PERFORMANCE EVALUATION OF COMPRESSION FOR BIOMEDICAL IMAGES USING COMPRESSED SENSING

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DECLARATION BY THE SCHOLAR

I hereby declare that the work reported in the M-Tech dissertation entitled **"PERFORMANCE EVALUATION OF COMPRESSION FOR BIOMEDICAL IMAGES USING COMPRESSED SENSING"** submitted at **Jaypee University of Information Technology, Waknaghat India,** is an authentic record of my work carried out under the supervision of **DR. MEENAKSHI SOOD**. I have not submitted this work elsewhere for any other degree or diploma.

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SUPERVISOR'S CERTIFICATE

This is to certify that the work reported in the M.Tech project report entitled **Performance Evaluation of Compression For Biomedical Images Using Compressed Sensing"** which is being submitted by **Urvashi** in fulfilment for the award of Masters of Technology in Electronics and Communication Engineering by the **Jaypee University of Information Technology**, is the record of candidate's own work carried out by her under my supervision. This work is original and has not been submitted partially or fully anywhere else for any other degree or diploma.

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Date: **Urvashi**

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ABSTRACT

For the effectual storage and transmission of signal in telemedicine, compression of medical images is one of the indispensable operations. Acquisition speed is always an issue in medical images like magnetic resonance imaging and computed tomography images. Compressed sensing came up as an inkling that achieves sparse signal with under sampled Nyquist rate. Compressed sensing is always astounding because only few samples can perfectly recover the entire signal is indeed a big achievement. In this paper different performance parameters peak signal to noise ratio, compression ratio, structural similarity index are evaluated for medical images by reconstruction algorithms like basic pursuit (l_1), least square (l_2), orthogonal matching pursuit. From these recovery algorithms, it is pointed that$l_1$norm minimization is most established convex optimization approach to achieve better quality image. Performance metrics peak signal to noise ratio and root mean square error are observed at different measurement samples and it is seen that peak signal to noise ratio increases with increased measurement and root mean square error decreases.

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LIST OF ABBREVIATIONS

BT	Basic Pursuit
BW	Band Width
CR	Compression Ratio
CS	Compressed Sensing
CT	Computed Tomography
DCT	Discrete cosine Transform
DFT	Discrete Fourier Transform
DSIM	Dissimilarity Structural Index
JPEG	Joint Photography Expert Group
LZW	Lempel-Zev-Welch
MRI	Magnetic Resonance Imaging
MSE	Mean Square Error
OMP	Orthogonal Matching Pursuit
PRD	Percentage Root Mean Square Error Difference
PSNR	Peak Signal- to -Noise Ratio
QoS	Quality of Service
RGB	Red Green Blue
SENSE	SENSitivity Encoding
SMASH	Simultaneous Acquisition of Spatial Harmonics
SSIM	Structural Similarity Index
TV	Total Variation

CHAPTER 1
INTRODUCTION

Amount of data traffic generated enormously with the rapid change in information technology and technological advancement produces massive amount of data especially in biomedical field like a typical hospital generates terabyte of data per year. Medical imaging techniques (MRI or CT scan) are used in radiology to image the internal human body structure and all the medical data is stored digitally. MRI image data is tremendously high as a single MRI image construction involves collecting the series of frames of data and it is very slow imaging modality as the images are acquired sequentially in time [1]. As data files of medical imaging are suitably high and also imaging modality is slow, so compression is necessary to reduce the file size and to increase the speed of imaging for efficient transmission and also for storage. Many hospitals have clinics and satellite centres in remote areas to deliver the health care service where distance is a critical factor and patient find hard time to travelling a distance to the hospital especially for diagnostic purposes. For the suitability of patients these hospitals make use of telemedicine to access dedicated health care facilities to rural, semi-urban and remote areas. This tele-radiology application allow the technician to take medical image (MRI) and send to the main hospital where is diagnostic radiologist can read the image and send back the diagnosis. But in case of emergency where time is important matter then there is a problem because a 10MB image will take approximately half an hour for transporting using high speed modems making compression a necessity [2]. Many compression schemes like transformation coding, fractal coding and vector quantization achieves very high compression ratio but at the cost of quality [3]. It is essential that compression and reconstruction of signal should be efficient without any loss of signal quality as little loss of quality especially in biomedical imaging is intolerable because it may diagnose erroneously.

1.1 Compression

Compression is a technique that reduces the file size and accelerates the speed for better storage and transmission. Main Objective of compression is to reduce redundant and irrelevance bits of data so that transmission and storage is done in an efficient form.

Need of compression is not only for storage purpose but also for transmission as it saves time, having compact representation of image and utilizes the bandwidth.

Fundamental components of compression:

Redundancy – remove duplicate bits from signal source.

Irrelevancy –Part of signal is neglected that is not noticeable by signal receiver namely Human Visual System (HVS)

1.2 Image compression techniques:

Compression is achieved by different compression techniques and all techniques have their merits and demerits. Some achieve good quality of reconstructed image but at the cost of compression and other achieve high compression ratio but not able to achieve better quality [3].

The image compression is broadly classified into two categories.

1. Lossless compression

a. Run length encoding
b. Huffman encoding
c. LZW encoding

2. Lossy compression

a. Transformation coding
b. Vector quantization
c. Fractal coding

These compression techniques include following schemes as shown in Figure1.1

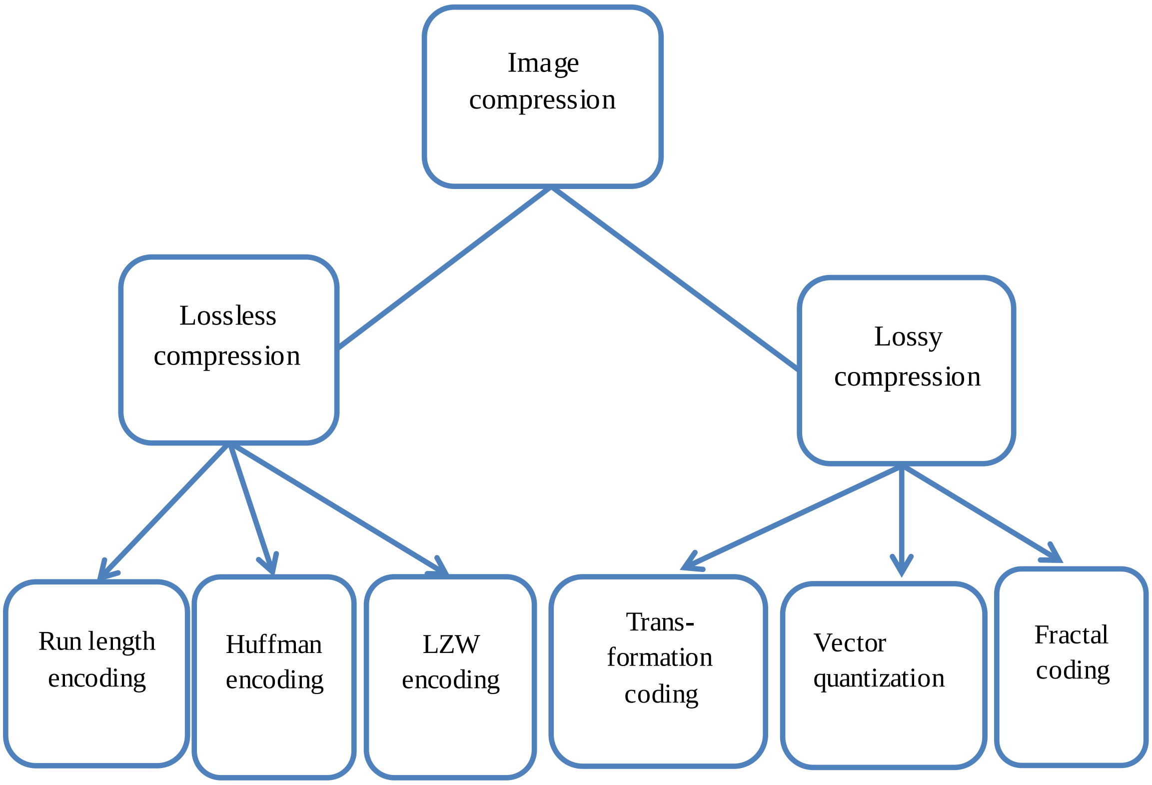

Figure 1.1 Different compression schemes

1.2.1 Lossless compression

In this category of compression, original image is reconstructed perfectly by the compressed image. In lossless compression quality of recovered image is good but high compression is not achieved as shown in Figure 1.2.

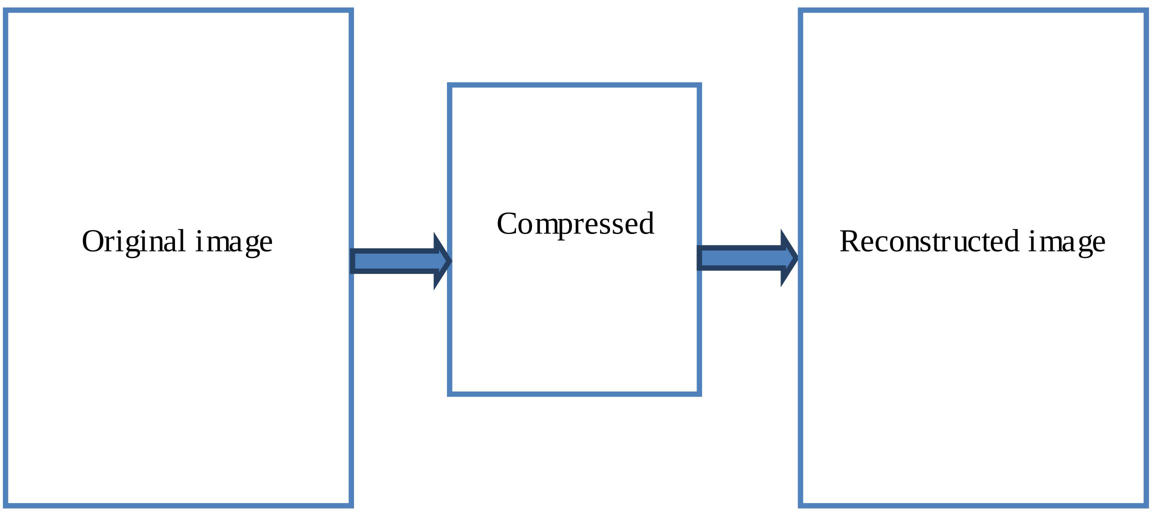

Figure 1.2 Basic view of Lossless compression

Lossless compression is preferred for purposes where the little loss of information is noticeable such as medical imaging, technical drawings or comics etc. Techniques include in lossless compression are:

a. Run length encoding: - In this compression technique, identical symbol sequence is replaced and it is known as run by shorter symbol. In case of repetitive data run length encoding is very useful. Run length code gray scale image is represented by (Vi, Ri) where Vi represents pixel intensity and Ri is number of successive pixels as shown in Figure1.4

20 20 20 20 15 15 8 8 8 8 8 40 40 40 18 18 18 18

{20, 4} {15, 2} {8, 5} {40, 3} {18, 4}

Figure 1.3: Run Length Encoding

b. Huffman coding: - This compression technique is based on the probability occurrence frequencies. Smaller number of bits is assign to symbol having high frequency while symbol having less frequency are assigned large number of bits.

c. Lempel-Zev-Welch (LZW): - It is commonly used in computer industries and is very. Compression of file is done by using table based lookup algorithm. Sequence of bits is taken and creates an entry in a dictionary. This coding technique is dictionary based coding and basically divided into two types, Static and Dynamic. In static dictionary coding, there is no change in coding once the code is assigned (encoding). Dictionary is stable in both sides. In case of dynamic, dictionary is not fixed, coding is updated fly.

1.2.2 Lossy compression

This type of compression is suitable for the purposes where little loss of quality is acceptable like natural images, photos etc. Compression ratio is highly achieved in this type of compression but at the cost of quality. Lossy compression is acceptable for applications where there is fast transmission of still images over the Internet. Less bandwidth is required for this type of compression. Basic view of lossy compression is shown in Figure 1.4

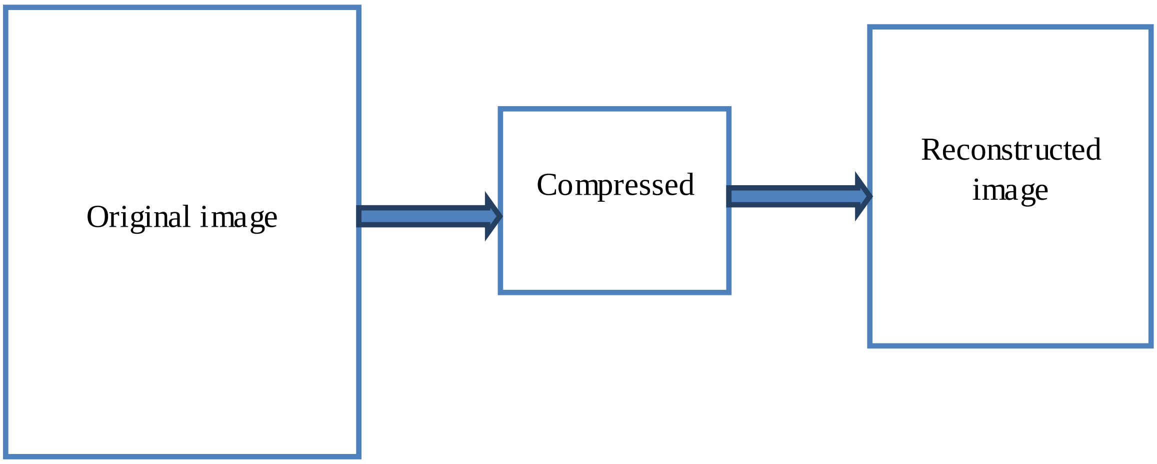

Figure 1.4: Basic view of lossy compression

Techniques include in lossy compression are:

a. Transformation Coding: - It is a compression type used for natural data like photographic images, audio signal etc. Lower quality of image is resulting from this type of compression technique. Discrete coding transform (DCT), discrete Fourier transform (DFT) are used to change original image pixels into frequency domain coefficient.

b. Vector Quantization: - It is a lossy compression technique that is based on the principle of block coding in which dictionary of fixed size vectors is develop and these are called code vectors. Dictionary index is used for encoding of original image vector. Thus sequence of indices represents the image that can be further entropy encoded [3, 4].

c. Fractal Coding: - For the fractal compression method, digital image is subdivided into sub-blocks and is based on fractals. This method is appropriate for natural images, based on the fact that part of an image is similar to other parts of same image. Parts of image are converted into mathematical data by fractal algorithm and these mathematical data is called fractal codes which are used to recover the original image.

Conventionally insight, signal is sampled at the sampling rate equal or greater to the Nyquist sampling rate [5]. In traditional compressing approaches, signal is acquired, sampled and then it is transformed, so these sampling and acquisition require huge amount of sensors and capacity for the storage purposes that leads high measurement cost, wastage of time [6]. However in many applications such as biological systems, astronomy and high speed analog to digital conversion, imaging speed is important. This process of sampling at full rate and apply compression algorithm can be uneconomical in terms of sensing equipment and sampling resources. Image compression techniques discussed above are based on the Nyquist sampling criteria. Recently Compressed Sensing (CS) came up as an idea for achieving the compression by using different sensing arrangement and it first proposed by Donoho and Candes [7, 8].

1.3 Compressed sensing

From various compression techniques, compressed sensing came up as an idea for achieving efficient acquisition and reconstruction of a signal. Unique capability of compressive sensing is to perform sensing and compression in a single step [9]. In various fields like biomedical, medical Imaging and satellite imaging, CS plays very important role as it helps to reconstruct the signal i.e., sparse in some domain using very few samples than required by the Nyquist sampling theory, where signal is sampled at a rate larger than highest frequency present in the signal [10]. Samples which were considered insufficient for sampling according to Nyquist criteria are used in CS for signal recovery. CS techniques can produce efficient results such as increased imaging speed, enhanced image quality and other benefits [11].

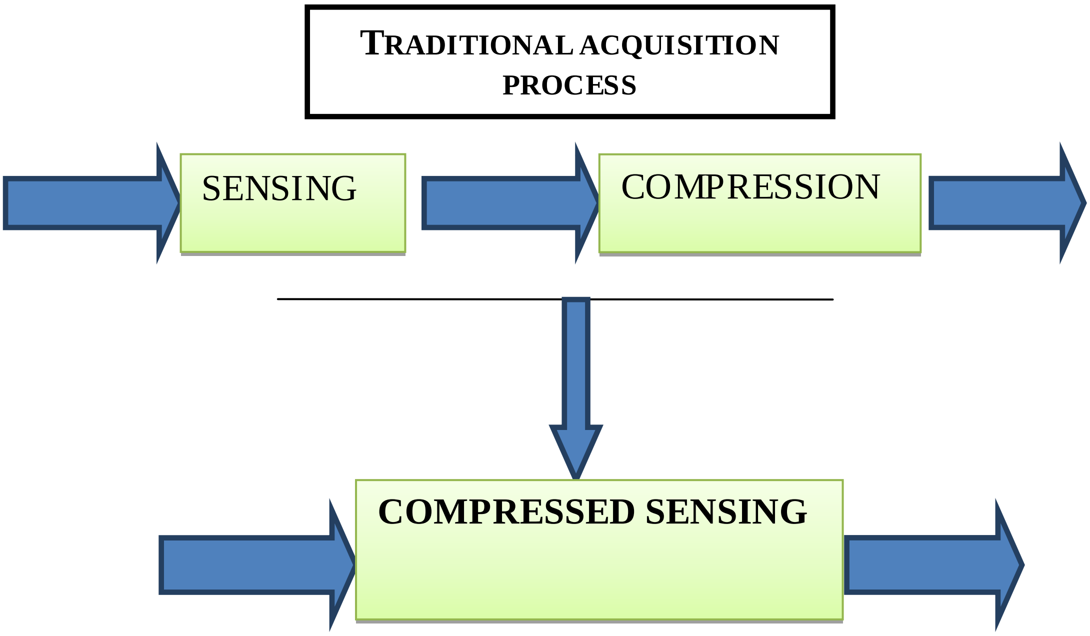

Figure 1.5: Basic block diagram of compressed sensing

CS is based on two conditions under which recovery is possible: sparsity and incoherence.

a. Sparsity: - which require a signal to be sparse in some domain. Signal is said to be sparse if it has many zeros and few non zero entries. CS requires the signal should be sparse in some domain for recovery. Only limited number of coefficients contains the vast majority of information and remaining coefficients are very small but not exactly zero. CS gives an accurate reconstruction if the signal is well approximated by taking large coefficients and treating the small valued coefficients as zero [12]. Main features of sparsity are that sparse signal is cheap to store/transmit and these coefficients are meaningful as they make more sense. Sparsity is important in compressed sensing as it determines how efficiently one can acquire the signal non-adaptively [13].

Considering a discrete time signal x and let x is a k-sparse in N-dimensional space

$$x=\Psi s \tag{1}$$

Where, Ψ is N×N sparsifying matrix, s is transform vector of dimension N×1 containing k non zero coefficients and k << N.

b. Incoherence: - which is applied through the isometric property which is sufficient for sparse signals. Coherence refers to an arithmetical quantity that evaluates the highest correlation between any two elements of the two different matrices. The matrices represent two different basis domains. Consider two different orthonormal basis Φ and Ψ of $\mathbb{R}^n$. and coherence between these two bases is defined by

$$\mu(\Phi,\Psi) = \sqrt{n} \cdot max|\langle \Phi_k, \Psi_k \rangle| \tag{2}$$

Above equation gives largest correlation between any two elements of the two bases and is shown as

$$\mu(\Phi,\Psi) \in [1,\sqrt{n}] \tag{3}$$

Sparsity and incoherence calculates the signal compressibility. If signal has higher sparsity in some domain Ψ that is incoherent to sampling domain Φ then it is more compressible [13]. Original signal can be recovered from m measurement samples if $\boldsymbol{\Phi\Psi}$ satisfy the Restricted Isometric Property (RIP) which is possible when $\boldsymbol{\Phi\Psi}$ are incoherent [8, 12].

1.4 Compressed Sensing (CS) for medical images

Image compression is very beneficial in medical science. Compression of medical images plays a key role as hospitals produce massive amount of data and all data is stored in digital form. Biomedical technology progresses day by day and clinic needs to store high volume of data of medical images and other biomedical signals about the patient. A typical 12 bit X-ray may be 2048 by 2560 pixels and this interprets 10,485,760 bytes of file size [2]. This has consequences for disk storage and image transmission time. Even there is steadily increment in disk storage, medical imagery data produced by radiology sections and hospitals has been increasing faster. Even if there is unlimited storage, still there is problem of transmitting that huge amount of medical data generated by hospital. The problem of storage and transmission of higher amount of data can be overcome if biomedical signals and other images of test results are compressed so that larger volume of data can be transmitted faster and store in hard disk. Compression scheme like transformation coding, fractal coding and vector quantization are not applied for compression of medical images because due to possible loss of valuable clinical information and as operation like enhancement may lead to additional degradation in compression. Different types of medical images are used for diagnosed and all these diagnostic images need to store regard compression on biomedical images. Compressed sensing (CS) shows significant promise in biomedical field. As a new sampling and recovery framework, it has been applied to less number of data in MRI. In this technique, MRI images can be recovered from the fewer samples provided signal is sparse in transform domain [14]. In general, radiological images are captured from multiple devices which differentiate from its data capturing mechanism. Owing to presence of external artifacts, huge amount of noisy data are also present sometimes which is not necessary to be recognized during diagnostic process. Hence, data is when subjected to compression, medical image will be compressed along with undesirable data. Therefore compressed sensing allows only the important clinical information to decomposed first using DWT (discrete wavelet transforms). CS is exciting for numerous motives: it allows accurate reconstruction of an image from fewer measurements samples than required by Nyquist criteria, it does not require close match between the sampling pattern and characteristic image structures. CS can also offer efficient results in terms of increased imaging speed, improved quality of image and also other benefits [11]. Compressed sensing is mostly has been applied on medical imaging especially MRI to reduce the scan time duration [6]. As a new sampling and recovery basis, it has been applied to reduced number of required data in MRI. MRI images can be recovered from fewer samples provided signal is sparse in some domain. It is supposed that CS may explore its appreciated involvement in medical image. MRI scanning takes a long time for scanning and during this scan time patient's breathing pattern, heart rate and position may change that can lead to degraded quality of image that can be non-diagnostic. Compressed sensing may reduce negative effects of variation in heart rate, breathing pattern and can also reduce the imaging time [14].

Magnetic Resonance Imaging (MRI): - Magnetic resonance imaging is commonly used technique in biomedical imaging for acquiring the inside image of human body structure. MRI is a type of scan that produce detailed images of human internal body structure by using strong magnetic fields and radio waves, magnet in MRI is very strong but there are no harmful effects from it. Contrast mechanism and excellent visualization of human body structure is offered by MRI [1]. MRI differs from CT-Scan as it does not use radiation while CT-scan uses ionizing which is harmful. MRI is used for examining problems such as tumours, soft tissue, blood vessel diseases etc. MRI provides detailed information about problem seen on an X-Ray, CT-scan or ultrasound scan. Body parts that are surrounded by bone tissues can be presented clearly by MRI Scan so this imaging technique is valuable when inspecting brain and spiral cord. Because detailed picture is offered by MRI-scan it is the best technique and when it comes to finding tumours in the brain it shows how much tumour spread into nearby brain tissue. Magnetic resonance imaging technique provides image with excellent contrast and clear diagnostic quality as compared to other imaging modality as X-ray scanner and CT-scanner. MRI imaging technique is not risky as there are no known dangers and one cannot feel any kind of pain during MRI scan. Magnetic is extremely powerful that is used in MRI but it is not dangerous and no effects from it. Pacemakers and other medical devices that contain iron can be affected by magnet.

There are different types of MRI scan like:

1) **Head MRI: -** MRI scanner can find the problems of the brain for tumors, nerve injury, bleeding in the brain and it can also look at other problems like problem in eyes, optic nerves and ears.
2) **Chest MRI: -** Scanner can show if the heart and lungs are damaged. It can find the problems of the heart valves, coronary blood vessels and may also be used for breast or lung cancer.

3) **MRA (Magnetic Resonance, Angiography): -**MRI scan are used to look at blood vessels and the flow of blood through them is called MRA.

4) **Bone and joint MRIs:** Discs and spine nerves can check by MRI for conditions like disc bulges and tumor in spinal.

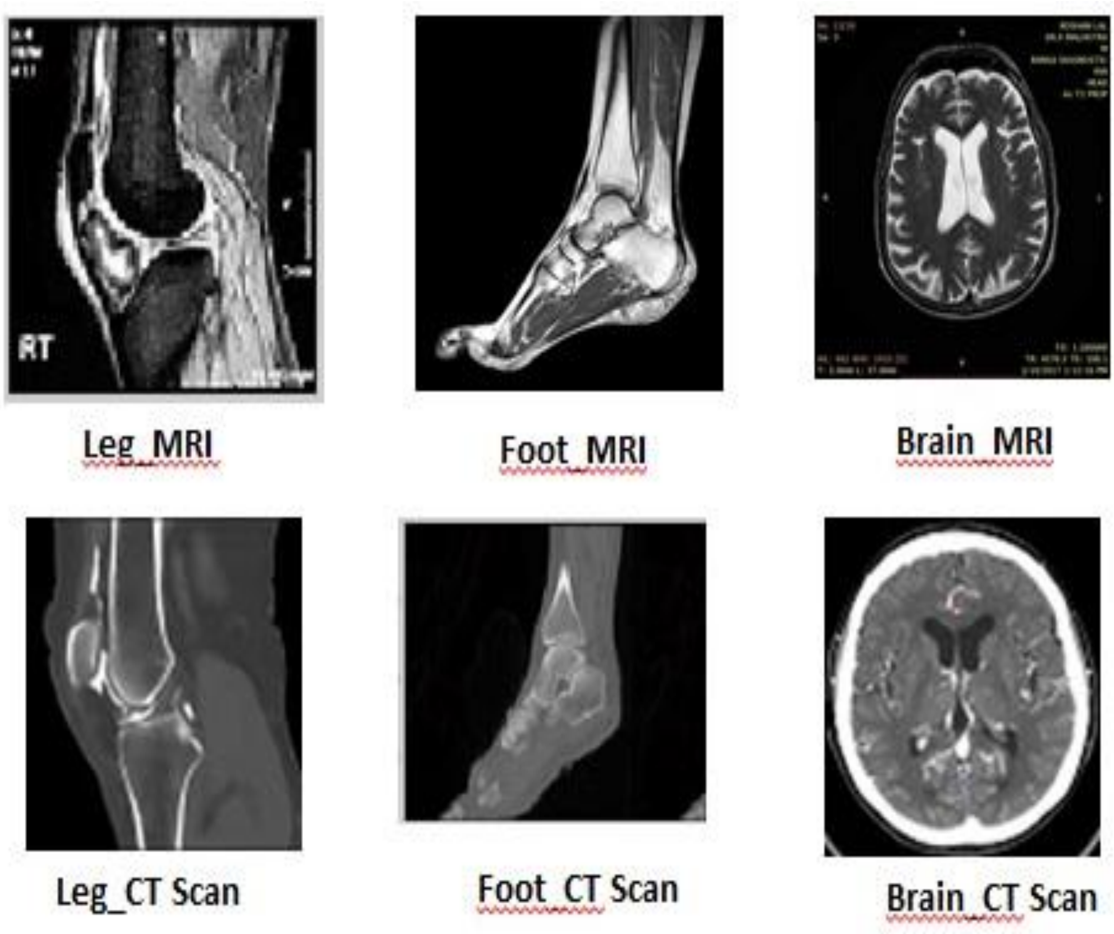

Figure 1.6: Different MRI and CT-scan images

1.5 Recovery Algorithms

For optimally reconstructing the signal, certain requirements should be satisfied such as stability, speed, uniform guarantee and efficiency. Convex optimization is a popular, due to high availability of efficient algorithms, higher accuracy of reconstruction and the guarantee of successful recovery [16]. Various reconstruction methods available in literature are briefed in the following section.

a. Basic Pursuit: - It consists of convex optimization methods like $\boldsymbol{l_1}$ minimization, Total Variation (TV) minimization which provides uniform guarantee over sparse signal. It is not optimally fast technique as large number of iterations involves in this pursuit but provide robustness under measurement noise and approximately sparse signals. It has high computational complexity and not optimally fast but on the other hand it is favoured technique as it offers high quality of reconstruction [17]. Reweighted l_1 norm minimization provides improved reconstruction quality as the normalized mean square error (NMSE) of this method is lower than without using reweighted algorithm.

b. Compressive Matched filter: - This reconstruction technique is the alternate of l1 norm minimization. If prior knowledge of the signal is known then this is very powerful technique as it is robust, optimal and fast. In general, complete knowledge of signal is not known, in this case basic pursuit (l_1 norm minimization) is preferred. For the purposes of testing the system, matched filter is used since it represents the best recovery possible and so exposes the limits of the system. Because it is fast, it allows hundreds of simulations in short amount of time.

c. Greedy method: - Other reconstruction techniques like matching pursuit, stage wise orthogonal matching and compressive sampling matching pursuit are involved in greedy pursuit. Greedy approach provides faster reconstruction than basic pursuit but most of them deliver smaller recoverable sparsity compared to l_1 norm minimization and often come without uniform guarantees and stability. Example of greedy algorithm for sparse recovery is orthogonal matching pursuit (OMP). Orthogonal matching pursuit works iteratively, in each iteration selecting the column of A having maximal projection onto the residual signal and adding it to the already selected columns. After a new column vector is selected, representation coefficients w.r.t vectors are chosen so far are found via least squares optimization. Although greedy pursuit is extremely faster but not optimally stable [17].

1.6 Performance Metrics

Reconstruction techniques for different medical images are examined with various evaluation metrics as Peak Signal to Noise Ratio (PSNR), Root Mean Square Error (RMSE), compression ratio, SSIM (structural similarity index), DSIM (dissimilarity index), PRD (percentage root mean difference) which express the amount of compression done and quality of an image. Amount of compression is done by calculating compression ratio and quality of an image is measured by PSNR, SSIM and RMSE.

PSNR: Quality of an image is express in terms of PSNR and its typical value is 30db for 8 bit depth. Higher the value of PSNR better is the quality of an image [18]. PSNR is calculated by

$$\mathbf{PSNR} = \mathbf{10}\ \mathbf{log_{10}}\ \frac{\mathbf{(255)^2}}{\mathbf{MSE}}$$

RMSE: PSNR and MSE are inversely related to each other. Root mean square error is the square root of error that is difference of original image and the reconstructed image as given by

$$\mathbf{RMSE} = \sqrt{\mathbf{MSE}}$$

$$\text{and } \mathbf{MSE} = \sum\sum \frac{\mathbf{(error)^2}}{\mathbf{rows} \times \mathbf{columns}}$$

PRD: Percentage root mean square error difference shows error difference between original image and reconstructed image and it is calculated by

$$\mathbf{PRD} = \sqrt{\mathbf{MSE}} \times \mathbf{100}$$

SSIM: It is the combination of comparative measures such as luminance, contrast and structure and based on mean and variance of the signal. Value of SSIM is in between 0 and 1 and reconstructed image is more similar to reference or original image if SSIM approaches to 1. Value towards 0 shows the dissimilarity between two images.

$$\textbf{SSIM (x,y)} = \frac{(2\mu_x\mu_y + c_1)(\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

Where, $c_1 = (k_1 l)^2$, $c_2 = (k_2 l)^2$

DSIM: It is dissimilarity index that is opposite to the structural similarity index of an image. Higher value of dissimilarity index shows lower quality of image and it is given by

$$\textbf{DDIM (x, y)} = \frac{(1 - \mathrm{ssim})}{2}$$

Compression Ratio: Compression ratio is the ratio of uncompressed data size to the compressed data size and CR should maintain in a way that quality of signal should also maintain.

$$\textbf{CR} = \frac{\textit{uncompressed data size}}{\textit{compressed data size}}$$

$$\textbf{Space saving} = 1 - \frac{1}{CR}$$

CHAPTER 2

OBJECTIVES AND SCOPES

The primary goal of this work is to compress the biomedical image using compressed sensing technique to utilize the bandwidth, buffering and transmission time. Generally a typical hospital generates terabyte of data per year [2]. Compression done in biomedical field helps mainly in the application of telemedicine for the expediency of the patients who have hard time to travel. This motivates to choose the project in the field of compression and biomedical.

For the fulfilment of project following objectives are set:

1) To implement compressed sensing technique for medical image compression and reconstruction.
2) To find the more efficient CS-recovery technique for medical image by exhaustive performance analysis of various reconstruction techniques.
3) To design a system that finally provides a tradeoff between compression ratio and image quality.

Project Scope

The proposed work is useful for the efficient storage & transportation of medical images.

Proposed work has scope in different fields:

1) **Medical imaging**: Medical imaging is the technique and process of creating visual representations of the interior body organs or tissues for clinical analysis and medical intervention. Medical imaging seeks to reveal internal structures hidden by the skin and bones and it is also used to diagnose and treat disease. Medical imaging also establishes a database of normal anatomy and physiology to make it possible to identify abnormalities. Thus there is a need for better image compression to facilitate medical imaging.

2) **Telemedicine:** - Telecommunication and information technology are used in telemedicine and it provides medical services from a distance and the information is transferred from one side to other side through electronic communication. Patients in rural areas can receive care from the doctor without need to visit to speciality hospitals. It removes the distance barriers. Thus there is a need for better image compression to serve the need of telemedicine and provide the prompt medical healthcare facility.

3) **Multimedia:** - Multimedia uses a combination of different content forms such as text, audio, images, animations, video and interactive content. Multimedia contrasts with media that use only rudimentary computer displays such as text-only or traditional forms of printed or hand-produced material. Multimedia can be recorded and played, displayed, interacted with or accessed by information content processing devices, such as computerized and electronic devices, but can also be part of a live performance. Hence there is a need for better image compression to facilitate these multimedia applications.

4) **Digital photography:** - Digital photography is a type of photography that uses cameras containing arrays of electronic photo detectors to capture images focused by a lens, as opposed to an exposure on photographic film. The captured images are digitized and stored as a computer file ready for further digital processing, viewing, digital publishing or printing. Therefore there is a need for better image compression to aid digital photography.

CHAPTER 3
LITERATURE REVIEW

A literature review was conducted to provide the knowledge base for the further innovative, safe and efficient design for compressed sensing magnetic resonance imaging (CS-MRI) that is well balanced between compression ratio (CR) and signal quality in contrast to existing of compressed sensing in medical images.

In [19], combination of compressed sensing (CS), PMRI and wireless transmission is proposed to increase the MR image acquisition scan time. However coils connected to receiver via coaxial cable leads many demerits like constraint space and crosstalk among coil hence to avoid these demerits, wireless transmission system is proposed which is based on 802.11 because it is capable to provide bit rate requirement at 11Mbps. At the receiver end two reconstruction methods i.e., simultaneous acquisition of spatial harmonics (SMASH) and SENSitivity Encoding (SENSE) are to reconstruct images.

In [20] authors have used OMP algorithm for reconstruction of an image. Author concluded that OMP has negligible additional complexity but enables a significant performance improvement in the reconstruction precision than traditional OMP.

In [21], improved reconstruction method for CSMRI with multichannel data is proposed. Various methods like SENSitivity encoding (SENSE) and simultaneous acquisition of spatial harmonics (SMASH) are investigated. SENSE combines the CS with array system for image recovery in each channel and reconstruction to each channel individually followed by Sum of Square (SOS) method. Better reconstruction quality technique is proposed by this paper i.e., l_1 norm minimization which recover more details and clear and sharper edges. In this it is concluded that it has lower normalize mean square error (NMSE), improved reconstruction quality with clear and sharp edges and less computational complexity but increasing number of measurements.

In [22], combine sparsifying transforms in CSMRI is proposed however generally compressed sensing MRI, mostly enforce the sparsity of image in single transform for example total variation (TV), wavelet etc. In this paper author proposed a new framework to combine the transform in CS-MRI. Each transform represent specific feature that other cannot like wavelet is good at isolating point discontinuities but fail to represent curve like image. Reconstructed curves are much clear than those of wavelet. Hence it is concluded that multi-transform improves image quality as compared to single sparsifying transform. Method adopted in this paper was Smooth l0 norm having NP hard problem i.e., replaced by l_1 minimization.

In [23] Prior information in CS reconstruction is used that spatial and temporal frequency domain is partially known from motion pattern of MR images. l_1 norm minimization is used for reconstruction. Dynamic image reconstruction from this method is more superior to existing methods when few numbers of measurements is used. Suppress more artifacts and preserve more details. Author concluded that prior knowledge of the dynamic MRI sequence is used to improve the quality of reconstruction and able to suppress more artifacts and preserve more details than conventional CS in dynamic MRI.

In [24] different compression algorithms are compared to find the optimal technique. Author examined the coding properties of the Wavelet, Curve-let, and Wave-atom transforms. Wavelet transform is well known multi resolution technique provide accurate temporal and spatial information and represent point singularity in 1-D and 2-D but fails to represent curve singularity in 2-D. Wave-atom capture the coherence of pattern across and along the oscillation but curve-let capture the pattern along the oscillation only. Author concluded that wave-atom is a best technique with high CR (compression ratio) & SNR (signal to noise ratio).

In [25] RMM (remote medical monitoring) system is proposed for discourses the biomedical data in disaster area. All the data is collected compressed and transmitted to the base station using wireless ADHOC network (WANETs). The WANETs are collection of several nodes and these nodes sending the medical data to the base station. Transmission of medical data requires Energy efficient approach is required for the transmission of medical data and fuzzy logic based route selection technique is proposed to provide compressed data and it exploits the lifetime of WANETs. Author concluded that lifetime of network is increase & hence maintain quality service (QoS) of WANETs.

In [26] Authors proposed a real time MRI reconstruction method and difference image between previous & current image frames is reconstructed and add this difference to the previous image to reconstruct the current image. Difference image is sparse & recover by using compressed sensing. Offline reconstruction method is considering T.V minimization and online reconstruction considering Kalman filtering method. Author concluded that the proposed method is worse than offline reconstruction & better than online reconstruction that means accuracy of recovered image is less than offline but more accuracy than the online technique. The online technique produces approximately 4 times faster reconstruction than proposed method but of lower quality. Proposed method yields worthy quality of reconstruction but difference images are required to be sparse.

Author in [18] has used wavelet techniques for medical image compression. Haar wavelet, Daubechie wavelet, Biorthognal wavelet and Coiflet wavelet were considered by author in this paper. All wavelets produced less PSNR and less compression ratio except Coiflet wavelet.

In [27] authors presented a technique where CS performance is more superior by assuming new set of parameters like number of low pass coefficients, auxiliary measurement, index ordering JPEG zigzag ordering. The algorithm is purely capable for l_1 minimization. Consequence of proposed system shows balance between compression ratio (CR) and quality of signal as compare to existing of compressed sensing in medical images. Author concluded that system has better performance than existing systems that is compression ratio (CR) enhanced to 40% & quality of recovered image is improved to 10% than existing system.

In [6] authors have applied wavelet transform along with compressed sensing and wavelet transform is use to generate a set of sparse components which is essential for compressed sensing. At various measurements calculation of PSNR and RMSE are done and it is observed that PSNR increased with increased measurement samples as compared to traditional techniques like JPEG 2000, JPEG.

CHAPTER 4

METHODOLOGY

In this work compressed sensing -magnetic resonance imaging (CS-MRI) is proposed for better acquisition, compression and storage. Reweighted l_1, norm minimization, least square (l_2) and OMP recovery algorithms are used for reconstruct the image efficiently.

4.1 Algorithm for CS

An input image say [x] of dimension $N \times 1$ is taken. A randomly generate measurement matrix [Φ] of $M \times N$ (M<<N) dimension but it will drop some information if generated randomly so use Gaussian distribution for random variables with zero mean (μ=0) and variance one (σ = 1). Then compressed measurement vector [y] of dimension $M \times 1$ is obtained by multiplying [x] with measurement matrix [Φ].

$$y=\Phi x \tag{4}$$

above equation represents the sampling process.

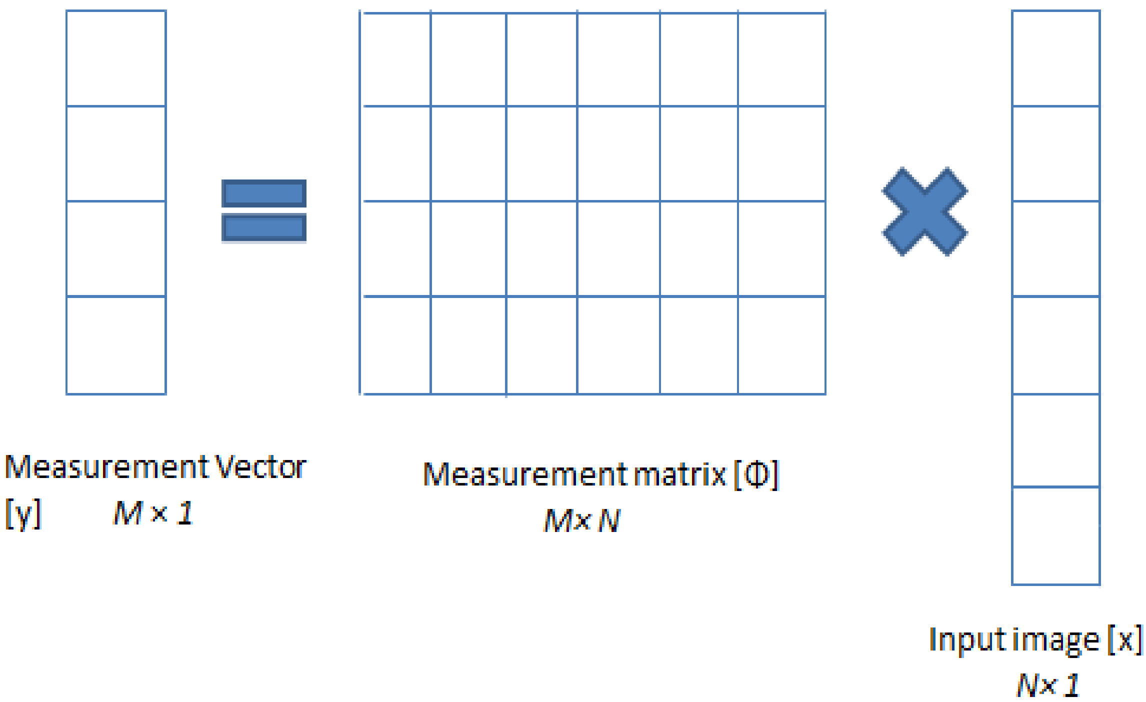

Figure 4.1: Sampling process structure of CS matrices

For the accurate recovery from very few samples, x should be sparse in some domain.

$$x=\Psi s \tag{5}$$

Where, Ψ is a sparsifying matrix of dimension $N\times N$ and s is transform vector containing $K<<N$ non zero coefficients. Second condition of CS recovery is $\Phi\Psi$ satisfies the isometric property of incoherence.

$$\Theta = \Phi\Psi \tag{6}$$

Overall sampling process becomes,

$$\theta = \Phi\Psi s \tag{7}$$

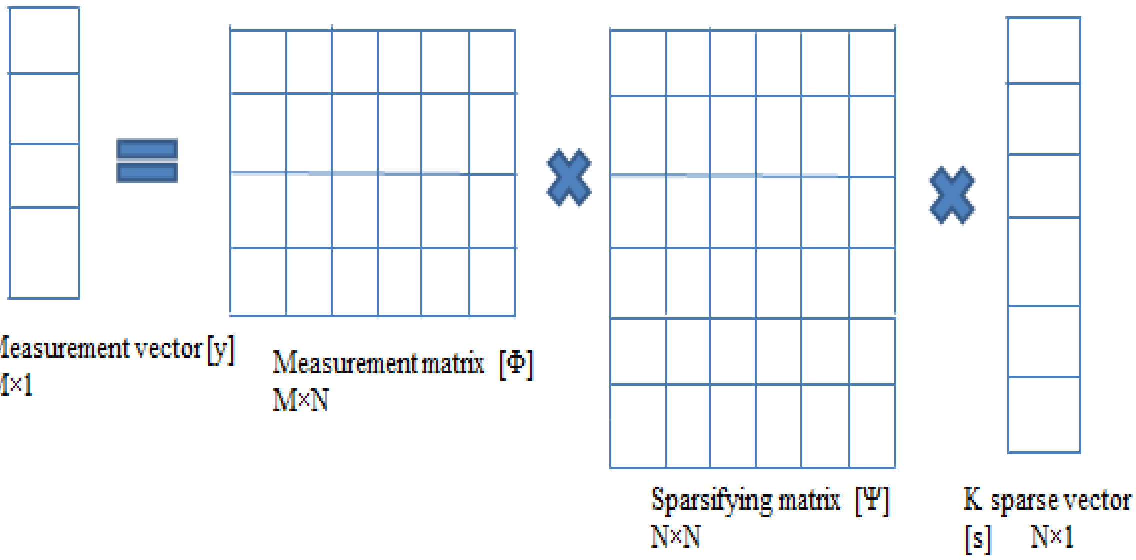

Figure 4.2: Complete structure of compressive signal sensing matrices

If Ψ is less coherent to the sampling domain Φ then the signal is more compressible [13].

Signal x can be reconstructed by solving the following optimization problem.

$$\mathbf{min}\left\|\boldsymbol{\Psi}^{-1}\boldsymbol{x}\right\|_{\boldsymbol{p}} \tag{8}$$

Where, p represents the signal sparsity. When p is taken as 0 then the above problem is reduced to l_0 norm minimization and it results to NP hard problem so it is replaced by l_1 norm minimization.

Algorithm of CS is as shown if Figure 4.3

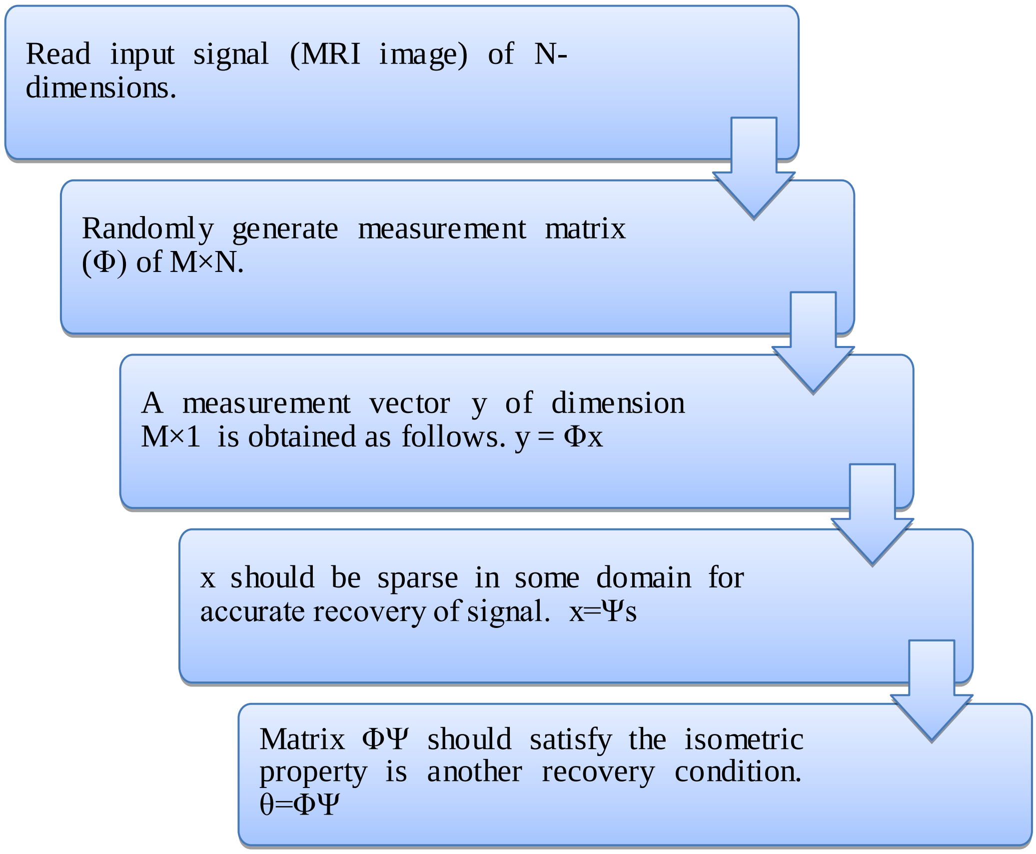

Figure 4.3: Steps of CS-MRI algorithm

4.2 l_1 norm minimization

Reweighted l_1 minimization is best established technique used to enhance the CS image reconstruction as compare to other recovery algorithms. Basic pursuit (l_1) norm minimization approach can provide stability and uniform guarantee [28]. Reweighted l_1 does not have linear bound on run time so it is not optimally slow but gives better recovery. Signal x can be reconstructed by solving the following optimization problem.

$$\min \left\| \Psi^{-1} s \right\|_p \tag{9}$$

Where, p represents the signal sparsity. When p is taken as 0 then the above problem is reduced to l_0 norm minimization and it marks to NP (non- deterministic polynomial) hard problem so p is taken as 1 and l_0 is replaced by l_1 norm minimization technique.

Reconstruction algorithm of l_1 norm minimization is as follows:

Iterative count is set to l=0 and $w_{i,j}^{(0)}=1$ for i= 1,….,m and j = 1,…,n. $w_{i,j}^{(0)}$ is the weights on pixel (i,j).

Weighted l_1 minimization problem is solved as:
Min $\||W_S\||_{1,}$ s.t $y = \Phi x$;

Update the weights:
$W_{I,J}^{\ L+1} = 1/\ s_{(i,j)}^{\ l} + \epsilon$

If specified maximum number of iteration attained by l then l_{max} is finished. Otherwise, increase the l and repeat step2.

Figure 4.4: Steps of l_1 algorithm

4.3 Design of CS-MRI system (encoder)

Figure 4.5 shows encoder side of compressed MRI system. In this, MRI image is taken which is further checked for its RGB content and converted into grey scale. Input image is then normalizing to increase its precision level to double. After that algorithm applies the compressed sensing technique for efficient compression of input image. Compressed bits are then subjected to quantization and result of quantized bits are calculated and then sending for entropy encoding. Compressed bits are then calculated and compression ratio using total number of bits of original image divided by total number of compressed image is computed. Compressed MRI image is then stored, transmitted and then reconstructed at the decoder end to get original image.

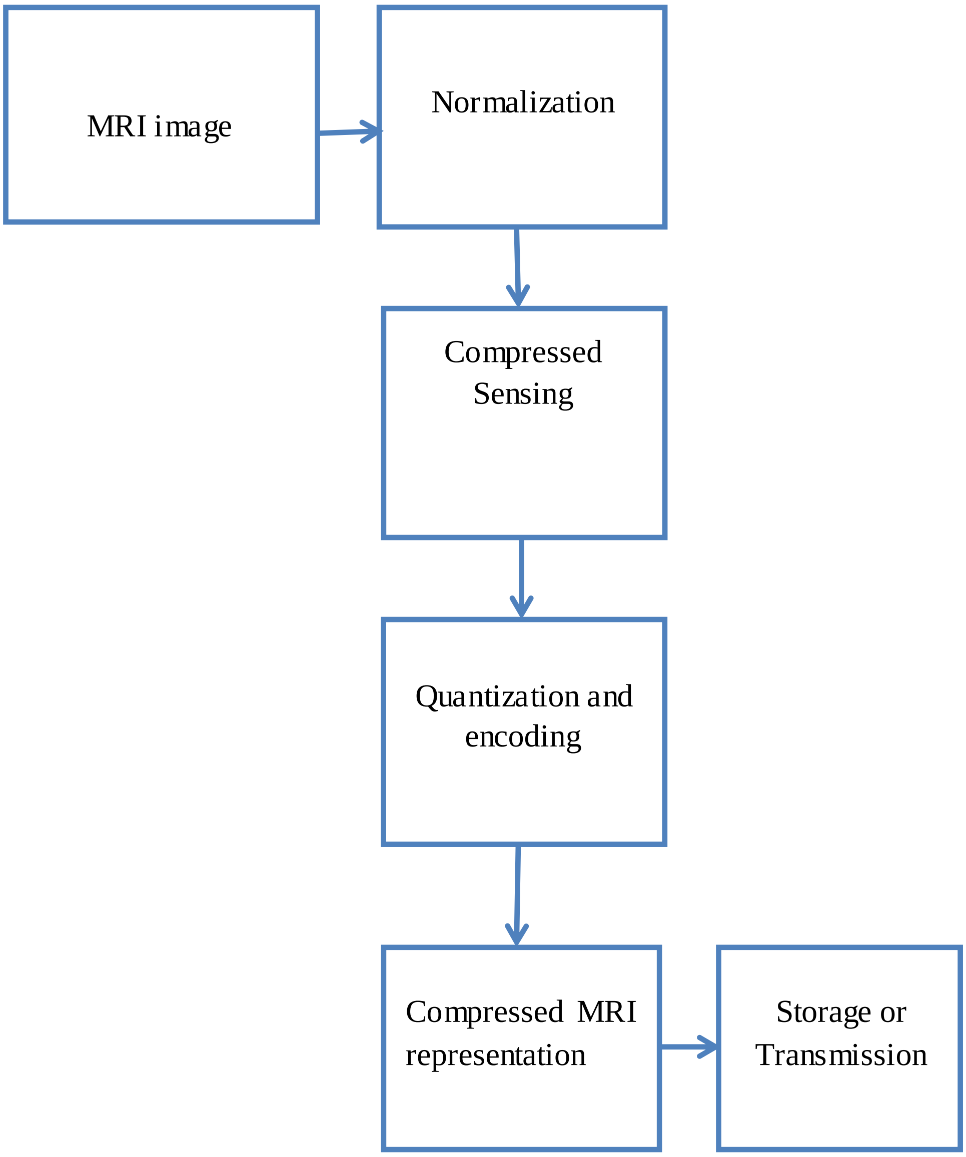

Figure 4.5: Flowchart for compressed MRI system (encoder)

4.4 Design of decoder:

At the decoder side, compressed image is taken as input and then these compressed bits are sent for decoded and de-quantization. Basic pursuit (l_1) norm minimization, least square (l_2) and OMP techniques are then applied for reconstructing compressed image to get the original image. Out of these three recovery algorithms l_1 norm minimization technique is optimally stable and gives high quality of reconstruction.

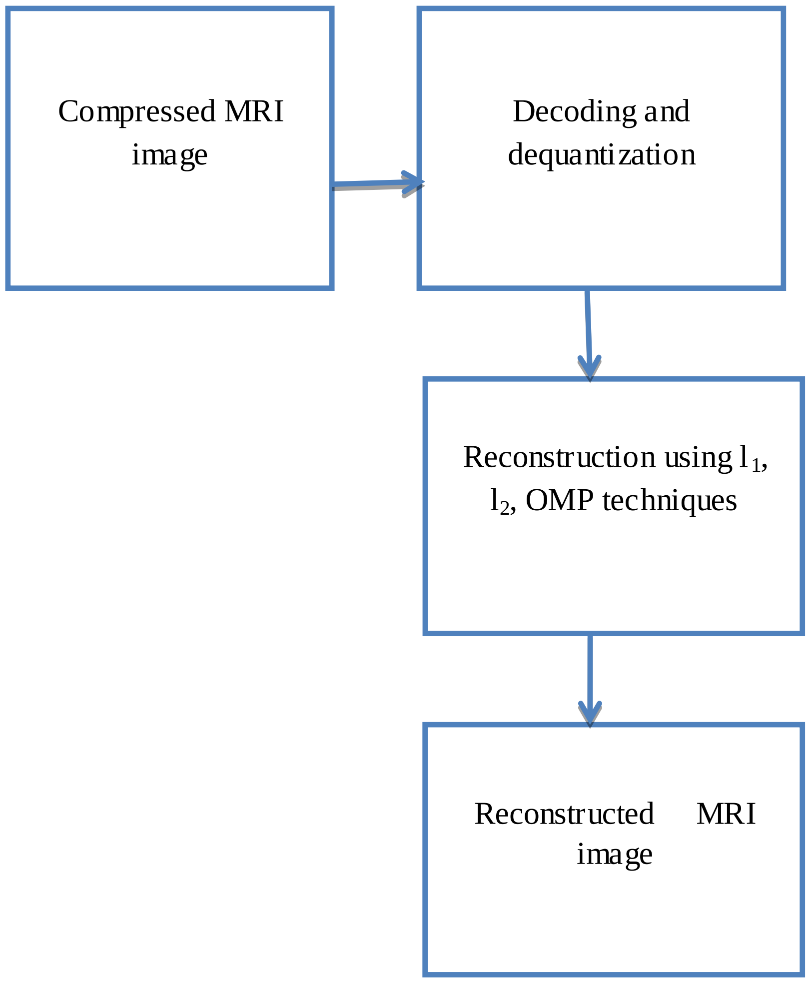

Figure 4.6: Flowchart for compressed MRI system (decoder)

CHAPTER 5

RESULTS

In this section simulation result of various MRI and CT-scan of benchmark collected from (www.physionet.org) and also real time images from local hospitals to check CS algorithm on patient's medical images obtained by radiology is discussed. All tests are performed on MATLAB 2013's and the compression experiments are performed on number of medical images.

5.1 Simulation results for CS when applied on random signals

Output waveforms are shown below when compressed sensing recovery is applied on random signals. Compressed sensing recovery of random signal for N (total number of samples) = 256, P (peaks) = 6 and varying the value of K (measurement samples) from 64 to 16 the outputs are observed as shown in figure 5.1(a) to 5.1(c).

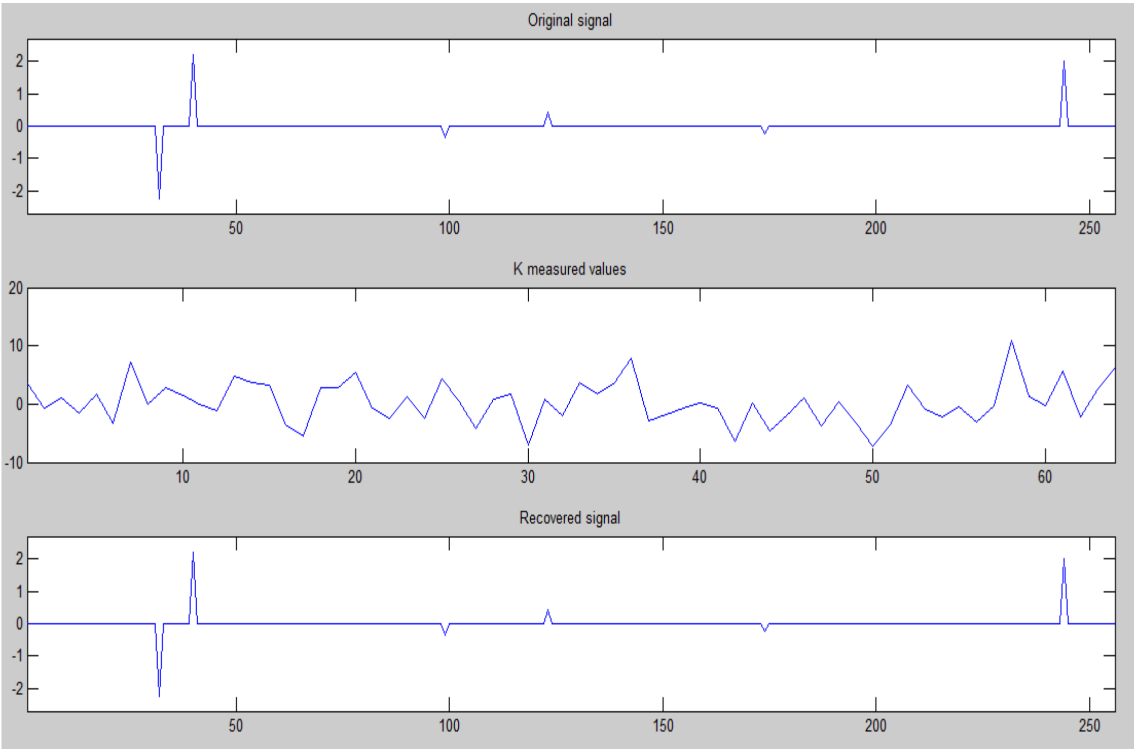

Figure 5.1(a): Output waveform for N=256, P=6 and k=64

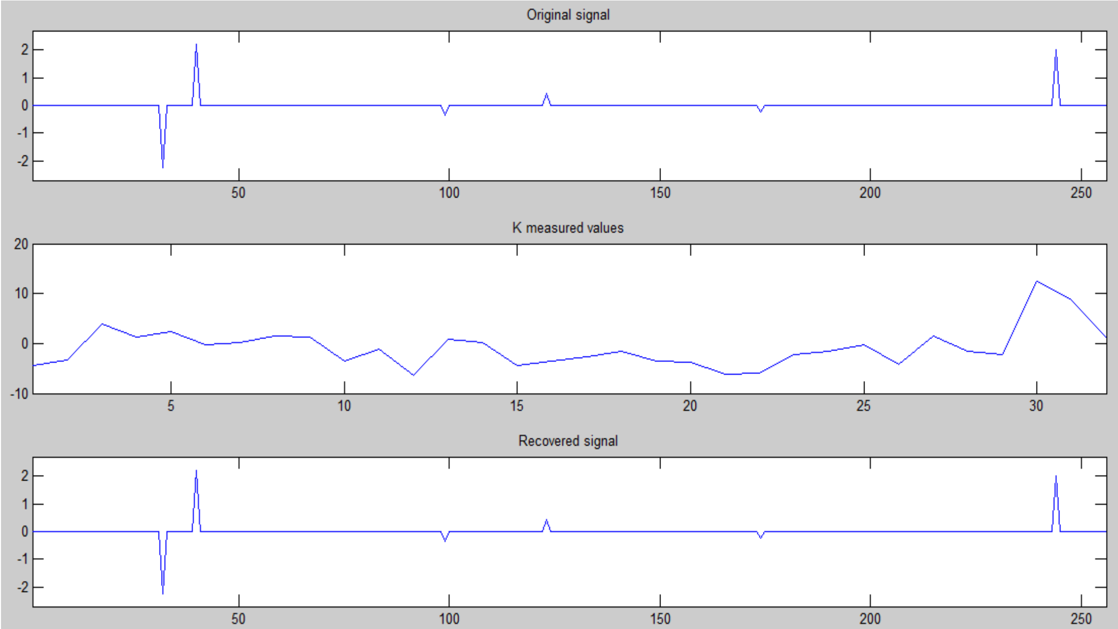

Figure 5.1(b): Output waveform for N=256, P=6 and k=32

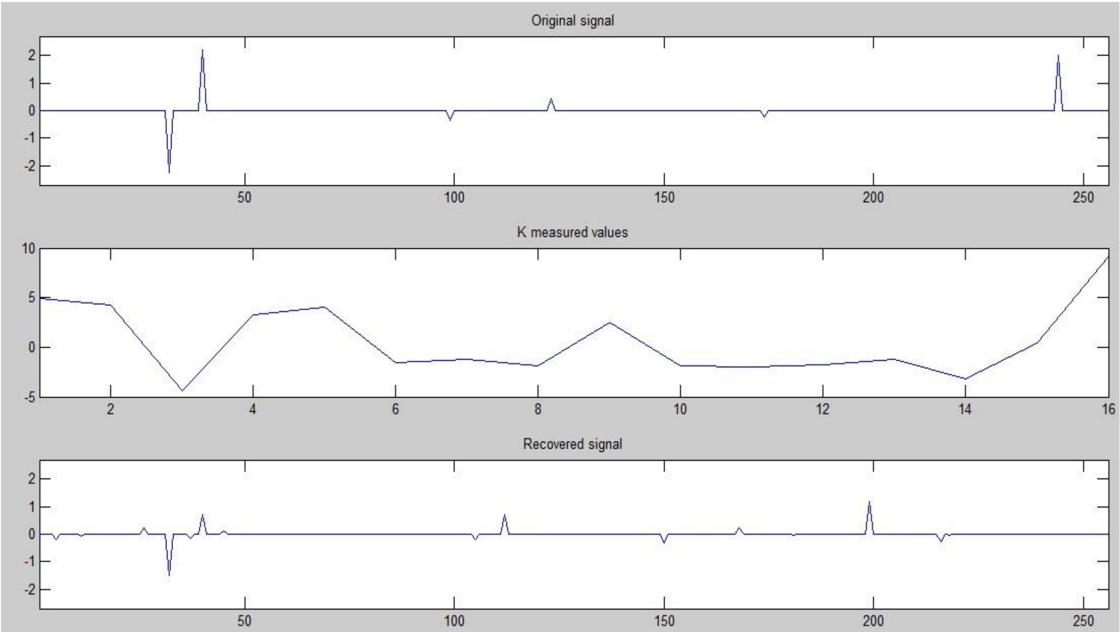

Figure 5.1(c): Output waveform for N=256, P=6 and K=16

It is estimated from above figure is that for K = 64 to 32 recovery of signal is approximately same as the original signal whereas if K is taken as 16 or any value less than 32, signal is recovered with noticeable distortions. Therefore for better recovery of signal, K should be adjusted such that there is balance between sampling rate and quality of recovery. As little loss of information in medical images is not tolerable because it gives wrong information and it may diagnose wrong.

5.2 Simulation results for CS when applied on image samples

Simulation results of CS algorithm on medical images (MRI or CT) recovered from three techniques least square (l_2) and basic pursuit (l_1) and Orthogonal Matching Pursuit (OMP) are obtained and shown in figures 5.2(a) to 5.2 (f). It is found that quality of reconstructed image from l_1 technique is better obtained than l_2 and OMP techniques as l_1 provides better spatial resolution and better contrast recovery. Histograms of original image, l_2, matching pursuit (OMP) and l_1 are also compared in figure figures 5.2(a) to 5.2 (f) for both MRI and CT-scan images.

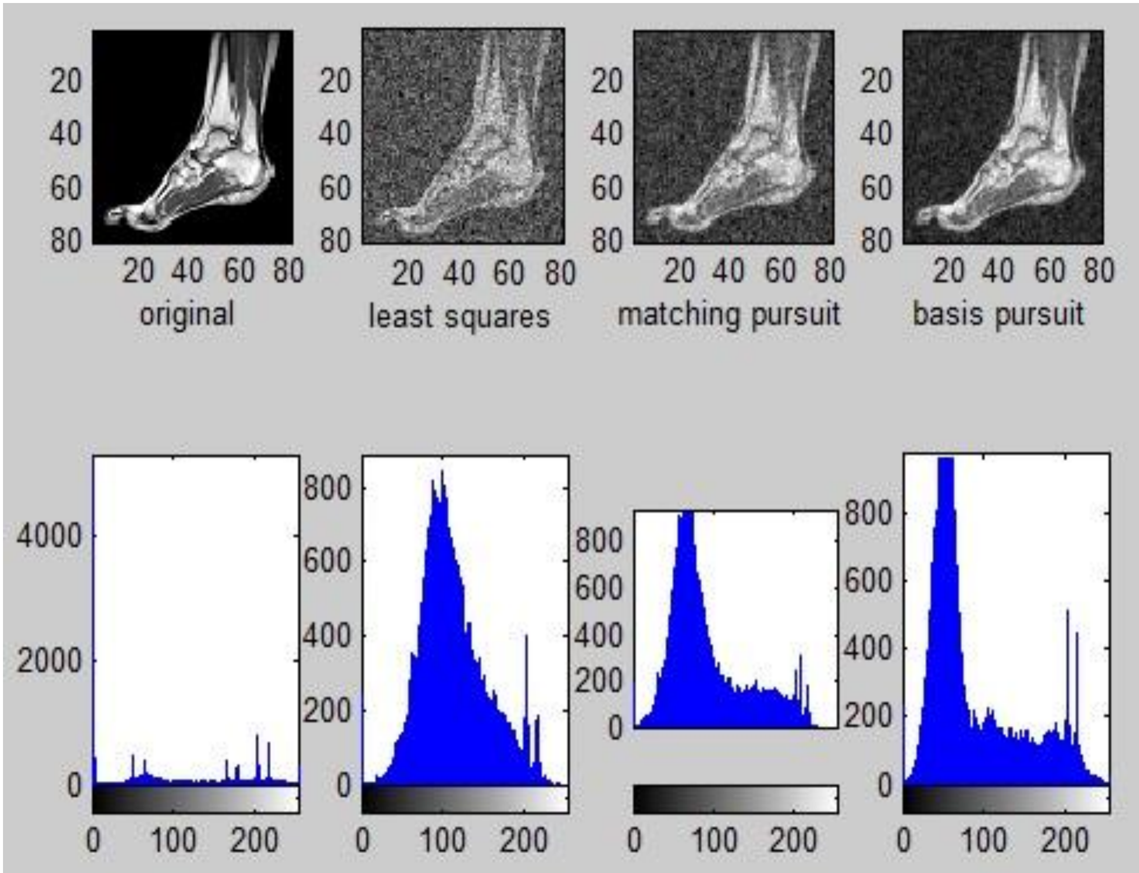

Figure 5.2(a): Original MRI-scan image of foot with reconstructed BP (l_1), least square (l_2) and Orthogonal matching pursuit (OMP) and their histograms.

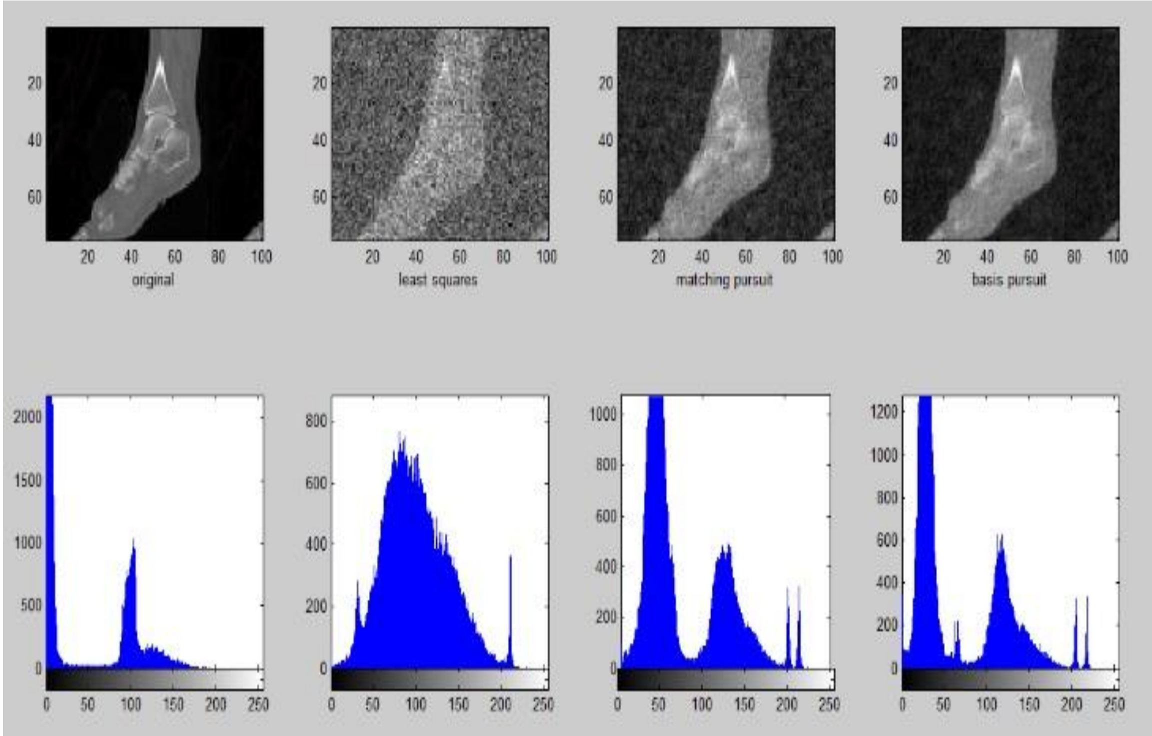

Figure 5.2(b): Original CT-scan image of foot with reconstructed BP (l_1), least square (l_2) and Orthogonal matching pursuit (OMP) and their histograms

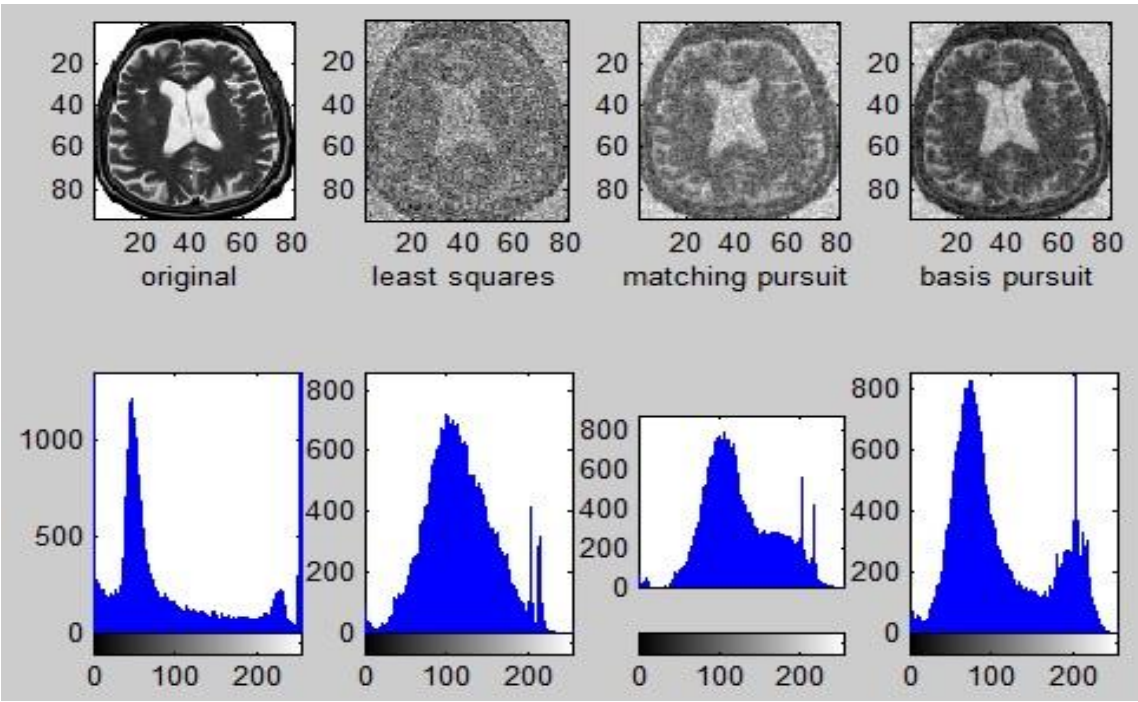

Figure 5.2(c): Original MRI-scan image of brain with reconstructed BP (l_1), least square (l_2) and Orthogonal matching pursuit (OMP) and their histograms.

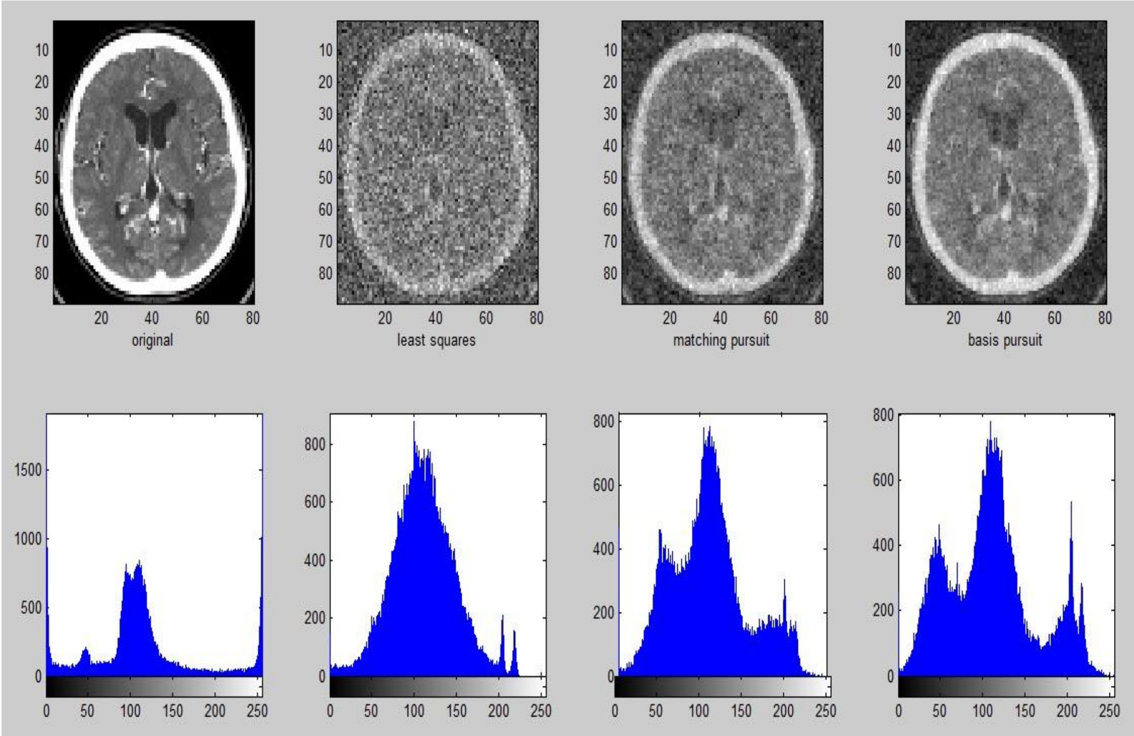

Figure 5.3(d): Original CT-scan image of brain with reconstructed BP (l_1), least square (l_2) and Orthogonal matching pursuit (OMP) and their histograms

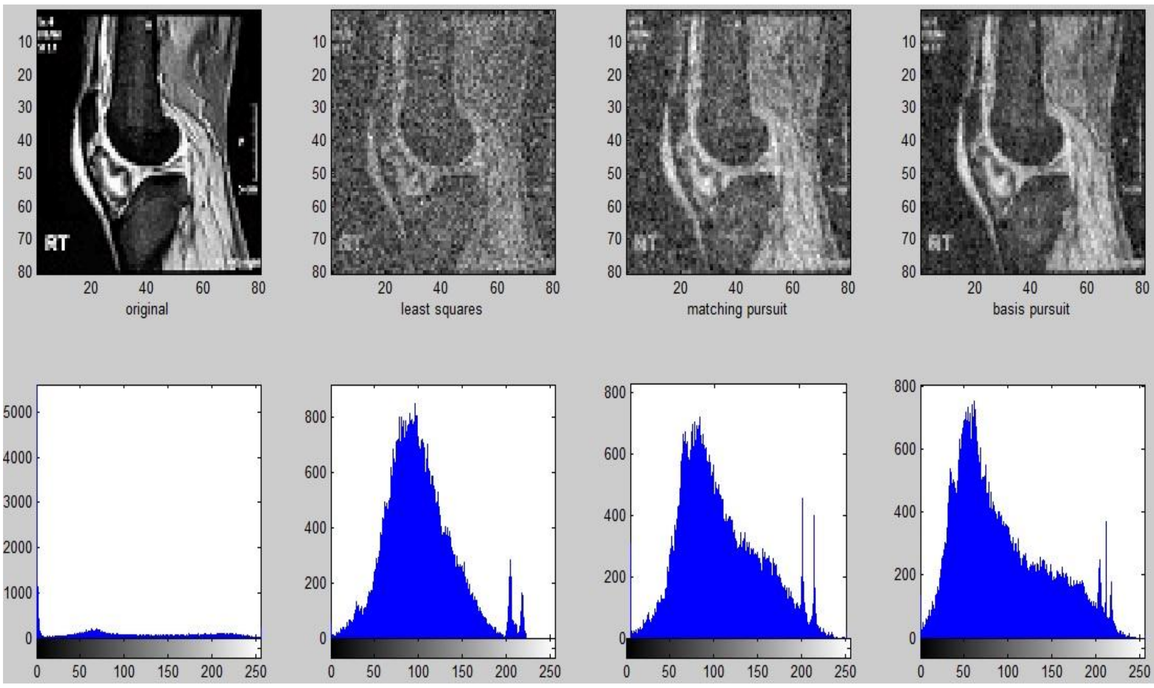

Figure 5.2(e): Original MRI image of leg with reconstructed BP (l_1), least square (l_2) and Orthogonal matching pursuit (OMP) and their histograms.

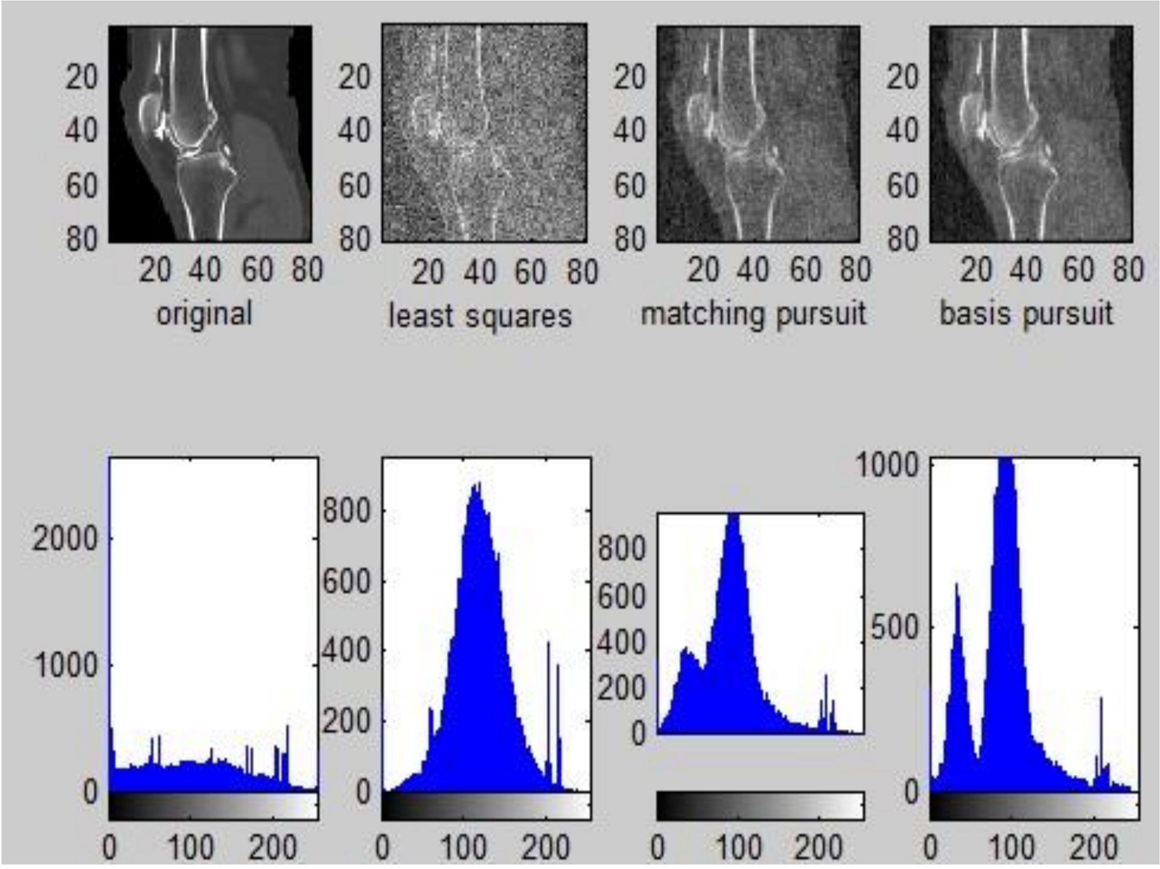

Figure 5.2(f): Original CT-scan image of leg with reconstructed BP (l_1), least square (l_2) and Orthogonal matching pursuit (OMP) and their histograms.

5.3 Structural analysis for different medical images

Structural analysis is also carried out for different medical image samples from all these three reconstruction techniques least square (l_2), basic pursuit (l_1) and matching pursuit techniques (OMP), which provides better assessment in contrast to peak signal to noise ratio (PSNR). PSNR should be preserved with reduced size, other way compression ratio should be maintained with worthy quality of recovered image. It is estimated that performance of basic pursuit (l_1) are better obtained than the least square (l_2) and OMP. Performance parameter (PSNR) of least square, OMP and basic pursuit for different MRI and CT images are shown in Table 5.1.

Table 5.1: Numerical analysis of Peak Signal to Noise Ratio (PSNR)

Image Samples	**Least square**	**OMP**	**Basic pursuit**
MRI_1 (Leg)	12.625	15.849	20.066
MRI_2 (Foot)	13.336	18.009	21.873
MRI_3 (Brain)	10.891	15.423	20.223
MRI_4 (Scalp)	13.2331	16.480	21.173
MRI_5 (Neck)	14.6520	17.531	22.919
CT_1 (Foot)	9.753	17.13	20.056
CT_2 (Leg)	14.401	22.322	25.921
CT_3 (Brain)	15.986	26.712	28.871
CT_4 (Chest)	8.8733	16.175	19.93
CT_5 (Chest-bones)	7.087	13.261	17.4937

From the graphical representation of PSNR as shown in Figure 5.3(a), it is clear that PSNR calculated from basic pursuit (l_1) technique is high as compare to other two recovery algorithms that is least square (l_2) technique gives very less value of PSNR and OMP produce better results than l_2 but it is inferior to l_1 recovery algorithm for all medical test images. It is seen that higher the value of PSNR, better the image quality achieves. So it is pointed that quality of the image is better obtained by basic pursuit recovery algorithm.

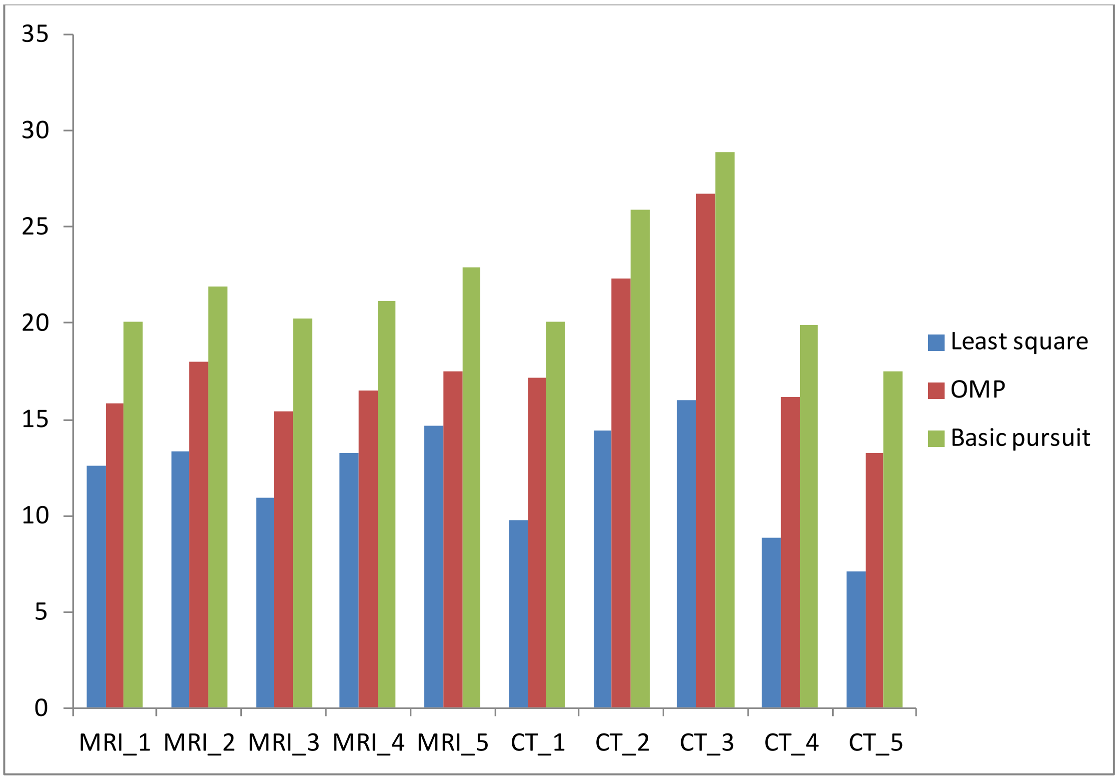

Figure 5.3(a): PSNR from different recovery techniques on medical images

RMSE is other important parameter shows quality of image by calculating error difference between original image and reconstructed image. It is calculated for different medical image samples from all these three reconstruction techniques least square (l_2), basic pursuit (l_1) and matching pursuit (OMP) techniques and it is found that RMSE is less when l_1 is used for recovery of image as compare to l_2 and OMP recovery algorithms. Error between original image and reconstructed image should be less for good quality of image and l_1 performs better as it produces lower RMSE. Values of RMSE obtained by recovery algorithms l_1, l_2 and OMP for different image samples are shown in Table 5.2

Table 5.2: Numerical analysis of Root mean square error (RMSE)

RMSE	Least square	OMP	Basic pursuit
MRI_1 (Leg)	59.830	41.288	25.408
MRI_2 (Foot)	55.151	32.191	20.632
MRI_3 (Brain)	91.971	43.358	24.855
MRI_4 (Scalp)	55.793	38.390	22.365
MRI_5 (Neck)	47.384	33.981	20.525
CT_1 (Foot)	84.281	35.016	25.433
CT_2 (Leg)	48.774	19.594	12.947
CT_3 (Brain)	40.477	14.419	9.213
CT_4 (Chest)	92.167	39.760	25.805
CT_5 (Chest-bones)	113.177	55.607	38.331

Values of RMSE is graphically represented in Figure 5.3 (b) and it is clear that the value of RMSE is higher obtained by l_2 that means error difference is more which is not desirable for good quality image. Lower the value of RMSE, better is the quality of an image. So from the calculation of error for different medical image samples from three techniques, it is noticed that l_1 achieves lower RMSE

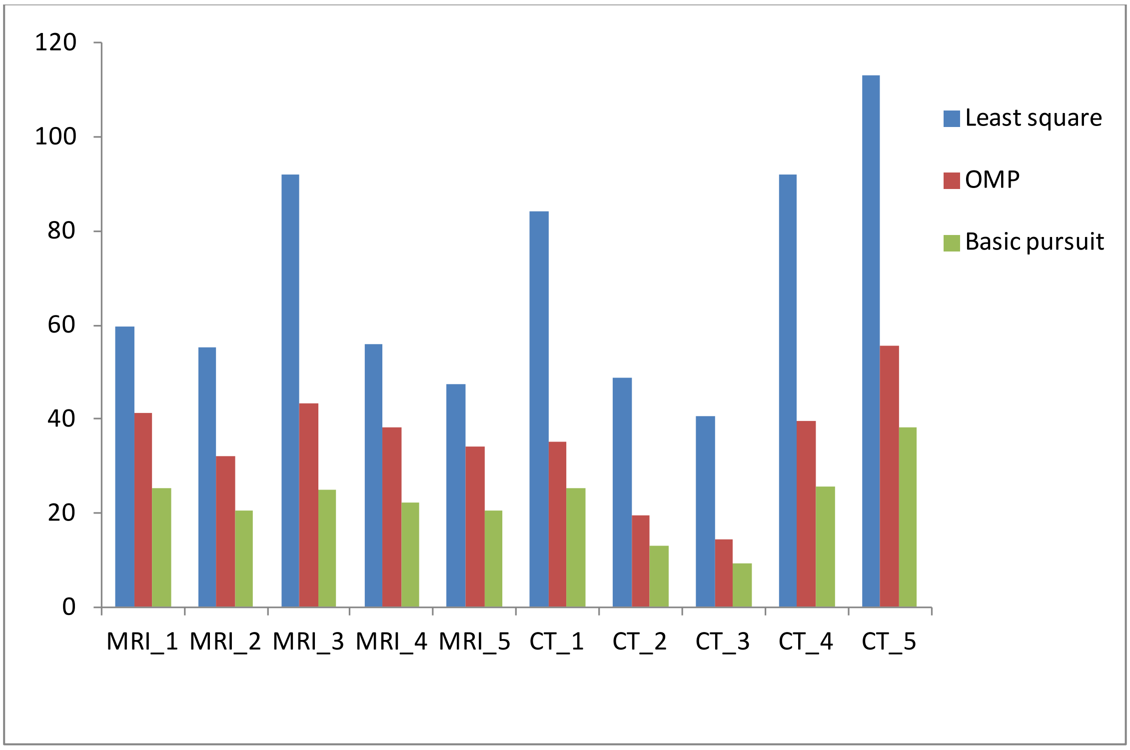

Figure 5.3(b): RMSE from different recovery techniques on medical images

Other image quality measurement parameter is structural similarity index (SSIM) that shows the similarity between two images. Values of SSIM lies between 0 to 1, SSIM value approaches to 1 shows reconstructed image is more similar to the original image and better quality is achieved with higher SSIM. Image degradation as perceived change in structural information is considered by SSIM. Values of SSIM for different medical images samples are calculated and shown in Table 5.3

Table 5.3: Numerical analysis of Structural Similarity Index (SSIM)

Image samples	**Least square**	**OMP**	**Basic pursuit**
MRI_1 (Leg)	0.343	0.501	0.671
MRI_2 (Foot)	0.282	0.424	0.519
MRI_3 (Brain)	0.216	0.519	0.724
MRI_4 (Scalp)	0.456	0.6372	0.798
MRI_5 (Neck)	0.32	0.441	0.604
CT_1 (Foot)	0.211	0.492	0.619
CT_2 (Leg)	0.209	0.491	0.645
CT_3 (Brain)	0.171	0.406	0.605
CT_4 (Chest)	0.201	0.443	0.611
CT_5 (Chest-bones)	0.175	0.4982	0.648

From the graph shown below in Figure 5.3(c), it is clear that higher values of SSIM are obtained from the BP (l_1) recovery technique from all these l_1, l_2 and OMP techniques. Minimum values of SSIM are obtained using least square (l_2). SSIM values for medical images by OMP are greater than l_2 but less than l_1 recovery techniques. It is pointed that reconstructed image is more similar to original image when it is recovered by l_1 reconstruction technique.

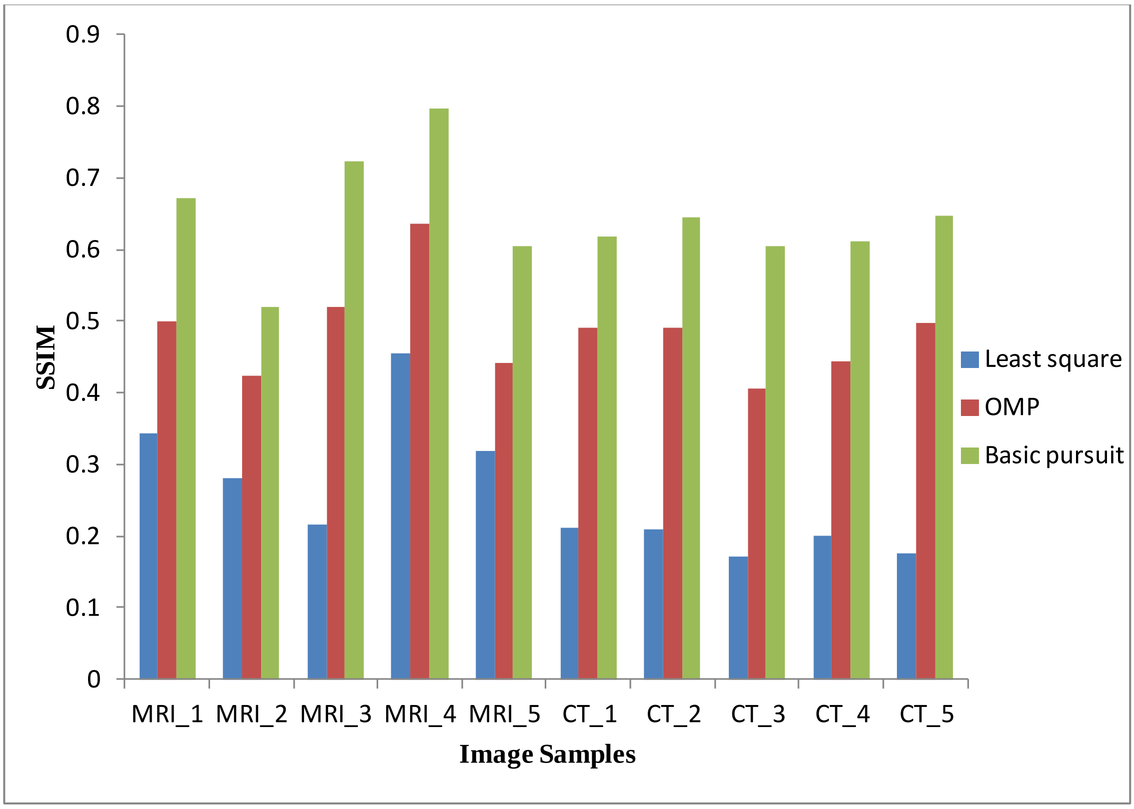

Figure 5.3(c): SSIM from different recovery techniques on medical images

DSIM shows dissimilarity index and it is inversely related to SSIM, better quality of image is obtained when the value of DSIM is lower. DSIM calculated for different image samples from three recovery techniques are shown in Table 5.4

Values of DSIM for medical image samples from three techniques are represented graphically as shown in Figure 5.3(d) and it clear from this representation is that l_2 achieves higher value of image and hence lower quality of image is produced by l_2. Better image quality is obtained by l_1 as DSIM calculated from l_1 is lower as compare to other two techniques of recovery.

Table 5.4: Numerical analysis of dissimilarity Index (DSIM)

Image Samples	Least square	OMP	Basic pursuit
MRI_1 (Leg)	0.321	0.249	0.164
MRI_2 (Foot)	0.358	0.287	0.240
MRI_3 (Brain)	0.391	0.240	0.137
MRI_4 (Scalp)	0.271	0.181	0.100
MRI_5 (Neck)	0.336	0.277	0.197
CT_1 (Foot)	0.391	0.252	0.191
CT_2 (Leg)	0.395	0.245	0.177
CT_3 (Brain)	0.414	0.296	0.197
CT_4 (Chest)	0.396	0.278	0.194
CT_5 (Chest-bones)	0.412	0.250	0.1760

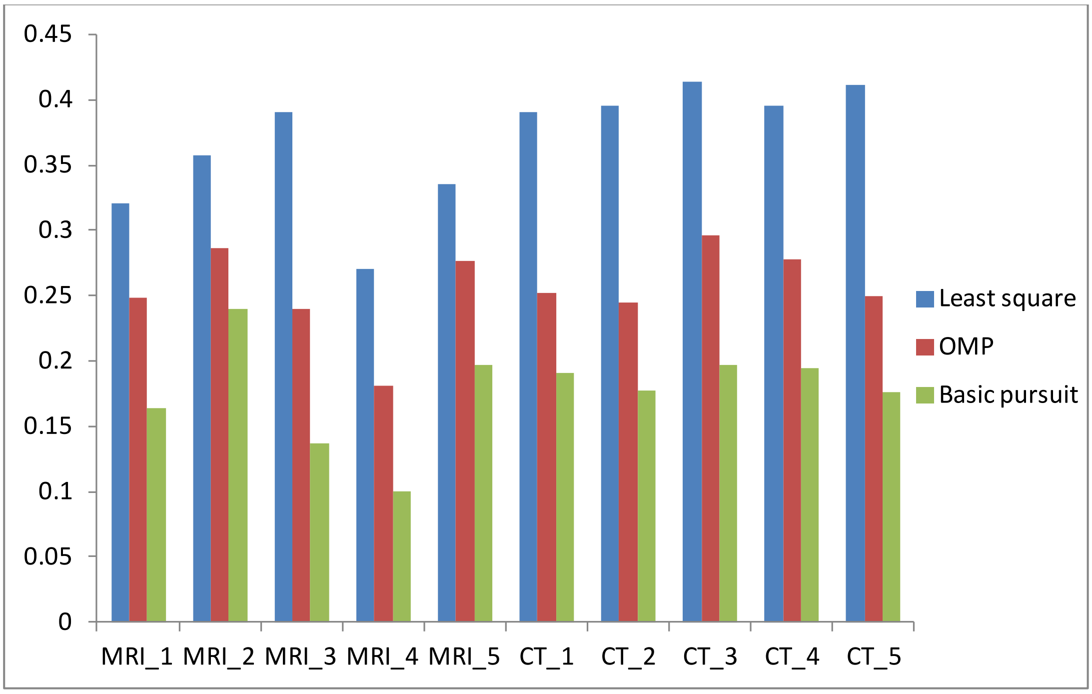

Figure 5.3(d): DSIM from different recovery techniques on medical images

Compression ratio (CR) is calculated for different image samples when CS applied on these images for compression and it calculated by ratio of uncompressed bits to the compressed bits. Compression ratio should be maintained with worthy quality of image. Compression ratio and space spacing for different image samples are shown in Table 5.5. Compression ratio for different image samples of MRI and CT-scan is graphically shown in Figure 5.3(e). Percentage of space saving is also calculated that how much space is save by compression of an image. Graphical representation for space saving is shown in Figure 5.4(f).

Table 5.5: Numerical analysis of Compression Ratio (CR) and space saving

Image samples	CR	Space saving
MRI_1 (Leg)	3.806	73.89%
MRI_2 (Foot)	6.062	83.36%
MRI_3 (Brain)	3.909	74.42%
MRI_4 (Scalp)	4.223	76.32%
MRI_5 (Neck)	3.851	74.03%
CT_1 (Foot)	4.223	76.32%
CT_2 (Leg)	3.710	73.1%
CT_3 (Brain)	3.981	74.12%
CT_4 (Chest)	3.710	73.04%
CT_5 (Chest-bones)	4.312	76.80%

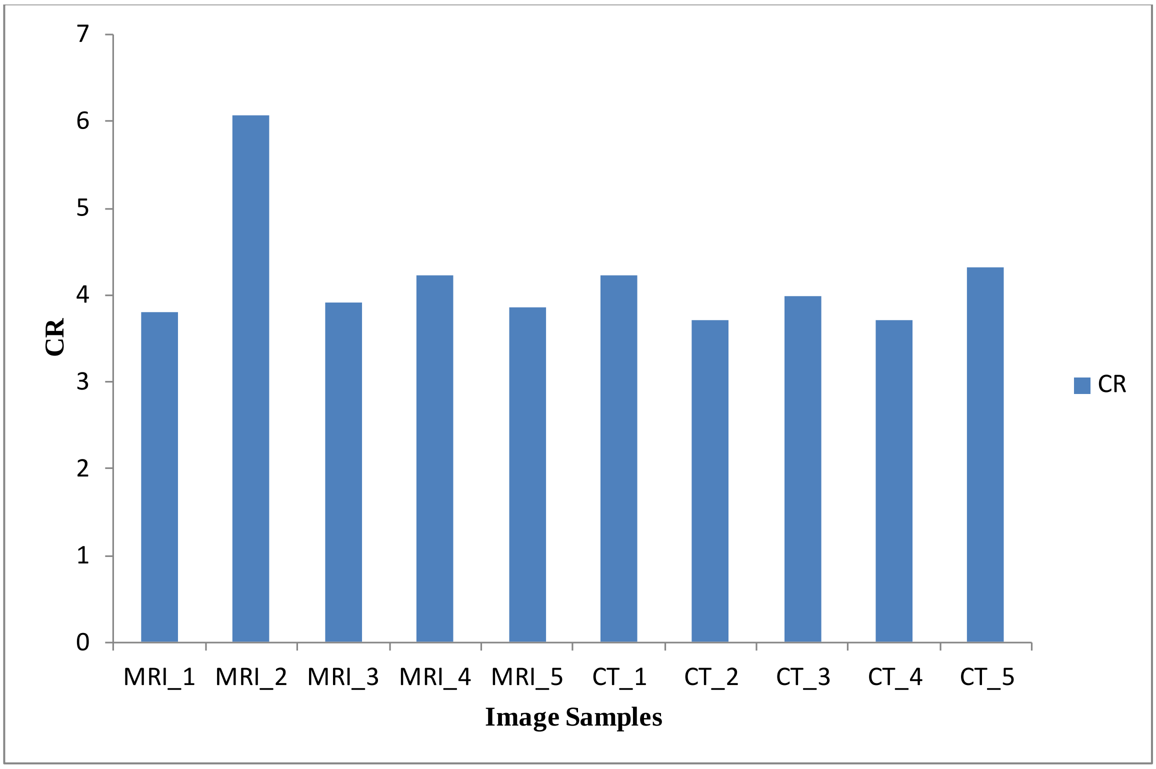

Figure 5.3(e): Compression Ratio for different image samples

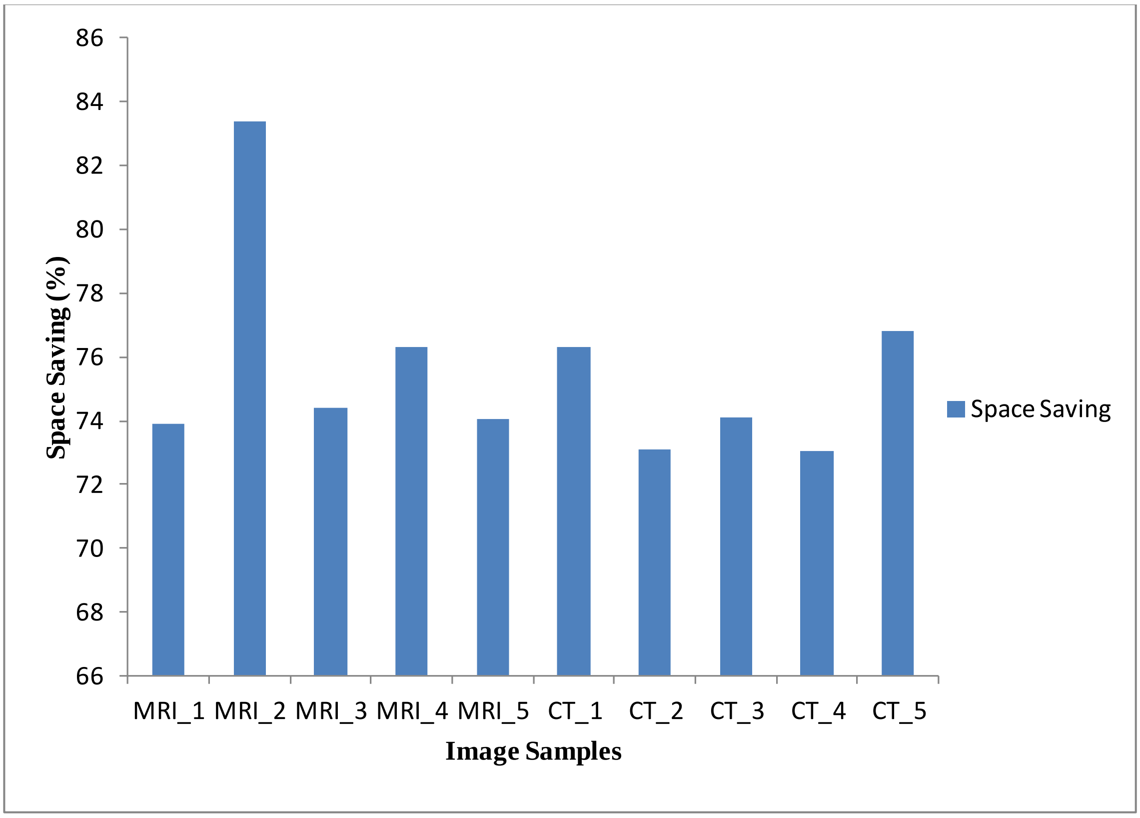

Figure 5.3(f): Space saving from compressive sensing

5.4 Performance analysis at different measurement samples

Performance of PSNR and RMSE is also observed at different measurement samples for MRI of foot. Performance parameter PSNR is calculated at measurement samples m = 1000, 2000 and also at 4000 from all three techniques when total number of samples (n) is 6400 (80×80) and m is any number less than n (m<<n). It is seen that PSNR is increase with increased measurement samples. Hence measurement sample is adjusted such that image is compressed and quality of image is also maintained.

PSNR is calculated for medical image sample (MRI_foot) at different measurement samples as shown in Table 5.6

Table 5.6: PSNR of foot-MRI image at different measurement samples by three recovery algorithms

Measurement samples	Basic pursuit (l_1)	Least square (l_2)	Orthogonal matching pursuit (OMP)
1000	15.271	9.28	12.37
2000	17.381	10.541	13.781
4000	21.873	13.336	18.00

When m =1000 value of PSNR is calculated from all these three techniques and it is found that it is very less about 9 to 15 db. As the value of m is varied from 1000 to 4000 or any value less than 6400 (n) then it is estimated that PSNR increased with increased number of measurement samples as shown in Figure 5.4 (a).

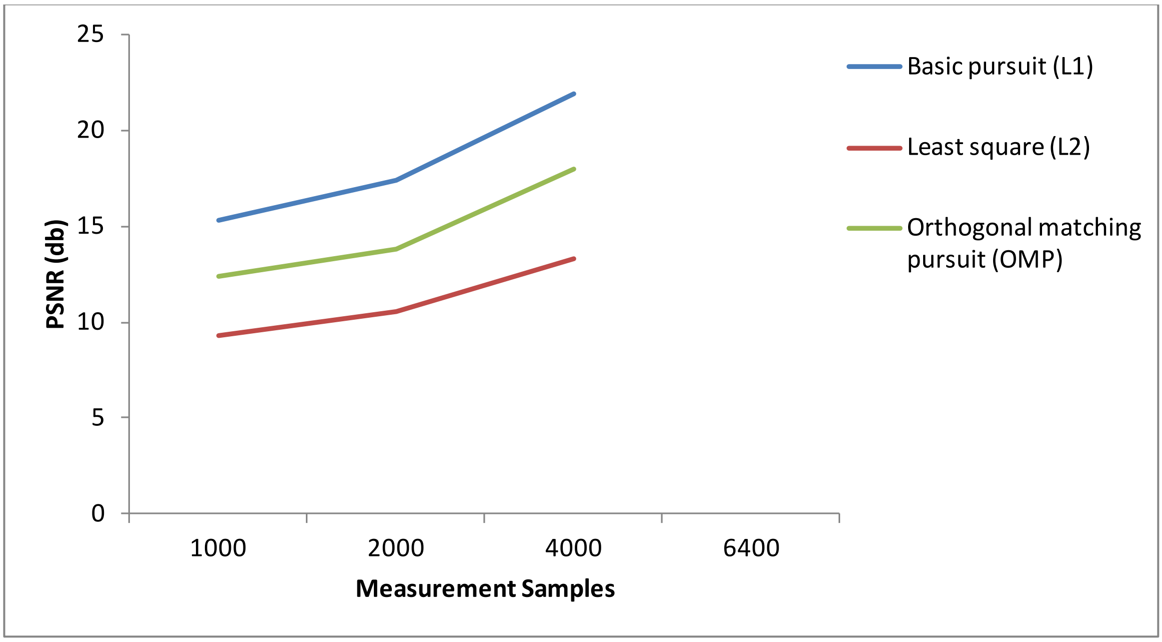

Figure 5.4(a): PSNR v/s Measurement samples for MRI of foot

When m =1000 value of RMSE is calculated from all these three techniques, it is found that it is high at low measurement samples and when value of m is varied from more than 1000 but less than total number of measurements (n) that is 6400 taken in this case. RMSE is calculated for medical image (MRI_foot) at different measurement samples as shown in Table 5.7

Table 5.7: RMSE of foot-MRI image at different measurement samples by three recovery algorithms

Measurement Samples	Basic pursuit (l_1)	Least square (l_2)	Orthogonal matching pursuit (OMP)
1000	39.3177	78.33	53.6162
2000	33.8660	74.4652	47.9367
4000	20.6327	55.1518	32.1917

PSNR and RMSE are inversely related to each other and it is estimated that RMSE decreases with increased number of measurement sample (m) as shown in Figure below 5.4 (b)

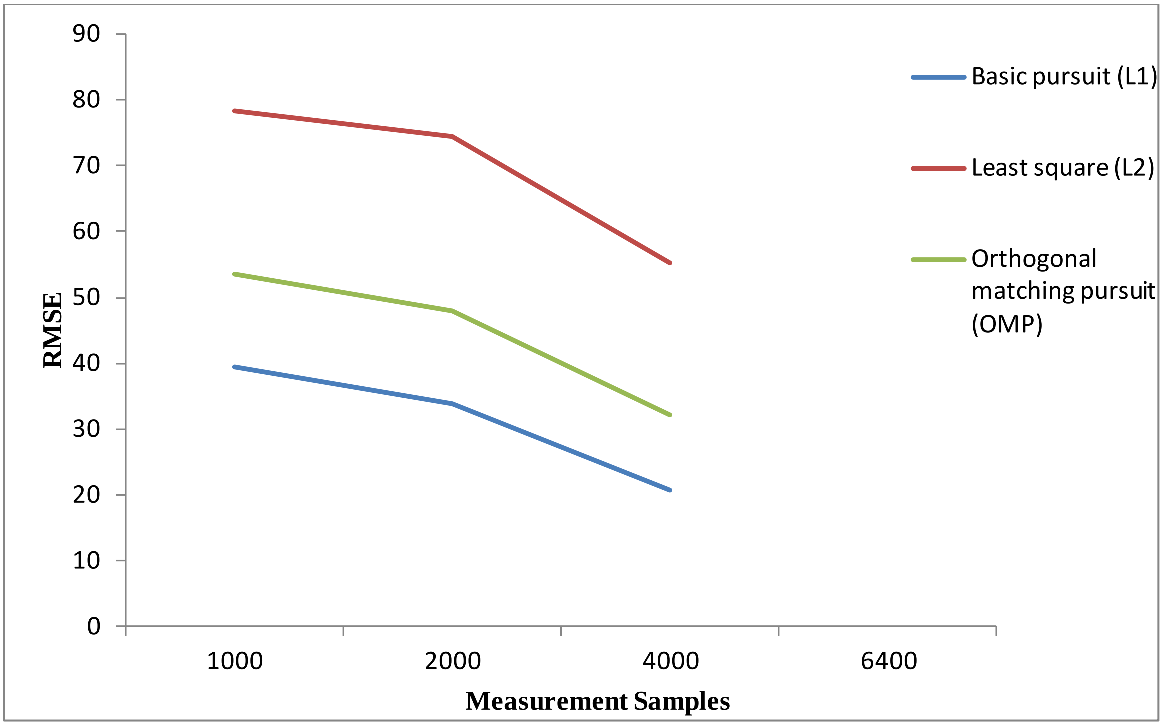

Figure 5.4(b): RMSE v/s Measurement samples for MRI of foot

Quality of image is improved when PSNR increases and error between original image and reconstructed image decreases with increased number of measurement samples. Figure 5.4 (c) and Figure 5.4 (d) shows reconstruction of image from l_1, l_2 and OMP at different measurement samples and noticeable difference in reconstructed images has been seen at different measurement samples. Quality of reconstructed image is good at higher number of samples by l_1 recovery algorithm.

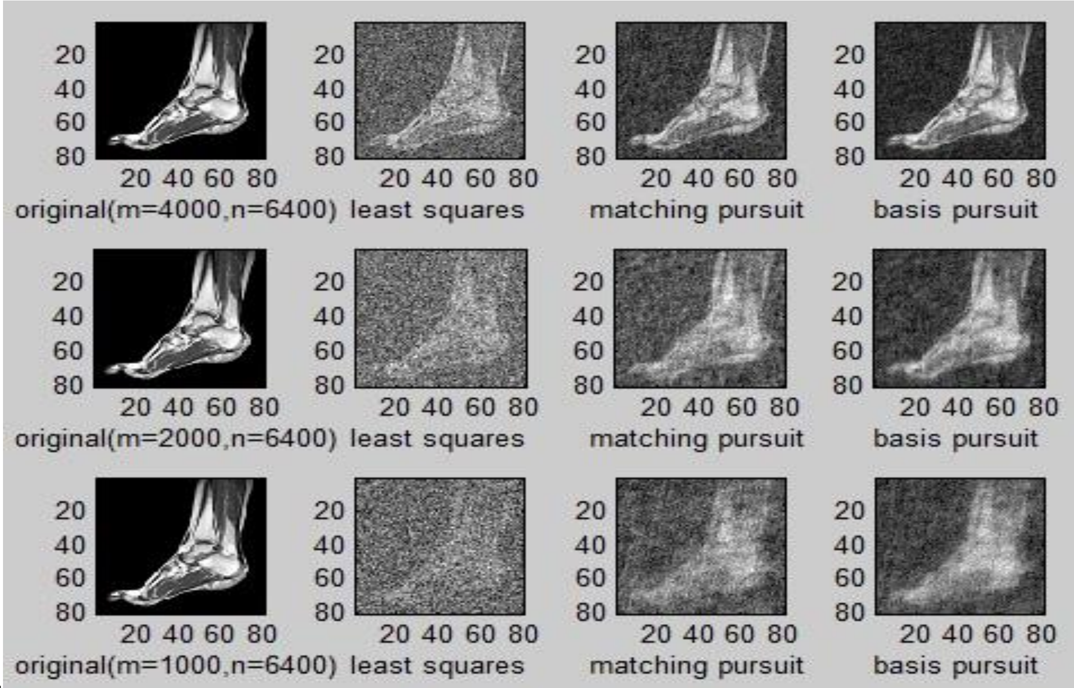

Figure 5.4(c): Original MRI image of foot with reconstructed l_1, l_2 and OMP at different measurement samples

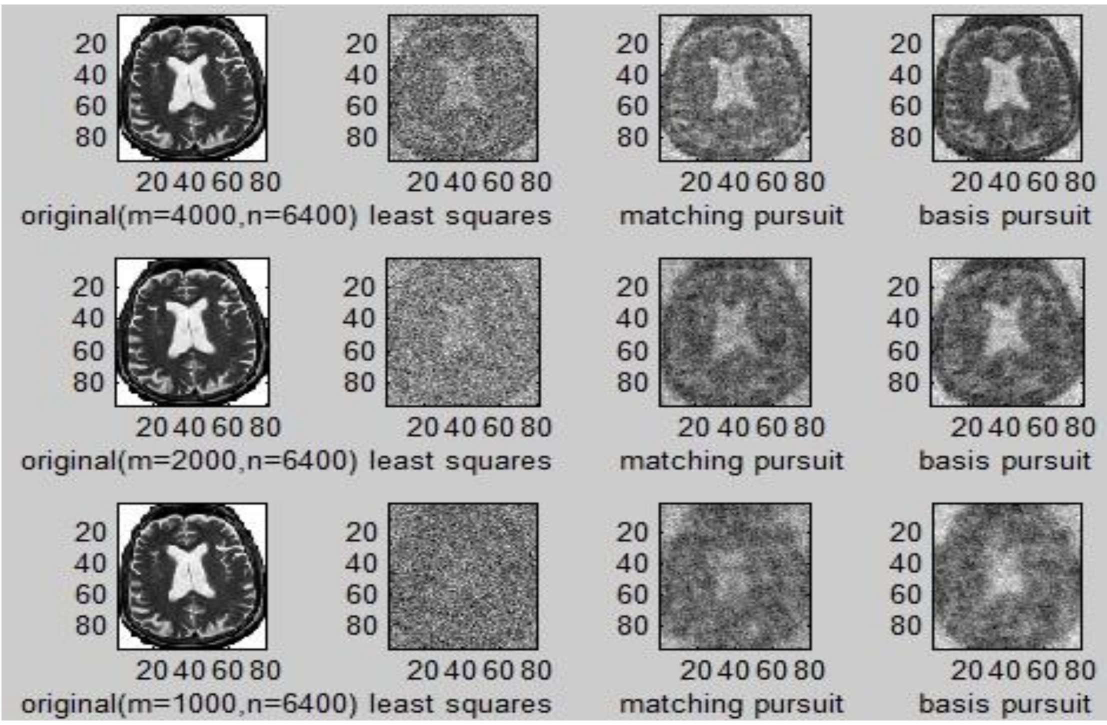

Figure 5.4(d): Original MRI image of foot with reconstructed l_1, l_2 and OMP at different measurement samples

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

Compressed sensing technique performs better compression and it is highly cost effective with reduced storage, less bandwidth and save transmission time. Compression ratio is calculated by ratio of uncompressed bits to the compressed bits and CS achieves good compression ratio. Three algorithms basic pursuit (l_1) and least square (l_2) and orthogonal matching pursuit (OMP) are used for reconstruction of images and different performance parameters like peak signal to noise ratio (PSNR), root mean square error (RMSE), performance root mean square difference (PRD), structural similarity index (SSIM), dissimilarity index (DSIM), compression ratio and percentage of space saving are calculated. Compression ratio is calculated at the encoder side which shows amount of compression done and other parameters shows the quality of an image which are calculated at decoder side for all these l_1, l_2 and OMP recovery algorithms. Outcome of this work is that recovery of an image is better obtained by l_1 as compare to l_2 and OMP recovery techniques. Consequence of performance parameter analysis shows that the performance of basic pursuit (l_1) is better obtained than other two recovery techniques. It is seen that OMP gave better results than least square but it is inferior to l_1. It is also concluded that PSNR of an image is increase with increased number of measurement samples and RMSE decreases.

CS technique can also be applied to various other medical images and CR can be improved by reducing the number of k-samples and quality of image can be improved by achieving high PSNR. The research team will explore it in future work and would be focusing on achieving high compression, while keeping the accuracy of reconstructed image.

Publication

[1] Urvashi, Charu Bhardwaj, Meenakshi Sood (2017) "Medical Image Compression using Compressed Sensing" *Proceedings of the International Conference on Computing for Sustainable Global Development, BVICAM*,. [4th: New Delhi: 1-3 March, 2017], pp.6258-6262.

[2] Urvashi, Charu Bhardwaj, Meenakshi Sood "Compression of MRI and CT-Scan images using compressed sensing" *International journal of Pharma and Bioscience*. ISSN No.[0975-6299]

(Under review)

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References

[1] S.Ravishankar and Y.Bresler, “Adaptive sampling design for compressed sensing MRI,” *Annual international conference of the IEEE EMBS*, September3, 2011.

[2] S.Shridevi, V.R.Vijaykumar, R.Anuja, “A Survey on various compression method for medical images,” *International journal of Intelligent System and Applications*, vol.3, pp.13-19, 2012.

[3] A.Lata, P.Singh, “Review of image compression techniques,” *International journal of Emerging Technology and Advanced Engineering*, vol.3, no.7, July 2013.

[4] S.Kaur, “A Review Paper on Image Compression Technique”, *Intermational Journal of Computer Science and Communication Engineering*, vol.5, no.1, pp.19-21, Feb. 2016.

[5] D.D.Liu, D.Liang, “Under sampled trajectory design for compressed sensing MRI”, *34th annual international conference of the IEEE EMBS*, 1Sep, 2012.

[6] M.M sevak, F.N Thakkar, R.K Kher, C.K modi. “CT image compression using compressed sensing and wavelet transform,” *International conference on communication system and network technology of IEEE.*, May,2012.

[7] E.Candes, M.Wakin, “An introduction to Compressive Sampling”, *IEEE signal processing magazine*,1053-5888, 2008 IEEE, March 2008.

[8] D.Donoho, “Compressed Sensing”, *IEEE Transaction on Information theory*, vol. 52, no. 4, April 2006.

[9] S. Foucart, H. Rauhut, “A Mathematical Introduction to Compressive Sensing” *Springer Science & Business Media*, 2013.

[10] N.Madhukumar, P.S Baiju, “MRI image compression using compressed sensing,” *International Journel of advanced research in electrical,electronics and instrumentation engineering*, vol.4, no.7, pp. 6434-6440, July 2015.

[11] “Guest Editorial compressive sensing for biomedical imaging,” *IEEE Transaction on medical imaging*, vol.30, no.5, may2011.

[12] E. Candès, J. Romberg, and T. Tao, “Robust uncertainty principles: Exact signal reconstruction from highly incomplete frequency information,” *IEEE Trans.Inform. Theory*, vol. 52, no. 2, pp. 489–509, 2006.

[13] M.Yousufbaig, E.M-K.Lai and Amal Punchihewa, “compressed video coding: A Review of the state-of-The-Art”.

[14] D-duan Liu, D.liang, X Liu, and Y.ting Zhang, "Under-sampling trajectory design for compressed sensing MRI," *Annual international conference of the IEEE EMBS,* September,2012.

[15] M. H. Moghari *et al.* , "Three-dimensional heart locator and compressed sensing for whole-heart MR angiography," *Magnetic Resonance in Medicine*, 2015.

[16] Y.Liu, M.DeVos, I. Gligorijevic. V.Matic, Y.Li and S.V.Huffel, "Multi-structural signal recovery for biomedical compressive sensing," *IEEE Transaction on Biomedical Engineering, vol.60, no.10.October 2013.*

[17] U.Bhatt, and Kishor Bammiya, "Medical image compression and reconstruction using compressed sensing," *JETIR, vol.4, no.5, pp. 1610-1616, may 2015.*

[18] K.Gopi, T.Rama Shri. Medical image compression using wavelets. IOSR Journal of VLSI and signal processing (IOSR-JVSP). June;4(2): 01-06.

[19] T.D.Tran, T.T.Duc, and T.T.Bui, "Combination CS and digital wireless transmission for MRI signals," *International conference of the IEEE.*, pp.4244-7997, 2010.

[20] X.Zhang, J.Wen, Y,Han and J.Villasenor. An improved compressive sensing reconstruction algorithm using linear/ non-linear mapping.

[21] C.H.Chang, and J.Ji, "Improved CSMRI with multichannel data using reweighted L1 minimization," *International conference of the IEEE.*, pp. 875-878, 2010.

[22] X.Qu, X.Cuo, D.Guo, C.Hu, and Z.Chen, "Compress sensing MRI with combined sparisifying transforms and smoothed l0 norm minimization," *International conference of the IEEE.*,pp. 626-629, 2010.

[23] D.Liang, and L.Ying, " Compress sensing dynamic MR imaging with partially known support," *International conference of the IEEE.*, pp. 2829-2832, 2010.

[24] M.Alhanjouri, "Multi-resolution analysis for medical image compression," *International journal of computer science & Information Technology.*, vol.3, no.6, pp.215-228, 2011.

[25] T.Dutta, "Medical data compression and transmission in wireless networks," *IEEE Sensors J.*, vol.15, no.2, pp. 778-786, Feb,2015.

[26] A.Majumdar, R.K.Ward, &T.Aboulnasr, "Compressed Sensing Based Real-Time Dynamic MRI Reconstruction,"*IEEE transaction on medical imaging.,* vol.32, no.6, pp.2253-2266, 2012.

[27] M.Lakshminarayana, and M.Sarvagya, "Algorithm to balance compression and single quality using novel compression sensing in medical images," *Advances in intelligent systems & computing.*, pp. 317-327, 2016.

[28] C.Zhao, S.Ma, J. Zhang, R.Xiong, and Wen Gao, "Video compressive sensing reconstruction via reweighted residual sparsity," *IEEE Transaction on Circuits and Systems for Video Technology*, pp. 1-14, 2015.