Reconstruction of MR Images using Sparse Signal Sequences in Frequency Domain

Deepak M D, Karthik P, Sreedhar Kumar S, Ravikumar H C

***Abstract:** A new strategy for signal acquisition has emerged called Compressed Sensing (CS). The compressed sensing has gained attention in the filed of computer science, electrical engineering and mathematics. The Compressed Sensing is a mathematical approach of reconstructing a signal that is acquired from the dimensionally reduced data coefficients/less number of samples i.e. less than the Niquist rate. The data coefficients are high frequency component and low frequency component. The high frequency components are due to the rapid changes in the images (edges) and low frequency correspond provide the coarse scale approximation of the image, i.e. fine continuos surface. The idea is to retain only coarse scale approximation of the image i.e. the significant components that constitute the compressed signal. This compressed signal is the sparse signal which is so helpful during medical scenarios. During the Medical Resonance Imaging (MRI) scans, the patient undergoes many kinds difficulties like uncomfortness, patients are afraid of the scanning devices, h/she cannot be stable or changing his body positions slightly. Due to all these reasons, there can be a chance of acquiring only the less number of samples during the process of MRI scan. Even though the numbers of samples are less than the Nyquist rate, the reconstruction is possible by using the compressed sensing technique. The work has been carried out in the frequency domain to achieve the sparsity. The comparative study is done on percentage of different levels of sparsity of the signal. This can be verified by using Peak Signal Noise Ratio (PSNR), Mean Square Error (MSE) and Structural similarity (SSIM) methods which are calculated between the reference image and the reconstructed image. The finite dimensional signal has a sparsity and compressible representation. This sparsified data can be recovered from small set of linear, non-adaptive measurements. The implementation is done by using MATLAB.*

***Keywords:** Compressed sensing, Magnetic Resonance Imaging (MRI), Niquist rate, Sparsity.*

I.INTRODUCTION

As said in the abstract, Compressed Sensing [1] is new strategy for signal acquisition. CS is a signal processing technique whose vision is to reconstruct the signal by using very less number of samples than actually needed. The actual number of samples required to reconstruct the signal must be more the Niquist rate. The Niquist rate states that in order to fully regenerate a signal it should be sampled at a rate which is two times the maximum frequency [2].

Revised Manuscript Received on January 5, 2020

Deepak M D, Research scholar, Dept. of CSE, KSSEM, Bengaluru-560109, India. E-mail :deepak.m.d@kssem.edu.in,

Karthik P, Professor, Dept. Of ECE, KSSEM, Bengaluru-560109, India. E-mail karthik.p@kssem.edu.in,

Sreedhar Kumar S, Professor, Dep of CSE, Dr. TTIT, KGF, Kolar-563120, Karnataka, India. E-mail: sree.dr.2018@gmail.com,

Ravikumar H C, Assistant Professor, Dept. of ECE, Gousia Engineering college, Ramanagaram, India. E-mail: raviec40@gmail.com

Magnetic Resonance Imaging [3] uses the radio waves and the electromagnetic waves to capture the internal organs of the body. MRI signals are generated mostly due to protons in the human body which is filled up mostly with water molecules. MRI scanning is a time consuming process to capture the details of the body parts. During the scanning, the patient undergoes a lot number of phenomenon activities like changing the body positions, doing a lot more respiratory activities, increasing his/her heart beats due to new medical environments or the scanning machine has undergone a alignment problems. Under these conditions, a good quality of MRI slice cannot be achieved. The best expression of the mage can be selected by reducing the pain of the patients. Even if the numbers of samples in the image are less than the Nyquist rate, the reconstruction of the signal is possible from a small set of linear non-adaptive measurements *[2*, 35, 36, 37, 38]. The sparsity [4] is an inherent characteristic of many signals which enables the signal to be stored in far few samples or less no of significant data. This sparsity represents the compression of the signal. There are two types of compression methods. They are lossy compression and lossless compression. In case of lossy compression, the reconstructed image is not the same as that of original image. But in case of lossless compression, both the original and reconstructed image will remain the same. Discrete cosine transforms (DCT)[5,6,8,9,10], Discrete Fourier Transform (DFT) [7] and Discrete wavelet transforms (DWT) [11,12,13,14] are examples of lossy compression techniques. The lossless compression techniques are Portable Network Graph (PNG), ZIP, MP3 and etc.

II.LITERATURE SURVEY

In the last three decades many of the authors reported distinct techniques to extract the features over the gray scale image in spatial [15-18,37] and frequency domains respectively. The author Badri in [19] has presented a compression method to process the gray scale image based on FFT and Sparse FFT techniques. The paper discusses about the concept of processing the data by using the DFT, FFT and Sparse FFT techniques. The comparative study of these techniques provides information regarding the impact of computations in number of operations.

The over all conclusion of the paper gives the information that sparse FFT is faster than FFT and FFT is faster than DFT with respect to number of operations in the processing.

In [20] the author Teddy has presented different methods namely DCT, DWT and FFT techniques respectively to Lossy Image Compression. This paper narrates about the concept of the compression and reconstruction of images using the FFT, DCT and DWT techniques. It is found from the results that lesser the amount of compression (lesser sparsity- introducing lesser number zeros in lesser places of insignificant coefficients), more will be quality during the reconstruction and more compression (more sparsity- introducing more number zeros in more places of insignificant coefficients), lesser will be the quality of reconstruction The authors in [21,22] have discussed about the compression of video frame for abject detection in the video sequences. This helps in fast processing of video frames in very less time and it also helps in providing the frame sequences at a very faster rate. Here the compression is applied on each of 4x4 block segments of the image by using Discrete Cosine Transforms. The signification information from each block is obtained and put in the matrix form in zigzag manner. This is applied for each of the video frames. So that computation processing and the storage requirements can be efficiently reduced.

Khaled Sahnoun has presented an On-Board Satellite Image Compression using the Fourier transform and Huffman coding in [23]. This paper discusses about the transmission and storage of the satellite images. The satellite images undergo a lot of disturbances like addition of noise into image during transmission, losing its original quality during the transmission from point of acquisition to the point of storage. For these reason the images in encoded and compressed using the Discrete Fourier Transforms by using the Huffman coding method. Here the original image is taken, and the Fourier transforms is applied. Then quantization is applied. The quantised image is then coded by the Huffman coding. Then finally, the resultant image is the compressed image of the satellite images.

In [24] the authors have been implemented a comparative study of standard Lossy Image Compression Techniques is discussed. The different techniques used are the predictive coding, transform coding and JPEG. The predictive coding provides the low compression rate where it removes the inter pixel redundancy. The disadvantages of this predictive coding are low compression rate, degradation such as granularity, slope overload and edge busyness. In Transform Coding, high compression rate is achieves. The high compression rate is achieves due to block coding in the frequency domain. The disadvantage of this technique is that, it is affected blocking artefacts [25]. In JPEG high compression can be achieved using the transform coding. The disadvantages are that it also faces the blocking artefacts [26]. The author Elma Hot in [27] has presented a Compressed sensing MRI based on masked DCT and DFT measurements. In this paper, the TWIST (Two-Step Iterative Shrinkage Thresholding) algorithm is used for calculating the sparse matrix from 2D FFT domain. In DFT the energy pixels (significant components) are at the corners of the measurement matrix (processed image). They all are brought together by applying the inverse FFT. So that the compactness is brought in the number of signal levels by putting only significant components at the centre of the image and other parts are made as sparse. So that compression is achieved. In DFT, the high frequency components are at the high left right corner of the processed image. Only left most corners is taken and the remaining portion is made as sparse. This is another way of compressing the samples. Here both DCT and DFT results are compared and verified that during reconstruction the DFT method will give better results compared to DFT. In [28] the author Vellaiappan has reported a method to comparison of DCT and Wavelets in Image coding. The author discusses about the concept of using the DCT and DWT for the compression and concludes regarding the energy compactness that is present in the Low frequency components of the transformed data. The high energy compacted data has helped in reconstructing the original data from the compressed and encode format.

M Lakshminarayana has reported a random sample measurement and reconstruction of medical image signal using compressive sensing in [29]. The author claimed that the concept of the modern ways of using the signal/image processing in the medical fields where compression and reconstruction of the signals is used for Telesurgery. But the traditional methods of compression and reconstruction are performed via DCT, FFT and DWT techniques. These techniques are old methods which are not much able to handle the noise factor that is occurring in the channel while receiving the compressed signal which in turn affects the Region of Interest (ROI) so that compressed sensing is being in this article results in providing a better result in the reconstruction of received compressed medical data signals.

The author Julien in [30] has presented a sparse modelling for image and vision processing, Foundations and Trends in Computer Graphics and Vision. This article discusses about the sparse modelling for the visual recognition and image processing. The systematic way how the sparsity can be viewed in the Discrete Cosine Transforms, Discrete Fourier Transforms and Wavelet transforms and how these techniques are used for the compressed sensing via L1 and L2 normalization techniques for the image recovery. Hence the DCT, FFT and DWT are viewed as form of sparse data containers.

In [32] the author Gary has reported Sparse Matrix Beamforming and Image Reconstruction for 2-D HIFU Monitoring Using Harmonic Motion Imaging for Focused Ultrasound (HMIFU) With In Vitro Validation. The paper discusses about the reconstruction of the medical image for the breast and pancreatic tumour diagnostic applications. Harmonized motion imaging for the focussed ultrasound using the sparse matrix-based beamforming is used for the reconstruction of the compressed data. Then finally, the resultant image is the compressed image of the satellite images. Figure 1 shows the original image used in the experimentation process of DCT/DFT/DWT to represent the sparsity that mimics the compressed sensing method.

Figure 1: Original Image

III.COMPRESSED SENSING

In many real time applications like the digital images taken by digital cameras, there is high in the Niquist rate, i.e. there will be too many samples and must be reduced or compressed to store or to transmit it. It is too expensive and difficult to store the density of the signal in real time because of its too large in tis storage requirements and transmission limitations like low bandwidth.

The compressed sensing is a mathematical approach for the implementation of sparsity by the way of dimensionality reduction. Compressed sensing method acquires the signal less than the Niquist rate which says that in order not to loose the information during the uniformly sampling the signal, it must be sampled at least double of its bandwidth.

The idea is to minimise the number of measurements by violating the Niquist rate in order to completely describe the signal by exploiting its compressibility.

Let x be a discrete time signal which is a column vector of NX1 in R^N with elements x[n], n=1,2 ,3,4,…N-1,N. Here the signal is nothing but a two dimensional image which is put in a 1-dimentional vector.

Let consider three vectors v1(1,0,0),v2(0,1,0) and V3(0,0,1). This forms the orthogonal basis of R^3. The inner product of these vectors is zero. i.e. $(v_1, v_2) = (v_1, v_3) = (v_2, v_3) = 0$. $||v_1|| = ||v_2|| = ||v_3|| = 1$. This means that $\{v_1, v_2, v_3\}$ is an orthonormal set. Inner-product space (R^N, (vi,vj)) can be used to construct other orthogonal bases of R^N. If A is the orthogonal basis of B, the every element of B can be written as $x = \sum_{x \in B} \frac{(x,b)}{||b^2||} b$.

When B is orthonormal, then $x = \sum_{b=0} (x, b), b$.

Any signal in R^N can be represented in terms of basis of NX1 vector $A = \{\psi\}_{i=1}^{N}$. Suppose the basis is ortho normal, forming the NXN basis matrix $\psi = [\psi 1|\psi 2|\psi 3|\psi 4|\psi 5 \ldots |\psi N]$. Then the signal x can be expressed as

$$x = \sum_{x-1}^{N} s_i \psi_i \qquad (1)$$

Where S is the NX1 column matrix of coefficients si= $(x, \psi_i) = \psi_i^T x$ where T is the transpose of matrix. And s is the ψ domain. So s and x are the equivalent representations of the same signal. Where x is in the time domain and s is the frequency domain.

The sparsity occurs in many natural signals and other types of generated signals which are compressible in nature. In equation 1, there exists a basis where, equation 1 has both small and large coefficients.

Consider M<N in the compressed sensing methods is the inner product between X and $\{\emptyset j\}_{j=1}^{M}$ as in yj=(x, $\emptyset j$). Here yi is put in terms of MX1 column matrix (vector) and measurement vectors $\emptyset j^T$ in terms of MXN matrix Φ.

$$\text{From 1, } y = \Phi x = \Phi s_i \psi_i = \Theta s_i, \qquad (2)$$

where $\Phi = \Phi\psi_i$ is an MXN matrix. Here the Φ is independent and does depend on any particular type of signal x. Figure 1 shows CS measurement in terms of Θ=Φψ with first 5 columns corresponding to nonzero s_i. The measurement matrix y is a linear combination of these 5 columns.The idea is to design a measurement matrix Φ by the method of dimensionality reduction from x to y where x ∈ R^N and y ∈ R^N. In order to reconstruct the x from the dimensionality reduced matrix y, some of the reconstruction algorithms need to be used.

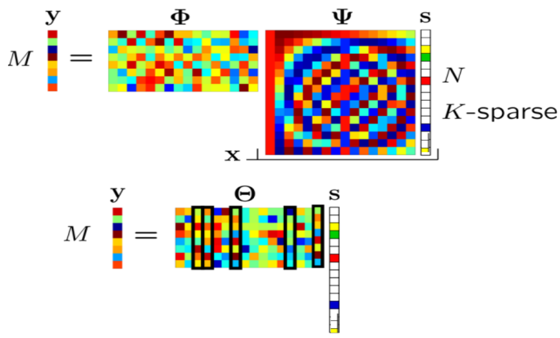

Figure 2: CS measurement in terms of Θ=Φψ with first 5 columns corresponding to nonzero s_i. The measurement matrix Y is a linear combination of these 5 columns.

IV. INTERPRETATION OF SPARSITY IN THE FREQUENCY DOMAIN

DCT [30] is the one used for the lossy image compression. DCT transforms the image from spatial domain into frequency domain. Here the large amount of information is stored at low frequency components of the signal. DCT has very large energy compaction at the upper left corner of the transformed image. These energy compactions are having much of the information about the image and are residing at the upper left corner of the transformed image. These components are retained, and remaining portion of the transformed image is replaced by zeros. For this sparse image, if the inverse DCT is applied, the reconstruction can be achieved.

The Equation for DCT is given by

$$D(i,j) = 1/\sqrt{2N}\, C(i)C(j)\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} p(x,y)\cos\left[\frac{(2x+1)i\pi}{2N}\right]\cos\left[\frac{(2y+1)i\pi}{2N}\right] \quad (3)$$

where $C(u)=\begin{cases}\frac{1}{\sqrt{2}} \text{ if } u=0\\ 1 \quad \text{if } u>0\end{cases}$ Where p (x, y) is the (x, y)th element of the image represented by the matrix p. N is the size of the block on which DCT is applied. The equation calculates one entry (i,j) position of the transformed image from the pixel values of the original image matrix.

Similarly, FFT [31, 32] is also one of the lossless compression techniques that convert the image from spatial domain to its frequency domain.

FFT is very similar to Discrete Fourier Transform (DFT). FFT is one that is characterized by the magnitude and phase of the signal. It gives the convolution operation on the input image which in turn brings about the energy compaction. This operation that reduces the signal of interest into small number of nonzero coefficients. These coefficients lie at the four corners of the image. These coefficients are called as significant components. These significant components are called as low frequency components. These components are having the much of the information about the image and are residing at the all the four corners of the transformed image. These components are retained, and remaining portion of the transformed image is replaced by Zeros. For this sparse image, if the inverse DFT is applied, the reconstruction can be achieved. So, the DFT is given by the equation

$$X(f) = \int_{-\infty}^{\infty} x(t).\, e^{-2j\pi ft}\, dt \quad (4)$$

$$x(t) = \int_{-\infty}^{\infty} X(f).\, e^{2j\pi ft}\, df \quad (5)$$

where t is time, f is frequency and x denote the input image. Note that, x is the signal at time domain and X is the signal in frequency domain. Equation 2 is called the Fourier Transform of x(t) and equation 2 is Inverse Fourier transform of X(f).

Discrete Wavelet transform [DWT] [33, 34] is one that provides the time and frequency components simultaneously which gives the time and frequency representation of the signal. Wavelets are used to represent and analyze multiresolution images. They are used for image compression and removal of noise. They are used in JPG 2000 standard. They are very used for 1 D signal. The time domain represents when and Fourier domain operations tell us the frequency. Wavelet transforms are a kind of filters used to localize the time and frequency component of the signal. It is extended version of the Short Time Fourier Transforms (STFT). That means in the STFT Fourier transformation of the signal is applied by using the shifted versions of the window (W). In the case of the wavelet transforms (WT), window (W) used itself is the wavelet. This wavelet window can not only be shifted but also be scaled. The window in the un-scaled and un-shifted format is called as mother wavelet. Here filtering operation is called as convolution operation. The convolution operation of different scaled and shifted versions of the window with the signal of interest results in providing the different levels of frequency and time localizations of the signal. This frequency and time localizations are helped in different types of processing of the signal such as segmentation, enhancement, compression and reconstruction. The only difference between the STFT and Wavelets Transforms is that in the case of STFT the window size will always remain constant and in the case of WT, the window size will undergo compression and expansion. In the case of STFT, the window is rectangular window but in the case of WT, the window is the form of a fixed length wave (such as square wave (HAAR Wavelet) or some kind of wave having some specified properties)). In the case of STFT, there is only one kind of window but in the case of wavelet transforms, there are two types of windows such as scaling window (scaling function (Φ)) and wavelet window (wavelet function(Ψ)).

The Wavelet transforms is given by the following equation as follows

$$F_{High\ Pass}(a,b) = \int_{-\infty}^{\infty} f(x)\Psi^{*}_{(a,b)}(t)dt \quad (6)$$

$$F_{Low\ Pass}(a,b) = \int_{-\infty}^{\infty} f(x)\Phi^{*}_{(a,b)}(t)dt \quad (7)$$

where * is the conjugate complex symbol. 'Ψ' is wavelet function to get high pass filter frequency components and 'Ψ' can be replaced by the scaling function ('Φ') to get the low pass filter frequency components. 'a' and 'b' are the dilation and translation factors respectively. f(x) is the input signal and 't' is the time axis.

When DWT is applied on the two dimensional signal, The input image is transformed into frequency domain. This frequency domain will be having four components such as low low, low high, high low, high high. Among these four components, low high, high low, high high are high frequency components and low low is the only low frequency component. These low frequency components constitute the significant component. Again the DWT is applied on the low low component in the second level and so on. Only the low low component of the inner most wavelet transform is considered and all other positions of the transformed image including the outer portions of the high frequency components are filled with zeros and constitute the sparsity. For this sparse image, if inverse Wavelet is applies, the reconstruction can be achieved.

V.COMPARISON STUDY OF DIFFERENT TRANSFORM TECHNIQUES

The Implementation of the sparsity based MRI image compression and reconstruction by using the frequency domain co-efficients of the DFT, DCT and DWT techniques as the measurements data is developed. So that we are interpreting the compressed sensing concept via the sparsity feature that is occurring through transformed coefficients in frequency domain of signal/image. The system takes an MRI image as an input image.

The image undergoes the transformation from spacial domain into frequency domain when it is passed through different transformation methods like DCT, DFT/FFT, and DWT. As a result of it, the image becomes the sparse image/signal. This sparse image represents the compressed form of the original image. The inverse operation of the DCT/FFT/DCT is applied on sparse image by appending the zeros to it to maintain the original size. And final the image is reconstructed. The comparison between the original image and reconstructed image is done through PSNR. Figure (2) describes the Block Diagram for exploitation the sparsity under frequency domain

.The system takes an MRI image as an input image. The image undergoes the transformation from spacial domain into frequency domain when it is passed through different transformation methods like DCT, DFT/FFT, and DWT. As a result of it, the image becomes the sparse image/signal. This sparse image represents the compressed form of the original image. The inverse operation of the DCT/FFT/DCT is applied on sparse image by appending the zeros to it to maintain the original size. And final the image is reconstructed. The comparison between the original image and reconstructed image is done through PSNR. Figure (2) describes the Block Diagram for exploitation the sparsity under frequency domain.

5.1 Algorithm

The steps to achieve the sparsity are as follows

Step1: Take the input image of 'M X N' dimensions where 'M' represents the number of rows and 'N' represents the number of columns.

Step2: Apply the transformation methods like DCT/FFT/DWT.

Step3: Apply the inverse DCT and inverse FFT and inverse DWT

Step4: Get the recovered image

Step5: Calculate the PSNR between the original and the reconstructed image.

The implementation details of the proposed algorithm which describes about the compression and reconstruction of the MRI images by making use of the sparsity feature of DCT/FFT/DWT concepts is shown in figure (1). The Discrete cosine transforms (DCT), Fast Fourier Transforms (FFT) and Discrete Wavelet Transforms (DWT) are used here to describe the different ways of sparsity. This sparsity is achieved in the frequency domain.

The way of converting the spatial domain of the image into frequency domain is called as transformation into frequency domain. This process is achieved through discrete Fourier transforms (DFT) and is given equation 3. Similarly Fast Fourier Transforms (FFT) will do the transformation of spacial domain of an image into frequency domain which is given by the equation 4. The inverse of it is given by equation 5. And also Discrete Wavelet Transforms (DWT) will also bring about the transformation of the spacial domain of an image into frequency domain which is given by equations 6 and 7. The equation 6 filters the high frequency components while equation 7 filters the low frequency components.

Table 1: Describes the comparative study of FFT/DCT/DWT

Computational method	Percentage of Sparsity of data	PSNR	RMSE	SSIM
	84.74121	11.66684	4.10E+03	0.005236
	81.53687	12.24906	3.62E+03	0.01516
	74.21265	12.77898	3.25E+03	0.026174
FFT	65.66772	13.23967	2.97E+03	0.040271
	84.74121	31.85033	14.58525	0.946994
	81.53687	33.1694	10.09383	0.966809
	74.21265	35.13539	6.275299	0.97828
DCT	65.66772	37.16003	3.862579	0.982024
	84.74121	14.44102	97.2482	0.300652
	81.53687	16.68001	72.74232	0.441532
	74.21265	20.20473	50.33095	0.707629
DWT	65.66772	26.78305	29.48836	0.921572

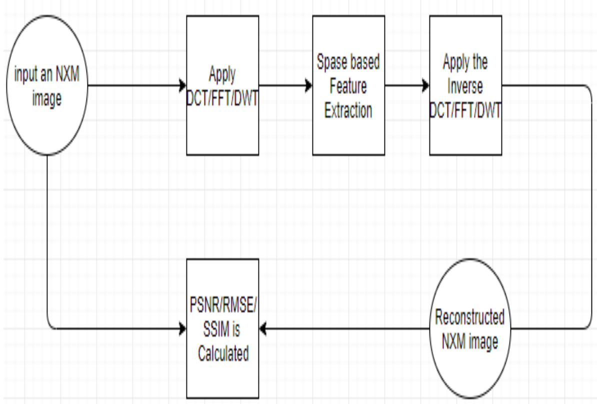

Figure 3: Block Diagram for exploitation of the sparsity under frequency domain

Retrieval Number: B7885129219/2020©BEIESP
DOI: 10.35940/ijitee.B7885.019320

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

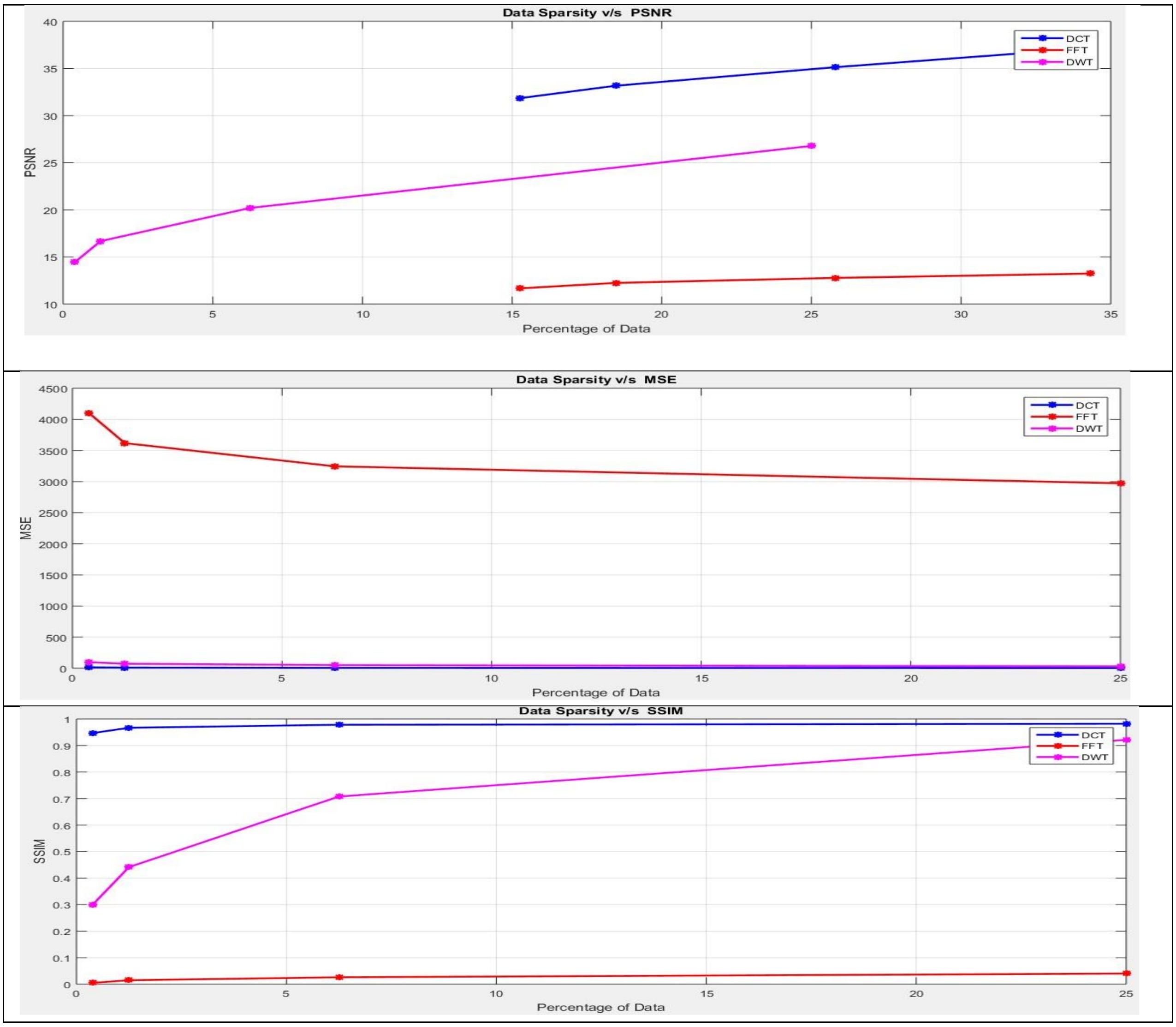

Figure 4: Data sparsity v/s PSNR /RMSE/SSIM

VI.RESULTS

The DCT, FFT and wavelet transforms shows a representation of the two dimentional signal in some representation called the frequency representation. A percentage of frequency in these representations is selected which represents the sparsity. The sparsity selection mimics the way that compressed sensing is all bout it is going to be done in the process of creating the measurement matrix. The results of the analysis made for the sparsity approach via FFT, DCT and DWT for the compressed sensing concept is shown table 1. In the transformed domain, the percentage of sparsity is considered for the reconstruction. PSNR of the reconstructed data with the original data is calculated for all the three cases. Figure (4) shows the plotting of the analysis PSNR, MSE and SSIM versus percentage of sparsity. Here, wavelet shows as consistent improvement in the reconstruction from the lower level sparsity to the higher level of sparsity when compared to the DCT and DWT cases. Figure (5) shows the results obtained by simulation for the MRI brain image for different methods of sparsity interpretation. Table (1) describes the comparative study of FFT, DCT and DWT based sparse analysis reconstruction of MRI images. In case of FFT, the percentage of sparsity is 65.66772, for which the PSNR, RMSE and SSIM values will be like 13.23967, 2.97E+03, 0.040271 respectively. Similarly, for DCT, PSNR, RMSE and SSIM values will be 37.16003, 3.862579, 0.982024 respectively for the same 65.66772 of sparsity . And finally in the same way of 65.66772 of sparsity, for wavelet transforms, PSNR, RMSE and SSIM values will be 26.78305, 29.48836, 0.921572 respectively. This shows that for wavelet and DCT transforms, it shows a incremental improvement in terms of PSNR, RMCE and SSIM.

VII.CONCLUSION

With many of the discussions in this article, DCT, FFT and WDT are known to be three different types of frequency representations of a signal which depict the how the signal can be represented or transformed into frequency domain. In all the three transform Techniques, an analysis is made about the sparsity of the data which is chosen from different aspects of the transform techniques on percentage basis. Comparative analysis is made among these methods where DCT and DWT are giving better results when compared to FFT in terms of percentage of data considered for sparsity. This sparsified data form different transformed techniques mimic the ways that the measurement matrix needs to be derived from the Compressed Sensing techniques.

.

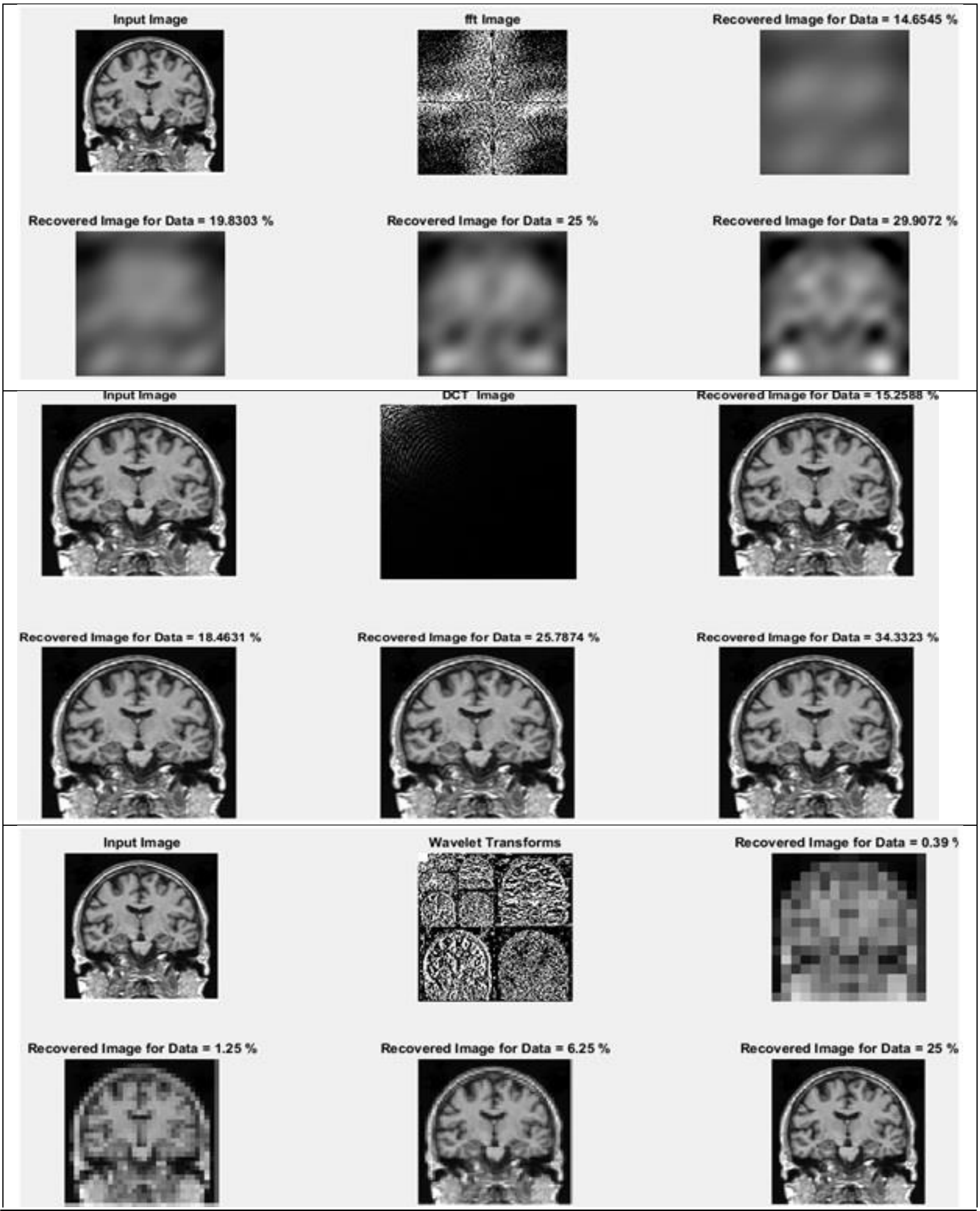

Figure 5: Results obtained by simulation for the MRI brain slice image for different methods of sparsity interpretation

ACKNOWLEDGMENT

We gratefully thank the Visvesvaraya Technological University, Gnana Sangama, Belagavi, Karnataka, India for the financial support extended to this research work. We also thank the K S School of Engineering and Management, Bengaluru for providing the facilities in doing this project completely.

REFERENCES

1. H.J. Landau, (1967)" Sampling, data transmission, and the Nyquist rate", Proceedings of the IEEE, Volume: 55 Issue: 10 ,pp. 1701 – 1706.
2. D.L. Donoho,(2006) " Compressed sensing", IEEE Trans. Inf. Theory, Vol 52, pp. 1289–1306.
3. G A Wright,(1997) "Magnetic resonace imaging", IEEE SIGNAL PROCESSING, Volume: 14, Issue:1, pp 56-66

4. Michael Lustig, David Donoho, and John M. Pauly (2007) “Sparse MRI: The Application of Compressed Sensing for Rapid MR Imaging”, Magnetic Resonance in Medicine, pp. 1182–1195.
5. Hang Wang, Dov Rosenfeld, Michael Braun, And Hong Yan,(1992) “Compression And Reconstruction of MR Images Using 2d Dct”, Mognetic Resonance Imaging, Vol. 10, Pp. 427-432.
6. Zhigang Wu,(2009) “An improved scaled DCT architecture”, IEEE Transactions on Consumer Electronics, Volume: 55 , Issue: 2 ,pp. 685 – 689.
7. Lawrence R. Johnson, Anil K. Jain (1981), “An Efficient Two-Dimensional FFT Algorithm”, IEEE Transactions on Pattern Analysis and Machine Intelligence Volume:PAMI-3,Issue 6.
8. R. Reininger , J. Gibson (1983) “Distributions of the Two-Dimensional DCT Coefficients for Images”, IEEE Transactions on Communications, Volume: 31 , Issue: 6 , pp. 835 - 839, Jun
9. N. Ahmed, T. Natarajan, and K. R. Rao, (1974) “Discrete cosine transform,” IEEE Trans. Cornput., vol. C-23, pp. 90-93.
10. K. N. Ngan and R. J. Clarke,(1980) “Lowpass filtering in the cosine transform domain,” in Proc. Int. Conf. oj Commun., Seattle, WA.
11. Laurent Brechet (2011) “IMAGE Resolution Enhancement by Using Discrete and Stationary Wavelet Decomposition IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 20, NO. 5.
12. Jie Liang (1998) ”Image coding using translation invariant wavelet transforms with symmetric extensions”, IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 7, NO. 5.
13. J. Liang and T. W. Parks,(1996) “A translation invariant wavelet representation algorithm and its Applications,” IEEE Trans. Signal Processing, vol. 44,pp. 225–232.
14. J. D. Villasenor, B. Belzer, and J. Liao (1995) “Wavelet filter evaluation for image compression,” IEEE Trans. Image Processing, vol. 4, pp.1053–1060.
15. M. Madheswaran, S. Sreedhar Kumar, R. Ravi, “Inherent Approach of Medical Image Pixels Classification Using an Improved Agglomerative Clustering Technique,” Research Journal of Biotechnology,, vol. 12, Special Issue 2, pp. 115-124, August 2017.
16. M. Madheswaran, S. Sreedhar kumar, “An Improved Frequency Based Agglomerative Clustering Algorithm for Detecting Distinct Clusters on Two Dimensional Dataset,” J. Eng. Technol. Res. (Academic Journal), vol. 9, no. 4, pp. 30-41, Dec. 2017.
17. S. Sreedhar kumar, M. Madheswaran, Vinutha B A, Manjunatha Singh H, Charan K V, “A Brief Survey of Unsupervised Agglomerative Hierarchical Clustering Schemes,” International Journal of Engineering & Technology (UAE) , vol.8, no.1, pp.29-37, Jan 2019.
18. Badri Narayan Mohapatra (2017) ” FFT and Sparse FFT techniques and applications”,Fourteenth International Conference on Wireless and Optical Communications Networks (WOCN), IEEE Publisher, 24-26.
19. Teddy Mantoro, (2017) “Comparison, Methods of DCT, DWT and FFT Techniques Approach on Lossy Image Compression”, 2017 International Conference on Computing, Engineering, and Design (ICCED), Kuala Lumpur, Malaysia.
20. Metin KAYA (2005), An Algorithm for Image Clustering and Compression, Turk J Elec Engin, VOL.13, NO.1
21. Kumar S (2102) “Moving Object Detection using Frame Interleaving and Clustering based Compression”, International Journal of Computer Technology & Applications, Vol 3 (4), 1583-1586.
22. A.J. Hussain (2018), Image Compression Techniques: A Survey in Lossless and Lossy algorithms,Neurocomputing, DOI:10.1016/j.neucom.2018.02.094.
23. Taubman, D., and Michael W. Marcellin (2013), "JPEG2000 Image Compression Fundamentals, Standards and Practice." Journal of Electronic Imaging, pp. 286-287.
24. J. Clarke (1995) “Transfer Coding of Images. Academic Press, London.
25. Elma Hot 2015 ”Compressed Sensing MRI using DCT and DFT Measurements” 4th Mediterranean Conference on Embedded Computing(MECO),Budva, Montenegro. Vol 3.
26. Vellaiappan Elamaran (2012), Comparison of DCT and Wavelets in Image coding,” International Conference on Computer Communication and Informatics.
27. M Lakshminarayana,(2015) “ Random Sample Measurement and Reconstruction of Medical Image Signal using Compressive Sensing”, Intl. Conference on Computing and Network Communications, (CoCoNet'15) , Trivandrum, India.
28. Julien Mairal,(2012) “Sparse Modeling for Image and Vision Processing”, Foundations and Trends in Computer Graphics and Vision Vol. 8, No. 2-3, DOI: 10.1561/0600000058.
29. Gary Y. Hou, (2014) “Sparse Matrix Beamforming and Image Reconstruction for 2-D HIFU Monitoring Using Harmonic Motion Imaging for Focused Ultrasound (HMIFU) With In Vitro Validation”, IEEE TRANSACTIONS ON MEDICAL IMAGING.
30. Bi, D., Xie, et.al,(2015) “A Sparsity Basis Selection Method for Compressed Sensing. IEEE Signal Processing Letters” VOL. 33, No. 11.
31. K. R. Rao and P. Yip(1990), Discrete Cosine Transform: Algorithms, Advantages, Applications, Academic Press, Boston.
32. Hang Wang,*Dov Rosenfeld, Michael Braun, And Hong Yan, 1992 “Compression And Reconstruction of MR Images Using 2d Dct”, Mognetic Resonance Imaging, Vol. 10, Pp. 427-432.
33. Ramkumar, G.V. Anand, (1997)An FFT-based technique for fast fractal image compression, Signal Processing Vol. 63, pp. 263-268,
34. S.G. Mallet, (1989) “theory for multiresolution signal decomposition: The wavelet representation”, IEEE Trans. Pattern Anal. Mach. Intel., Vol. 11(7), pp. 674-693.
35. Z. Wang and B. R. Hunt,(1985) “The discrete Wavelet transform”, Applied Mathematics and Computation, Vol. 16, pp. 19–48.
36. R. Krishnamoorthy, S. Sreedhar kumar, “An Improved Agglomerative Clustering Algorithm for Outlier Detection,” Applied Mathematics and Information Sciences (NSP), vol. 10, no. 3, pp. 1125-1138, May 2016
37. Richard Baraniuk, Compressive Sensing, Lecture Notes in IEEE Signal Processing Magazine, Volume 24, July 2007.

AUTHORS: PROFILE

Mr. Deepak M D is a research scholar in the Dept. of Computer Science and Engineering, at K S School of Engineeinng and Management Bengaluru, affliated to VTU. He completed his masters in computer Science and Engineering at UBDTCE, Davangere University, Davangere India. He ia a life member of ISTE. His areas of interest are image processing, Machine learning, Bigdata analytics, and pattern recognition and multimedia concepts.

Dr. P. Karthik has received the PhD degree in the Department of Electronics and Communication Engineering. He is presently working as Professor in the Department of ECE at K S School of Engineeirng and Management, Bengaluru. He has more than 10 years of experience in teaching and has published papers in 4 International Journals, 3 International Conferences and 4 National Conferences. His academic excellence involve associating with other Institutions / Universities to conduct various activities like workshop, guest lecturer etc., he has motivated students to do mini projects and publishing papers. He has done about 15 journals and 30 conference research articles. His areas of specialization are Embedded Systems, Networks and Communication. He is a IEEE member.

Dr. Sreedhar Kumar S is currently working as Professor.and Head, Department of CSE at Dr. TTIT KGF, Kolar, Karnataka. He has completed his PhD from Anna University, Chennai. His academic excellence involves associating with other Institutions / Universities to conduct various activities like workshop, guest lecturer etc He is life member of MISTE. He has published more than 10 research articles in more than 10 journals. His areas of interest are medical image processing, machine learning, deep learning, bigdata analytics, Artificail Intelligence etc. He is a member of ISTE.

Mr. Ravikumar H C is currently working as Assistant Professor in Dept of ECE, Ghousia College of Engineering, Ramanagaram, Karnataka, India.. He has done his masters in VLSI design and embedded systems from VTU Belagavi. His areas of interest are image processing, Machine learmning, Bigdata analytics, pattern recognition and multimedia concepts.