PERFORMANCE EVALUATION OF COMPRESSION FOR IMAGES AND VIDEOS USING COMPRESSIVE SENSING TECHNIQUE

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UNDER THE GUIDANCE OF

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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 IMAGES AND VIDEOS USING COMPRESSIVE SENSING TECHNIQUE"** 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. dissertation entitled **"Performance Evaluation of Compression for Images and Videos using Compressive Sensing Technique"** which is being submitted by **Charu Bhardwaj** in fulfillment for the award of Masters of Technology in Electronics and Communication Engineering by **the Jaypee University of Information Technology, Waknaghat, India**, is the record of candidate's own work carried out by him/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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ABSTRACT

Compressed sensing is an optimization based formalized framework based upon sub-Nyquist sampling principle of exploiting only the sparse signal of interest. It exploits the sparsity of the signal to reconstruct it from less number of measurements than required by the Nyquist sampling criteria. A nascent field of compressive sensing is explored in this paper for accurate acquisition and reconstruction of signals, images and video sequences. The algorithm is proposed for compression and efficient recovery of image and video based on the concept of compressive sensing. Three basic reconstruction techniques (Basic Pursuit (l_1) Minimization, Least Square (l_2) Minimization and Orthogonal Matching Pursuit) are applied on image samples and they are compared based on quality performance criteria. The performance parameters like compression ratio, peak signal to noise ratio and structural similarity index are evaluated for different image and video samples for critical analysis of these performance parameters is done for different reconstruction schemes. Finally it is concluded that compressive sensing based approach is better than the traditional compression schemes and Basic Pursuit (l_1) methods gives the better image quality with a tradeoff among other parameters enabling faster acquisition, compression and reconstruction.

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LIST OF ABBREVIATIONS

AVC	Advanced Video Coding
BER	Bit Error Rate
CR	Compression Ratio
CS	Compressive Sensing
CVS	Compressive Video Sensing
DCT	Discrete Cosine Transform
DSSIM	Structural dissimilarity Index
GOP	Group of Picture
ITU	International Telecommunication Union
IEC	International Electro-technical Commission
JPEG	Joint Photographic Expert Group
KLT	Kanade–Lucas–Tomasi Feature Tracker
LTE	Long Term Evolution
LZW	Lempel Ziv Welch
MH	Multi-hypothesis
MPEG	Moving Picture Expert Group
MSE	Mean Square Error
OMP	Orthogonal Matching Pursuit
OMP-PKS	Orthogonal Matching Pursuit with Partially Known Support
PCA	Principal Component Analysis
POCS	Projection onto Convex Set
PRD	Percentage Root Mean Square Difference
PSNR	Peak Signal to Noise Ratio
QCIF	Quarter Common Intermediate Format
RMS	Root Mean Square
RS	Random Sub-sampling
SCI	Sparsity Concentration Index
SNR	Signal to Noise Ratio
SSIM	Structural Similarity Index
SVD	Singular Value Decomposition
TV	Total Variation

CHAPTER 1

INTRODUCTION

Compression is basically a competent solution for signal representation in a more compact and robust form so as to facilitate efficient storage and transmission. In the past few decades, compression techniques and its applications have developed quite significantly. Image and video coding standards like JPEG [1], MPEG and H.26x [2] are widely explored. But these coding standards do not provide simple and quick compression and decompression as they involve complex encoders and decoders [2, 3].

Thus these conventional coding techniques are needed to be re-evaluated for applications like video surveillance, telemedicine, space and satellite imaging, sports broadcasting, etc. There are numerous facts motivating for the need of compression in the modern technological world. NASA satellites generate terabytes of data per day, hospitals generate terabytes of data per year and data amount is very large for ultra high definition. Specifically concerning telemedicine, patients are diagnosed from a distance using tele-radiology under the supervision of basic technician. In this application, there is a need for faster communication so that the diagnostic radiologist can examine the patient without delay. In case of emergency, time is an important issue thus compression is needed not only for storage but also to increase the processing time [4].

Conventionally in image and video capturing systems, sampling is based on Nyquist Criteria in which the original signal is sampled at a rate greater than or equal to twice the signal bandwidth. In some applications, the Nyquist rate is too high and it increases computational complexity for compression specifically at the encoder side. This increased sampling rate enhances the complexity of the sensing hardware [5]. Various spatial and temporal redundancies are exploited for compression at the encoder end causing the encoding process to be more computationally complex than the decoder. It leads to tremendous wastage of resources in terms of power and complexity at the encoder side [6]. Thus to facilitate the need of image and video compression to deliver the modern applications there is a need to develop an efficient system having reduced acquisition complexity combined with flexible decoding process.

Therefore an emerging technology of compressive sensing incorporates a new paradigm for signal acquisition and reconstruction and has drawn a lot of researcher's attention. It is a novel approach for data acquisition and compression which overcomes the limitations of the traditional methods. Compressive sampling is based on sub-Nyquist sampling of sparse signals of interest [7]-[9]. CS utilizes the sparse or nearly sparse signal to recover the original signal using less number of linear measurements by the means of convex optimization approaches or some greedy recovery algorithms, relative to conventional schemes exploiting the entire ensemble of signal samples [10].

In the following sections of this chapter, firstly the main focus is drawn on the need of compression in the present scenario. Further the discussion is elaborated to various image and video compression techniques.

1.1 Compression

Compression is the basic need of the present scenario for efficient storage and transmission of data and this data may be in the form of a signal, image, video, etc. Compression basically reduces irrelevance and redundancy from the data. There is the need for compression for the following purposes.

- Save time, better transmission and storage.
- Compact representation.
- Bandwidth utilization.

There are various types of signal compression techniques like bandwidth compression, data compression, lossy compression, lossless compression, image and video compression. Main focus of this work is drawn on image and video compression techniques, specifically concerning the compression and reconstruction of image and video signals.

1.1.1 Image Compression Techniques

Image compression basically relies on two types of compression techniques those are lossless and lossy compression.

Lossless compression involves run-length encoding, Huffman coding, LZW coding, etc. whereas lossy compression comprises of transform coding, vector quantization, fractal coding, etc. Specifically concerning the transform based image compression techniques, there are three mostly used techniques; JPEG, JPEG2000 and wavelet transform [1].

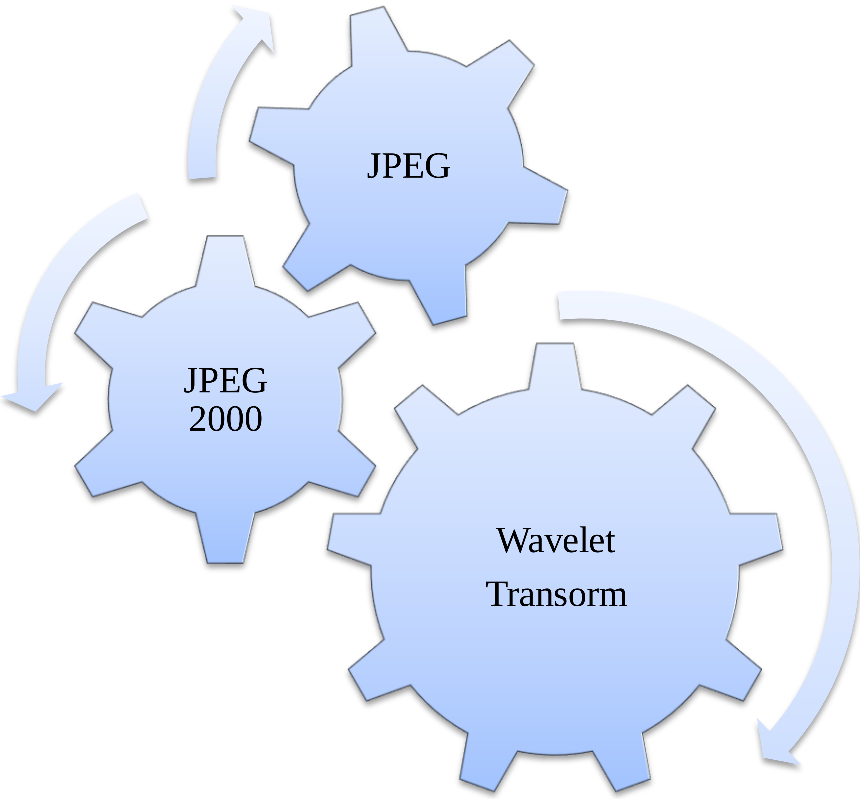

Figure 1.1: Transform based Image Compression Techniques

1) **JPEG:** It is a DCT based Image Coding Standard designed for compressing colored or grayscale images by firstly partitioning the image into non overlapped 8×8 blocks. Then Discrete Cosine Transform (DCT) is applied to each block to convert the gray levels of pixels in the spatial domain into coefficients in the frequency domain. The coefficients are normalized by different scales according to the quantization table provided by JPEG standard. The quantized coefficients are then rearranged in an order to be further compressed by an efficient lossless coding strategy like run length coding Huffman coding, arithmetic coding, etc. The loss of information is only encountered in the coefficient quantization process. To achieve better decoding quality, an adaptive quantization table may be used instead of using the standard quantization.

2) **JPEG2000:** This is an improved version of JPEG compression standard for lossy and lossless compression and is nearly same as JPEG. It extends the initial JPEG

standard to provide increased flexibility in both the compression of continuous tone still images and access to the compressed data.

3) **Wavelet Transform:** The functions that are defined over a finite interval having the average value zero are referred to as wavelets. The idea of wavelet transform is to represent any arbitrary function as superposition of a set of such wavelets or basis functions. These basis functions or baby wavelets are obtained from a single prototype wavelet called the mother wavelet, by dilation or scaling or shifting. The Discrete Wavelet Transform of a finite length signal x(n) having N components is expressed as an N×N matrix.

1.1.2 Video Compression Techniques

Various video compression techniques are as follows:

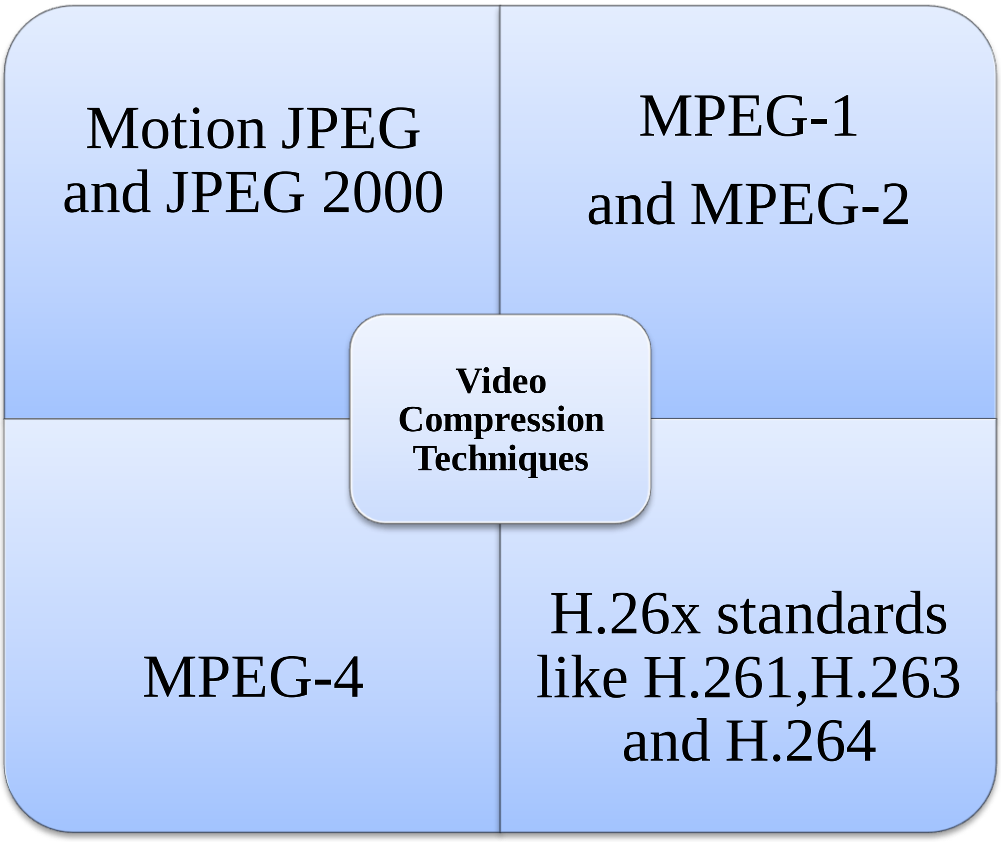

Figure 1.2: Video Compression Techniques

1) **Motion JPEG:** A digital video can be represented as a series of JPEG pictures displayed over time referred to as motion JPEG. Similar to the advantages of single still JPEG picture, Motion JPEG is also flexible in terms of quality as well as compression ratio. But it has the limitation that since it uses only a series of still pictures it does not make the usage of video compression techniques, therefore resulting in slightly lower compression ratio for video sequences as compared to other video compression techniques.

2) **Motion JPEG 2000:** Similar to JPEG and Motion JPEG, JPEG 2000 can also be used to represent a video signal. The advantages are equal to JPEG 2000, i.e., a slightly better compression ratio compared to JPEG but at the cost of complexity. The disadvantage is also same as that of Motion JPEG. Since it is a still picture compression technique it doesn't take any advantages of the video sequence compression resulting in a lower compression ratio as compared to real video compression techniques.

3) **MPEG-1:** MPEG-1 video compression standard is the first public standard of the MPEG committee that is based upon the same technique that is used in JPEG. In addition to that it also includes techniques for efficient coding of a video sequence. In MPEG video, only the new parts of the video sequence is included together with information of the moving parts during the transmission of the video sequence to limit the bandwidth consumption. When displayed it appears as the original video sequence again. This technique basically focuses on compression ratio rather than picture quality.

4) **MPEG-2:** MPEG-2 is the "Generic Coding of Moving Pictures and Associated Audio" targeted at TV transmission and other applications capable of 4 Mbps and higher data rates. MPEG-2 features very high picture quality. MPEG-2 supports interlaced video formats, increased image quality, and other features aimed at HDTV. MPEG-2 is a compatible extension of MPEG-1, meaning that an MPEG-2 decoder can also decode MPEG-1 streams. MPEG-2 audio will supply up to five full bandwidth channels (left, right, center, and two surround channels), plus an additional low-frequency enhancement channel, or up to seven commentary

channels. The MPEG-2 systems standard specifies how to combine multiple audio, video, and private-data streams into a single multiplexed stream and supports a wide range of broadcast, telecommunications, computing, and storage applications. MPEG-2 also provides more advanced techniques to enhance the video quality at the same bit-rate on the expense of the need for far more complex equipment. Therefore these features are not suitable for use in real-time surveillance applications. As a note, DVD movies are compressed using the techniques of MPEG-2.

5) **MPEG-4:** MPEG-4 supports even lower bandwidth consuming applications along with high picture quality and almost unlimited bandwidth. Most of the differences between MPEG-2 and MPEG-4 are features not related to video coding and therefore not related to surveillance applications. MPEG involves fully encoding only key frames through the JPEG algorithm and estimating the motion changes between these key frames. Since minimal information is sent between every four or five frames, a significant reduction in bits required to describe the image results. The MPEG encoder is very complex and places a very heavy computational load for motion estimation. Decoding is much simpler and can be done by desktop CPUs or with low cost decoder chips.

6) **H.261:** H.261 is a motion compression algorithm video coding standard developed specifically for videoconferencing, though it may be employed for any motion video compression task. H.261 encoding is based on the discrete cosine transform (DCT) and allows for fully-encoding only certain frames (INTRA-frame) while encoding the differences between other frames (INTER-frame). The main elements of the H.261 source coder are prediction, block transformation, quantization, and entropy coding. While the decoder requires prediction, motion compensation is an option.

7) **H.263:** H.263 is the video codec introduced with ITU recommendation "Multimedia Terminal for Low Bit-rate Visual Telephone Services". H.324 is for videoconferencing over the analog phone network. While video is an option under H.324, any terminal supporting video must support both H.263 and H.261. H.263 is a structurally similar refinement to H.261 and is backward compatible with H.261.

At bandwidths under 1000 kbps, H.263 picture quality is superior to that of H.261. Images are greatly improved by using a required 1/2 pixel new motion estimation rather than the optional integer estimation used in H.261. Half pixel techniques give better matches, and are noticeably superior with low resolution images.

8) **H.264:** H.264 is the result of a joint project between the ITU-T's Video coding Experts group and the ISO/IEC Moving Picture Experts Group (MPEG). ITU-T has named it as H.264, whereas it is called MPEG-4 Part 10/AVC by ISO/IEC since it is presented as a new part in its MPEG-4 suite. H.264 has some goals and supports the following services:

- At fixed video quality, it delivers an average bit rate reduction of 50% as compared to any other video standard.
- Provides error robustness to tolerate the transmission errors over various networks.
- Supports low latency capabilities along with better quality for higher latency.
- It provides simpler implementation with straightforward syntax specification.
- Exact match decoding defined by how some calculations are to be made by an encoder and a decoder so as to avoid errors from accumulating.

After reviewing various image and video compression techniques [11] in detail, it was found that traditional image or video capturing systems samples at Nyquist Shannon sampling theorem that requires a sampling rate greater or equal to twice the bandwidth of the signal. This sampling rate is sometimes too high for many applications leading to an increase in computational complexity at the encoder end and adds to the complexity of the sensing hardware. Thus reduced acquisition complexity combined with flexible decoding process is required to facilitate the need of image and video compression to deliver the modern applications.

Therefore an emerging technology of compressive sensing, overcoming the limitations of the traditional methods, incorporates a new paradigm for signal acquisition and reconstruction and it is briefly discussed in the next section.

1.2 Compressive Sensing

The theory of compressive sensing was built from the idea that signal may still be recovered through the less number of samples that was considered to be insufficient for Shannon's sampling criteria.

Compressive sampling deals with the sampling of sparse signals of interest rather than collecting the entire set of signal samples. CS exploits the sparse or nearly sparse signal representation for efficient acquisition using less number of linear measurements via convex optimization approach [12].

The aim of compressive sensing is to achieve sensing and compression in a single step by changing the sensing pattern [13]. This process is shown in figure 1.3.

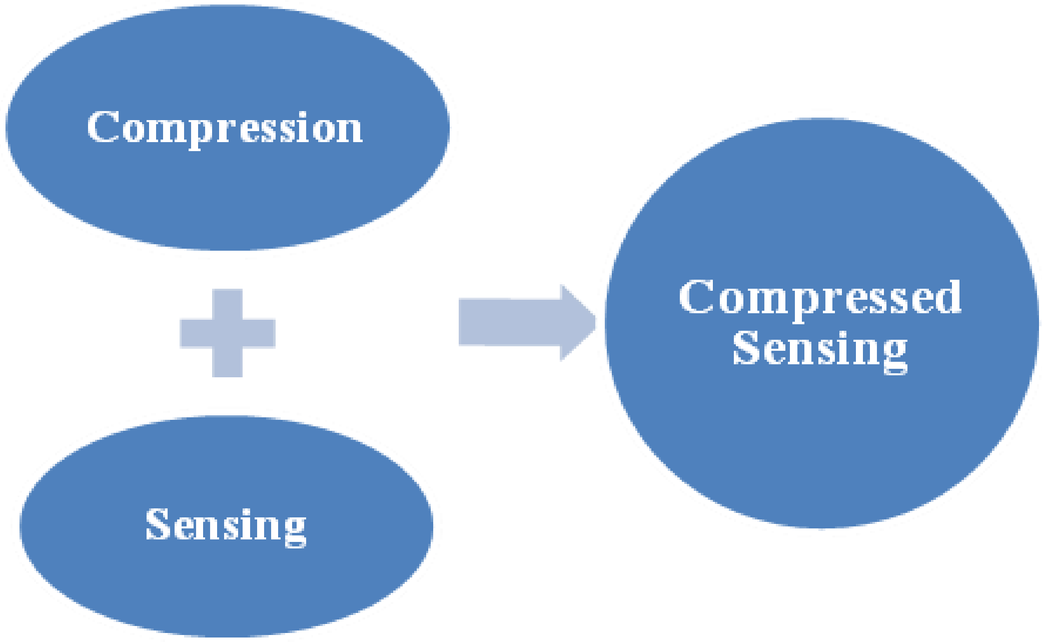

Figure 1.3: Block diagram of Compressed Sensing

CS recovery is based upon two principles –

- Sparsity
- Incoherence

Sparsity represents the signal of interest, while isometric property of incoherence restricts the sensing scheme.

a) **Sparsity:** Sparsity of a signal signifies that it has smaller amount of non- zero coefficients and many zero coefficients. For applying compressed sensing on a signal, that signal should be sparse in any domain. Majority of signal information lies in the fewer non-zero coefficients and the other coefficients are not exactly zero but have very small value. Thus for such signals, exact reconstruction is not possible but the signal can be approximately estimated considering only large coefficients for computation and tending the small coefficient values to zero [14]. In this way we have a sparse signal.

Specifically a signal x is considered sparse if it has k non-zero values i.e. $\|x\|_p = k$, where $\|x\|_p$ represents the p-norm of signal x.

The idea of sparsity and redundancy are interchangeable. Thus a signal that is non-sparse, but redundant, can be expressed as a sparse signal in some another basis. Any redundant signal x can be expressed as a sparse signal $\tilde{x}$ where,

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

where $\Psi \in R^{N\times N}$ is a suitable basis for sparse expression [15].

b) **Incoherence:** Coherence basically refers to a statistical quantity that evaluates the highest correlation between any two elements from two different matrices. Let us consider two orthonormal basis Φ and Ψ of R^n. The coherence between these two bases is defined by

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

which gives the largest correlation between any two elements of the two bases. It can be shown that

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

The compressibility of a signal is computed by both these factors; sparsity and incoherence. A signal is more compressible if it has higher sparsity in the representation domain Ψ that is less coherent to the sensing domain Φ [16].

1.3 Sensing and Sampling

Sensors are used to sample a signal and record a reading. But in case of CS, the sensors have to sense and compress at the same time in a single step. This can be achieved by taking a linear measure of the signal to be sensed. Rather than measuring the entire ensemble of the signal, the CS sensor measures the signal on an alternate vector space using a pre-defined set of vectors. This sampling constitutes a measurement of the signal having lower dimensions than the signal itself.

Considering the matrix, M (less than N) measurements on k-sparse N dimensional signal using a sensing matrix $\Phi \in R^{M\times N}$ as

$$y = \Phi x \quad (4)$$

Each element in y represents a linear combination of the signal vector x with the vectors in the sensing matrix Φ. It was mentioned earlier that CS is based on the principle of sparsity.

Thus the above equation assumes x to be k-sparse and if x is not sparse itself, it can be re-expressed as a sparse signal $\tilde{x}$ in Ψ domain as in eq. (1) using eq. (4) this can be modified as

$$y = \Phi\Psi\tilde{x} \quad (5)$$

Or $$y = \Theta\tilde{x} \text{ where } \Phi\Psi = \Theta \quad (6)$$

here Φ is referred to as sensing matrix or measurement matrix and Ψ as sparsifying matrix. It is assumed that x is k-sparse with Ψ = I, identity matrix [17].

1.4 Reconstruction Methods

The core requirement of CS problem is to find the solution to the under-determined system of equations $y = \Phi x$ and then reconstruct the signal.

Optimal signal reconstruction relies on better stability, uniform guaranteed and efficient reconstruction. There are various approaches to find reconstructed signal some of those are investigated and are described below.

1.4.1 Minimum l_2 norm reconstruction

The most commonly used scheme to solve a system of equation (y = Φx) to find the minimum energy solution. The main advantage of the l_2 norm minimization scheme is the simplicity of the solution, but the solution is almost always an incorrect one. The signal reconstruction is completely away from the optimum solution and the image has unwanted "aliasing-like" artifacts [18].

1.4.2 Minimum l_0 norm reconstruction

It is an algorithm that can implement this will be guaranteed to find the exact solution. A k-sparse signal can be exactly recovered by using as few as 2k random measurements. However, the solution involves checking every combination of K-sparse vectors in an N-dimensional space for one that satisfies the given system of equation i.e. $y = \Phi x$. This is an NP-complete problem and cannot be implemented [18].

1.4.3 Basic Pursuit (l_1 minimization)

Basis Pursuit or l_1 minimization was one of the first methods that were suggested for reconstruction in the CS problem. This allowed the use of the convex l_1 norm to find the optimum solution. It consists of convex optimization methods which provide a robust solution giving a stable and guaranteed reconstruction. The l_1 norm minimization technique serves as a compromise between the l_0 norm and the l_2 norm methods. The l_1 norm is a convex optimization technique and due to the very high dimensionalities of the signals involved, this convex relaxation almost always finds the exact solution. There are a wide variety of efficient and accurate convex optimization software packages that can be used to solve the problem as $\min\|\tilde{x}\|_1$, subject to $\|\Phi\tilde{x} - y\|_2 \leq \in$ where $\in$ represents the upper tolerance bound for the energy of the reconstruction error. This method is not optimally fast as involves number of iterations increasing the computational complexity. However, it is the most preferred reconstruction method as it provides guaranteed high quality reconstruction [19].

1.4.4 Minimum Total Variation Reconstruction

Total Variation (TV) minimization is a modified l_1 minimization technique that is particularly successful for imaging applications. TV minimization is based on the fact that most images are sparse in the gradient, and hence have few intensity variations. $\min\|\tilde{x}\|_{TV}$, subject to $\|\Phi\tilde{x} - y\|_2 \leq \in$ defines the TV minimization method for reconstruction from CS measurements, where $\in$ represents the upper tolerance bound for the energy of the reconstruction error [18].

1.4.5 Greedy Pursuit

Algorithms like Compressive Sampling Matching Pursuit, stage-wise Orthogonal Matching Pursuit and Regularization Orthogonal Matching Pursuit falls into this category. Apart from the l_1 norm minimization techniques described above, there have been a wide array of greedy algorithms designed to iteratively find the best solution satisfying $y = \Phi x$. Subsequent to every iteration the algorithm finds an estimated signal by finding the maximum correlation between the measurement residual and the columns of the measurement matrix. The residual is in turn computed by subtracting the contribution of the current signal estimate from the measurements. The new signal estimate comes from the measurements and the columns of the matrix that have high correlation with the residual. There are multiple alternatives of greedy algorithms used for compressed sensing reconstruction [20]. This reconstruction method gives simpler implementation and faster running speed as compared to l_1 minimization. This method delivers smaller recoverable sparsity compared to l_1 minimization and less guaranteed reconstruction [21].

1.5 Performance Evaluation Parameters

Various performance evaluation parameters are used in this research work like mean square error (MSE), percentage root mean square difference (PRD), and peak signal-to-noise ratio (PSNR). Other parameters like structural similarity index (SSIM) and dissimilarity index (DSSIM) are based on human visual system are also utilized.

1.5.1 PSNR (Peak Signal to Noise Ratio): This image quality based parameter is calculated using MSE i.e. given by averaging the squared intensity of the original and recovered image or video pixels.

$$MSE = \sum\sum \frac{error^2}{rows \times columns}$$

$$PSNR = 10 \log \frac{(peak\ value\ (256))^2}{MSE}$$

1.5.2 PRD (Percentage Root Mean Square Difference): It gives the percentage root mean square difference of the MSE value i.e. the averaged measure of squared intensity of original and recovered image or video pixels.

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

1.5.3 SSIM (Structural Similarity Index): SSIM is based on statistical values of image or video attributes like luminance, brightness, texture, contrast and orientation. Its value lies between 0 and 1 and the reconstructed signal is structurally similar to the original signal if it approaches 1. SSIM between original image x and reconstructed image y is given by,

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

Dissimilarity index giving the similarity variation of reconstructed signal as compared to the original one is given by,

$$DSSIM = \frac{1 - SSIM(x,y)}{2}$$

1.5.4 CR (Compression Ratio) and Space Saving: Compression ratio (CR) and space saving is calculated at the encoder side by taking the ratio of compressed bits to the original image bits.

$$CR = \frac{Compressed\ bits}{Uncomressed\ bits}$$

$$Space\ saving = \left(1 - \frac{1}{CR}\right) \times 100\%$$

CHAPTER 2

OBJECTIVES AND SCOPE

The major motivation to develop this project is the need of compression in the present scenario for efficient storage and transmission of data. Data amount is very large usually in terabytes for hospitals, NASA satellite imaging and also for ultra high definition applications. All these tangible statistics motivated for the need for fast and efficient image and video compression technique as proposed in this project.

Thus, to facilitate the need of image and video compression to deliver the modern applications the following objectives are framed:

- ❖ To develop an efficient approach for better acquisition, compression and reconstruction technique using CS is the main aim of this research work.

- ❖ Formulation of an efficient image and video compression using compressed sensing technique which would result in reduction in data size to reduce the storage and bandwidth requirements.

- ❖ Critical analysis of a number of performance metrics evaluated for different reconstruction schemes so as to provide performance guarantees for better recovery and less distortion in compressed image and video sequence.

Project Scope

For applications like video surveillance, telemedicine, space and satellite imaging, sports broadcasting, etc. there is a need to reassess the conventional coding techniques. The proposed work can be used for efficient compression and reconstruction of image and video data. This project has scope in various fields like;

- **Telemedicine:** Telemedicine was originally created as a way to treat patients who were located in remote places, far away from local health facilities or in areas of with shortages of medical professionals. In emergency conditions, the patient wants to waste less time and get immediate care for urgent conditions when they need it. This expectation for more convenient care collectively with the unavailability of overburdened medical professionals has led to an increase in the requirement for faster and proficient telemedicine facility. Hence, there is a need for better image compression to serve the need of telemedicine and provide the immediate medical healthcare service.

- **Multimedia applications:** Multimedia is content that uses a combination of different content forms such as text, audio, images, animations, video and interactive content. Multimedia can be recorded and played, displayed, interacted with or accessed by information content processing devices like electronic devices. Hence there is a need for better image compression to facilitate these multimedia applications.

- **Digital video and video-conferencing:** Digital video is a representation of moving visual images in the form of digital data. Digital video comprises a series digital images displayed in rapid succession. Video-conferencing is the conduct of telecommunication technologies to facilitate the two-way video and audio transmissions at two or more locations simultaneously. This also needs faster storage and transmission service and thus compression is needed.

- **Medical imaging:** Medical imaging is the technique 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 to aid medical diagnose to treat the diseases. Thus there is a need for better image compression to facilitate medical imaging.

- **Space and satellite imaging:** Satellite imaging consists of collecting the images of Earth or other planets by the means of satellites. These imaging satellites are government owned and also some of them are operated by businesses around the world. Organizations such as NASA generate terabytes of imaging data per day raising the need for image compression in this field to facilitate faster communication.

- **Weather forecasting:** Weather forecasting is the application of science and technology that is used to predict the atmospheric state for a given location. Weather forecasts are made by collecting the quantitative images or data about the present atmospheric state at a given place and using scientific understanding of atmospheric processes to predict the atmospheric changes. Thus there is a need for better compression to facilitate weather forecasting applications.

CHAPTER 3

LITERATURE REVIEW

The literature review deals with critical analysis of any published piece of knowledge through study of the literature and comparison of those prior research findings to draw a conclusion which supports the proposed research work.

The literature review of the research work provides an overview of the technical perspective of various researchers on the topic of compressive sensing technique.

Emmanuel Candes, mutually with Justin Romberg and Terry Tao, contributed to the theory of Compressed Sensing (CS) [7-9] to be applied for audio, image or video signals but the condition is that the signal should be sparse in any domain. A signal can be acquired at much lower rate than the Nyquist criteria using this sampling theory. Thousands of research papers are motivated by CS technique from 2006 till date.

In [22] it was examined that CS can prove to be a revolutionary technique for signal acquisition and recovery. The key advantages are faster data acquisition using fewer samples, decreased computational complexity, low transmission power, small traffic volume and time delay. In [23], various issues of emerging technologies were highlighted predicting the growth in demand for bandwidth. Thus, in this paper, author discussed various video compression techniques and concluded that H.264/AVC has various improvements in terms of better coding efficiency, like flexibility, robustness and application domains. It was found that still a lot of possibilities were there for improving video compression techniques.

In [24], authors used Orthogonal matching Pursuit (OMP) and Non- Linear Mapping techniques and compared these techniques with the convex optimization methods. It gives lower complexity, fast running speed, better reconstruction and low power consumption than convex optimization approach. But on the contrary, convex optimization approach gives guaranteed reconstruction. In [25], a video reconstruction framework was proposed from frame-by-frame 2D CS acquisition, based on 3D total variation (TV). On comparing the scheme with the existing reconstruction methods, it was found that 3D-TV regularization outputs gives better qualitative properties than the conventional methods especially for sharp edges and fewer motion artefacts.

In [26], a hierarchical frame framework to address video recovery problem based on video compressed sensing theory was explored. Spatial and temporal correlation of video sequence is utilized to improve recovery by employing unequal sub-rate in different layers and incorporating the techniques like 3D patch matching, hard thresholding and gradient descent in iterative fashion. Experimental results depicts that the developed video CS recovery strategy is able to increase the recovery to a great extent as compared to the existing methods. In [27] authors proposed a compressed-sensing-domain l_1 norm maximization scheme for compressed-sensed surveillance video processing. Both qualitative and quantitative results depict the effectiveness of the adaptive CS- l_1-PCA methods as compared to its non- adaptive counterparts for different types of video surveillances. Future scope in this work is to deal video surveillance challenges like detecting moving objects with static parts, removing shadow cast by the objects and addressing the camouflage problem.

In [28], a multi-hypothesis compressed video sensing strategy is recommended that exploits video frames sparsity for signal reconstruction at the decoder end. The simulation results for different video sequences verify that the proposed technique attains higher reconstruction accuracy for video frames along with less computational complexity. Authors in [29] discussed a two-stage MH reconstruction scheme integrating measurement-domain MH prediction with the pixel-domain MH prediction. The technique proposed in this paper gives better results than the state-of-the-art MH prediction algorithm at 1dB gain when 0.1 sampling rate is taken. It also increases the prediction accuracy. In [30] authors employed a support estimate scheme that focuses the measurements coefficients having larger values of a signal i.e. compressible. The recovery performance of standard CS using l_1 minimization is compared with the adaptive recovery using weighted l_1 minimization. Better reconstruction quality is experienced because adaptive l_1 minimization is used.

Literature review for this dissertation work includes the study of numerous research papers contributing to the research field of compressive sensing. Table 3.1 and table 3.2 give the tabular representation about the existing techniques of compressive sensing applied on images and video signals. The discussion includes the problem addressed by the authors, techniques used by the researchers to mitigate the problems and the inference drawn from the study including the performance parameters investigated along with the limitations of the work.

Table 3.1: Reviews of CS Techniques applied on images given by Prior Researchers

Sr. no.	Authors	Problem addressed	Techniques used	Inference drawn and Parameters evaluated	Limitations
1.	Han [31]-2008	Image reconstruction to remove sense and sparse components.	Compressive sensing (CS) and Projection onto convex set (POCS)	PSNR, Rate distortion, Total error	Computational complexity
2.	Ma [32]-2008	To minimize non-smooth function on large datasets for better reconstruction.	Total Variation (TV), L_1-minimization, Wavelets	SNR, Relative error	Needs better image quality and storage.
3.	Nagesh [33]-2009	Recognition and recovery of invariant facial expressions along with feature extraction.	Compressive sensing (CS)	Storage space, Recognition rate	Uses multiple views of scenes.
4.	Wright [34]-2009	Human face recognition with invariant expression from illumination and disguise.	Sparse representation via L_1-minimization technique	Recognition rates, Sparsity Concentration Index(SCI)	In addition to recognition, object detection is also needed.
5.	Yang [35]-2010	Fast signal reconstruction using Fourier data for CS.	RecPF-reconstruction from partial Fourier data	Stable, robust and efficient. Relative error, Objection function	Computational complexity is more.

6.	Sen [36]-2011	CS application for reduction in rendering rate to find unrendered pixel values.	Compressive rendering	Better quality and accurate reconstruction MSE is calculated.	Uses very low sampling densities.
7.	Chen [37] 2012	Object detection and tracking for video surveillance with minimum data samples.	Real time CS L_1 tracking, Motion detection algorithms.	Faster tracking with high resolution, less storage and better recovery	Outcomes not benchmarked.
8.	Serwuthisarn [38]-2012	Better image reconstruction along with the removal of Gaussian noise effect.	OMP-PKS and RS based on Compressed sensing.	PSNR Better image quality with low measurements.	Reconstruction needs to be improved for impulsive and Gaussian noise.
9.	Hemalatha [39]-2013	Energy consumption analysis for image transmission suing CS along with rate distortion analysis.	BinDCT and Noiselet based CS.	PSNR, reduced bit rate and compression ratio	Energy consumption is to be reduced more.
10.	Liu [40]-2013	Signal recovery using sub-Nyquist samples with CS for Biomedical signals.	L_1-TV, TV-minimization, Nuclear norm minimization.	Mean L_1 error, accurate recovery	No benchmarked outcomes.

Table 3.2: Reviews of CS Techniques applied on videos given by Prior Researchers

Sr. no.	Authors	Problem addressed	Techniques used	Inference drawn and Parameters evaluated	Limitations
1.	Pudlewski [41]-2010	To outline the video parameters on received video of CS for multi-hop WSN.	Adaptive parity based channel coding	SSIM, BER, Quantization rate, image quality, low degradation	Enhanced recovered signal quality
2.	Chaozhu [42]-2011	To improve compression efficiency and reduce System complexity.	Distributed video coding based on CS, L_1-minimization .	PSNR, compression ratio, better quality, less complex.	Not much significant novelty
3.	Mansour [43]-2012	Measurements to be focused on large valued coefficients of compressible signal.	Adaptive CS scheme, weighted L_1 minimization	SNR, QCIF	Less extensive outcome analysis
4.	Sankaranarayanan[44]-2012	CS is exploited for Spatial Multiplexing Cameras	CS multi-scale video sensing and recovery framework, L_1-norm recovery	Relative speed, frame rate	Outcome not benchmark
5.	Chen[45] - 2013	Noise analysis for heterogeneous receiver	CS based wireless video multicast	PSNR, low complexity encoding, better transmission	Less visual perception

6.	Pudlewski [46]-2013	Better video quality transmission by evaluating transmission power at multimedia sensor nodes.	Relay assisted CVS	SNR, MSE, SSIM Gives better quality video.	Minor PSNR enhancement only.
7.	Pudlewski [47]-2013	Reduced energy, computational complexity and lack to resilience to channel error.	CVS, H.264/AVC intra, Motion JPEG.	SSIM, BER, good video quality, low energy consumption.	Main focus is on h.264 and M-JPEG.
8.	Yuan [48] 2013	Motion estimation within the scene and to adapt compression ratio for video capturing.	Adaptive temporal CS for video, Block matching algorithm	PSNR, Compression ratio	Embed the real time framework into hardware prototype.
9.	Liu [49]-2013	Direct video acquisition from CS sampling with no sophisticated encoding	Karhunen-Loeve based technique (KLT), K-SVD	PSNR Good reconstruction quality	No efficient encoding and decoding scheme. No recovery algorithms considered.
10.	Iliadis [50]-2013	Video compressive sensing framework for single pixel camera	Multiple measurement vectors	PSNR, Visual quality	Only minor SNR enhancement Not evaluated on other datasets.

CHAPTER 4

METHODOLOGY ADOPTED

In chapter 1, various image and video compression techniques are discussed and based on the drawbacks of traditional compression schemes, CS technique is chosen for better compression and reconstruction using less number of samples than required by the Nyquist criteria.

In this work, a compressive signal sensing technique is proposed for various signals may be 1D, 2D or 3D enabling faster acquisition, compression and reconstruction as compared to traditional compression schemes. Algorithms for compressed sensing applied on images, reweighted l_1 minimization and algorithm of CS applied on video are explained in the following sections. Details of encoder, decoder and performance parameters are also given in the following sections.

4.1 Dataset

In this work, a compressive sensing technique is assessed for various benchmark datasets enabling faster acquisition, compression and reconstruction. Algorithm is checked on random signal, numerous standard images and also on benchmark video sequences.

4.2 Algorithm for CS

For x being an input signal of dimension N×1 and Φ representing a M×N measurement matrix. CS acquisition can be expressed as

$$y = \Phi x \tag{7}$$

where y is M×1 vector representing the obtained measurements.

Assuming that x is represented in the form of N×N sparsifying basis matrix Ψ such that $x = \Psi\tilde{x}$.

If $\tilde{x}$ (i.e. N×1 transform vector) only consist of K<<N significant coefficients, then x is K-sparse in Ψ domain. Thus using CS theory, a K-spare signal can be reconstructed if matrix ΦΨ satisfies the isometric property [4, 5].

The signal x could be reconstructed by solving the following optimization problem;

$$\min \left\| \Psi^{-1} \mathrm{x} \right\|_p \text{ , subject to } y = \Phi \mathrm{x} \tag{8}$$

Here the subscript p represents the signal sparsity. If p is 0, solving the above optimization problem the solution becomes complex and gives a NP-hard problem. Therefore, to reduce complexity and to make the convex problem easier, p is taken as 1. The flowchart of compressive sensing algorithm is depicted in figure 4.1.

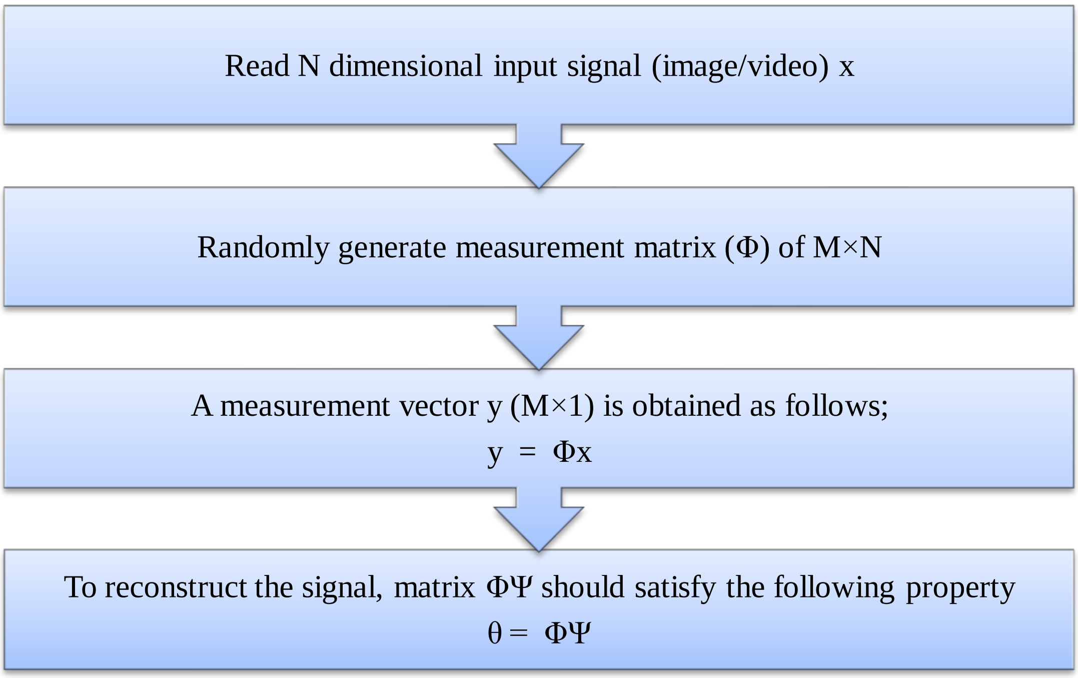

Figure 4.1: Flowchart of Compressed Sensing Algorithm

4.3 Reweighted l_1 minimization

It is a basic iterative convex optimization method providing uniform guaranteed reconstruction, stability and robustness but on the cost of increased complexity [4, 5]. The computed value of the current solution gives the weights used for next iteration.

The algorithm is described as follows:

1) The iterative count is set to 0 and initial weight is given by $w_i^{(0)} = 1$, for $i = 1, \dots, \mathrm{N}$.
2) The weighted l_1 minimization problem is solved by using the following solution;

$$\min \|W\tilde{x}\|_1 \text{ , subject to } y = \Phi x \tag{9}$$

3) Weights are updated for each $i = 1, \ldots, N$.

$$w_i^{(j+1)} = \frac{1}{|\tilde{x}_i^{(j)}| + \epsilon} \tag{10}$$

Here ϵ is a small positive number to prevent zero-valued denominator.

4) After j has attained a specific maximum number of iteration $j_{\max}$ the convergence is terminated; otherwise j is incremented and steps 2 and 3 are repeated.

4.4 Design of Encoder

The Compressive Sensing System Encoder is designed as follows.

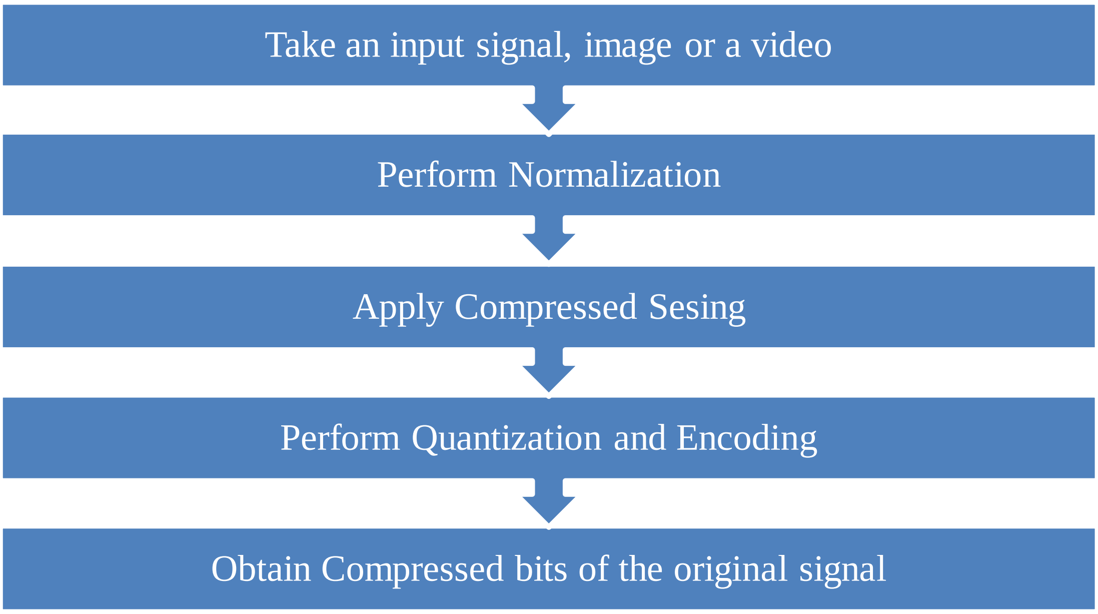

Figure 4.2: Flow chart of Compressive Sensing System (Encoder)

Firstly, a signal, image or a video sequence is taken as the input and is checked for its RGB content and then it is further converted to grayscale matrix coefficients. The coefficients having values smaller than a predefined threshold value are discarded using normalization process. A very few remaining significant coefficients are left, only a small subset of the original signal, reducing the number of measurement samples to represent the signal. It gives a method to acquire only fewer significant coefficients by sampling them at a rate less than that required by Shannon's theorem. After normalizing, compressed sensing is applied by exploiting the fewer measurements. Further the compressed bits are quantized and encoded and it results in the generation of compressed bits.

The compressed bits are then stored and transmitted. Compression ratio (CR) and space saving is also calculated at the encoder side by taking the ratio of the original image bits to the compressed bits.

4.5 Design of Decoder

At the decoder side, the compressed bits are taken and de-quantization and decoding is performed on the compressed bits. This step is followed by l_1- minimization and the final outcome is then results into the reconstructed signal, image or video sequence. Finally the proposed system is checked for its signal quality by calculating its peak signal to noise ratio (PSNR), structural similarity index (SSIM) and percentage root mean square difference (PRD). These parameters for the reconstructed signal are compared with the original signal. The flowchart of decoder side of compressive sensing system is depicted in the following figure 4.3.

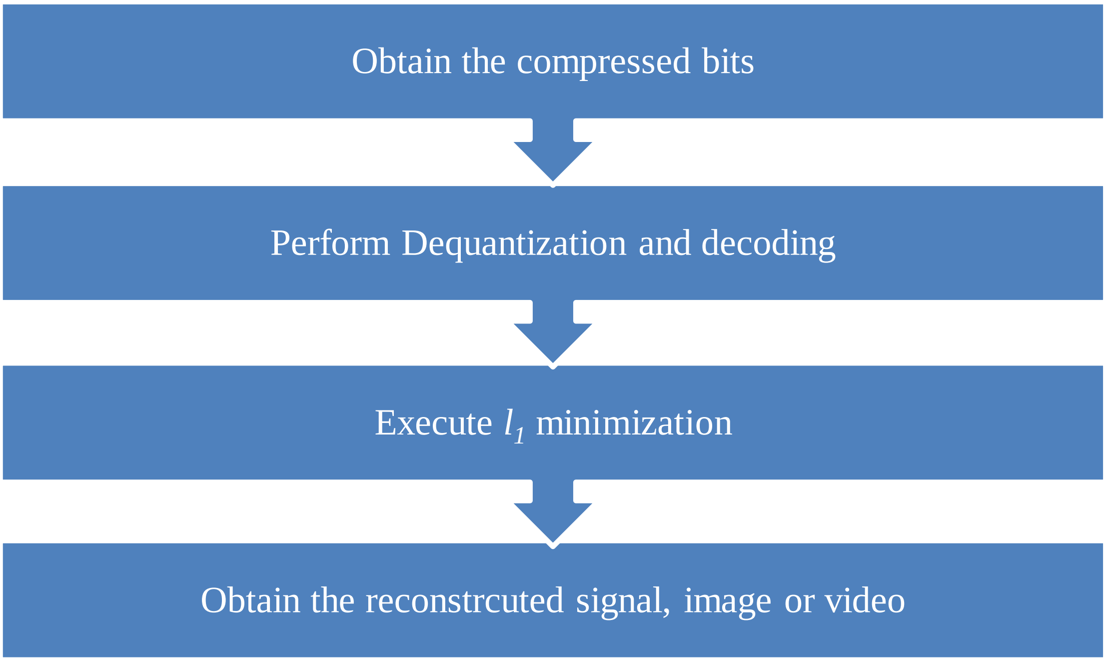

Figure 4.3: Flow chart of Compressive Sensing System (decoder)

Performance parameters of original and the reconstructed image using l_1 technique are compared and evaluated.

These performance parameters are important which give an idea of the image quality of the reconstructed image and compare it to the original image quality. Thus PSNR, MSE, RMS value, PRD, SSIM and DSSIM are important signal quality parameters which are calculated at the decoder side.

4.6 Algorithm for CS applied on video

The dissertation work also aims at applying the Compressive sensing technique on video signals. Therefore motion compensation technique is used for accurate recovery of a video signal by exploiting the motion vector for a reference frame. The compressive sensing algorithm for CS applied on video signal is given in the following figure 4.4.

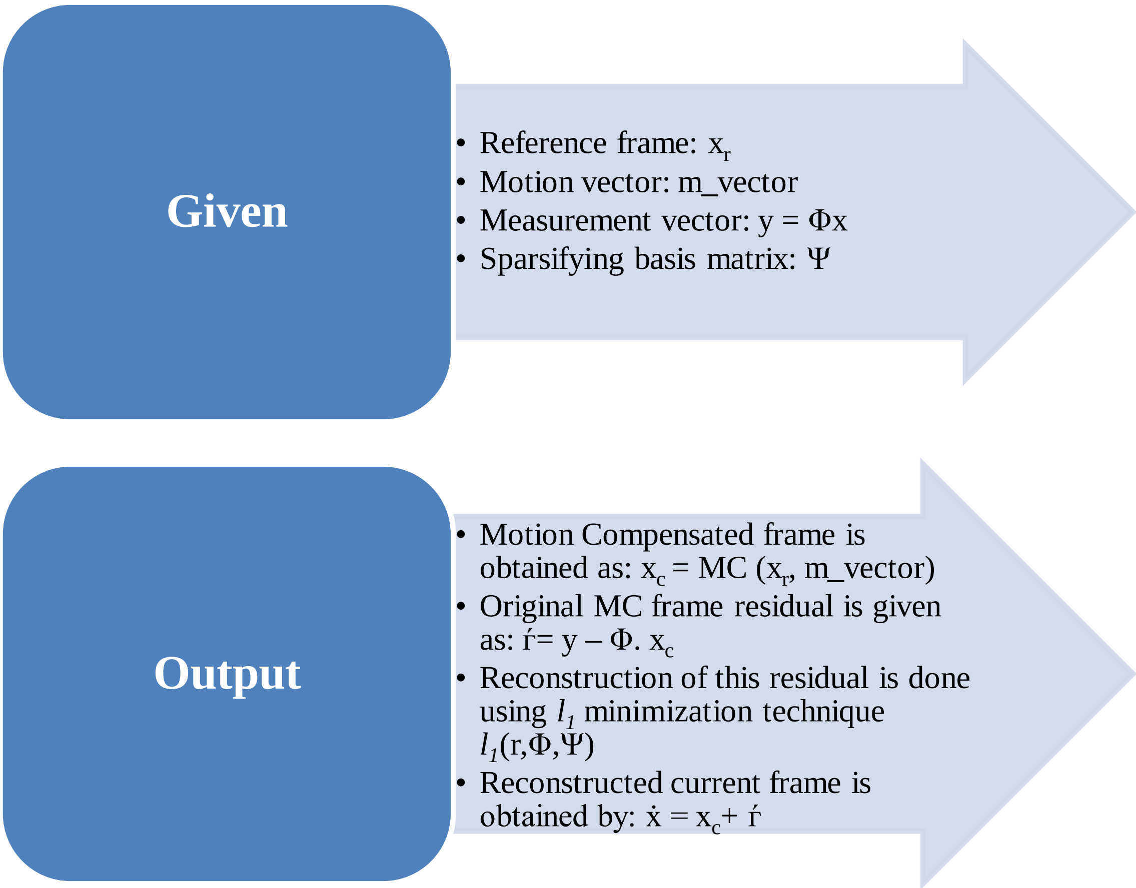

Figure 4.4: Algorithm for CS applied on video

CHAPTER 5

RESULTS AND DISCUSSION

Different methods for each aspect of the compressive signal sensing are explored for benchmark images to assess and critically evaluate the performance of CS. Compressive sensing is firstly applied on random signal and the reconstructed signal is observed. Then compressive sensing is applied on images and further on video signals. All simulations are done using Matlab 2013a.

5.1 Simulation results for CS applied on random signal

The compressed sensing recovery scheme is applied for a random signal with original signal samples N=128, peaks P=4 and varying measurement samples K from 64 to 16 to analyze the changes in the recovered signal. The results obtained are the graphs shown in figure 5.1.

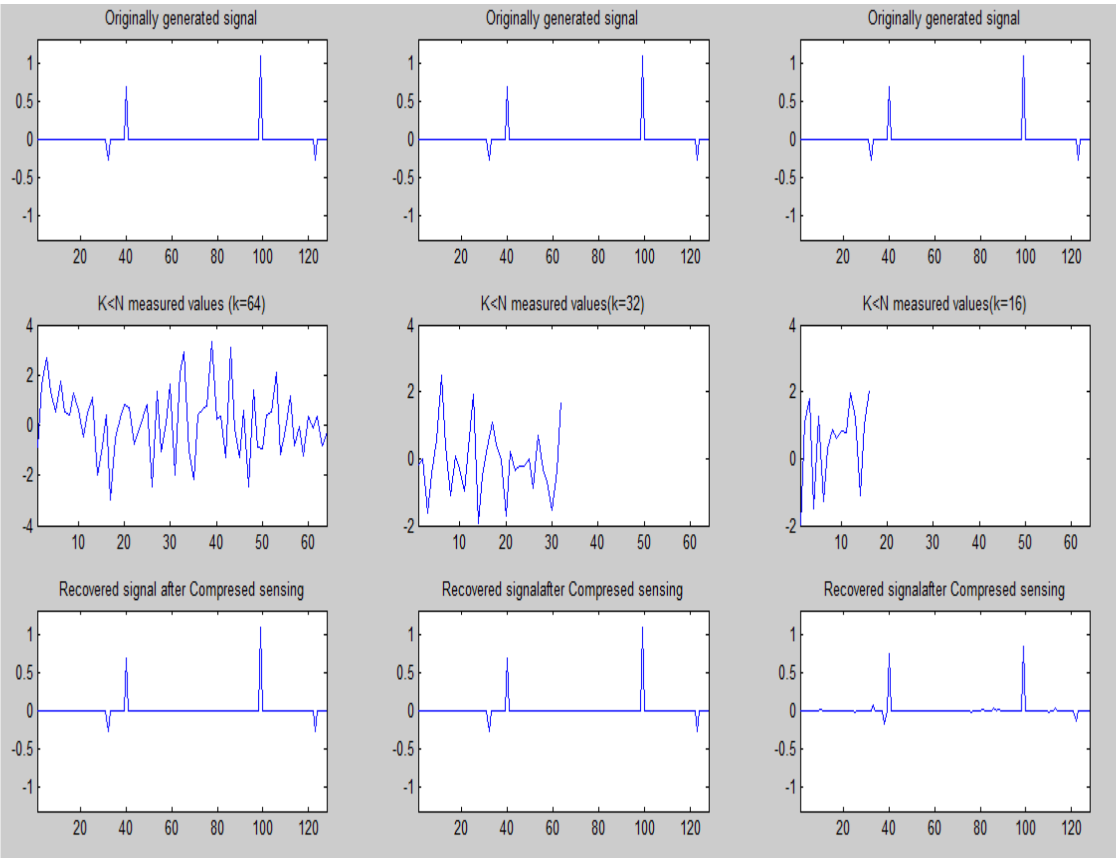

Figure 5.1: Results for N=128 (total samples), Peaks =4 and K (measurement values of samples) is varied from 64 to 16

The recovered signal after compressed sensing for N=128, peaks (P) = 4 (fix) and setting K=64 is observed to be exactly same as the original signal. On changing K from 64 to 32, a little distortion is noticed which can be ignored. While on changing K from 32 to 16, the original signal is not recovered and distortion becomes noticeable.

Thus from this compressive sampling performed on a random signal, it is depicted that the value of K measurement samples should be taken such that sampling rate is also low and original signal is recovered accurately.

5.2 Simulation results for CS applied on different images

5.2.1 Priliminary Results:

Initially in partial part of this dissertation work, compressive sensing was applied on the different test images and then they were reconstructed based on two reconstruction techniques that are basic pursuit (l_1) and least square minimization (l_2). Then the subplot of the original reshaped image was taken along with the reconstructed images by both these techniques. Subplots of original reshaped image along with the reconstructed images were taken and also there histograms were also taken to analyze which one is the better reconstruction approach. PSNR and MSE were compared for both these techniques. Output screenshots for some test images are shown in figure 5.2(a) to 5.2(b).

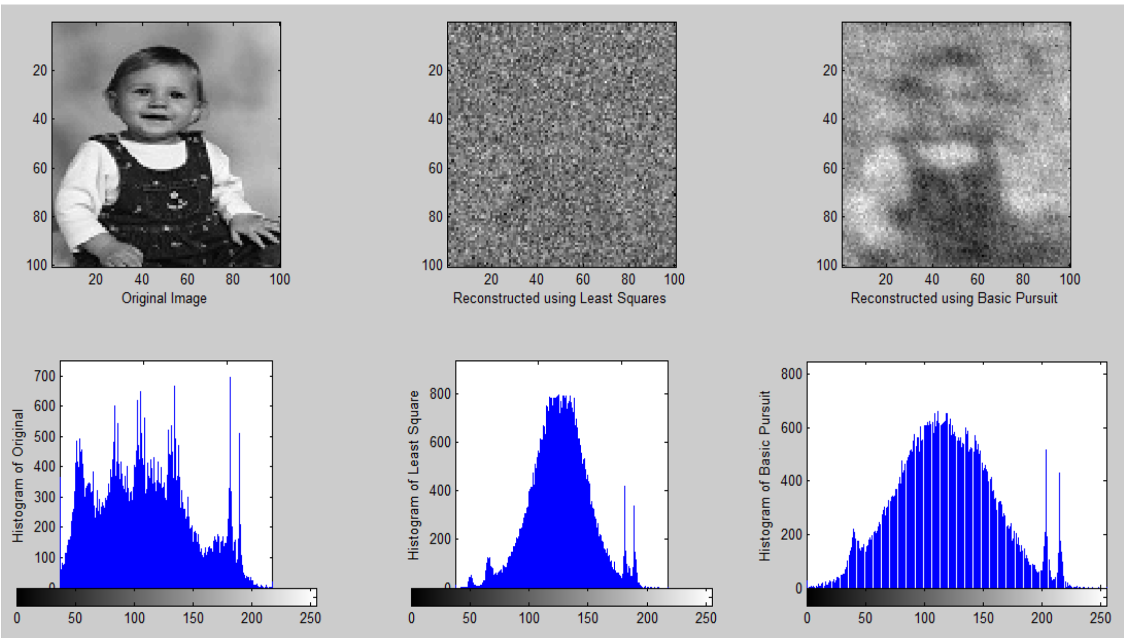

Figure 5.2(a): Comparison of original (grayscale) image with reconstructed using BP (l_1) and l_2

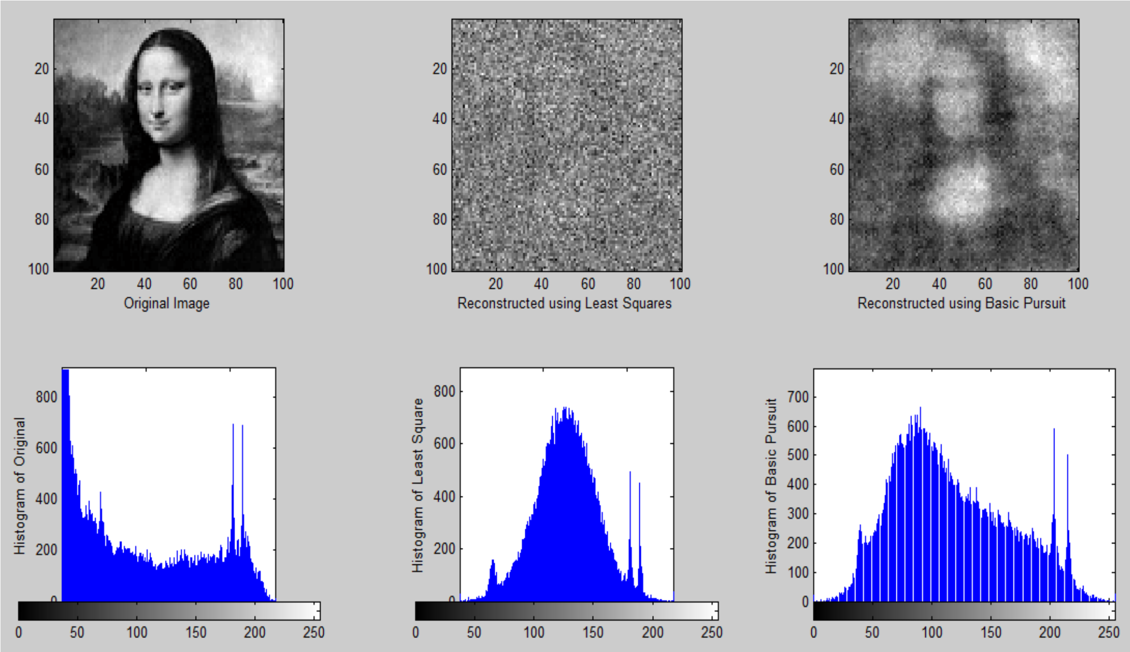

Figure 5.2(b): Comparison of original (monalisa) image with reconstructed using BP (l_1) and l_2

A comparison of PSNR, MSE and CR for different test images was listed in table 5.1. From this table, it was seen that PSNR for BP (l_1) reconstruction method is twice as better as that of reconstructed using l_2 method and on the other hand, MSE for l_2 is more than that of BP (l_1).

Table 5.1: PSNR, MSE and CR comparison for different images

Sr. No.	**Test Images**	**PSNR using BP (l_1) (dB)**	**PSNR using l_2(dB)**	**MSE using BP (l_1)**	**MSE using l_2**	**CR**
1.	Baboon	18.6148	6.5361	894.5456	1.4437e+04	8.723
2.	Bird	13.5346	7.4631	1.1061e+03	1.9529e+04	6.810
3.	Cameraman	15.5750	6.0799	1.8013e+03	1.6036e+04	5.989
4.	Coast_guard	19.4760	2.6398	733.6373	3.5408e+04	8.241
5.	Flowers	18.1913	3.8248	986.1686	2.6953e+04	7.783
6.	Girlface	16.6828	8.7488	1.3957e+03	8.6737e+03	7.109
7.	Grayscale	16.6078	6.1687	1.4200e+03	1.5711e+04	6.415

8.	Lena	15.8718	6.5726	1.7469e+03	1.1393e+04	6.042
9.	Monalisa	16.3648	8.0088	1.5018e+03	1.0285e+04	7.880
10.	Peppers	17.0955	4.7555	1.2692e+03	2.1754e+04	5.984
11.	Random	18.6212	9.4452	893.2333	7.3886e+03	7.571
12.	Yellow_flower1	19.5236	9.7151	725.6324	6.9433e+03	6.107

On evaluating both the reconstruction techniques, it was analyzed that reconstruction using BP (l_1) gives better result than least square (l_2) method but still the reconstructed images were not of good quality. Thus there was a scope for further improvement in results for its image quality in the later part of the dissertation.

5.2.2 Modified Results for CS applied on images:

Then in this part of the dissertation, compressive sensing technique is applied on image samples which are reconstructed based on three reconstruction techniques that are basic pursuit (l_1), orthogonal matching pursuit (OMP) and least square minimization (l_2). Subplots of the histograms along with the recovered signals are taken for comparison of original image with the reconstructed one and to choose the best reconstruction approach out of three evaluated reconstruction methods are shown in figure 5.3(a), 5.3(b), 5.3(c) and 5.3(d).

Various performance parameters are also compared for all the reconstruction techniques.

Performance parameters evaluated for some benchmark images using all the three reconstruction methods is tabulated in tables 5.2(a), 5.2(b), 5.3(a), 5.3(b), 5.4(a), 5.4(b), 5.5(a) and 5.5(b).

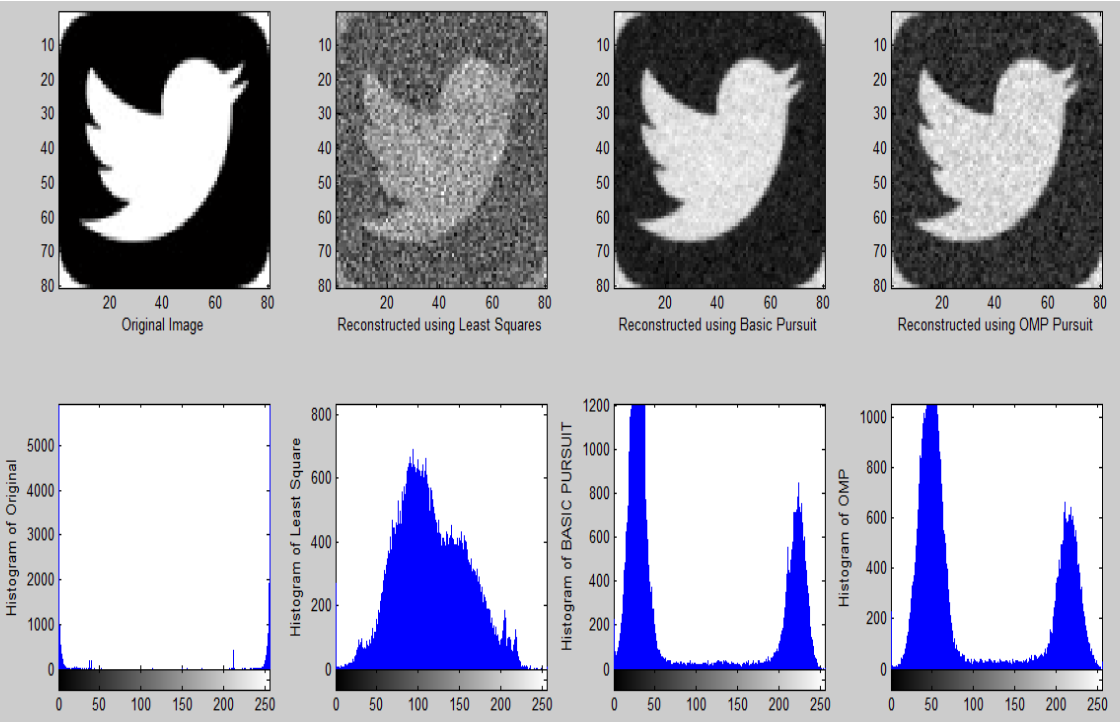

Figure 5.3(a): Reconstructed images and histograms for image sample bird using l_2, l_1 and OMP reconstruction techniques

Table 5.2(a): Image Quality Performance Parameters for CS applied on image sample- bird

Image sample	Technique used	PSNR	MSE	SSIM	DSSIM	RMS	PRD
Bird	L_1(BP)	23.513	289.612	0.455	0.273	17.021	9.983
	L_2(Least)	9.017	8.15e+03	0.134	0.433	90.292	71.831
	OMP	21.817	427.937	0.388	0.306	20.685	12.186

Table 5.2(b): Compression Performance Analysis for CS applied on image sample- bird

Image sample	CR	Space saving
Bird	6.810	85.316

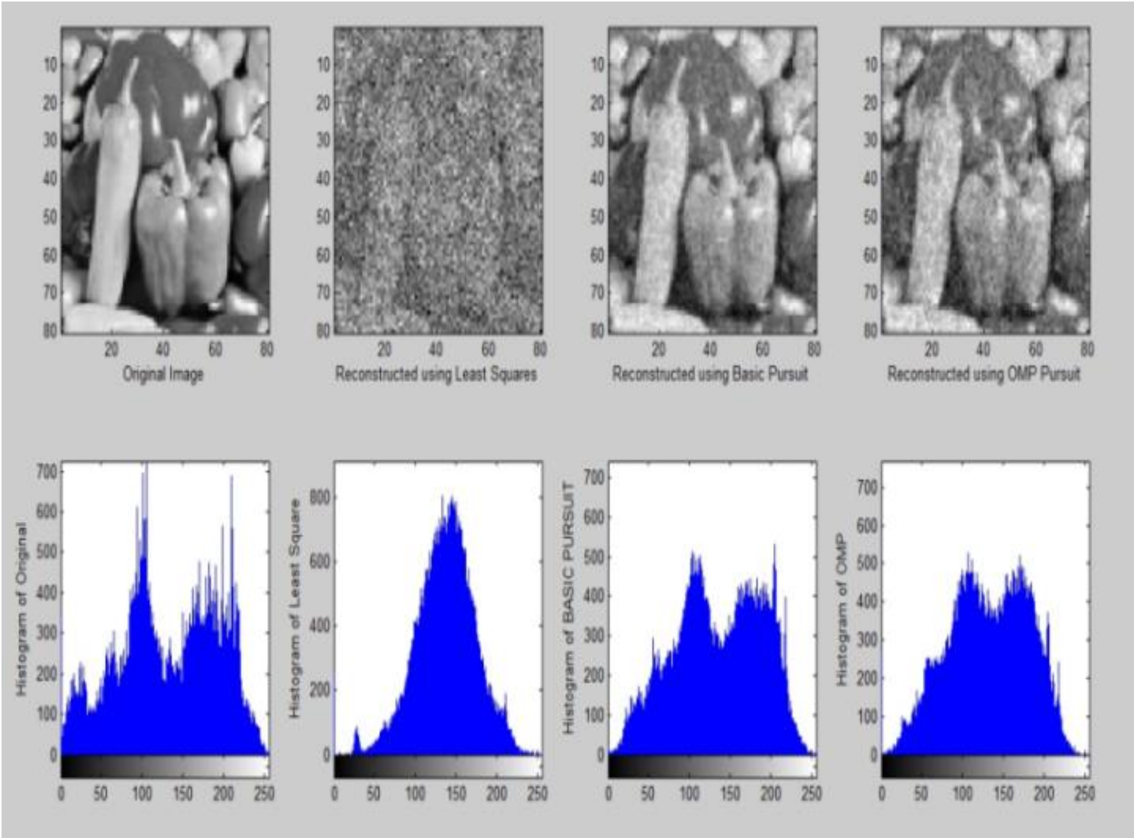

Figure 5.3(b): Reconstructed images and histograms for image sample peppers using l_2, l_1 and OMP reconstruction techniques

Table 5.3(a): Image Quality Performance Parameters for CS applied on image sample- peppers

Image sample	Technique used	PSNR	MSE	SSIM	DSSIM	RMS	PRD
Peppers	L_1(BP)	26.371	149.971	0.824	0.088	12.247	9.157
	L_2(Least)	10.229	6.167e+03	0.180	0.410	78.534	73.609
	OMP	22.793	341.839	0.696	0.152	18.489	13.841

Table 5.3(b): Compression Performance Analysis for CS applied on image sample- peppers

Image sample	CR	Space saving
Peppers	5.964	83.232

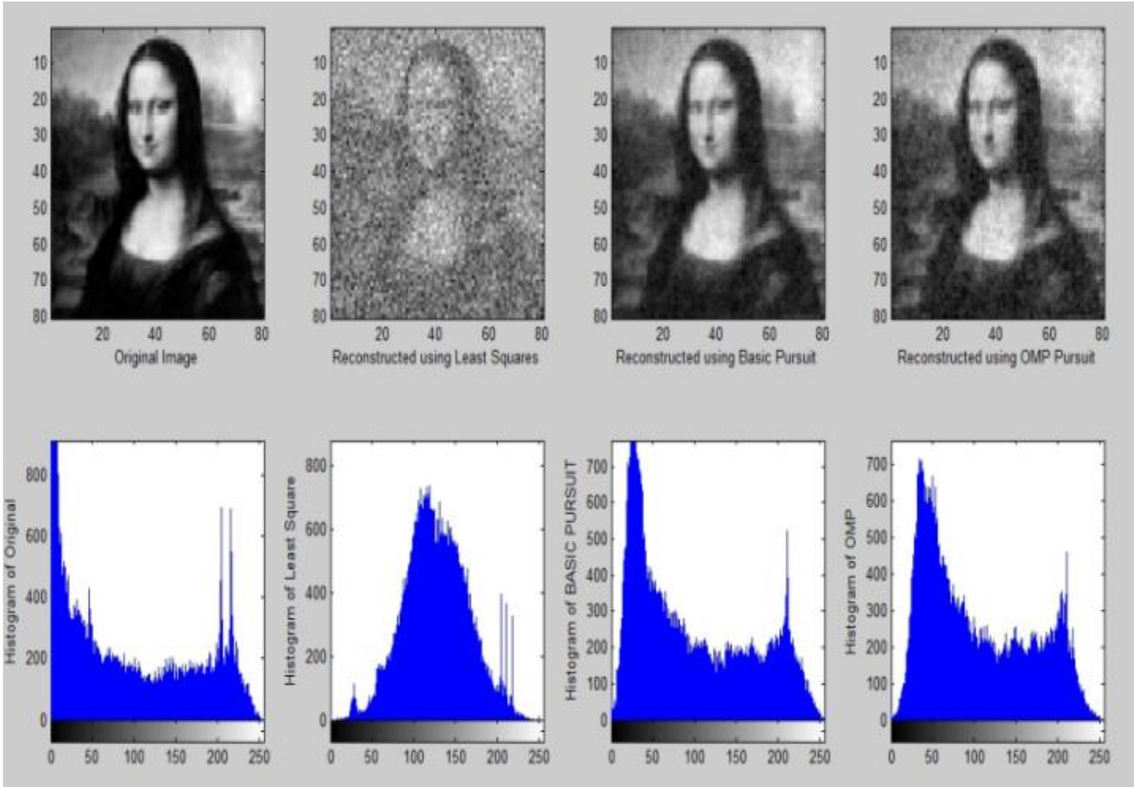

Figure 5.3(c): Reconstructed images and histograms for image sample monalisa using l_2, l_1 and OMP reconstruction techniques

Table 5.4(a): Image Quality Performance Parameters for CS applied on image sample- monalisa

Image sample	Technique used	PSNR	MSE	SSIM	DSSIM	RMS	PRD
Monalisa	L_1(BP)	29.191	78.259	0.854	0.073	8.846	7.565
	L_2(Least)	11.803	4.294e+03	0.172	0.414	65.525	72.713
	OMP	25.896	167.286	0.736	0.132	12.934	10.989

Table 5.4(b): Compression Performance Analysis for CS applied on image sample- monalisa

Image sample	CR	Space saving
Monalisa	7.881	87.315

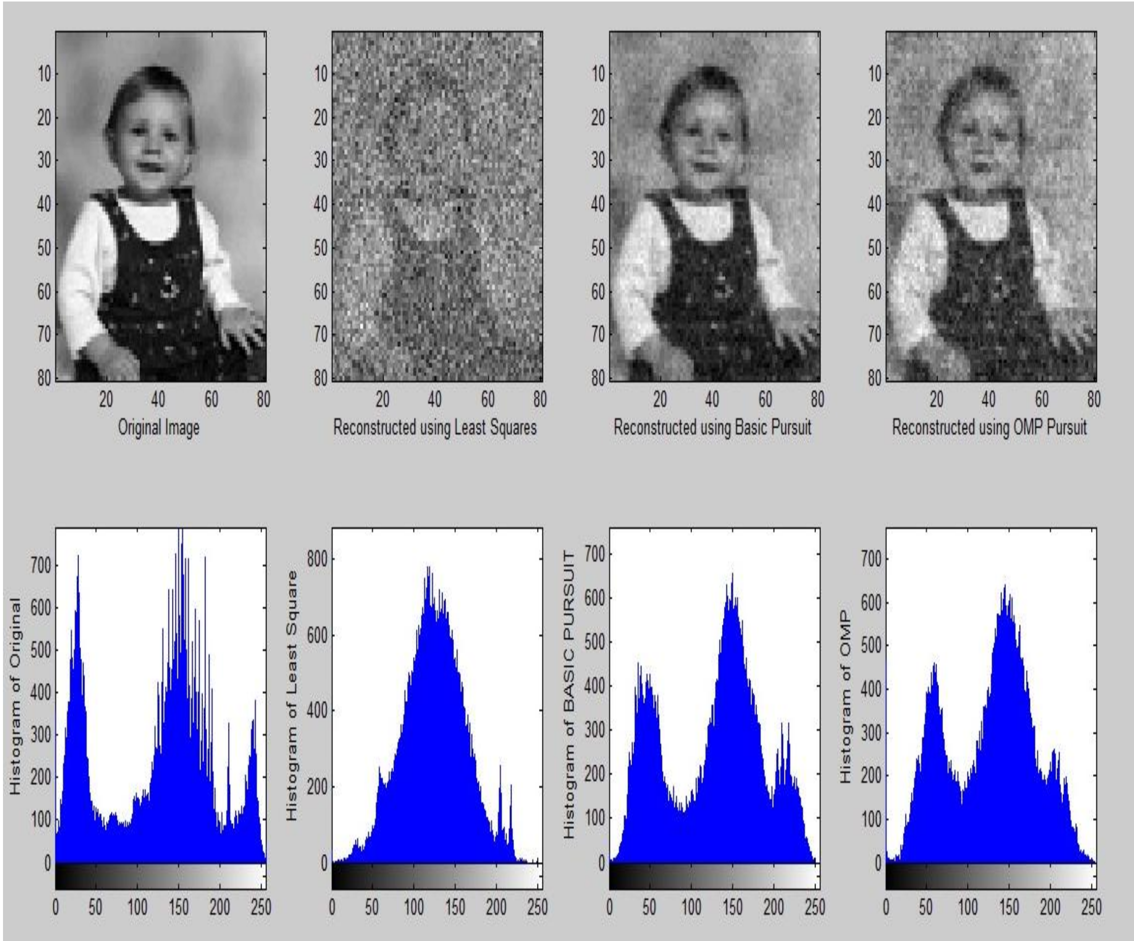

Figure 5.3(d): Reconstructed images and histograms for image sample grayscale using l_2, l_1 and OMP reconstruction techniques

Table 5.5(a): Image Quality Performance Parameters for CS applied on image sample- grayscale

Image sample	**Technique used**	**PSNR**	**MSE**	**SSIM**	**DSSIM**	**RMS**	**PRD**
Grayscale	L_1(BP)	26.967	130.713	0.775	0.112	11.433	8.121
	L_2(Least)	10.100	6.35e+03	0.159	0.421	79.715	72.646
	OMP	23.186	312.198	0.629	0.185	17.669	12.587

Table 5.5(b): Compression Performance Analysis for CS applied on image sample- grayscale

Image sample	CR	Space saving
Grayscale	6.415	84.412

On evaluating the different reconstruction techniques, it was analyzed that reconstruction l_1 gives better result than OMP and l_2 method as it gives near resemblance to the original image.

Peak signal to noise ratio is an important image quality parameter that gives the quality measure in terms of pixel value of the image. PSNR is calculated using mean square error (MSE) that is indicates the error value given by averaging the squared intensity of the original and recovered image or video pixels. Percentage root mean square difference gives the square root of MSE value in percentage terms. Higher is the quality lower will be the PRD value.

It was observed that PSNR for l_1 reconstruction method is best among all the three reconstruction methods and on the other hand, PRD for l_2 is more than that of l_1 and OMP technique. PSNR is highest for the image sample having maximum number of pixels and it also depends upon pixel intensity.

SSIM is based on statistical values of image attributes like luminance, brightness, texture, contrast and orientation. Its value lies between 0 and 1 and the reconstructed signal is structurally similar to the original signal if it approaches 1. It can be noted that SSIM value approaches to 1 for l_1 norm- minimization and OMP technique and its value is more close to 1 for l_1 (Basic pursuit) reconstruction method.

Compression ratio is calculated by taking the ratio of compressed bits to the original image bits.

A number of standard image samples are evaluated for three reconstruction techniques and list of those images along with their performance parameters is given in the following table 5.6(a) and 5.6(b).

Table 5.6(a): Performance Evaluation Parameters for different image samples

Image samples	Technique used	PSNR	MSE	SSIM	DSSIM	RMS	PRD
Baboon	L_1(BP)	22.634	354.497	0.627	0.186	18.828	14.851
	L_2(Least)	8.867	8.439e+03	0.089	0.455	91.869	99.482
	OMP	19.037	811.662	0.438	0.281	28.489	22.229
Cameraman	L_1(BP)	24.322	240.357	0.604	0.197	15.504	11.262
	L_2(Least)	9.257	7.715e+03	0.121	0.439	87.834	85.621
	OMP	20.694	554.127	0.458	0.271	23.539	17.195
Coast_guard	L_1(BP)	28.601	89.747	0.661	0.169	9.474	4.635
	L_2(Least)	5.357	1.894e+04	0.038	0.481	137.614	90.338
	OMP	25.207	196.041	0.485	0.257	14.002	6.847
Einstien	L_1(BP)	27.163	124.953	0.725	0.137	11.178	9.487
	L_2(Least)	10.452	5.859e+03	0.091	0.455	76.545	87.763
	OMP	23.256	307.268	0.523	0.238	17.529	14.793
Lena	L_1(BP)	26.203	155.866	0.825	0.087	12.485	10.445
	L_2(Least)	11.491	4.613e+03	0.217	0.392	67.917	73.624
	OMP	22.939	330.494	0.716	0.142	18.179	15.049
Yellow_flower	L_1(BP)	29.125	79.527	0.834	0.083	8.918	9.219
	L_2(Least)	13.734	2.752e+03	0.191	0.404	52.459	69.546
	OMP	25.226	195.173	0.687	0.156	13.970	14.112

Table 5.6(b): Compression Performance Analysis for different image samples

Image sample	CR	Space saving
Baboon	8.732	88.536
Cameraman	5.989	83.303
Coast_guard	8.241	87.865
Einstien	6.598	84.846
Lena	6.042	83.449
Yellow_flower	6.107	83.625

A comparative graphical analysis of PSNR, SSIM, PRD and CR of different reconstruction methods is done below for pictorial representation of the performance parameters is shown in figure 5.4(a) to 5.4(f).

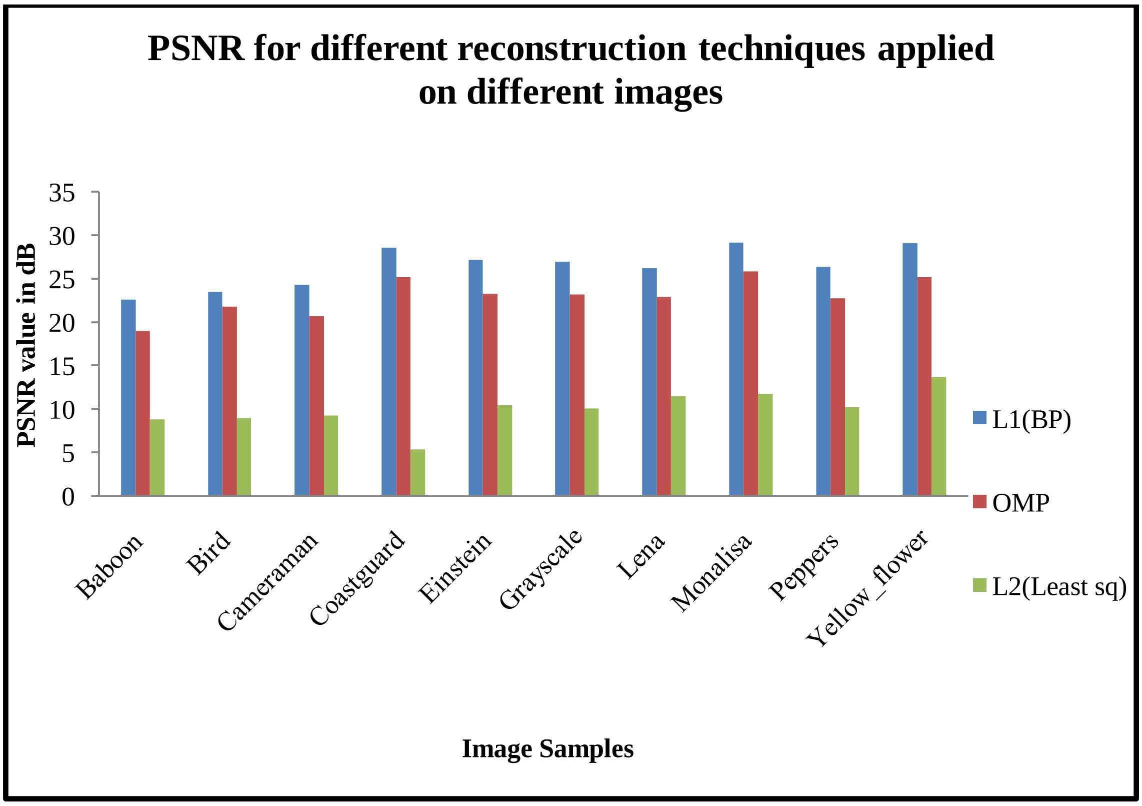

Figure 5.4(a): Peak signal to noise ratio for different image samples

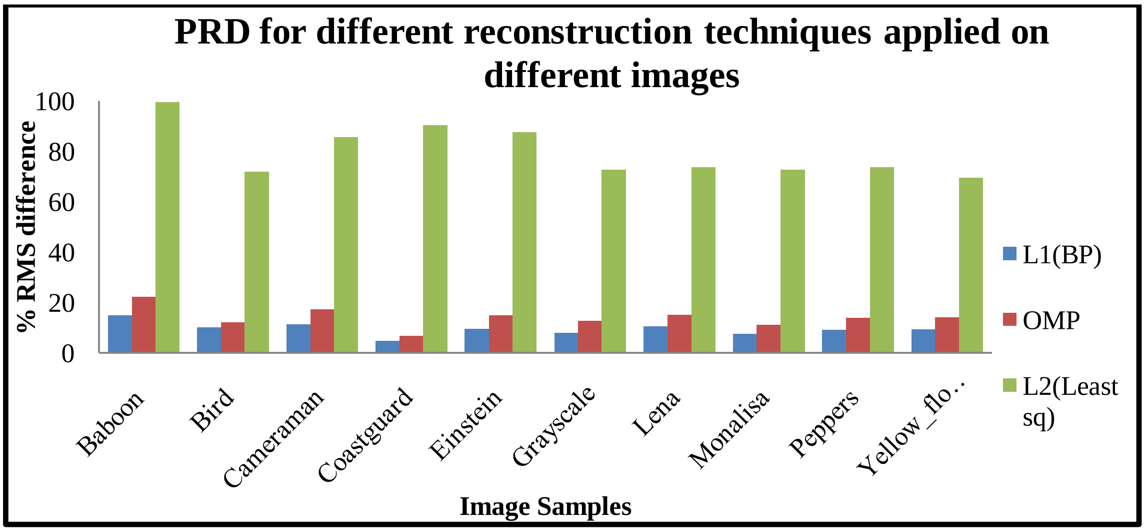

Figure 5.4(b): Percentage root mean square difference for different image samples

The comparison chart in figure 5.4(a) and 5.4(b) gives the clear vision of PSNR and PRD outcome for the simulations done on different sample images for three reconstruction techniques. Form figure 5.4(a) it is clear that PSNR is highest for l_1 than it is acceptable for OMP algorithm but for l_2 norm minimization it falls down to approximately half the value of l_1 norm minimization technique. PRD on the other hand is highest for l_2 norm minimization and then it reduces for OMP and minimum for basic pursuit (l_1) method. This is indicated in figure 5.4(b).

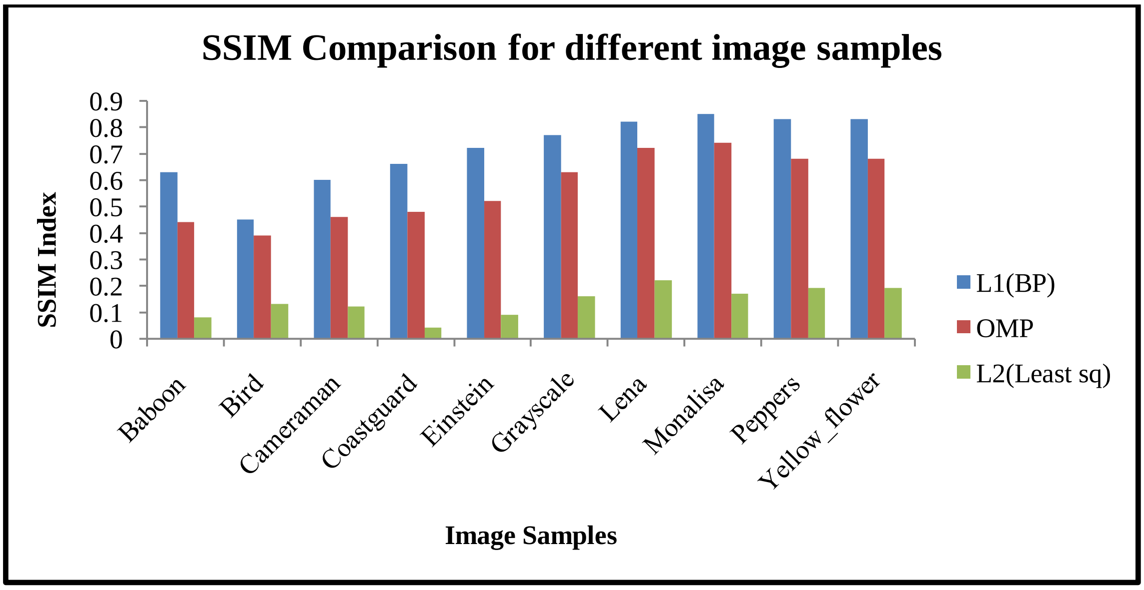

Figure 5.4(c): Structural similarity index for different image samples

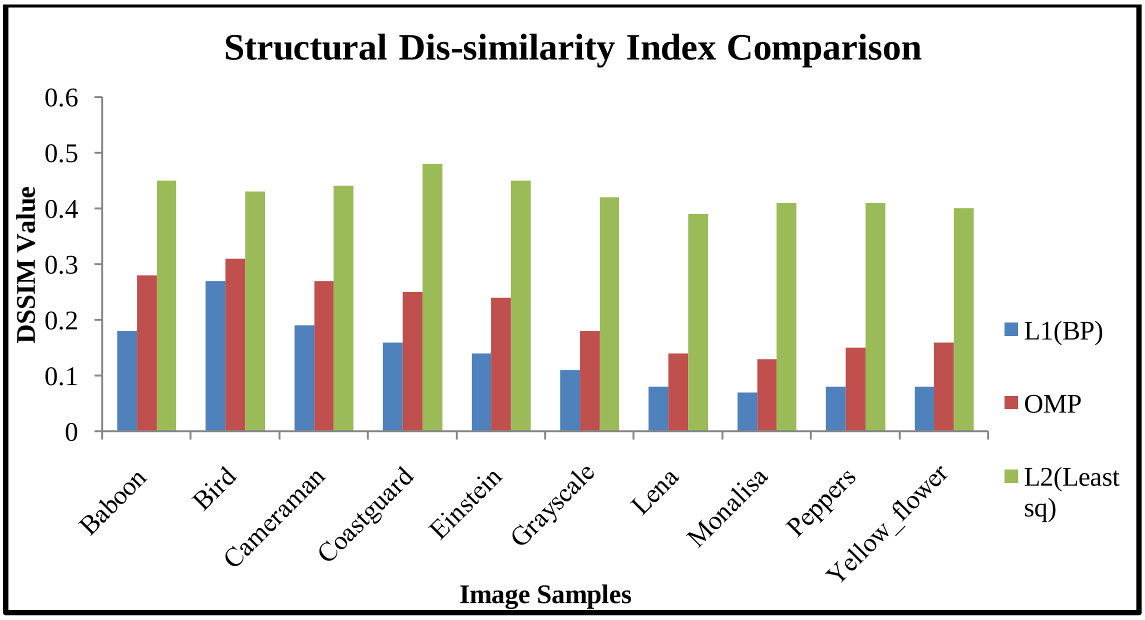

Figure 5.4(d): Structural Dis-similarity index for different image samples

The graphs in figure 5.4(c) and 5.4(d) gives the similarity and dissimilarity comparison of different images. The SSIM value can be seen in figure 5.4 (c), it is approaching to 1 for l_1 method and it falls towards 0 for the other two methods. DSSIM as depicted in figure 5.4(d) is highest for l_2 method and least for l_1 norm minimization method.

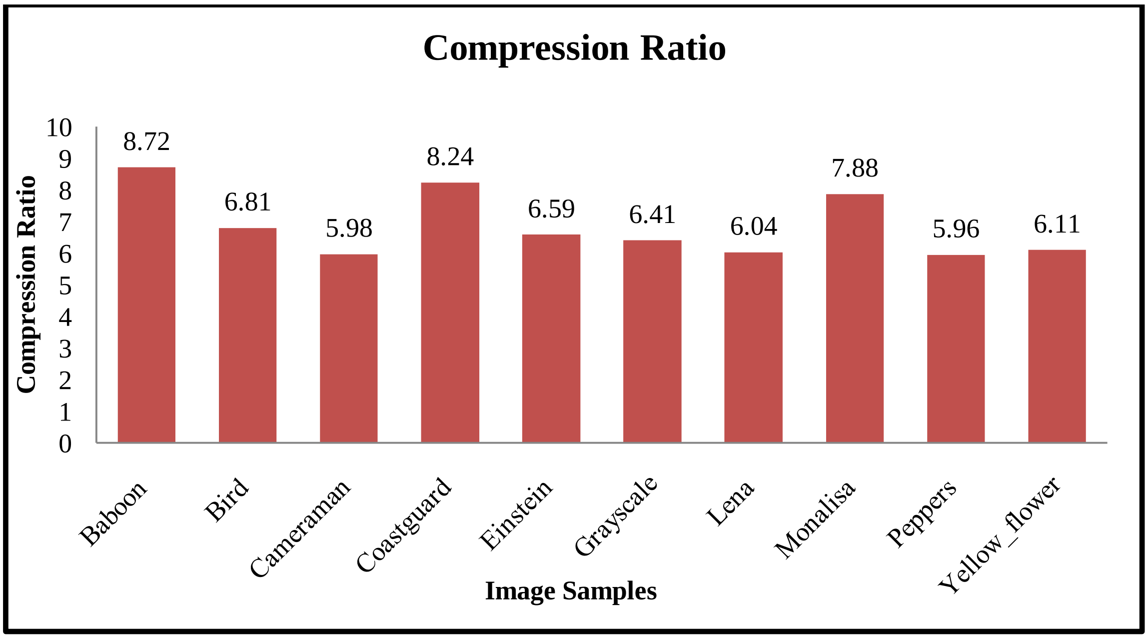

Figure 5.4(e): Compression Ratio for different image samples

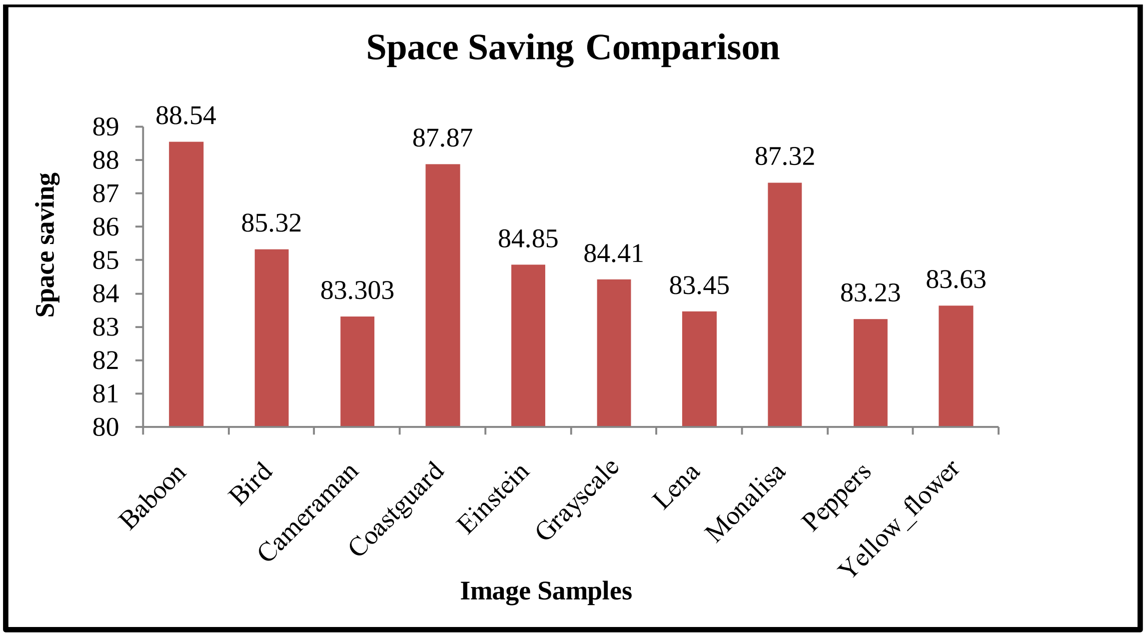

Figure 5.4(f): Space Saving analysis for different image samples

The bar chart in figure 5.4(e) gives the compression ratio of different image samples computed at the encoder side and depending upon the number of bits in the original and the compressed bits its value varies for different image samples. Also space saving comparison is shown in figure 5.4(f) and it shows that the maximum compressed image saves maximum of the space used to store that particular image.

It should also be noted that all these performance parameters are evaluated for original N dimensional signal x for N = 6400 and the samples taken M = 4000. As the number of samples decreased recovered image quality reduces and so does the value of image quality performance parameters like PSNR and SSIM whereas it does not affect the parameters like CR and Space saving as they are calculated at the encoder side.

This is evident from figures 5.5(a) and 5.5(b) that the image quality increases as the samples are increased and the graphical representation of increasing PSNR, PRD and SSIM is depicted in figures 5.5(c), 5.5(d) and 5.5(e) and their values are tabulated in table 5.7 (a), 5.7 (b) and 5.7 (c).

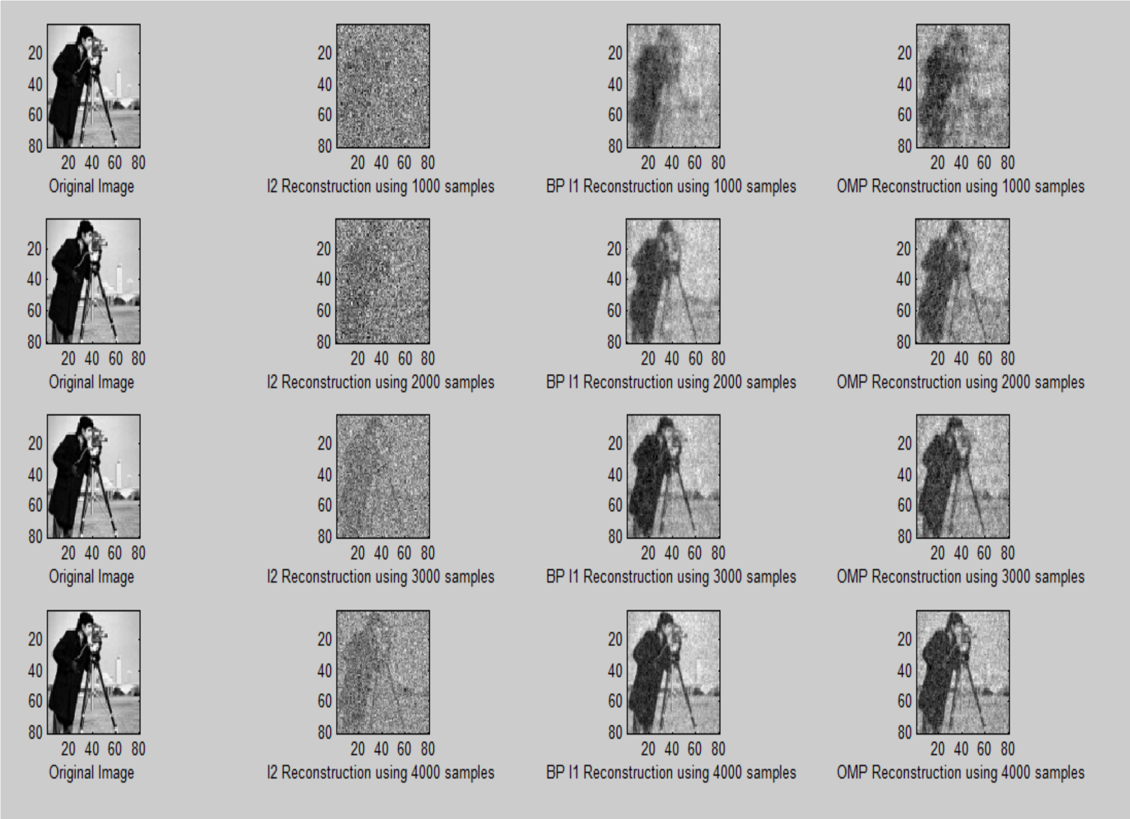

Figure 5.5(a): Reconstructed cameraman image for varying samples from 1000 to 4000

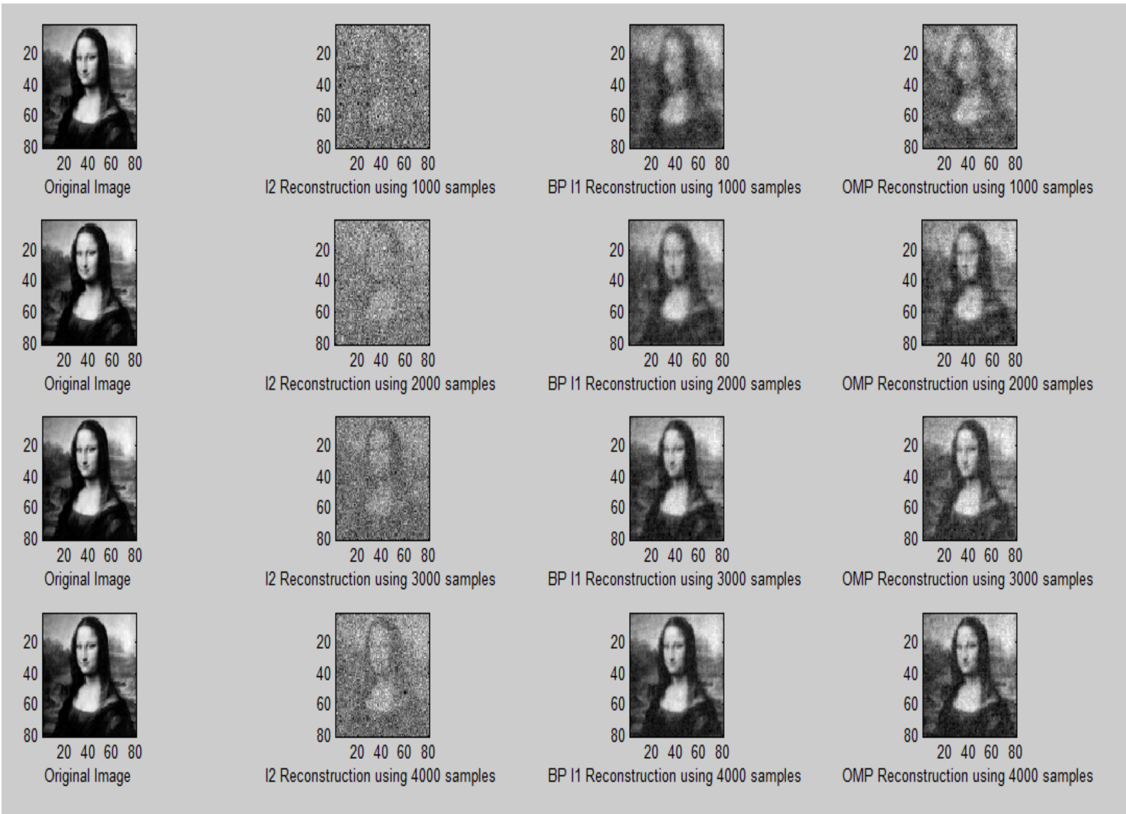

Figure 5.5(b): Reconstructed Monalisa image for varying samples from 1000 to 4000

Table 5.7(a): PSNR table for varying samples from 1000 to 4000: Monalisa image

Image sample	Techniques used	1000 samples	2000 samples	3000 samples	4000 samples
Monalisa	BP (l_1)	13.85	16.36	22.04	29.19
	OMP	10.89	14.29	19.89	25.89
	l_2 (least sq)	5.12	8	9.13	11.81

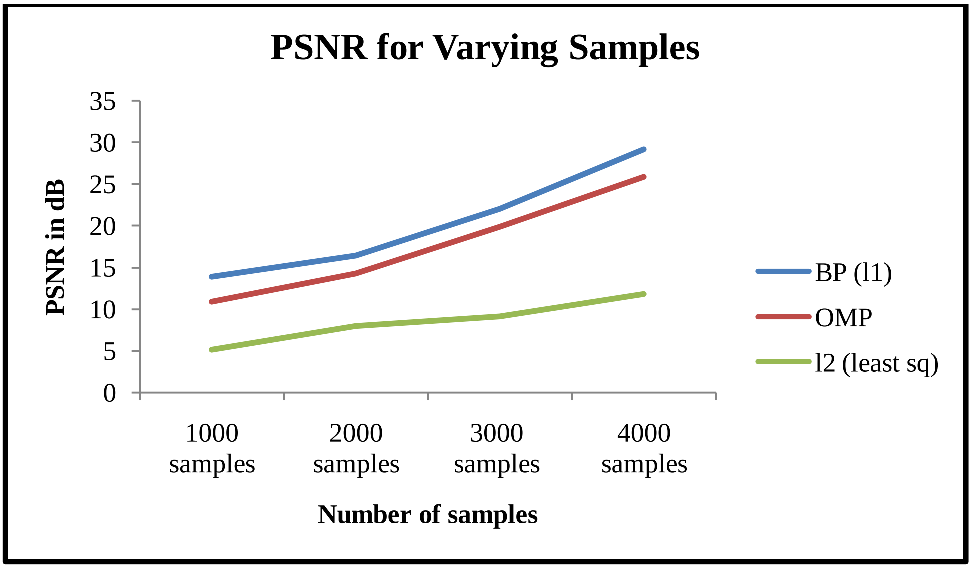

Figure 5.5(c): PSNR comparison for varying samples from 1000 to 4000: Monalisa image

From figure 5.5(c) is can be seen that PSNR value increases as the number of samples increases and maximum PSNR value is given by basic pursuit (l_1) norm minimization technique

Table 5.7(b): PRD table for varying samples from 1000 to 4000: Monalisa image

Image sample	Techniques used	1000 samples	2000 samples	3000 samples	4000 samples
Monalisa	BP (l_1)	20.287	17.25	12.017	7.565
	OMP	23.187	18.19	15.98	10.989
	l_2(least sq)	92.38	88.19	82.96	72.713

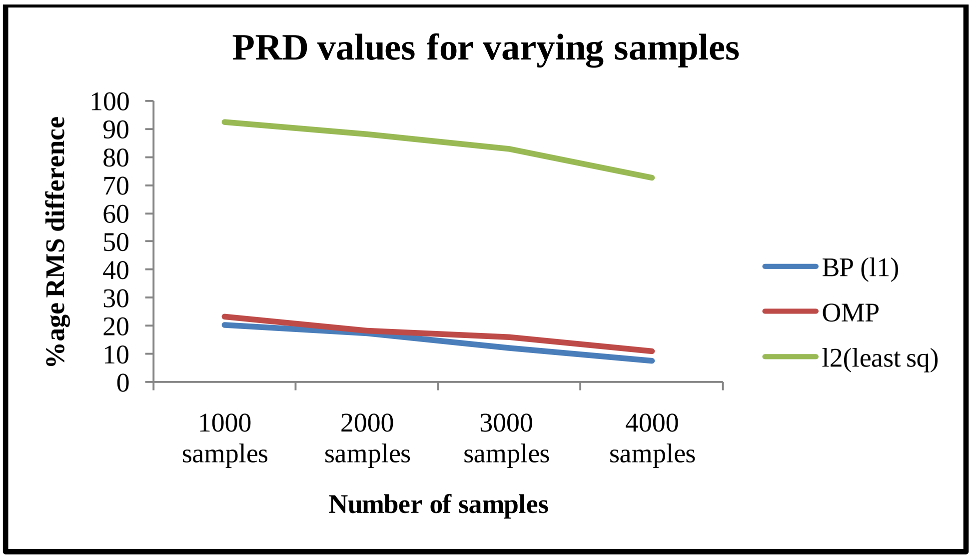

Figure 5.5(d): PRD comparison for varying samples from 1000 to 4000: Monalisa image

Table 5.7(c): SSIM table for varying samples from 1000 to 4000: Monalisa image

Image sample	**Techniques used**	**1000 samples**	**2000 samples**	**3000 samples**	**4000 samples**
Monalisa	BP (l_1)	0.467	0.512	0.678	0.854
	OMP	0.331	0.458	0.589	0.736
	l_2(least sq)	0.003	0.09	0.11	0.172

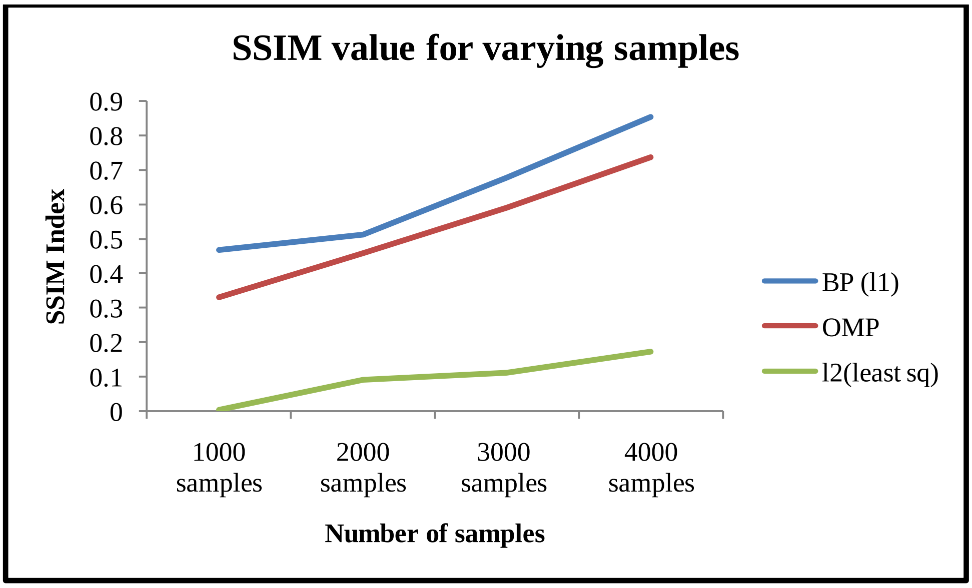

Figure 5.5(e): SSIM comparison for varying samples from 1000 to 4000: Monalisa image

From figure 5.5(d) it can be seen that PRD value reduces with increasing the number of samples. PRD value is minimum for 4000 samples taken for l_1 norm minimization method. Also from figure 5.5(e), SSIM approaches to 1 for 4000 samples using l_1 norm minimization reconstruction.

For all the three reconstruction methods, namely, l_2 norm minimization, basic pursuit (l_1) norm minimization and orthogonal matching pursuit, the reconstruction quality increases with the increase in the number of samples. The best recovery is possible for 4000 samples taken for basic pursuit (l_1) norm minimization technique.

5.3 Simulation result of CS applied on video

Our research paper also aims at applying CS on video signals. The simulation results for 21th to 25th frames of the video sequence are given in figures 5.6(a) to 5.6(e).

Figure 5.6(a): Simulation result for 21th frame when CS applied is on video

Figure 5.6(b): Simulation result for 22th frame when CS applied is on video

Figure 5.6(c): Simulation result for 23th frame when CS applied is on video

Figure 5.6(d): Simulation result for 24th frame when CS applied is on video

Figure 5.6(e): Simulation result for 25th frame when CS applied is on video

The original video has 145 frames but the time elapsed for applying the CS reconstruction algorithm on the entire video sequence is very large.

Thus to reduce the running time and to check the validity of the algorithm the output video signal is obtained for 1^{st} 25 frames of the original video having total 145 frames.

Time elapsed for each frame to be reconstructed is 2-3 minutes (approximately).

The input and output reconstructed 21^{th} to 25^{th} frames comparisons are done in figures 5.6(a) to 5.6(e) for compressive sensing applied on a sample video and the PSNR values are observed between 60 to 65 dB.

CHAPTER 6

CONCLUSION

The performance of compressed sensing is evaluated for a random signal, for different benchmark images and also for video signals. For CS recovery of a random signal, value of samples should be taken such that there is a tradeoff between the accurate recovery and sampling rate.

Various performance parameters are evaluated for different images and out of them, Basic pursuit *(l_1)* reconstruction method is proved superior to other implemented methods. It was analyzed that reconstruction l_1 gives better result than OMP and l_2 method as it gives near resemblance to the original image. Peak signal to noise ratio is an important image quality parameter that gives the quality measure in terms of pixel value of the image. PSNR depends upon pixel intensity and SSIM depends upon the human eye perception of similarity. Percentage root mean square difference gives the square root of MSE value in percentage terms. Higher is the quality lower will be the PRD value. PRD is minimum for BP (l_1) and PSNR is maximum for this method.

Trade off is maintained between the image quality and compression ratio. Compressed sensing is also applied on video signal and performance parameters are evaluated.

In this research work, after evaluating numerous performance parameters for different reconstruction algorithms, it was concluded that that PSNR for l_1 reconstruction method is best among all the three reconstruction methods. On the other hand, PRD for l_2 is more than that of l_1 and OMP technique. It was observed PSNR is highest for the image having maximum number of pixels and it also depends upon pixel intensity. Another performance evaluation parameter SSIM value also approaches to 1 for l_1 norm-minimization reconstruction method. Compression ratio is calculated by taking the ratio of compressed bits to the original image bits.

Thus a compressed sensing based system is considered that enables faster acquisition, compression and reconstruction as compared to traditional compression systems is obtained.

PUBLICATIONS

1. Charu Bhardwaj, Urvashi, Meenakshi Sood (2017), “Performance evaluation of compressive signal sensing” *Proceedings of the International Conference on Computing for Sustainable Global Development, BVICAM,* [4th: New Delhi: 1-3 March 2017], pp.6253-6257.
2. Charu Bhardwaj, Urvashi, Meenakshi Sood, “Implementation and Performance Assessment of Compressed Sensing for Images and Video Signal” *Communicated in Journal of Global Pharma Technology* (ISSN: 0975-8542).

(Under Review)

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