High Resolution Image Reconstruction using Fast Compressed Sensing based on Iterations

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Abstract: - As a powerful high resolution image modeling technique, compressive sensing (CS) has been successfully applied in digital image processing and various image applications. 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. In addition, the proposed method achieves good PNSR and SSIM values, and has shown faster convergence rate when performed the MFR ITA under the CS domain. Furthermore the graphical representation demonstrated that the proposed method achieves better performance in terms of the SNR reconstruction and the probability of successfully recovered signal, and also outperforms several other methods.

Key-Words: - 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.

In past several a method has proposed based on pixel based [3], the method was very unique but operated on every pixels consumed large processing and the cost would be increased. The image fusion method has been used based on the compressed sensing (CS) method [4-6] and 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 accurate 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, the dual pulse coupled neural network (DPCCN), using multi focus scheme based on the CS concept [6], 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. Some methods fuse the measurement of the sparse signal and then processed based on the CS, this method was required long computational processing time [8]. The multi-focus image method was the efficient method related to the image fusion using the weighted function has been done in previous works [6]. It has shown that the results have been recovered image but required large computational cost and time. Some of the reconstructions of image were required large mathematical calculations by fusing the measurement matrix. Developed the algorithms which can solve the L_1 minimization problem has been applied successfully to many applications such as biomedical, image and signal processing. However this methodology achieved a great success of sparse signal but has fewer artefacts to overcome this problem of the Augemented Lagrangian Method (ALM), which was efficient method to resolve the minimization problem but it has some limitation because of low convergence rate [9]. Many traditional image reconstruction algorithms based on the fusion method to reconstruct an image have been applied to section of the images recently [4-6]. These methods included the pyramid based method [10], and discrete wavelet transform [11] 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 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 minimizes the noise present in image prior to discretizes 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 validity of proposed method, by comparing the reconstruction of SNR in the presence of multiple noise with iterative hard thresholding (IHT) and, the probability of recovered signal by fixing the number of measurements to 150, therefore achieve an enhanced reconstruction quality images by using the proposed method.

The paper is organized as follows. In Section 2 we discussed the problem formulation and modeling by introducing Multilook and Modified Frame Reconstruction ITA methods. The compressive image fusion and Total Variation methods are introduced in Section 3. In Section 4 presents the error analysis and performance of MFR ITA. The simulations results are given in Section 5. Finally, Section 6 concludes this paper.

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 Fig. 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 $\mathrm{X_i}$ 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 $\mathrm{M} \times \mathrm{N}$, and assuming that $\mathrm{M} < \mathrm{N}$. Secondly, the sampled result are 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.

2.1 Multilook and Compressed Sensing

Compressed sensing has shown that the sparse or compressible can be done by using low rate acquisition process [12]. The multilook processing is widely used to reduce speckle method in the image processing and the SAR imaging [13], 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,

$$y_i = \theta_i x_i \quad (4)$$

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

The matrix form can be expressed as,

$$[Y] = [\Theta][\Phi] \quad (6)$$

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

Because 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 [14-15], yet the original signal is reconstructed it can be recovered perfectly by using optimization procedures.

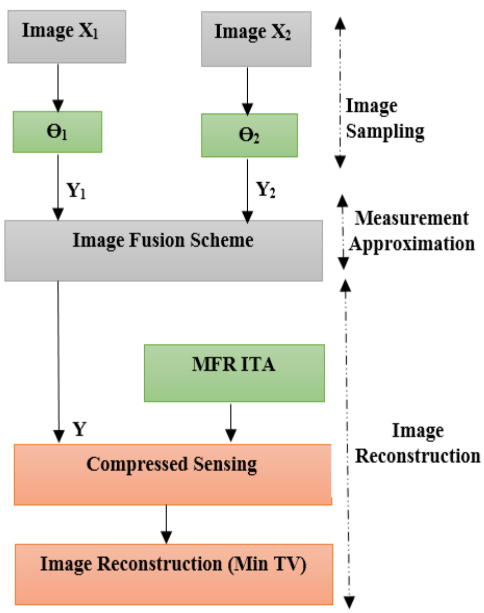


Fig. 1: Block diagram of proposed method.

Without loss generality, we consider the input images are X_1 and X_2 Fig. 1 is the block diagram of proposed method of reconstruction of high resolution images. X_1 and X_2 are processed by look formation in the sub images forms under multilook domain, so that the fusion method processes each of input images. Once the sampled results are obtained, then the sampled results Y_1 and Y_2 are fused in to a complete set of measurement Y. Finally, we process the complete measurement with the CS, based on modified frame reconstruction (MFR) ITA by updating and thresholding to achieve the high resolution image using total variation (TV).

2.2 Modified Frame Reconstruction 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 [16-17],

$$x_i^0 = 0$$
$$x_i^n = H\,(b_i^n) \quad (7)$$

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 involves two steps, 1) update and 2) thresholding. The iteration used to extract the useful information from residual and thresholding will suppress the alias effect and gives the sparsity of the signal.

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

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 image frame bounds for s sparse vectors. From Eq. (7), the sparse vectors can be recovered.

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

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 Image Reconstruction

Image reconstruction play an important 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 Proposed Compressive Image Fusion

In previous work, although the wavelet based method was 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]. Studies have shown the traditional fusion scheme cannot be applied to the CS domain because of low spatial process, and it is used if the signal is sparse in some basis, likewise its measurement encodes the salient information of it [4]. The fusion scheme have maximum of absolute values (MAV) which is used widely in the wavelet domain [18], 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. 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 weighting factors, which are key factors for the fuse 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, then using minimum total variation TV (Min-TV) algorithm to reconstruct the Images.

3.2 Total Variation Image Reconstruction Model

The TV regularization method has been successfully reduced the image noise and blur [19] to reconstruct the image by achieving, this method has improved the contrast and the brightness of the reconstructed image. As the fast and efficient recovery algorithm based on the CS theory, it has studied the impacts of the CS methodology 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,

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

Eq. (14) is the optimization problem, where β is assumed to represent the coefficient of y_i which is regularization factor.

In order to solve Eq. (14), the sparse orthogonal decomposition (OMP) traditional method has been used, and the original signal is reconstructed by optimization problem. In general the image can be reconstructed by taking the inverse orthonormal transform of Eq. (4), but the problem is arisen by non-linearity problem when the transformation is taken, so these approaches are not synchronizes with measurement matrices. We need to solve above problem and recovery of the sparse signal by the MFR ITA method. In order to estimates x_i from y_i in Eq. (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 [13] and the problem persist of the sparsity has been resolved,

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

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 Eq. (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,

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

It needs to analyse 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 Based ITA Algorithm 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 [16], the algorithm has been proposed algorithm for iterative shrinkage of non-convex problems [20]. 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 [16-17]. The reconstruction error of the MFR ITA at iteration time t is bounded as follow.

$$\left\|x^{(\mathrm{k})} - x^s\right\|^2 \leq 2^{-\mathrm{k}}\|x^s\|^2 + 4\mu\sqrt{1+\delta_{\mathrm{s}}}\|e\|^2 \qquad (17)$$

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.

$$y_i = \theta_i x_i + \mathrm{N_{noise}} \qquad (18)$$

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, $\left\|x_i^s - x_i^{n+1}\right\|$ and assuming $x_i = x_i^s$, now x_i needs to be sparse, then it is easily to use the triangle inequality to obtain the inequality for x_i^s,

$$\|x_i^s - x_i^{n+1}\| \leq \left\|x^{\mathrm{s}}_{\mathrm{B^{n+1}}} - b_i^{\mathrm{n+1}}\right\| + \left\|x^{\mathrm{n+1}}_{\mathrm{B^{n+1}}} - b_i^{\mathrm{n+1}}\right\| \qquad (19)$$

Start the bounding $\left\|x_i^{n+1} - b_i^{n+1}\right\|^2$, 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.

$$\|x_i^{\mathrm{n+1}} - b_i^{\mathrm{n+1}}\|^2 \leq \|x^{\mathrm{s}} - b_i^{\mathrm{n+1}}\|^2 \qquad (20)$$

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

$$\left\|x_i^s - x_i^{n+1}\right\|^2 \leq 2\left\|x^s_{B^{n+1}} - b_i^{n+1}\right\|^2 \qquad (21)$$

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

$$b_i^{n+1} = x^n_{B^{n+1}} + \mu_i\,\theta^T_{B^{n+1}}[\theta_i x_i - (\theta_i x_i^n + N_{noise})] \quad (22)$$

The error of bounding estimation is satisfied as,

$$\begin{aligned} &\|x_i^s - x_i^{n+1}\|^2 \\ &\leq 2\left\|x^s_{B^{n+1}} - x^n_{B^{n+1}} - \mu_i\theta^T_{B^{n+1}} r_i^n\theta_i - \mu_i\theta^T_{B^{n+1}}N_{noise}\right\|^2 \\ &\leq 2\left\|r_i^n\theta_i - \mu_i\theta^T_{B^{n+1}}r_i^n\theta_i\right\| + \left\|\mu_i\theta^T_{B^{n+1}}N_{noise}\right\|^2 \\ &\leq 2\left\|x^s_{B^{n+1}} - x^n_{B^{n+1}} - \mu_i\theta^T_{B^{n+1}} r_i^n\theta_i - \mu_i\theta^T_{B^{n+1}}N_{noise}\right\|_2 \\ &\leq 2\left\|\left(I - \mu_i\theta^T_{B^{n+1}}\theta_{B^{n+1}}\right)r^n_{B^{n+1}}\right\|^2 \\ &+2\mu_i\left\{\left\|\theta^T_{B^{n+1}}\theta_{B^n\setminus B^{n+1}}r^n_{B^n\setminus B^{n+1}}\right\|^2 + \left\|\theta^T_{B^{n+1}}N_{noise}\right\|^2\right\} \end{aligned} \qquad (23)$$

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 $r^{n+1} = r^{n+1}_{B^{n+1}} + r^n_{B^{n+1}\setminus B^n}$. 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,

$$|B^n \cup B^{n+1}| = |T \cup T^n \cup T^{n+1}| \leq \mathrm{s} + 2\bar{\mathrm{s}} \qquad (24)$$

Each set T^n has maximum $\bar{s}$ entries and $T \leq s$ using the basic properties of isometric constant Lemma [14] $\delta_{\mathrm{s}+2\bar{\mathrm{s}}} > \delta_{\mathrm{s}}$, and we define that $\mu_i = \sqrt{1+\delta_{\mathrm{s}}}$.

$$\left\|x_{B^{n+1}} - x^{n+1}_{B^{n+1}}\right\|^2 \leq 2\delta_{\mathrm{s}}\left\|r^n_{B^{n+1}}\right\|^2 + 2\delta_{\mathrm{s}+2\bar{\mathrm{s}}}\left\|r^n_{\mathrm{B^n}\setminus\mathrm{B^{n+1}}}\right\|^2 + \mu_i \qquad (25)$$

As we know that $r^n_{B^{n+1}}$ and $r^n_{B^n\setminus B^{n+1}}$ 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,

$$\|r^{\mathrm{n+1}}\|^2 \leq \sqrt{8}\delta_{\mathrm{s}+2\bar{\mathrm{s}}}\|r^{\mathrm{n}}\|^2 + \mu_i \qquad (26)$$

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

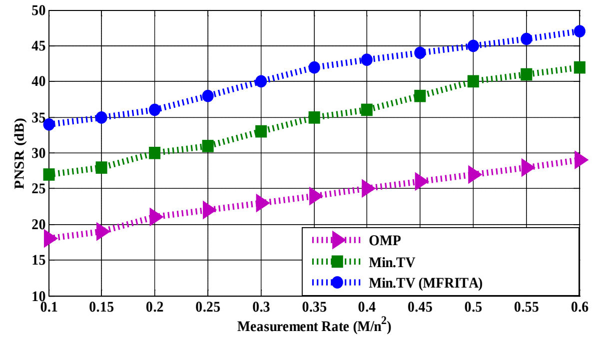
$$\|r^n\|^2 \le \rho^n \|x_i\|^2 + \mu_i \sum_{n=0}^{n} \rho^n \quad (27)$$

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 fulfil conditions.

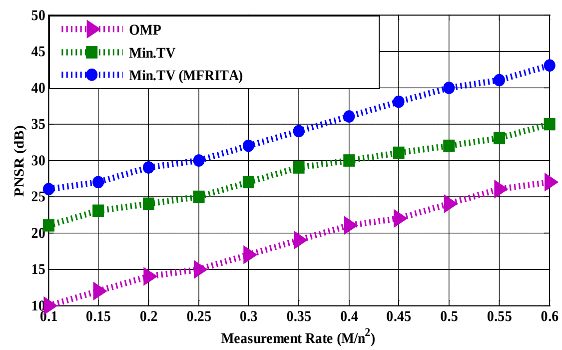
5 Simulation Results

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. The PNSRs comparisons of traditional methods likewise the OMP, the Min TV and the Min TV (MFR ITA), the quality of reconstructed image is increases as increasing the iterations and get the better PNSR. In Fig. 2 the various experiments have been done to evaluate the performance and it has been shown that the Min TV (MFR ITA) yields much better performance of recovering the original signals comparatively with traditional methods likewise the OMP and the Min TV which are not robust. The PNSRs is better as increasing of the number of iterations. The measurement M/n^2 is taken along the *x*-axes it is basically the rate of CS measurement converge with the MFR ITA over the original sparse signal, as we examined that reconstruction process consume sufficient computational time by using the proposed method because of the propose method.

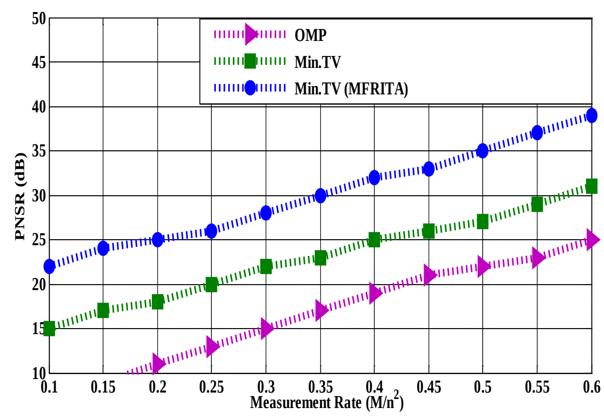
Fig. 2(a) - (c) are shown the image restoration results illustrating the convergence speed and PNSRs of the different methods. It is found that the result of the Min TV (MFR ITA) has achieved good PNSR and faster convergence, as compared to the OMP and the Min TV methods from the evaluation of the PNSRs. 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 would show better enhancement of images that can get by taking more measurements, but the objectives to recover the better quality images by using the proposed MFR ITA method.



(a)



(b)



(c)

Fig. 2: PNSRs of Reconstruction of image with different iterations for different iterations, (a) 200, (b) 100, (c) 50.

Fig. 3 is the average PNSR comparison of proposed method with others traditional methods. It is sampled the value of each iterations likewise 50, 100 and 200, respectively, of three methods, the proposed method has a good PNSR compared with other traditional methods. Thus it is recovered the better resolution reconstructed image and achieved the fastest convergence rate of the MFR ITA compared with the OMP and the Min TV.

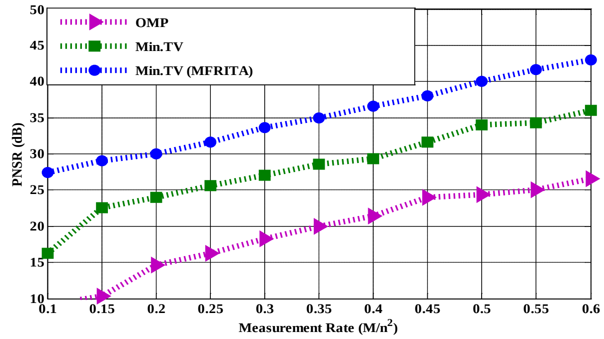


Fig. 3: Average PNSR of Reconstruction of images.

Table 1 is listed the average PNSR value verify the robustness and effectiveness of the Min TV (MFR ITA). It is clear that the proposed method display good PNSR and better reconstruction of image, and when the values of the measurement are increased the PNSR of the proposed method also are increased.

TABLE 1: Comparison of average PNSR

Measurements (m/n2)	OMP(dB)	Min TV (dB)	Min TV (MFR ITA) (dB)
0.1	9.3	16.3	27.4
0.2	14.3	24	30
0.3	18.3	27	33.6
0.4	21.4	29.3	36.6
0.5	24.4	34	40
0.6	26.6	36	43

In order to evaluate the performance of proposed method, it can use efficient techniques to analysis the measure the quality of the reconstructed image [21] for the original and reconstructed image.

$$error = \frac{\|x_{recon} - x\|^2}{\|x\|^2} \quad (28)$$

Fig. 4 is the comparison of the reconstruction errors of the proposed method and two others methods, the OMP and the improved OMP. The graphical represents highlighted that the three methods can reconstruct image with the certain measurements times. It is found that the reconstruction errors of the OMP and the improved OMP have slight differences because of the measurement time of the reconstruction image. The reconstruction error of the proposed based on MFR ITA shows minimized compared with two traditional methods, and it can recover the most information using our proposed method.

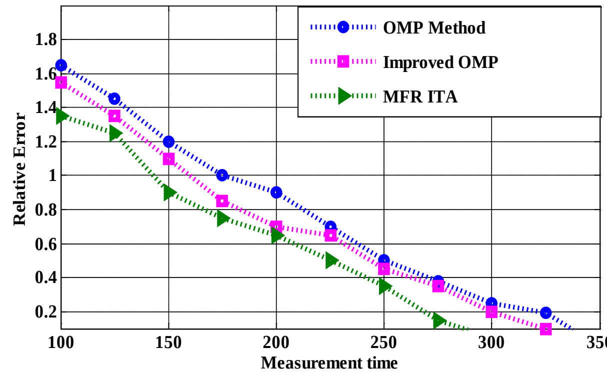


Fig. 4: Errors behaviour of reconstruction.

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 Fig.5 the results of reconstructions of the Min-TV (MFR ITA) has shown, when performed the 50 iterations performed see fig 5 (b) on it, it recovered the most part of the image but with less resolution, contrast and blurriness present, as it increases the iterations to 100 see fig.5 (c), the good quality image is achieved but still there is still some blurriness and blurred artefacts with less contrast and brightness. In Fig 5 (d) after 200 iterations, it is clearly demonstrated it achieves better resolution reconstructed image with good contrast and high resolution and outperforms several methods in terms of visual comparison, resolution. Furthermore it is shown that with increasing number of iterations the quality of image is better and achieved the good PNSR.

Table 2 lists the proposed method MFR ITA compared with the Iterative Hard Thresholding (IHT) in the presence of different noise values likewise n =0.5, 1 and 2. The MFR ITA is very effective and robust method, we can see that the MFR ITA generates the good SNR at every measurement values (see Fig.7), we assume when the measurement is 3, reconstruction SNR is zero of all methods in the presence of noise, basically it is starting point of the measurement for all n values, when the measurement start increasing the MFR ITA has achieved the good reconstruction SNR in the presence of noise compared with the Iterative Hard Thresholding (IHT).

TABLE 2: SNR comparisons of proposed method with IHT in the presence of different noise values.

Measurement	MFR ITA n =2	IHT n =2	MFR ITA n =1	IHT n =1	MFR ITA n =0.5	IHT n =0.5
3	0	0	0	0	0	0
4	0.2	0	0	0.2	0.1	0
5	16	16	8	6	0.8	0.6
6	24	22	14	14	9	6
7	35	30	18	16.5	10.5	8
8	37	34	21	19	15	12
9	41	40	26.5	24.5	21	18
10	43	42	30.5	28.5	23	20

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

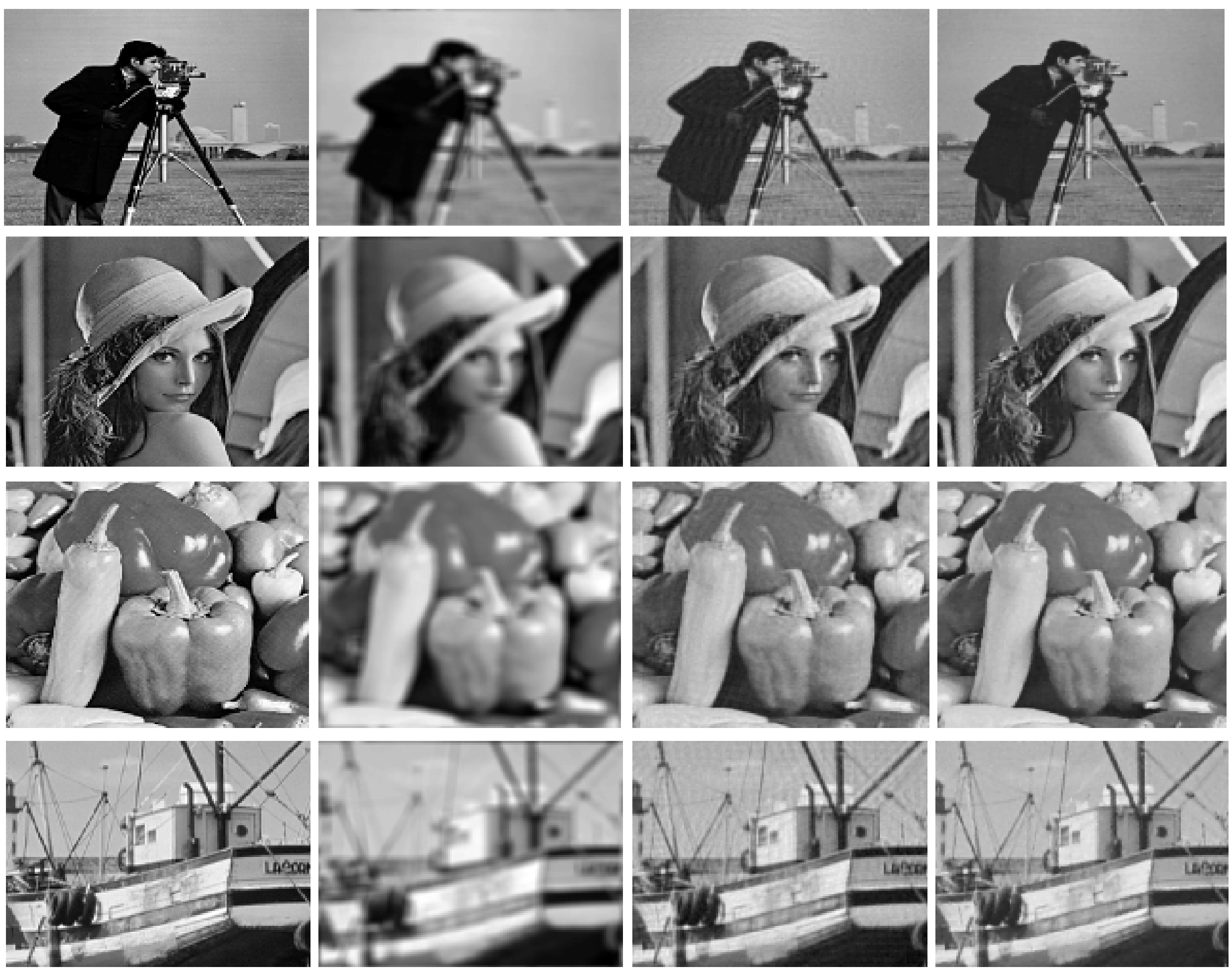


Fig. 5: Reconstruction of Images (Cameraman, Lena, Peppers, and Boat) with Different Iterations.

TABLE 3: SSIM Comparisons of Proposed method

Image	OMP Method	Improved OMP	Proposed Method
Cameraman	0.802	0.812	0.825
Lena	0.792	0.819	0.841
Peppers	0.765	0.794	0.822
Boat	0.762	0.792	0.826

Fig. 6 shows the comparison of the SSIM values with different scheme by implementing on four test images (Cameraman, Lena, Peppers, and Boat). The average SSIM value in Table 3 from Fig.6, and the objective assessment in terms of SSIM values, demonstrate that the proposed method achieved good reconstruction quality of image based on different iterations, and outperforms several competent method.

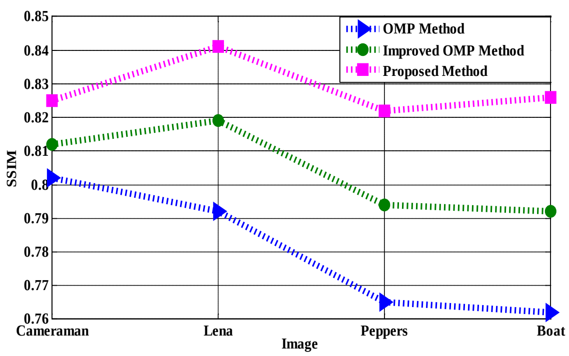


Fig. 6: SSIM comparison of proposed method.

The Fig. 7 is plotted the curves between SNR (dB) with number of samples (Log_2). The performance of MFR ITA with the presence of noise model, we evaluate behaviour 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 would recovers the signal. The noise model of as we defined earlier is n =0.5, 1and 2 respectively. The performance behavior has been shown in Fig. 7 which is $n \in [1,2]$.The MFR ITA yielding 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 using the proposed method.

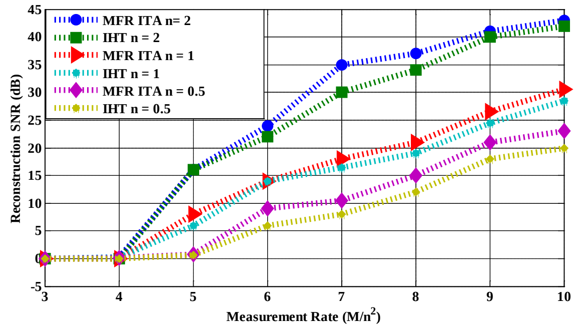


Fig. 7: Performance of MFR ITA in terms of noise values.

The performance of the successful recovered signal are demonstrated in Fig.8, the graph plot between the number of measurements and PNSR, to measure the probability of recovered signal, we assume some parameters, the length of the signal is 1000 and the sparsity signal is fixed at 150 the accuracy of the reconstruction growing with the knowing number of measurements, it also seems that reduces the number of measurements required to perfectly recovered the signal.

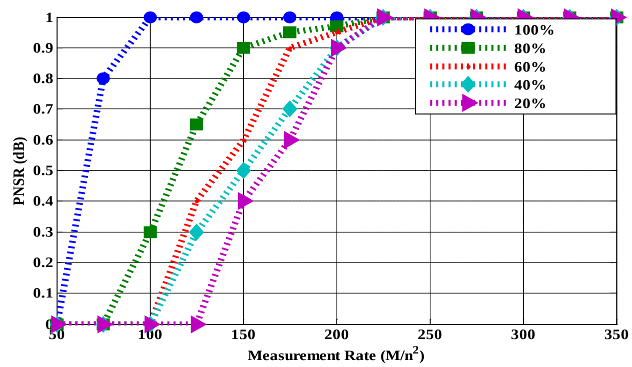


Fig. 8: Probability of Successfully Recovered Signal.

6 Conclusions

In this paper, we have proposed a new reconstruction method MFR ITA based on the CS as compare with the conventional OMP method. The proposed method is based on CS algorithm by defining updating and thresholding mechanism of MFR ITA scheme. A fusion scheme based on SD of the measurement has been introduced to fusing the image in CS domain to achieve and get the balance resolution of the pixels and then apply 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 traditional methods namely as, OMP and Min TV methods. Furthermore to demonstrate the performance of the proposed method firstly, we have done the reconstruction SNR in the presence of noise value and compared with the traditional IHT method secondly, the probability of successfully recovered signal has been done. It has shown that the proposed methods achieves a better improvements, and outperforms several other methods and, which also provides good reconstruction efficiency.

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