$$x = \frac{1}{n\times n}\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} x_{ij} \tag{11}$$

where x_{ij} is the pixel in i^{th} and j^{th} column of $n\times n$ image x_i.

We introduced the weighting fusion based on the SD measurement of input images. The larger the SD has contained more useful information and dispersed gray scale. It is needed to convert the standard deviation to the fused measurement, suppose Y is the fuse measurement, it can be written as follow,

$$Y = w_1 Y_1 + w_2 Y_2 \tag{12}$$

$$w_1 = \frac{\sigma_1}{\sigma_1+\sigma_2}, w_2 = \frac{\sigma_2}{\sigma_1+\sigma_2} \tag{13}$$

where w_1 and w_2 are the weighting factors which is the key factors for the fusing the measurement. Once the measurements are obtained, it can be applied in the CS based on the MFR ITA, we determine the update and thresholding for the recovery of the sparse signal and then using the minimum total variation TV (Min-TV) algorithm to reconstruct the Images.

3.2. Image Reconstruction via Total Variation

The TV regularization method has been successfully reduced the image noise and blur to reconstruct the image. This method has improved the contrast and the brightness of the reconstructed image [18]. We utilized the CS based on the MFR ITA to reconstruct the images. The estimation of x_i from the measurement y_i is the ill posed problem, the original signal need to be recover which satisfy the follow relation,

$$\|y_i - min\|x_i\|\|^2 = \|\theta_i x_i - min\|x_i\|\|^2 \le \beta\|x_i\|^2 \tag{14}$$

Eq. (14) is the optimization problem, where β is assumed to represent the coefficient of y_i which is regularization factor. In past the sparse orthogonal decomposition (OMP) traditional method was used. In general the image can be reconstructed by taking the inverse orthonormal transform of (4), but the non-linearity problem is arisen when the transformation is taken. Therefore, these approach is not synchronizes with measurement matrices. The proposed overcome this problem by recover the sparse signal using the MFR ITA method.

In order to estimates x_i from y_i (14), the optimization of regularization factor β is responsible for the reconstruct the sparse signal in the form of the imaging, the L_q regularization theory is used [12] and the problem persist of the sparsity has been resolved,

$$x_i = \sum_{j=1}^{J} \sqrt{|x_i^j|} \approx \|x_i^J\| \tag{15}$$

where j is the number of looks, we need to convert the signal into the two-dimensional (2D) image based on the gradient of the sparsity of the signal (15), which is the multilook processing of the linear problem formulation of recover the sparse signal, and it is used to suppress the speckle effect arises when perform the threshold.

The Min-TV method is used for the image reconstruction [4], which subjects to the follow condition,

$$y_i = \theta_i x_i \,, \text{ Min TV } (x_i) \tag{16}$$

It needs to analyze the performance of the recovery of the CS based in the images and evaluate the peak signal to the noise ratio (PNSR) of the proposed method based on the MFR ITA.

4. Modified Frame Reconstruction ITA Error Analysis

The MFR ITA is very simple and efficient method that does not requires matrix inversion at any of point and gives the significantly reduces [15]. Let $x^{(t)}$ is the solution of the iteration at time t and the initial $x^{(0)}$ to the zero vector. If there is no unique set, a set can be either selected randomly or based on predefining ordering s, which is proved as the convergence [16]. The reconstruction error of the MFR ITA at iteration time t is bounded as follow.

$$\|x^{(\mathrm{k})} - x^s\|^2 \le 2^{-\mathrm{k}}\|x^s\|^2 + 4\mu\sqrt{1+\delta_s}\|e\|^2 \tag{17}$$

Assume x^s as a best sparse approximation to the x term, whereas δ_s is constant with all sparse s vector x and e is the observation error of the sparse signal. Now considering the noise is occurred in the reconstruction processing in the measurement matrix.

$$y_i = \theta_i x_i + \mathrm{N_{noise}} \tag{18}$$

where θ_i is the measurement and N_{noise} denotes the sampling vector containing noise in measurement matrix.

It is introduced the boundaries $T = supp\ (x_i)$ and$T^n = supp\ (x_i^n)$, the boundary of the sparse vector is given by $B^n = T \cup T^n$. Now considering the error from the threshold value,$\|x_i^s - x_i^{n+1}\|$ and let assume $x_i = x_i^s$, now x_i needs to be sparse, then it is easily to use the triangle inequality to obtain the inequality for x_i^s,

$$\|x_i^s - x_i^{n+1}\| \le \|x_{\mathrm{B^{n+1}}}^{\mathrm{s}} - b_i^{\mathrm{n+1}}\| + \|x_{\mathrm{B^{n+1}}}^{\mathrm{n+1}} - b_i^{\mathrm{n+1}}\| \tag{19}$$

Start the bounding$\|x_i^{n+1} - b_i^{n+1}\|^2$, because x^{n+1} is the thresholding form of b^{n+1}, it achieves the best s sparse signal approximation x_i^s, thus x_i^{n+1} is closest to b^n than x_i.

$$\|x_i^{\mathrm{n+1}} - b_i^{\mathrm{n+1}}\|^2 \le \|x^{\mathrm{s}} - b_i^{\mathrm{n+1}}\|^2 \tag{20}$$

The iterations error for n+1 bounded is given by,

$$\|x_i^s - x_i^{n+1}\|^2 \le 2\|x_{B^{n+1}}^s - b_i^{n+1}\|^2 \tag{21}$$

When the signal is measured, it is corrupted by the noise, so (8) can be expanded as follow,

$$b_i^{n+1} = x_{B^{n+1}}^n + \mu_i\ \theta_{B^{n+1}}^T[\theta_i x_i - (\theta_i x_i^n + N_{noise})] \tag{22}$$

The error of bounding estimation is satisfied as,

$$\begin{aligned}
&\left\|x_i^s - x_i^{n+1}\right\|^2 \\
&\le 2\left\|x_{B^{n+1}}^s - x_{B^{n+1}}^n - \mu_i\theta_{B^{n+1}}^T r_i^n\theta_i - \mu_i\theta_{B^{n+1}}^T N_{noise}\right\|^2 \\
&\le 2\left\|r_i^n\theta_i - \mu_i\theta_{B^{n+1}}^T r_i^n\theta_i\right\| + \left\|\mu_i\theta_{B^{n+1}}^T N_{noise}\right\|^2 \\
&\le 2\left\|x_{B^{n+1}}^s - x_{B^{n+1}}^n - \mu_i\theta_{B^{n+1}}^T r_i^n\theta_i - \mu_i\theta_{B^{n+1}}^T N_{noise}\right\|_2 \\
&\le 2\left\|\left(I - \mu_i\theta_{B^{n+1}}^T\theta_{B^{n+1}}\right)r_{B^{n+1}}^n\right\|^2 \\
&\qquad +2\mu_i\left\{\left\|\theta_{B^{n+1}}^T\theta_{B^n\setminus B^{n+1}}r_{B^n\setminus B^{n+1}}^n\right\|^2 + \left\|\theta_{B^{n+1}}^T N_{noise}\right\|^2\right\}
\end{aligned} \tag{23}$$

where $r_i^n = x_i - x_i^n$. Repeated the step of the triangle inequality and the residual is separated into two parts, and$r^{n+1} = r_{B^{n+1}}^{n+1} + r_{B^{n+1}\setminus B^n}^n$. Index $B^n\setminus B^{n+1}$ is the disjoint representation of B^{n+1} and $B^n \cup B^{n+1}$, then it will transformed into,

$$|B^n \cup B^{n+1}| = |T \cup T^n \cup T^{n+1}| \le s + 2\bar{s} \tag{24}$$

Each set T^n has maximum $\bar{s}$ entries and $T \le s$ using the basic properties of isometric constant Lemma [13] $\delta_{s+2\bar{s}} > \delta_s$, and we define that $\mu_i = \sqrt{1+\delta_s}$.

$$\left\|x_{B^{n+1}} - x_{B^{n+1}}^{n+1}\right\|^2 \le 2\delta_s\left\|r_{B^{n+1}}^n\right\|^2 + \ 2\delta_{s+2\bar{s}}\left\|r_{B^n\setminus B^{n+1}}^n\right\|^2 + \mu_i \tag{25}$$

As we know that $r_{B^{n+1}}^n$ and $r_{B^n\setminus B^{n+1}}^n$ are sets of disjoints, Now assume that $m, n \in R^n$ be an orthogonal vector then it turned to be and the estimation error at iterations $n+1$ is bounding by,

$$\|r^{n+1}\|^2 \le \sqrt{8}\delta_{s+2\bar{s}}\|r^n\|^2 + \mu_i \tag{26}$$

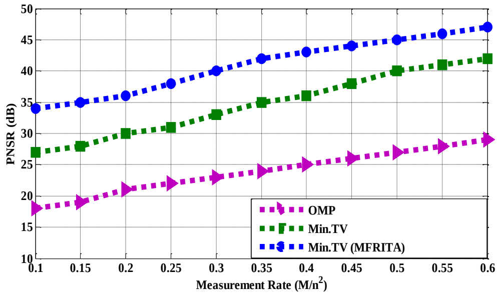
Eq. (26) is a recursive error bound, assume $\rho = \sqrt{8}\delta_{s+2\bar{s}}$ and at initial point $x_i = 0$.

$$\|r^n\|^2 \le \rho^n\|x_i\|^2 + \mu_i\sum_{n=0}^{n}\rho^n \tag{27}$$

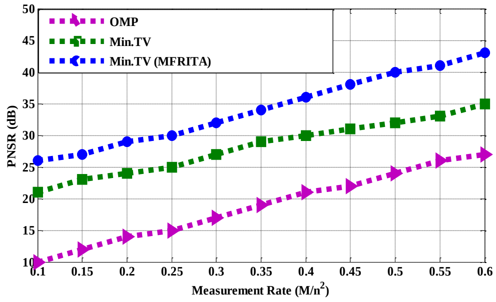
Faster convergence of algorithm $\rho = \sqrt{8}\delta_{s+2\bar{s}} < 1$ and the limitation for better stable system is much less than 1, which is yielding the sufficient conditions. The recovery of MFR ITA conditions for stable recovery of the sparse signal $\delta_s < \frac{1}{\sqrt{32}}$ and it is the stronger required condition, as we consider $\delta_{s+2\bar{s}} > \delta_s$ having RIP of smaller order it means that θ_i measurement matrix requires fewer rows to fulfill conditions.

5. Simulation Results

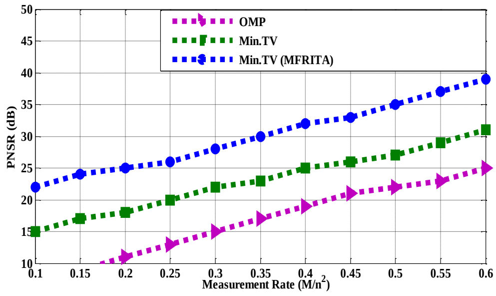
To analyze the performance behavior of CS based on the MFR ITA recovery method on the image, the image has been treated as vectorization into a $n^2 \times 1$ column vector, the measurement is $Y \in R^M$ and the dimension of the measurement matrix is θ_i. In Figure 2(a)-(c) shows the image restoration results illustrating the PNSRs with different methods. It is found that the result of the Min TV (MFR ITA) has achieved good PNSR as compared to the OMP and the Min TV method. For 50 iterations, the PNSR is better and the MFR ITA method has good results comparatively with others methods as increasing to 100 and 200 iterations of the MFR ITA, the PNSR is shown good result and achieved better reconstruction of image. The graphical representation shows better enhancement of images that can get by taking more measurements, but the objectives is to recover the better quality images by using the proposed MFR ITA method.



(a)



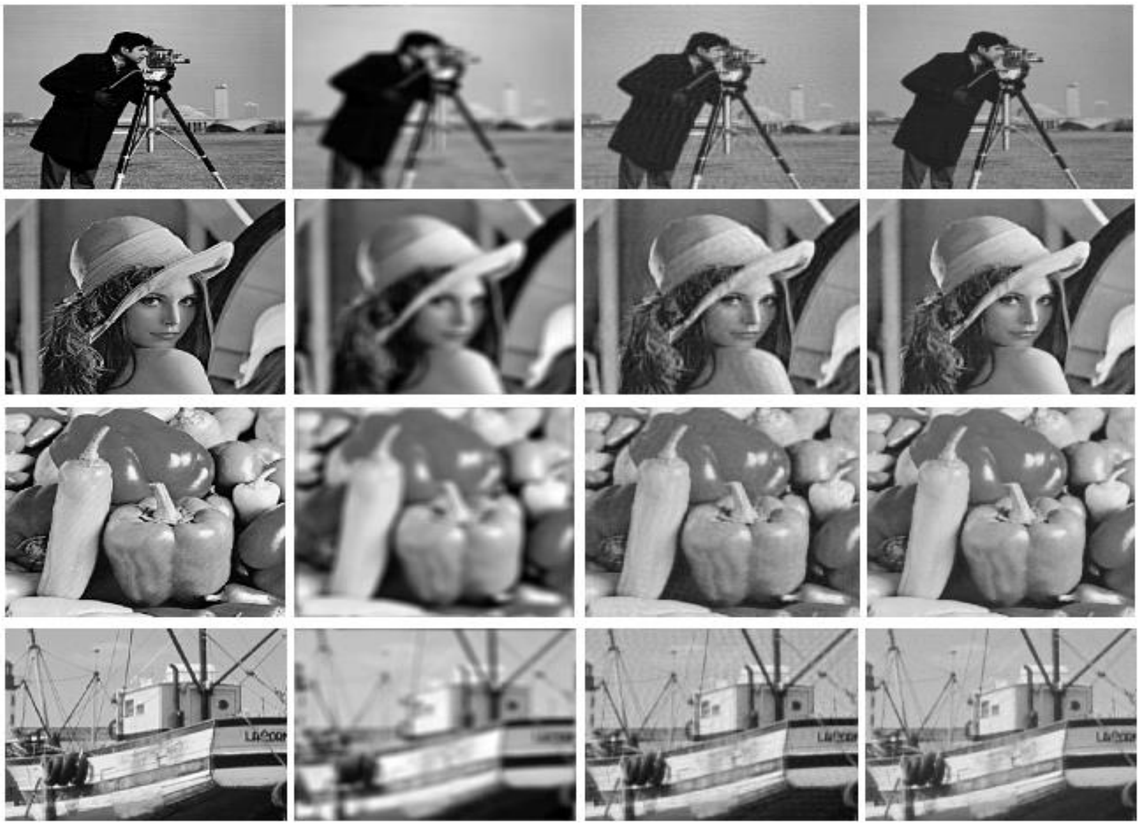
(b)



(c)

Figure 2. PNSRS Comparison with Different Iterations for Different Iterations, (a) 200, (b) 100, (c) 50

In this part, we performed the simulation on the four test images such as (cameraman, lena, peppers, and boat) with the image size of 256×256 to demonstrate the visual effect and efficiency of the proposed method based on MFR ITA with different iterations. In Figure 3 the results of reconstructions of the Min-TV (MFR ITA) has shown, when performed the 50 iterations performed, it recovered the most part of the image but with less resolution, contrast and blurriness present, as it increases the iterations to 100. The good quality image is achieved but still there is still some blurriness and blurred artifacts with less contrast and brightness. In Figure 3(d) after 200 iterations, it is clearly demonstrated it achieves better resolution reconstructed image with good contrast image and outperforms several methods in terms of visual comparison, resolution. Furthermore, the quality of image is better as we increase the number of iterations thus, achieved the good PNSR.



(a) Input image (b) Iteration Image 50 (c) Iteration Image 100 (d) Iteration Image 200

Figure 3. Reconstruction of Image (Cameraman, Lena, Peppers and Boat) with Different Iterations

Figure 4 shows the comparison of the SSIM values with different scheme by implementing on four test images (Cameraman, Lena, Peppers, and Boat). The objective assessment in terms of SSIM values demonstrated that the proposed method achieved good reconstruction quality of image based on different iterations, and outperforms several competent method.

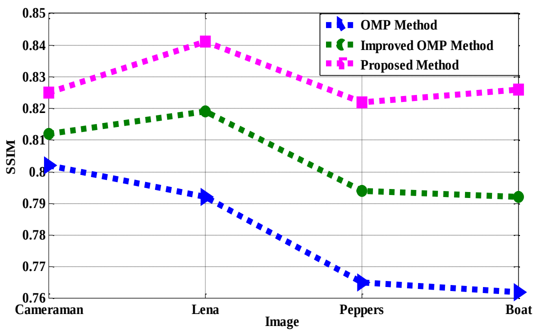


Figure 4. SSIM Comparison of Proposed Method

The Figure 5 is plotted the curves between SNR (dB) with number of samples (Log_2). The performance of MFR ITA in the presence of noise model, we evaluate behavior of MFR ITA as the numbers of measurement varies for different levels of signals. In this case the number measurement is varied from 8 to 1024, as measurement increases we can recovers the signal. The noise model of as we defined earlier is n =0.5, 1 and 2 respectively. The MFR ITA yield enhanced reconstruction from few less samples, but in case of n = 0.5 more samples are required to achieved the fair and better reconstruction. If we compare MFR ITA with IHT at n = 1 and 2 it means that MFR ITA required less measurements for fixed sparse signal, thus we achieved good SNRs at n = 1 and 2 by using the proposed method.

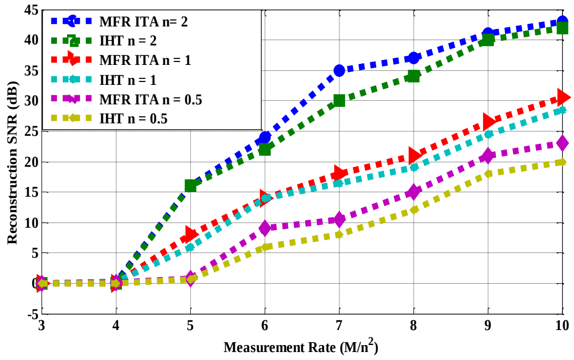


Figure 5. Performance of MFR ITA in terms of Noise Values

6. Conclusion

In this paper, we proposed a new method to reconstruct a high resolution image based on CS with MFR ITA technique. Firstly, we introduced the fusion technique based on SD measurement to fuse the image in CS domain to achieve the balance resolution of pixel of the reconstructed image. Finally, applied Min-TV optimization to reconstruct the high resolution images based on MFR ITA. The Simulation results and SSIM values demonstrated that MFR ITA yield a better reconstruction of image. The image resolution and quality increases as we increases the number of iterations and achieved better PNSR and SSIM values compared with other competent methods. Furthermore, to validate the performance of the proposed method, we have done the reconstruction SNR in the presence of noise value and compared with the traditional IHT method. It can be seen that the proposed method achieved better recovery of signal and good SNR, while the IHT suspected to the noise and leads to be unsatisfactory reconstruction.

References

[1] D. L. Donoho, "Compressed sensing", IEEE Trans. on Information Theory, vol. 52, no. 4, **(2006)**, pp. 1289-1306.
[2] E. J. Candes and M. B. Wakin, "An introduction to compressive sampling", IEEE Signal Processing Magazine, vol. 25, no. 2, **(2008)**, pp. 21-30.
[3] V. S. Petrovic and C. S. Xydeas, "Gradient-based multi resolution image fusion", IEEE Trans. on Image Processing, vol. 13, no. 2, **(2004)**, pp. 228-237.
[4] X. Li and S.Y. Qin, "Efficient fusion for infrared and visible images based on compressive sensing principle", IET Image Processing, vol. 5, no. 2, **(2011)**, pp. 141-147.
[5] Z. Z. Yang and Z. Yang, "Novel multifocus image fusion and reconstruction framework based on compressed sensing", IET Image Processing, vol. 7, no. 9, **(2013)**, pp. 837-847.
[6] K. Bin, W. Zhu and J. Yan, "Fusion framework for multi-focus images based on compressed sensing", IET Image Processing, vol. 7, no. 4, **(2013)**, pp. 290-299.
[7] W. Tao and Z. Qin, "An application of compressive sensing for image fusion", International Journal of Computer Mathematics, vol. 88, no. 18, **(2011)**, pp. 3915-3930.
[8] X. Luo, J. Zhang, J. Yang and Q, Dai, "Classification-based image-fusion framework for compressive imaging", Journal of Electronic Imaging, vol. 19, no. 3, **(2010)**.
[9] S. Firooz, "Comparative image fusion analysis", Proceedings of the IEEE Intern. Conference on Computer Vision and Pattern Recognition (CVPR), San Diego, USA, **(2005)**, pp. 1-8,

[10] H. Wang, J. Peng and W. Wu, "Fusion algorithm for multisensor images based on discrete multiwavelet transform", IEEE Proceedings-Vision, Image and Signal Processing, vol. 149, no. 5, **(2002)**, pp. 283-289.
[11] L. C Potter, E. Ertin, J. T. Parker and M. Cetin, "Sparsity and compressed sensing in radar imaging", IEEE Proceedings, vol. 98, no. 6, **(2010)**, pp. 1006-1020.
[12] F. Jian, Z. Xu, B. Zhang, W. Hong and Y. Wu, "Compressed sensing SAR imaging with multilook processing", Computer vision and pattern recognition, arxiv: 1310.7217, **(2013)**.
[13] E. J. Candes and T. Tao, "Near-optimal signal recovery from random projections: Universal encoding strategies", IEEE Trans. on Information Theory, vol. 52, no. 12, **(2006)**, pp. 5406-5425.
[14] E. J Candes, "The restricted isometry property and its implications for compressed sensing", Comptes Rendus Mathematique, vol. 346, no. 9, **(2008)**, pp. 589-592.
[15] B. Thomas and M. E. Davies, "Iterative hard thresholding for compressed sensing", Applied and Computational Harmonic Analysis, vol. 27, no. 3, **(2009)**, pp. 265-274.
[16] B. Thomas and M. E. Davies, "How to use the iterative hard thresholding algorithm", In SPARS'09-Signal Processing with Adaptive Sparse Structured Representations, **(2009)**.
[17] W. Tao, N. Canagarajah and A. Achim, "Compressive image fusion", Proceedings of the IEEE Intern. Conference on Image Processing (ICIP), San Diego, USA, **(2008)**, pp. 1308-1311.
[18] P. Blomgren and T.F. Chan, "Color TV: total variation methods for restoration of vector-valued images", IEEE Trans. on Image Processing, vol. 7, no. 3, **(1998)**, pp. 304-309.