# Efficient Modified FCS Algorithm for Compressed MR Image Reconstruction

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**Abstract :** In recent work, FCSA has shown an efficient algorithm for MR image reconstruction by linear combination of least square data fitting, TV and L1 norm regularization algorithms. FCSA based reconstructed MR image had improved results compared to CS methods. In our paper, we are going to propose a reconstruction algorithm which improves the FCSA algorithm in two algorithms. Firstly, MR image will be enhanced by proposed bicubic and bilateral method. Secondly, the enhanced MR image will be resolved by proposed image resolution method. These two algorithms improve the compression technique and image reconstruction. Our performance evaluation results have shown better results comparatively.

Keywords: Bicubic and bilinear method, FCSA, least square data fitting, L1 norm regularization, TV.

## I. INTRODUCTION

Compressed Sensing has become extensive applications in medical image processing [1, 2]. Compressive sensing is a non-adaptive signal sampling framework that collects samples from sparse signals; which can be used to reconstruct the original signal. Magnetic Resonance Imaging is technique to reduce image acquisition time. Compressed Sensing is a recent development in image processing with technical elements that allow an image to be compressed, and recovered which reduce the number of samples during image acquisition.

In Medical Image analysis, medical data from patient reports are taken in the form of DICOM images. These DICOM images will provide the information about the patient depending on the disease or replacement of organ. In diagnostics device applications patient data has to be computerized in to digital formats. These digital formatted DICOM images has to be analyzed for exact patient data.

Huge amount of DICOM images are stored in diagnostic device, where the patient scan copies are stored in digital form. These data may be varied based on the patient's information to be analyzed. The amount of data storage in diagnostic machine may vary, mostly on patient's data, format of the scan segments and type of diagnostics taking place. For these diagnostic machines, they require large memory location to store the patient's data in DICOM format. But diagnostic machines are made with a fixed memory space, further improvement of these are not possible.

And in real time application medical images have to be transmitted based on the availability of patient location, for this we require an efficient method to transmit the patients data without any loss. While transmitting patient information in the form of DICOM images, they have to be converted in to a standard image format.

To transmit DICOM image, without the loss of patient's information, we need to implement an efficient algorithm which improves the computational complexity of the algorithm developed.

Apart from these, to store large amount of patient's information we need an image compression technique which will improve the storage capacity of the patient's information in diagnostic machines. MR image compression includes two stages. Firstly, image of given parameters will be compressed based on compressive sensing and secondly compressed image have to be reconstructed efficiently by improving reconstruction accuracy, iteration time, peak signal to noise ratio (PSNR) and compression ratio (CR). As a forward step, there are proposed compressive techniques for MR image compression. They are

- 1. Iterative Shrinkage Thresholding Algorithm (ISTA)
- 2. Fast Iterative Shrinkage Thresholding Algorithm (FISTA)
- 3. Composite Splitting Denoising (CSD)
- 4. Composite Splitting Algorithms (CSA)
- 5. Fast Composite Splitting Algorithms (FCSA)
- 6. Fast Composite Splitting Algorithms (FCSA-MRI)

These compressive techniques have shown great results in compressing the MR image, we are proposing an enhanced and improved FCSA algorithms which improves the MR image reconstruction. We had studied practically and implemented the proposed algorithm on the data collected from three patients scan DICOM images. Patient's data which we had taken for analysis are tabulated in table 1.

	Patient 01	Patient 02	Patient 03
Scan MR image			
Part of MR image	3DMR_Renal_Arteries	3DMR_Heart	3DMR_Spine
Size of MR image	10.9KB	19 KB	106 KB

We had taken these patients MR image and analyzed these images with previously proposed methods and compared with our proposed algorithm of modified FCSA algorithm.

Our proposed algorithm with comparative results, iteration time and PSNR had shown better results than the proposed algorithms. In our proposed method we are using bicubic and bilateral methods with super resolution method to improve the compression rate of 20: 1 value and reconstruction accuracy of 81 % with PSNR of 38.73 which shows a reliable transmission of MR image through a communication link in the vicinity of patient's location. Based on our proposed algorithm, MR image can be encoded using a MR image encoder which provides a loss less reconstruction of the original image.

Our proposed algorithm had shown better results compared to previously proposed algorithms.

## II. METHODOLOGY: ALGORITHMS REVIEW

Reviews of algorithms [1, 2]; developed to improve the compression ratio and recovery time of original compressive sensing image.

Algorithm 1: Iterative Shrinkage Thresholding Algorithm (ISTA): Reconstructed image is expressed by equation:

$$x^{k} = prox_{\rho} (g)(x^{k-1} - \rho Df(x^{k-1}))...Eqn.1$$

Algorithm 2: Fast Iterative Shrinkage Thresholding Algorithm (FISTA)  $\begin{aligned} x^{k} &= prox_{\rho}\left(g\right)(r^{k} - \rho Df(x^{k})) \\ t^{k+1} &= (1 + \sqrt{(1 + 4(t^{k})2))/2} \\ r^{k+1} &= x^{k} + (t^{k} - 1/t^{k+1})(x^{k} - x^{k-1}) \dots Eqn.2 \end{aligned}$ 

Algorithm 3: Composite Splitting Denoising (CSD)  $x^{i}$ =arg min  $_{x} (1/2m\rho)||x-z_{i}^{j-1}||^{2} + g_{i} (B_{i}x) \dots Eqn.3$ 

Algorithm 4: Composite Splitting Algorithms (CSA)  $y_i^k = prox_{\rho}(g_i)(B_i(x^{k-1}-((1/L) \oplus f_i(x^{k-1})))) \dots Eqn.4$ 

Algorithm 5: Fast Composite Splitting Algorithms (FCSA)

 $y_i^{k} = prox_0(g_i)(B_i(x^{k}-((1/L) \oplus f_i(x^{k})))) \dots Eqn.5$ 

 $\begin{array}{c} \mbox{Algorithm 6: Fast Composite Splitting Algorithms -MRI} \\ x_g = r^k - \rho Df(r^k) \\ x_1 = prox_{\rho}(2\alpha \|x\|_{TV})(x_g) \\ x_2 = prox\rho(2\beta \|\Phi x\|_1)(x_g) \\ xk = (x_1 + x_2)/2 \\ t^{k+1} = (1 + \sqrt{(1 + 4(t^k)2)})/2 \\ r^{k+1} = x^k + (t^k - 1/t^{k+1})(x^k - x^{k-1}) \dots Eqn.6 \end{array}$ 

Algorithm 7: Our proposed Modified Fast Composite Splitting Algorithm -MRI

 $\begin{array}{c} x_g \!\!=\!\! r^{k\!+\!1} \!\!-\!\!\rho \!\! D f\!(r^{k\!+\!1}) \\ x_1 \!\!=\!\! prox_\rho(2\alpha \|x\|_{TV} \!\!+\!\!2.5 \|\partial\|_{TV})(x_g \!\!+\!\!x_i) \\ x_2 \!\!=\!\! prox\rho(2\beta \|\Phi x\|_1 \!\!+\!\!2.5 \|\dot{\omega}\|_1) (x_g \!\!+\!\!x_i) \\ xk \!\!=\!\! ((x_1 \!\!+\!\!x_2)/2) \!\!+\! (\|\partial\|_{TV} \!\!*\, \|\dot{\omega}\|_1) \\ t^{k\!+\!1} \!\!=\!\! (1 \!\!+\!\!\sqrt{(1 \!\!+\! (t^k))})/2 \\ r^{k\!+\!1} \!\!=\!\! x^k \!\!+\! (t^k \!\!-\! 1/t^{k\!+\!1})(x^k \!\!-\! x^{k\!-\!1}) \dots Eqn.7 \end{array}$ 

In our paper, we are going to propose a MR Image reconstruction algorithm which improves the FCSA algorithm in two algorithms based on high resolution image enhancement methods [6, 7] improving the compression technique comparatively.

This paper is organized as follows. In chapter 3, proposed algorithm has been illustrated with a MR image containing patient scanned kidneys image. In chapter 4 comparative results have been shown with the previous proposed methods. Chapter 5 clearly illustrates the conclusion of the research algorithm proposed. Future research work has been proposed in chapter 6.

### III. PROGRESSIVE APPROACH TO OUR PROPOSED COMPRESSION MODEL MODIFIED FAST COMPOSITE SPLITTING ALGORITHM (MFCSA)

In our propose algorithm of MR image compressive sensing algorithm, an improved version of FCSA is presented. Proposed algorithm is as follows:

Step 01: Select a MR image for analysis.



Figure 1: Original MR Image.

Step 02: Resize the image in to [256 256]



Figure 2: Resized MR Image.

Step 03: Let the MR image be represented by Z.

Step 04: Analyze the partial FT x and sampling parameter y, as y=Zx [1]. Step 05: Enhance the MR image by bicubic and bilateral method using

- a. Assign w=5; sigma = [2 2.5] and [2.5 2];
- b. Compute sigma r = 100\*sigma(2);
- *c.* Design filter coefficients(-w:w,-w:w);
- *d.* Compute signal filter values  $G = \exp(-(X.^2+Y.^2)/(2*sigma(1)^2));$
- e. Apply bilateral filter.
- f. Extract local regions iMin, iMax, jMin and jMax. by computing JJ = A(iMin:iMax,jMin:jMax);
- g. Compute Gaussian intensity weights by  $H = \exp(-(JJ-A(i,j)).^2/(2*sigma(2)^2));$
- *h.* Calculate bilateral filter response by F = H.\*G((iMin:iMax)-i+w+1,(jMin:jMax)-j+w+1);



Figure 3: Enhanced MR image by bicubic and bilateral method.

Step 06: Further image resolution method is applied on enhanced MR image super interpolation resolution method using

- *Compute Sparse on given image* а.
- Assign lambda = .1; k = 0; tol = .001;*b*.
- Compute interpolation method by resolution technique С.



Figure 4: Enhanced MR image by super interpolation resolution method.

Step 07: High resolution and enhanced MR image will be further processed with modified FCSA algorithm using

- *Assign iterations* =0; *iterno*=*iterno*+1; а.
- Assign yp=y; yg=y-(A'\*(A\*y)-Atb)/Lx; *b*.
- c. Compute denoising TV on iterative shrinking image. d. Compute  $x_g = r^{k+1} \rho Df(r^{k+1})$
- Compute  $x_1 = prox_{\rho}(2\alpha||x||_{TV}+2.5||\partial||_{TV})(x_g+x_i)$ е.
- Compute  $x_2 = prox\rho(2\beta||\Phi x||_1 + 2.5||\omega||_1)$  ( $x_g + x_i$ ) f.
- Compute  $x_2^{k-1} prosp(2p) = x_{111}^{k-1} \dots prosp(2p)$ g.
- h.
- i.



Figure 5: Enhanced MR image by modified FCSA algorithm.

Step 08: Proposed modified FCSA compressed MR image will be analyzed with PSNR values of original MR image.

Step 09: Reconstructed MR image will be compared with FCSA, CSA, RecPF, TVCMRI and Sparse MRI algorithms [3, 4] with iteration time and PSNR.

Step 10: Comparative Results are analyzed with Modified FCSA Algorithm, High Resolution FCSA Algorithm and High Resolution with Interpolation FCSA Algorithm. These results have shown a better improvement in the FCSA Algorithm. Comparative results for 3DMR Renal Arteries MR Image are tabulated in Table 1.

Table 1 Comparative Results: 3DMR Renal Arteries
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	`Modified I	FCSA	HRFCSA			– HRIFCSA					
METH	IMAGE	ITER_TI	PSN	METH	IMAGE	ITER_T	PPS	METH	IMAGE	ITER_TI	PS
OD		ME	R	OD		IME	NR	OD		ME	NR
	Original			CG	J.	24.85sec	9.74	CG	J.	24.87sec	8.8 8
CG		25.29sec	11.7 2	TVCM RI	A CON	5.19sec	14.16	TVCM RI		5.21sec	13. 65

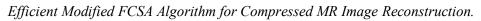
	1.C 1 ECGA	A1 • 1 C	$\alpha$ 1		D ( )
Efficient Mc	A = A = A = A	Algorithm to	nr ( amnrossod	ΜΚ ΙΜΠΟΡ	Reconstruction.
		111201 111111 10	n Compressea	min innage.	

TVCM RI	C L	5.15sec	15.4 9	RecPF	e de la compañía de la	5.07sec	14.81	RecPF	inte	5.07sec	14. 36
RecPF	and the second s	5.07sec	16.0 4	CSA		4.52sec	25.06	CSA		4.43sec	26. 60
CSA	ale a	4.41sec	22.3 5	FCSA		4.38sec	13.13	FCSA		4.35sec	13. 52
Modifie d FCSA (Propos ed)	C	4.43sec	22.2 7	HRFCS A (Propos ed)		4.46sec	30.10	HRIFC SA (Propos ed)		4.48sec	34. 25

**IV. PERFORMANCE EVALUATION AND COMPARATIVE RESULTS** In our paper, we had taken three MR images Renal Arteries, Heart and Spine. These MR images are analyzed with proposed FCSA algorithm and previously proposed methods. Comparative results are tabulated in Table 1, 2 and 3.

Modified FCSA				HRFCS	4	HRIFCSA					
METHO	IMAGE	ITER_TI	PSN	METHO	IMAGE	ITER_TI	PSN	METHO	IMAGE	ITER_TI	PSN
D		ME	R	D		ME	R	D		ME	R
	Original			CG		25.69sec	7.03	CG		25.01sec	6.31
CG		26.04sec	9.86	TVCMR I		5.18sec	12.9 1	TVCMR I		5.21sec	12.1 7
TVCMR I		5.26sec	14.4 3	RecPF		5.05sec	13.9 7	RecPF		5.13sec	13.5 0
RecPF		5.07sec	15.2 0	CSA		4.45sec	26.2 4	CSA		4.45sec	29.2 2
CSA		4.43sec	18.3 2	FCSA		4.43sec	13.7 2	FCSA		4.37sec	15.1 2

Table 2 Comparative Results: Heart
HDECSA



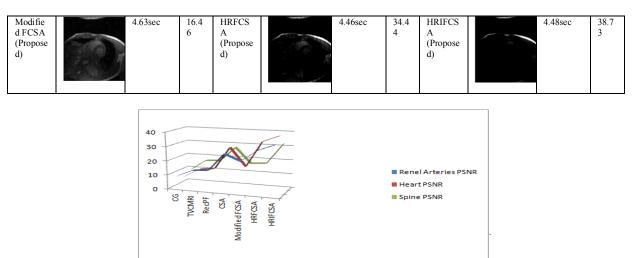


Figure 6: Comparative Results between CG, TVCMRI, RecPF, CSA, Modified FCSA, HRFCSA and HRIFCSA for Arteries, Heart and Spine MR Images.

Modified FCSA				HRFCSA			HRIFCSA				
METH OD	IMAGE	ITER_TI ME	PSN R	METH OD	IMAGE	ITER_TI ME	PSNR	METH OD	IMAGE	ITER_TI ME	PSNR
	Original			CG		24.82sec	11.5738 32	CG	K	24.84sec	9.4151 03
CG		25.10sec	11.3 8	TVCM RI		5.23sec	17.17	TVCM RI		5.23sec	16.68
TVCM RI		5.30sec	16.6 2	RecPF	l	5.01sec	17.79	RecPF		5.02sec	17.34
RecPF		5.05sec	17.3 4	CSA	l	4.46sec	19.80	CSA		4.45sec	27.63
CSA		4.48sec	19.2 2	FCSA	l	4.41sec	10.42	FCSA	L.	4.41sec	13.70
Modifie d FCSA (Propos ed)		4.52sec	16.7 3	HRFCS A (Propos ed)	l	4.48sec	17.51	HRIFC SA (Propos ed)		4.45sec	31.85

Table 3	Compara	tive F	Results:	Spine

Comparative results shown improved FCSA compared to the FCSA algorithm. So from the comparative results iteration time and PSNR clearly indicates that the high resolution and interpolation method will improve FCSA Algorithm.

## V. CONCLUSION

The proposed modified FCSA, HRFCSA and HRIFCSA algorithm can be applicable to low resolution MR images and for volumetric analysis of MR images. Our proposed algorithm had shown better comparative results. An efficient compression technique for MR Images is proposed in our algorithm.

### VI. FUTURE RESEARCH

Our proposed method can be further applicable to CT images and DICOM Images where special extraction of image is necessary. Further our algorithm can be applicable to high compressive image decoder for compressive sensing.

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