VISVESVARAYA TECHNOLOGICAL UNIVERSITY
Jnana Sangama, Belagavi - 590 018

MINI - PROJECT REPORT ON

Development of a Compressive Sensing Model for Data Compression and Reconstruction

Submitted in partial fulfillment for the Award of Degree of
Bachelor of Engineering
in
Electronics and Communication Engineering

Submitted by

Sumukha M	1RN18EC160
Aditya Venkata Sheshu	1RN18EC167
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Under the Guidance of
Sanjay M. Belgaonkar
Assistant Professor

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING
(Accredited by NBA for the Academic years 2018-19, 2019-20, 2020-21 and 2021-22)

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Channasandra, Dr.Vishnuvardhan Road, Bengaluru-560098.

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Acknowledgement

The joy and satisfaction that accompany the successful completion of any task would be incomplete without thanking those who made it possible. We consider ourselves proud to be a part of RNS Institute of Technology, the institution which moulded us in all our endeavors.
We express our gratitude to our beloved Chairman late **Dr.R N Shetty** and **MD Satish R Shetty** for providing state of art facilities.

We would like to express our sincere thanks to **Dr. M K Venkatesha**, Principal and **Dr. Vipula Singh**, Professor and HOD, Department of ECE, for their valuable guidance and encouragement throughout our program.

We express our profound gratitude to the coordinators who have given valuable suggestions and guidance throughout the project. We would like to express our sincere gratitude to our guide **Sanjay M Belgaonkar** & reviewer **Prakash Tunga P.**, Assistant Professors, Department of ECE, for their guidance, continuous support and motivation in completing the project successfully.

Finally, we take this opportunity to extend our earnest gratitude and respect to our parents, teaching and non-teaching staff of the department, the library staff and all our friends who have directly or indirectly supported us.

Sumukha M

Aditya Venkata Sheshu

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Yadunand G Kamath

Abstract

Our mini project is centred around the concept of Compressive Sensing (CS). CS is a recent advancement in signal processing. It is a sensing modality, which compresses the signal being acquired at the time of sensing. Engineers who have studied the Nyquist sampling theorem believe that a signal can be reconstructed only if it is sampled at the Nyquist rate. Due to several advantages over the conventional Nyquist sampling theorem, such as less memory storage and higher data transmission rate, CS is now one of the most active areas in research. The objective of our project is to implement the CS concept for data compression and reconstruction. We have implemented the concept through a MATLAB code and have developed a model on Simulink. Our model involves Data Acquisition followed by Reconstruction. Our project also involves performing compressive sensing and testing the reconstruction algorithm for various audio signals.

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Acronyms

CS : Compressive Sensing

CVX : Convex Optimization

PCB : Printed Circuit Board

FPGA : Field Programmable Gate Array

DSP : Digital Signal Processor

HDL : Hardware Descriptive Language

DCT : Discrete Cosine Transform

FFT : Fast Fourier Transform

DST : Discrete Sine Transform

MIMO : Multiple-Input Multiple-Output

BP : Basis Pursuit

SNR : Signal to Noise Ratio

MSE : Mean Squared Error

MAE : Mean Absolute Error

Chapter 1

Introduction

This chapter deals with the origin and fundamentals of CS along with its basic theory, pros and cons and applications. It also briefs about the objectives and motivation of this project.

1.1 History of Compressive Sensing

Engineers who have studied the Nyquist sampling theorem believe that a signal can be reconstructed only if it is sampled at the Nyquist rate. Due to several advantages over the conventional Nyquist sampling theorem [1], such as less memory storage and higher data transmission rate, Compressed Sensing, has emerged as an area that opens new perspectives in signal acquisition and processing. After the famous Shanon sampling theorem, introduction of compressive sensing (CS) is like a major breakthrough in signal processing community. CS was introduced by Donoho, Candès, Romberg, and Tao in 2004 [2]. It appears as an alternative to the traditional sampling theory, endeavoring to reduce the required number of samples for successful signal reconstruction. In practice, compressive sensing aims to provide saving in sensing resources, transmission, and storage capacities and to facilitate signal processing in the circumstances when certain data are unavailable.

1.2 Objectives

1. To develop CS – Acquisition model

    - Conversion of data into a single vector.
    - Defining random matrix.

2. To develop CS – Reconstruction model
   - Defining the reconstruction matrix.
   - Finalizing the CS reconstruction algorithm.

1.3 Motivation

The fundamental approach for signal reconstruction from its measurements is defined by the Shannon-Nyquist sampling theorem which states that the sampling rate needs to be at least twice the maximum signal frequency. In the discrete case, the number of measurements should be at least equal to the signal length in order to be exactly reconstructed. However, this approach may require large storage space, significant sensing time, heavy power consumption, and large number of sensors. Compressive sensing (CS) is a novel theory that goes beyond the traditional approach [1] It shows that a sparse signal can be reconstructed from much fewer incoherent measurements. The basic assumption in CS approach is that most of the signals in real applications have a concise representation in a certain transform domain where only few of them are significant, while the rest are zero or negligible. By using Compressive sensing which uses very less samples to reconstruct the sparse signal back which can overcome above mentioned problem statement.This can also save amount of data storage, time and improve the quality of reconstruction with lesser number of samples. The aim of CS is to achieve sensing and compression in a single step. This recovery is exact if signal being sensed has a low information rate (means it is sparse in original or some transform domain). Number of samples needed for exact recovery depends on particular reconstruction algorithm being used.CS handles noise gracefully and reconstruction error is minimal. It asserts that one can recover certain signals and images from far fewer samples or measurements than traditional methods use. Hence the purpose is to utilize this concept and this analogy of sparsity in order to perform efficient data processing.

1.4 Theory and Scope

Compressive sensing has a wide scope in many applications as described further. Its implementation for audio signals can be done using the methodologies briefly illustrated as follows:

Basic theory of CS presently consists of two components: Recoverability and stability. Recoverability addresses the central questions: what types of measurement matrices and recovery procedures ensure exact recovery of all k-sparse signals (those having exactly k-non zeros) and how many measurements are sufficient to guarantee such a recovery? [1].On the other hand, stability addresses the robustness issues in recovery when measurements are noisy and/or sparsity is inexact. There are a number of earlier works that have laid the groundwork for the existing CS theory, especially pioneering works by Donoho and his co-workers.

The two most important principles of CS theory are Sparsity and incoherence [1].

1. Sparsity, which expresses the idea that the information rate of a continuous time signal may be much smaller than suggested by its bandwidth, or that a discrete time signal depends on a number of degrees of freedom which is comparably much smaller than its (finite) length.

2. Incoherence, which extends the duality between time and frequency and expresses the idea that objects having a sparse representation in must be spread out in the domain in which they are acquired.

Features of compressive sensing are as follows:

1. Compresses the acquired signal at the time of sensing.

2. Allows sampling the signal at a rate much below the Nyquist sampling rate.

3. Can faithfully reconstruct original signal back from fewer compressive measurements. [2]

The reconstruction methodologies in CS were inferred from [6]. The reconstruction methodologies employed in this project are l1 norm minimization and basis pursuit which are illustrated below:

l1 norm minimization : L1-minimization refers to finding the minimum L1-norm solution to an under-determined linear system b=Ax. Under certain conditions as described in compressive sensing theory, the minimum L1-norm solution is also the sparsest solution [7]. This is centered around the concept of norm. L1 Norm is the sum of the magnitudes of the vectors in a space. It is the most natural way of measure distance between vectors, that is the sum of absolute difference of the components of the vectors. In this norm, all the components of the vector are weighted equally. Having, for example, the vector X = [3,4]:

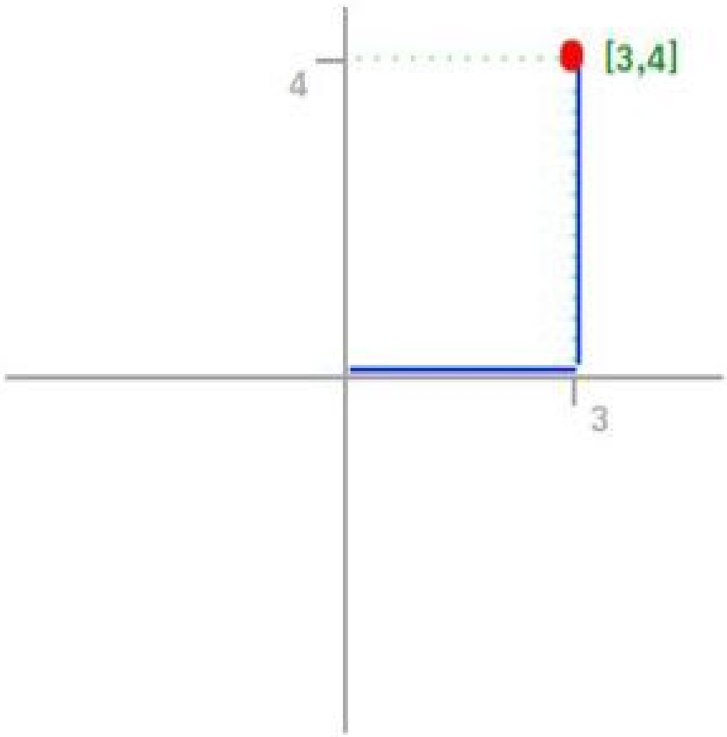

Figure 1.1: L1 Norm Example

As you can see in the graphic, the L1 norm is the distance you have to travel between the origin (0,0) to the destination (3,4), in a way that resembles how a taxicab drives between city blocks to arrive at its destination.

The l1 norm has been also employed through the the basis pursuit approach involves a similar analogy of regression and finding the solution to under-determined system of linear equations. Basis pursuit (BP) is a principle for decomposing a signal into an "optimal" superposition of dictionary elements. Basis pursuit is the mathematical optimization problem of the form:

$\min_x \|x\|_1 \quad subject - to \quad y = Ax, \min_x \|x\|_1 \quad subject - to \quad y = Ax,$

where x is a N × 1 solution vector (signal), y is a M × 1 vector of observations (measurements), A is a M × N transform matrix (usually measurement matrix).

It is usually applied in cases where there is an underetermined system of linear equations y = Ax that must be exactly satisfied, and the sparsest solution in the L1 sense is desired.

When it is desirable to trade off exact equality of Ax and y in exchange for a sparser x, basis pursuit is preferred. Basis pursuit is equivalent to linear programming.

1.5 Advantages and Disadvantages

Advantages of CS:

- The introduction of CS theory to the problem of designing an RF receiver indicates that the approach is indeed feasible, and that it will reduce the size,weight, and cost of the receiver. This comes at a cost of an increased noise figure and an increased amount of computation required.
- It permits the use of lower-rate, but higher performance ADCs, also introduction of CS can substantially improve the dynamic

range of a receiver system. It is also easy to change the sparsifying transform and select the one which gives the best results when compared.

- Number of data transmissions is reduced and also reduces energy consumption.
- Higher compression rates at lower bandwidth by exploiting spatial redundancies.

Disadvantages of CS:

- The overall transmission cost and distribution of the traffic load more evenly throughout the network using compressing sensing is high.
- Increased computational cost at encoder and also sensitive to propagation of reconstruction errors.
- Latency due to increase in iterative reconstruction process.

1.6 Applications

Compressive Sensing finds its applications [3] especially in the areas:

- **Biomedical applications** - Medical Imaging: CS is being actively pursued for medical imaging, particularly in Magnetic Resonance Imaging (MRI). MR images, like angiograms, have sparsity properties, in domains such as Fourier or wavelet basis. Generally, MRI is a costly and time consuming process because of its data collection process which is dependent upon physical and physiological constraints. However, the introduction of CS based techniques has improved the image quality through reduction in the number of collected measurements and by taking advantage of their implicit sparsity. MRI is an active area of research for CS community and in recent past, a number of CS algorithms have been specifically designed for it.

- **Communication systems** : The emerging solutions for future wireless communications will require very broad frequency bandwidth, hundreds or even thousands of antennas, and ultra-densely deployed base stations to support a plethora of wireless activities. These unconventional requirements inevitably put an overweight burden on current signal processing techniques based on Nyquist's sampling, e.g. prohibitively large overheads, unaffordable complexity, and high resource consumption. Fortunately, the advanced compressive sensing (CS) techniques offer a sub-Nyquist sampling approach in the future large-scale communication systems. Having its promising features, CS has attracted significant interest from both industry and academia, and its applications to practical wireless communications systems are anticipating.

  In an early version, CS is regarded as a branch of algorithms to reconstruct the sparse signals of an underdetermined linear system in a computationally efficient manner. This version of CS is widely considered in channel estimation for massive multiple-input multiple-output (MIMO) systems, active user detection (AUD) for massive Internet of Things (IoT) networks, non-orthogonal multiple access (NOMA), where the inherent sparsity in all aspects of wireless networks is harnessed. Further, the concept of Bayesian CS (BCS) is proposed and developed. The algorithms based on BCS, like sparse Bayesian learning and approximate message passing, infers the sparse signal from the Bayesian viewpoint by considering sophisticated a priori. BCS is not limited to the conventional linear model. Thus, it is suitable for solving challenging non-linear problems in communication systems, such as CE and data detection with low-precision analog-to-digital converters (ADCs). As recent research progress, a new version of CS with a bilinear property has emerged. The bilinear CS is dedicated to solving the CS problem when there exists uncertainty for both the measurement matrices and sparse signals. The applications of bilinear CS to wireless communications are reported in the cascaded CE for reconfigurable intelligent surface (RIS)-based MIMO systems, joint AUD and CE, and so on.

- **Computer Vision and Image Processing** : Imaging and computer vision have been two extensively researched areas which have directly or indirectly contributed to the technological advancement in visual computing. Image representation, recognition, modeling, enhancement, restoration, analysis and reconstruction from projections have been few of the areas which have been looked at in a different way after the introduction of Compressive Sensing. With the plethora of data available, it is very important to choose which datum to pick from the vast set of data. Recently developed compressed sensing provides direction in selecting the most important data. The challenging task of computer vision has been and will be to develop systems which mimic, represent and analyze the behavior charaterized by human beings.The systems which aim at understanding and representing such behavior should have highly accurate sensing and acquisition capabilities. This must be followed by certain pre-processing for input data formatting, actual methodology of feature formation and analysis, followed by post-processing such as enhancement and restoration. The following steps outline some of the steps involved in a typical computer vision system.

1.7 Tasks Performed

The following indicates the work done in our model based implementation related to compressive sensing of audio:

- Development of CS-Acquisition model
- Development CS – Reconstruction model
- Code Generation in MATLAB using C language and HDL programming

1.8 Organisation of Report

- **Chapter 1 :** The overview of compressive sensing and introduction is discussed in chapter 1 helps in understanding general idea about CS.

- **Chapter 2:** It deals with literature survey which was carried on to understand various concepts and research's which are presently being carried on.

- **Chapter 4 :** Here we define the project design and development with various concepts and methodologies of compressive sensing and optimization techniques.

- **Chapter 3:** Problem definition is explained, planning and Scheduling the project is presented with the Gantt chart, software and hardware requirements are listed with the figure, block diagrams of the conceptual model.

- **Chapter 5:** This chapter deals with different approaches, coding details,code efficiency, testing approach, modifications and improvements.

- **Chapter 6:** The results and outcomes are analyzed with the output plots of the signals.

- **Chapter 7:** Conclusion and future scope are discussed

Chapter 2

Literature survey

The following references were made while understanding and utilizing the concept of CS in our project.

Article[1]: Emmanuel J. Candes and Michael B. Wakin:"An Introduction to Compressive Sampling"- This article surveys the theory of compressive sampling, also known as compressed sensing or CS, a novel sensing/sampling paradigm that goes against the common wisdom in data acquisition. CS theory asserts that one can recover certain signals and images from far fewer samples or measurements than traditional methods use. To make this possible, CS relies on two principles: sparsity, which pertains to the signals of interest, and incoherence, which pertains to the sensing modality.

- Sparsity expresses the idea that the "information rate" of a continuous time signal may be much smaller than suggested by its bandwidth, or that a discrete-time signal depends on a number of degrees of freedom which is comparably much smaller than its (finite) length. More precisely, CS exploits the fact that many natural signals are sparse or compressible in the sense that they have concise representations when expressed in the proper basis psi.

- Incoherence extends the duality between time and frequency and expresses the idea that objects having a sparse representation in psi must be spread out in the domain in which they are acquired, just as a Dirac or a spike in the time domain is spread out in the frequency domain. Put differently, incoherence says that unlike the signal of interest, the sampling/sensing waveforms have an extremely dense representation in psi.

Article[2] : Meenu Rani, S. B. Dhok, And R. B. Deshmukh, "A systematicReview of Compressive sensing: Concepts, Implementations andApplications"- After the famous Shanon sampling theorem, introduction of compressive sensing (CS) is like a major breakthrough in signal processing community. CS was introduced by Donoho, Candès, Romberg, and Tao in 2004. Sparsity is the inherent property of those signals for which, whole of the information contained in the signal can be represented only with the help of few significant components, as compared to the total length of the signal. Acquisition of sparse signals using traditional methods requires: i) sampling using Nyquist-criterion, which results in too many samples compared to the actual information contents of the signal, ii) compressing the signal by computing necessary transform coefficients for all the samples, retaining only larger coefficients and discarding the smaller ones for storage/transmission purposes. Another limitation of sampling using Nyquist-rate is that the rate at which sampling has to be done, may not be practical always.

CS finds its applications especially in the areas i) where, number of sensors are limited due to high cost, e.g., non-visible wavelengths, ii) where, taking measurements is too expensive, e.g., high speed A/D converters, imaging via neutron scattering, iii) where, sensing is time consuming, e.g., medical imaging, iv) where, sensing is power constrained, etc.

Article[3]: Mohammed M. Abo-Zahhad1, Aziza I. Hussein2, Abdelfatah M.Mohamed, "Compressive Sensing Algorithms for Signal Process-ing Applications: A Survey" - This article illustrated the properties of CS , introducing the concept of incoherence and also various transformation matrices that can be employed for compressive sensing. Various Signal reconstruction algorithms were also reffered and step wise problem formulation of CS was taken into picture described in this article. Sensing matrices - Random and deterministic was also inferred.

Article[4]: S.E. Pinto, L.E. Mendoza, E.G. Florez, "Compressive sensing in FPGA and microcontroller" - This paper show the hardware implementation of the technique known as Compressive Sensing (CS). CS work develops in a sparse space (dense few). We used to obtain sparse signals Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT), and Discrete Wavelet Transform (DWT). We demostred that speech, electromyography and electrocardiogram signals can be reconstructed from few samples (projection). These projections were physically transmitted to a computer for reconstruction using L1 magic and demostrate that CS projections obtained were correct. The implementation CS showed relevant results, increase in speed and developing new communications. The implementation was performed in a Field Programmable Gate Array (FPGA) SPARTAN 3E and 18F4550 microcontroller. The results showed that is possible the reconstruct signals, breaking Shannon and Nyquist's theory.

Article[5]: Dr. Amit M. Joshi, Dr. Chitrakant Sahu, Dr.M Ravikumar, Dr.Samar Ansari,"Hardware Implementation of Compressive Sensingfor Image Compression"-basis matrices and thier properties were reffered from this article. The different basis matrices and sensing matrices are considered which satisfy the Restricted Isometric Property (RIP) and Independent and Identically Distributed (IID). The hardware implementation of CS is covered to have real-time compression for various image-based applications. The performance is observed regarding SNR, compression ratio, and correlation. The reconstruction algorithms are implemented on MATLAB platform. The obtained results show satisfactory performance for CS based image compression.

Article[6]: Irena Orovi C, Vladan Papi C, Cornel Ioana, Xiumei Li, and Srd-jan Stankovi c,"Algorithms for Compressive Sensing Signal Reconstruction with Applications"- This paper gave us an idea of the reconstruction algorithms and the process of reconstruction utilized in compressive sensing .The l1-minimization problems in CS signal reconstruction are usually solved using the convex optimization methods. In addition, there exist greedy methods for sparse signal recovery which allow faster computation compared to L1-minimization. Greedy algorithms can be divided into two major groups: greedy pursuit methods and thresholding-based methods. In practical applications, the widely used ones are the orthogonal matching pursuit (OMP) and compressive sampling matching pursuit (CoSaMP) from the group of greedy pursuit methods, while from the thresholding group the iterative hard thresholding (IHT) is commonly used due to its simplicity, although it may not be always efficient in providing an exact solution. Some of these algorithms are discussed in detail in this section. further reconstructon algorithms such as matching pursuit and orthogonal matching pursuit was inferred

Book[7]:Steve L Brunton , J Nathan Kutz -Data Driven-Science and Engineering - The book by Steve Brunton and Nathan Kutz was helpful in giving us some MATLAB and Python based illustrations of compressive sensing along with various data processing applications and signal processing concepts.

Chapter 3

CS - Requirements and Preliminaries

This chapter encapsulates the basic preliminaries which the concept of CS is all about with respect to our project , and illustrates the requirements taken into account in employing it.

3.1 Problem Definition

Communications and signal processing systems are considered efficient and promising if it uses the least number of resources to obtain the best results.

- The fundamental approach for signal reconstruction from its measurements is defined by the Shannon-Nyquist sampling theorem which states that the sampling rate needs to be at least twice the maximum signal frequency. In the discrete case, the number of measurements should be at least equal to the signal length in order to be exactly reconstructed.[2]
- However, this approach may require large storage space, significant sensing time, heavy power consumption, and large number of sensors.
- Compressive sensing (CS) is a novel theory that goes beyond the traditional approach. It shows that a sparse signal can be reconstructed from much fewer incoherent measurements [1]. The basic assumption in CS approach is that most of the signals in real applications have a concise representation in a certain transform domain

where only few of them are significant, while the rest are zero or negligible.

- This process can save both memory and time and is proven to be much more efficient than the well-established Nyquist Sampling Theorem.

Fig 3.1 illustrates the analogy of CS with traditional Nyquist sampling depicted as a framework

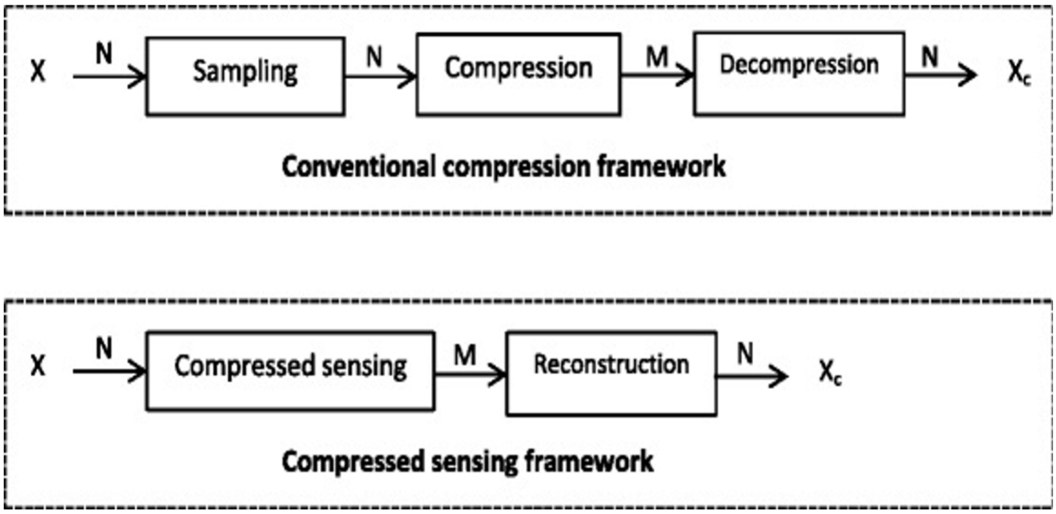

Figure 3.1: CS Framework

Summarizing the problem intended to be tackled by this project, it is to do away with the drawbacks of the traditional approach by introducing CS and utilizing it in developing a model for data compression and reconstruction .

3.2 Planning and Scheduling

Figure 3.2: Gantt chart of project schedule

- submitted our Synopsis on 7-May-2021
- submitted our Progress Report 1 on 29-May-2021
- submitted our Progress Report 1 on 9-June-2021
- submitted our Phase 1 Presentation on 16-June-2021
- submitted our Phase 2 Presentation and Final Report on 13-Aug-2021

3.3 Software and Hardware Requirements

SOFTWARE AND HARDWARE DETAILS:

- 8/16 GB – RAM LAPTOP
- MATLAB – Simulink (2018 onwards), Inclusive of MATLAB Code Converter toolbox and Signal Processing toolbox
- Code Composer (CC) Studio

- FPGA/DS Processor

SPECIFICATIONS:

- Floating-Point DS Processor: TMS3206713 (Texas Instruments)
- FPGA: Spartan 6 - XC6SLX9, Package-TQG144

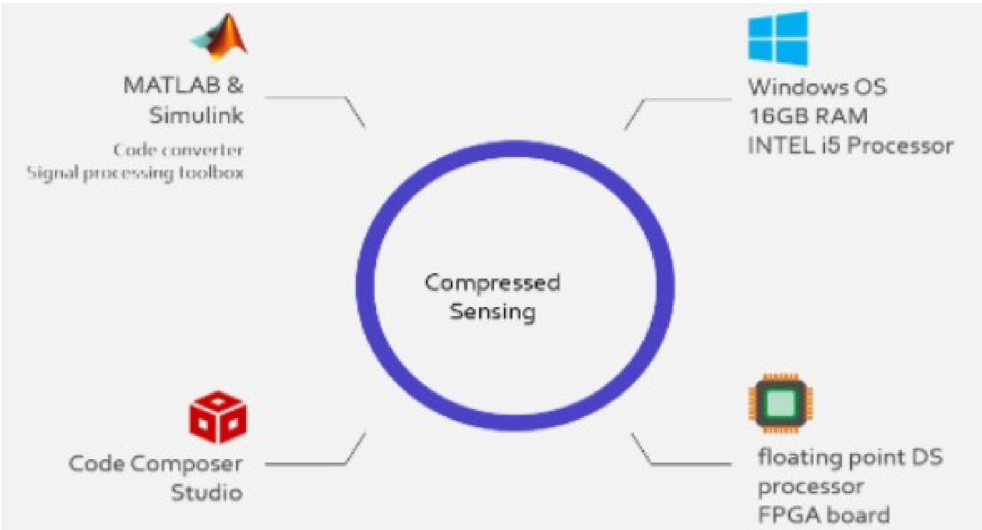

Figure 3.3: Software and Hardware Requirements

3.4 Working

The notion of compressive sensing and its working can be illustrated as follows

First, we have the equation y equals psi times x. Represented pictorially in the matrix form, y is the vector form of the input signal that contains the data of the sampled input. The matrix psi represents the basis matrix which can be either a DCT, DWT etc depending on the input, and x is the sparse representation of input. A sparse representation means that it is the vector having very few non zero elements. This equation depicts that When an input signal is transformed in a suitable basis we obtain its sparse representation that is the transformed input. So we choose a basis in which the coefficients are sparse and this equation therefore tells us that there exists a basis in which the signal is compressible. We would be getting back to this equation as it's involved further.

The equation b equals phi times y is where compressed sensing essentially comes into the picture. This tells us how we can massively down-sample the signal governed by making a sampling or a sensing matrix. Therefore we are sensing only the required samples and hence the term compressed sensing. Representing in its matrix form phi is the sensing matrix which we design suitably in order to sense a very few samples in y and give it to the vector b. Hence this equation tells us the actual points to sample the signal, and b is the vector of compressive measurements.

In the next equation, using equation 1, substituting for y, we can rewrite it in the form of Ax = b, as shown, where A equals phi times psi. This is where the reconstruction of the signal comes into picture .

Since we know that the signal can be represented sparsely and we also have the compressive measurements. We solve for x in equation 3 To recover the sparse vector x. This is termed as sparse signal recovery. Knowing this vector we can use equation one, i.e. y equals psi into x, to obtain the original signal back.

The Figures 3.4 and 3.5 depict the matrices involved in computing the equations.

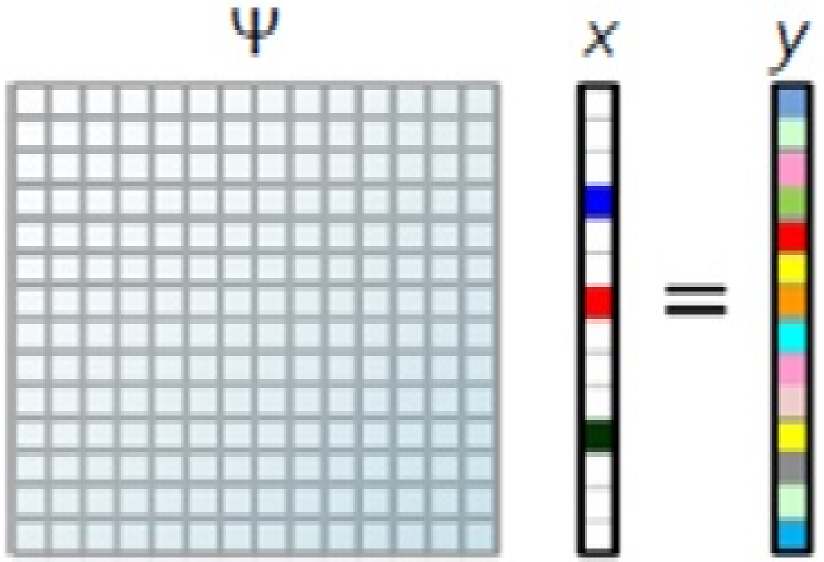

Figure 3.4: Transformation of a given signal in a suitable basis.

The Figure 3.4 shows that a signal can be transformed in a given basis back and fourth. when a suitable transformation/basis matrix is applied to a signal vector, we obtain its sparse representation (vector with very few non zero elements)

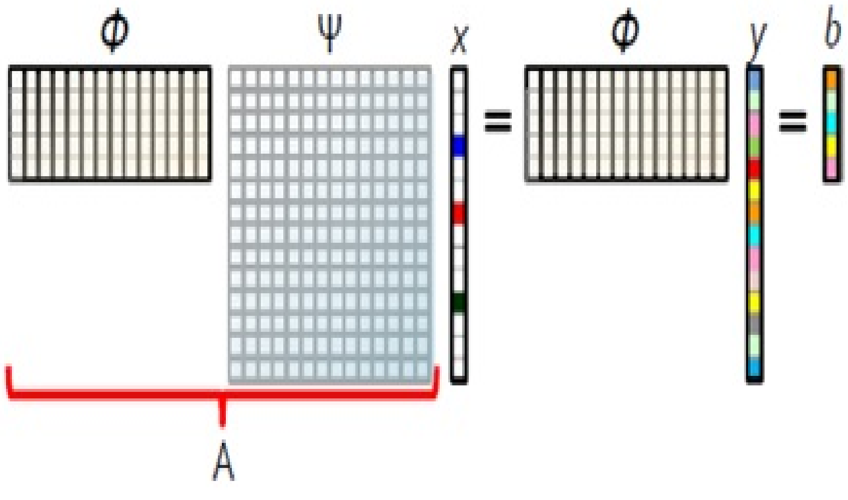

Figure 3.5: computation of sparse signal recovery

Upon substitution, as mentioned earlier we equate the compressed measurements and then utilize it to reconstruct the original signal when the suitable inverse transformation is applied.

Chapter 4

Compressive Sensing Model

The main objective of our project is to develop a compressive sensing model for data compression and reconstruction. The implementation of models comes into picture in this chapter. The problem pertaining to the concept of CS involves two key steps in handling the data. The Data Acquisition followed by Data Reconstruction. To implement this, the entire system is divided into two major modules.

4.1 Model 1: Data Acquisition

The Data Acquisition Model - To begin with, we first need to acquire our data samples from the signal. For this, we have designed the Data Acquisition model. This model is based on how the samples are acquired at a sub nyquist rate in order to successfully reconstruct the signal. It involves the formulation of a matrix that represents the original signal vector as its data points multiplied by a matrix i.e the sensing matrix which would sample these points producing a very few, compressed measurements.

Describing the design as a high level illustration, the steps used to organise, manage and manipulate data in order to achieve compressive sensing are as follows:

1. The input audio signals are stored in files of '.wav' format.
2. We have selected audio signals of different durations.
3. To obtain the data samples, the file is read in MATLAB using existing in-built functions.

4. After obtaining data samples, required operations are performed to manipulate the data.

5. All operation results are stored in the MATLAB vector variables for further use.

6. The size and values of all data can be accessed from the MATLAB workspace

7. The result variables are finally mapped to our Simulink model

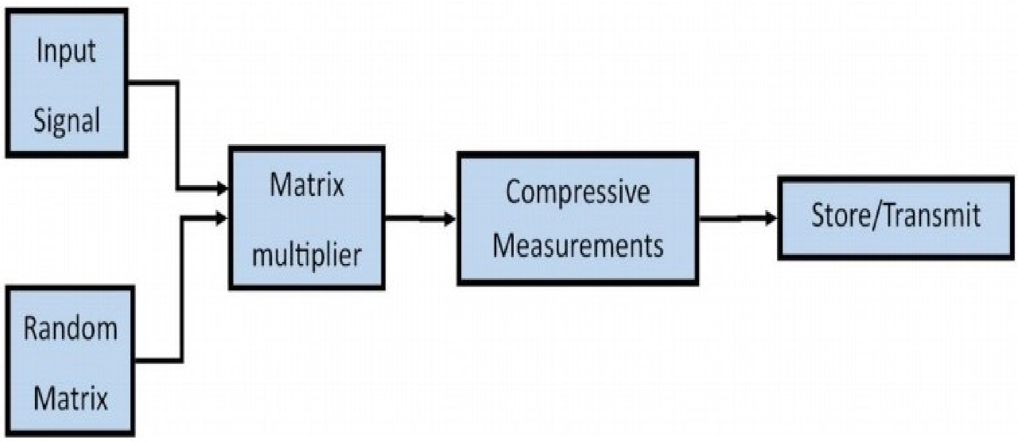

Figure 4.1: Data Acquisition Model

Fig 4.1 illustrates this process, that yields a matrix of compressive measurements indicating the points to efficiently down-sample the signal in order for its successive reconstruction and hence compressive sensing to work.

The **sensing matrix** is developed by using a random approach to sense a very few points of the sampled input signal, to produce a vector of compressive measurements indicating the specific points where to sample the signal for this compressive, sub nyquist approach. Fig 4.2 depicts the same. As mentioned in chapter 2, the sensing matrix can be incorporated and mathematically computed using either the deterministic or the random approach.the deterministic approach involves the computation of the matrix that follows a certain mathematical criteria. The sensing matrix computation also depends on the nature of the system of linear equations (underdetermined or overdetermined) In this case of compressive sensing the equations follow an undetermined system . and In this project we incorporate the random approach for generating a sensing matrix using the randi function in MATLAB.

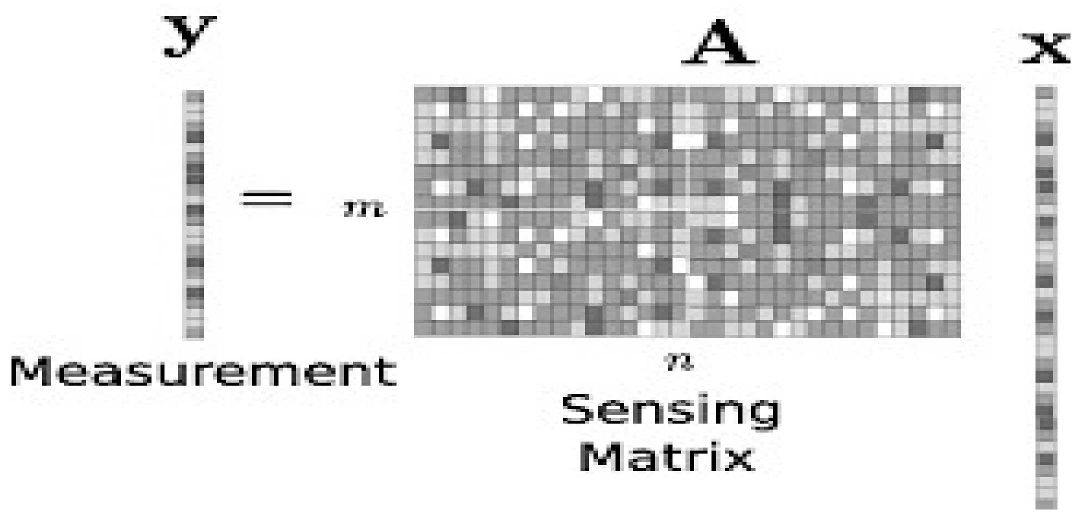

Figure 4.2: The sensing matrix senses the few measurements using a random or deterministic approach

4.2 Model 2: Data Reconstruction

The reconstruction model follows the data acquisition where in the obtained down-sampled measurements are used to reconstruct the original signal by employing the reconstruction matrix. For this we have used L1-norm and Basis Pursuit which are a few reconstruction methodologies. L1- norm is employed by coding in MATLAB as a user defined function, as well as incorporating the Convex Optimisation software in MATLAB, which finds the optimal solution of the under-determined linear equation (Ax = b), thereby giving us the reconstructed signal. Finally, the results obtained using the different approaches and different algorithms are compared.

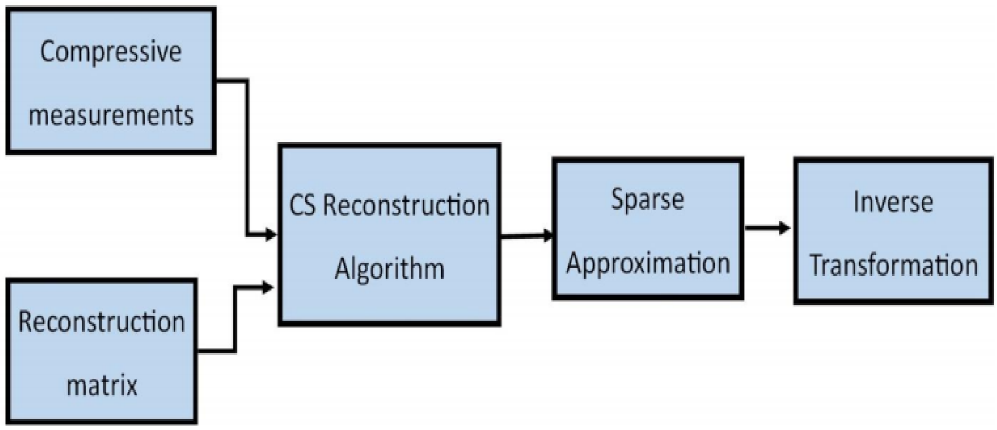

Figure 4.3: Data Reconstruction Model

In this manner , as depicted in fig 4.3 the data is subjected to the implementation of compressive sampling and recovered

4.3 Algorithm for Model Development

4.3.1 Data Acquisition Algorithm

Fig 4.4 illustrates the steps in the algorithm for data acquisition

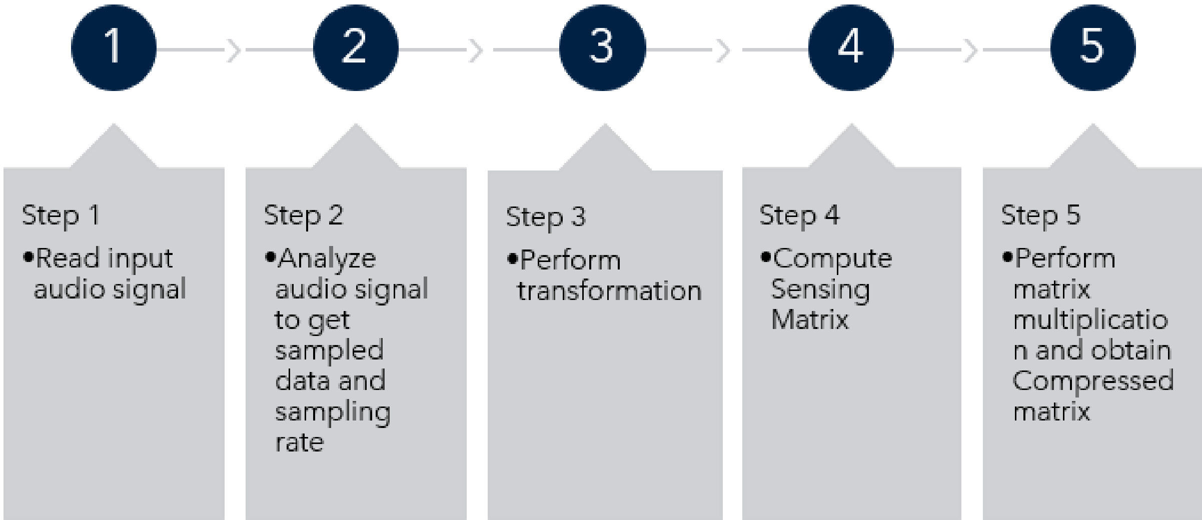

Figure 4.4: Data acquisition Algorithm

- In step 1, we are reading an input signal (it can be image,video,audio). In this project it is audio signals of different durations,using inbuilt function audioread().
- In step 2, we sample the read audio at a given rate in order to get its data representation of samples, stored as a vector in MATLAB
- In step 3, we perform transformation techniques (dct,dst,fft).
- In step 4, we compute sensing matrix using random approach.
- Ultimately, in step 5, we perform matrix multiplication and obtain the compressed matrix, these data sets are used for the reconstruction process.

This comprises the data acquisition part of compressive sensing where a set of compressive measurements are obtained indicating the down-sampled points of data measurements that can be done to satisfy CS

4.3.2 Reconstruction Algorithm

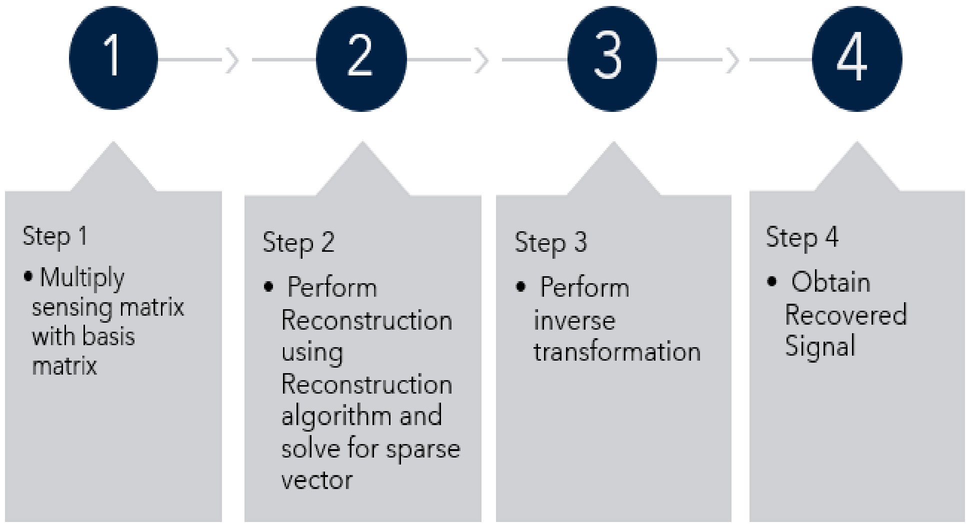

Figure 4.5: Data Reconstruction Algorithm

- In step 1, we multiply sensing matrix with basis matrix
- Instep 2, we perform reconstruction using reconstruction algorithms like L1 norm, Basis pursuit , and solve for sparse vector.
- In step 3, we perform inverse transformation using techniques like idct, idst, ifft.
- Finally,In step 4, We obtain the recovered signal.

Fig 4.5 summarizes the reconstruction part , where the signal is reconstructed from its downsampled measurements using certain reconstruction methodologies incorporated as the reconstruction matrix Above two algorithms (**Data acquisition and Reconstruciton**) shows the steps to obtain the samples, process it and reconstruct it.

4.4 Flowchart of working model

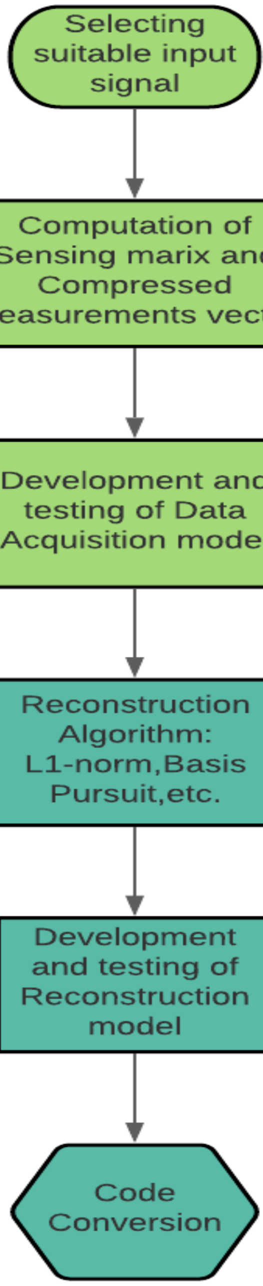

Figure 4.6: Flowchart representing both CS models

The entire project can be summarized in simple steps as illustrated in Fig 4.6. The light-green shaded blocks depict the data acquisition part of CS, whereas teal-blue shaded blocks depict the data reconstruction process of CS.

Chapter 5

Methodology

The methodologies succcesfully incorporated for the computation of various steps in Compressive sensing of audio signal are illustrated in this chapter along with the brief details of code results

5.1 Approaches

- First, the code for Data Acquisition is designed. Some of the parameters kept in mind while designing this are-
  - Input audio signal of suitable file format
  - Number of data samples
  - Sampling rate
  - Computation of Random matrix
  - Obtaining the Compressed measurements vector
  - Recording the Compression ratio
- Then, the Data Acquisition model is designed in SIMULINK.
- Next, the code for Data Reconstruction is developed. Some of the parameters kept in mind while designing this are-
  - Using reconstruction methodologies like L1-norm, Basis pursuit to successfully perform sparse signal recovery
  - Performing suitable inverse transformation to recover the signal
  - Comparison of compressed and reconstructed data with different methodologies employed.

- Then, the Data Reconstruction model is designed in SIMULINK.
- Following this , code conversion is done for the purpose of hardware implementation, where we employ the MATLAB coder to generate the C code.

5.2 Convex Optimization

CVX is a MATLAB-based modeling system for convex optimization. CVX turns MATLAB into a modeling language, allowing constraints and objectives to be specified using standard MATLAB expression syntax. n its default mode, CVX supports a particular approach to convex optimization that we call disciplined convex programming. Under this approach, convex functions and sets are built up from a small set of rules from convex analysis, starting from a base library of convex functions and sets. Constraints and objectives that are expressed using these rules are automatically transformed to a canonical form and solved. For more information on disciplined convex programming, see these resources; for the basics of convex analysis and convex optimization, see the book Convex Optimization.

CVX also supports geometric programming (GP) through the use of a special GP mode. Geometric programs are not convex, but can be made so by applying a certain transformation. In this mode, CVX allows GPs to be constructed in their native, nonconvex form, transforms them automatically to a solvable convex form, and translates the numerical results back to the original problem.

We have incorporated this software in MATLAB for testing its outputs for l1 norm minimization of audio signal inputs.

5.3 Coding Details and code efficiency:

- The coding of data acquisition followed by the coding of a reconstruction algorithm for reconstruction is done in MATLAB.

  We also employ the convex optimization software that is integrated with MATLAB as mentioned earlier.

- The ***code efficiency*** is recognized to be higher, when the convex optimization software is used where we simply optimize the underdetermined linear equation subject to the constraint Ax = b which is done internally and hence involves a very few lines of code.

  However the final results and the comparison using different approaches show a varied degree of changes in the results obtained as depicted in the tabulated comparison table.

  The ***compression ratio*** measured as 2.5 is kept constant throughout (as the sparsity and input samples are not varied)

5.4 Testing Approach

For data acquisition we observe a vector of compressed measurements as a result of the matrix multiplication as the output in the SIMULINK display block as well as the command window. In order to ***test*** the efficiency at this stage we can utilize the compression ratio parameter to understand the extent to which our original data is compressed. this is done by dividing K by N,i.e, number of output samples divided by the number of random samples or the degree of sparsity.

When we arrive at the procedure of reconstructing the signal, we test the performance of the reconstruction algorithms that vary under different conditions of the input audio. The Reconstruction algorithms - ***L1 norm*** and ***Basis Pursuit*** are employed and its performance is tested when subjected to the different audio signals of varied durations and tones after they are compressed in the process of data acquisition.

Chapter 6

Results and Inference

This chapter explains the developed simulink models,comparisions of snr values of different methods along with the plots
The development of data acquisition and reconstruction model is done using SIMULINK and the results are obtained for different audio signals (duration) that are tested with different basis matrices representing the transformations - DCT , DFT and DST the testing of reconstruction methodologies is also done as described earlier and is tabulated

The Models Obtained are depicted below-

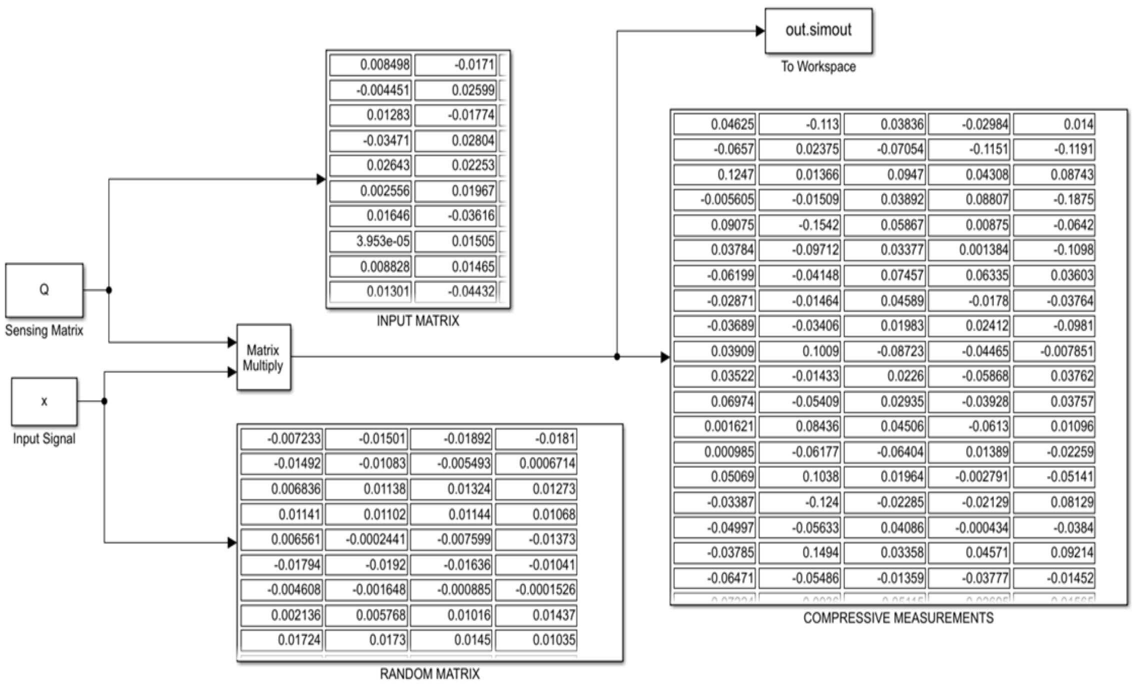

Figure 6.1: Data acquisition Model in SIMULINK

The above model depicted in Fig 6.1 comprises of the sensing matrix block and the input signal block that are multiplied by using matrix multiply block. As illustrated in chapter 3, the output of this model i.e the matrix of compressive measurements is obtained.

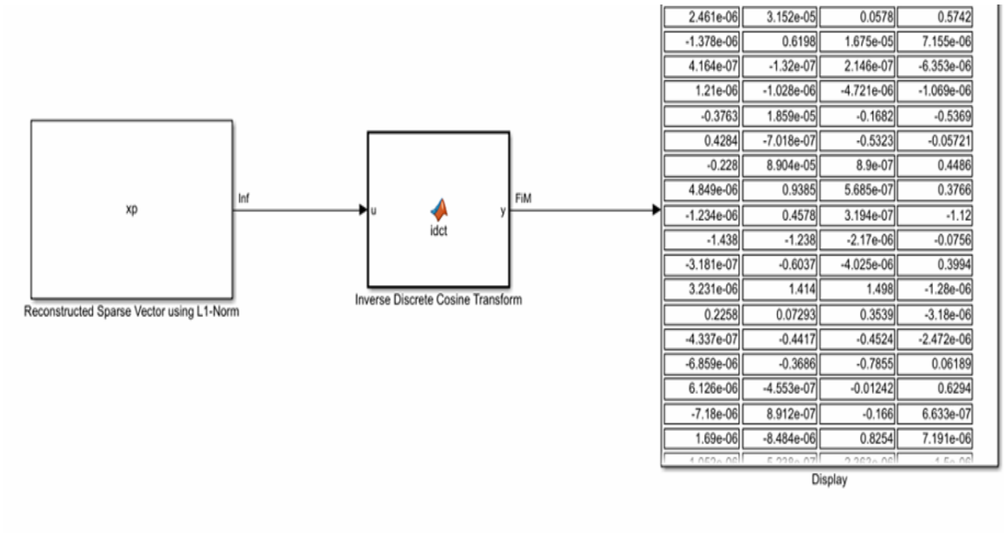

Figure 6.2: Reconstruction Model in SIMULINK

The reconstruction model as shown in Fig 6.2 comprises of the block which consists of the variable that stores the reconstructed sparse vector which is passed through the matlab function block i.e IDCT in order to get the reconstructed signal matix.

Fig 6.3 shows the comparison of signal to noise ratio of the different signals where CS is implemented using L1 norm minimization , with and without the Convex optimization software.

	Using CVX				Using L1-Norm code			
	0.2 secs	3 secs	5 secs	6 secs	0.2 secs	3 secs	5 secs	6 secs
DCT	0.6345	0.05	1.5714	1.7885	0.5666	0.004	2.0202	2.0678
DST	60.5945	60.0371	61.8453	1.9614	0.4767	0.0484	1.4414	2.3233
FFT	62.0597	66.0226	62.1371	61.5987	36.663	0.0257	37.7301	38.8256

Figure 6.3: Comparision of SNR values in db

This implementation can be observed by the plots shown below for one of the audio signals (duration - 0.2 sec).

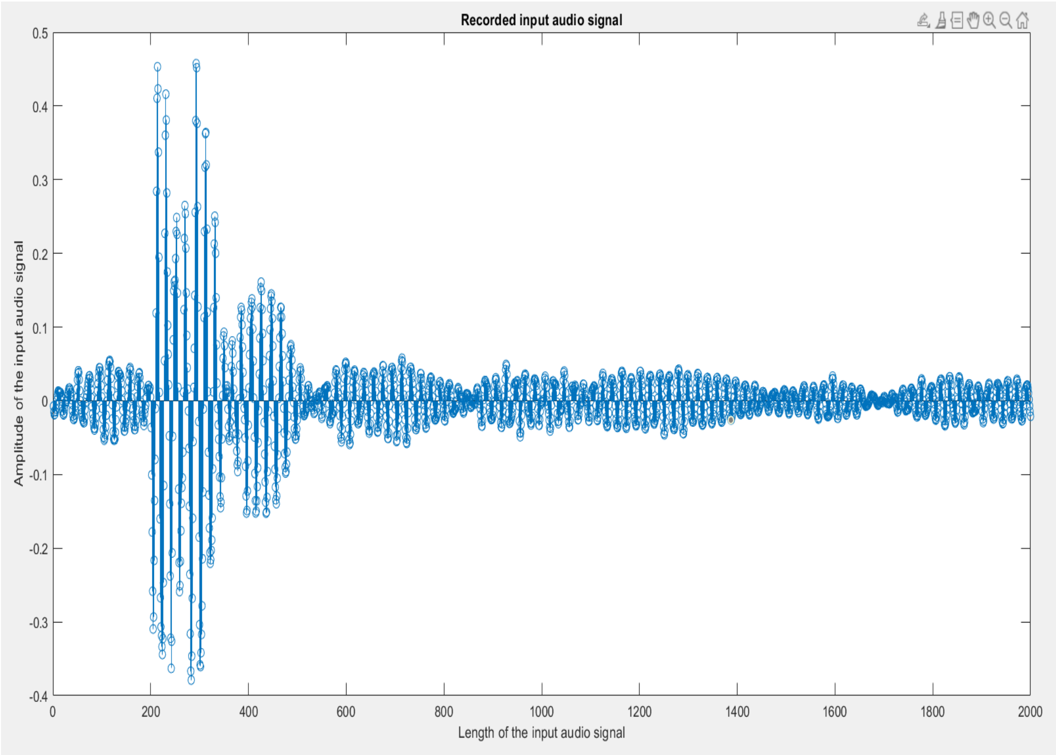

Figure 6.4: Input Audio Signal

The above plot is that of an input audio signal which is included as a .wav file in the matlab directory , of duration 0.2 seconds before employing the acqusition and reconstruction methodologies , we read this audio file and sample at an appropriate rate using the audio read function in matlab the sound function can be used to hear this signal before and after reconstruction

Output plots Using CVX [dct]:

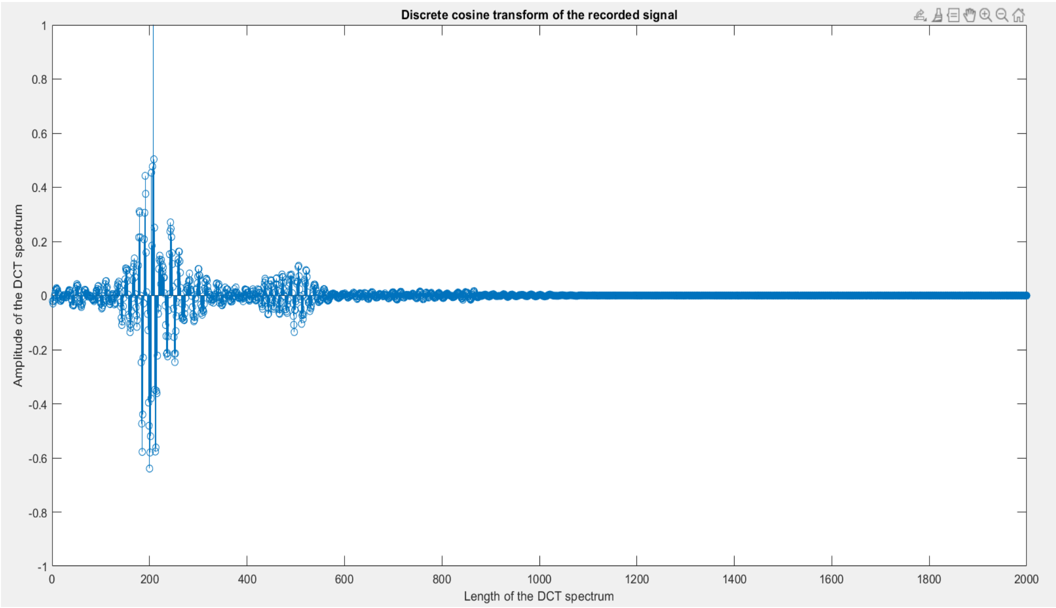

Figure 6.5: DCT

The above plot shows the Discrete consine transformed representation of the audio signal when the convex optimization (CVX) is utilized. This is the frequency domain sparse representation of the input audio.

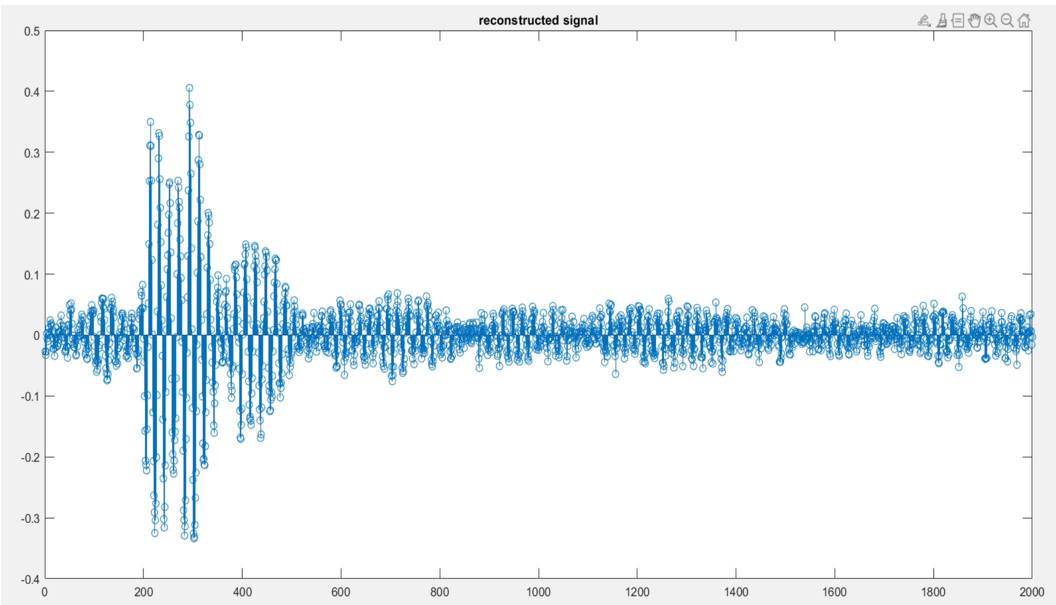

Figure 6.6: Reconstructed Signal

Reconstructed signal using CVX in discrete cosine transform is observed

Output plots Using CVX [**DST**]:

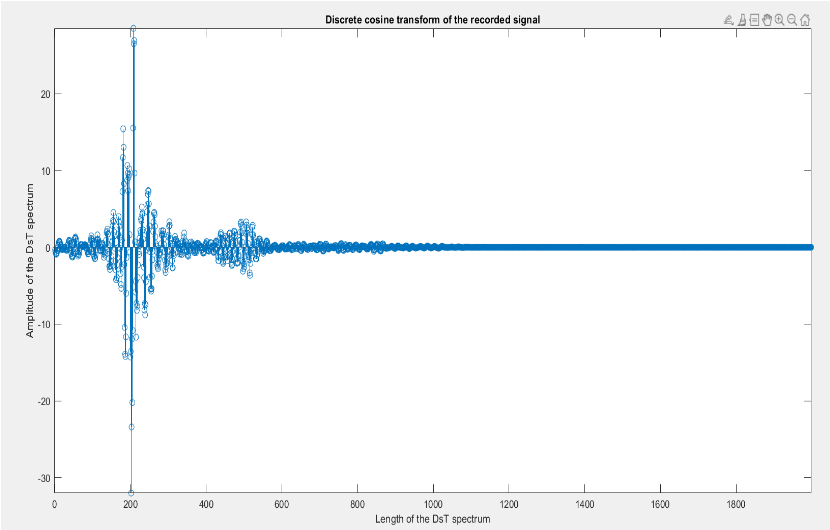

Figure 6.7: DST

The above plot shows the Discrete sine Transform using CVX as a frequency domain sparse representation of the signal when subjected to DST .The higher aplitudes similarly indicate larger coefficients of the transform matrix incorporated.

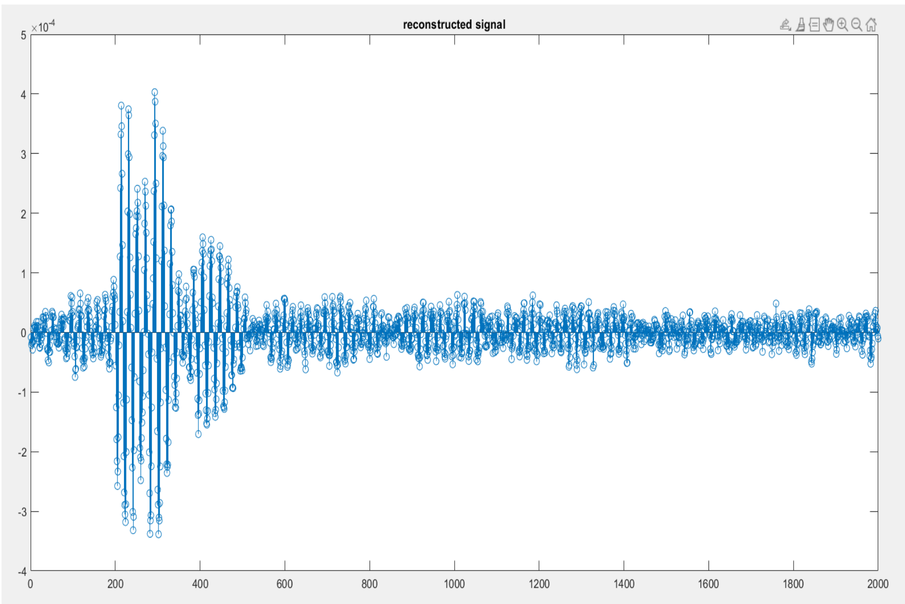

Figure 6.8: Reconstructed signal

This plot shows the Reconstructed signal using CVX in discrete sine transform.

Output plots Using CVX [**FFT**]:

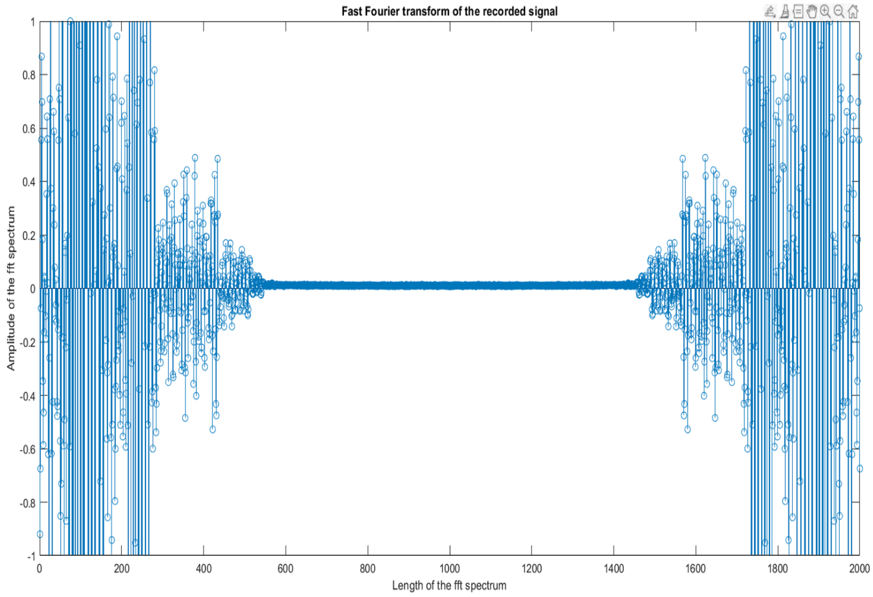

Figure 6.9: FFT

The above plot shows the Fast fourier Transform using CVX.

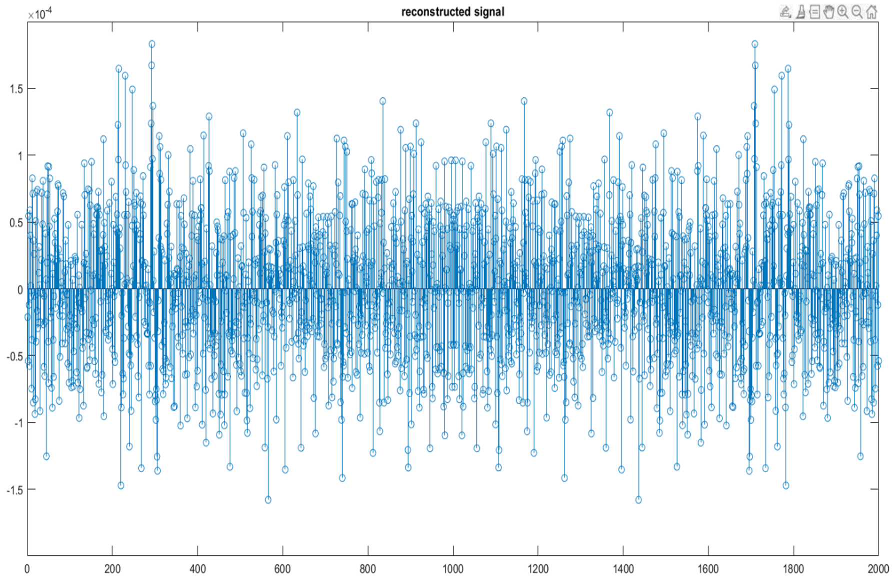

Figure 6.10: Reconstructed signal

The Reconstructed signal using CVX in fast fourier transform is observed.

Output plots Using L1 norm code i.e without CVX **[DCT]:**

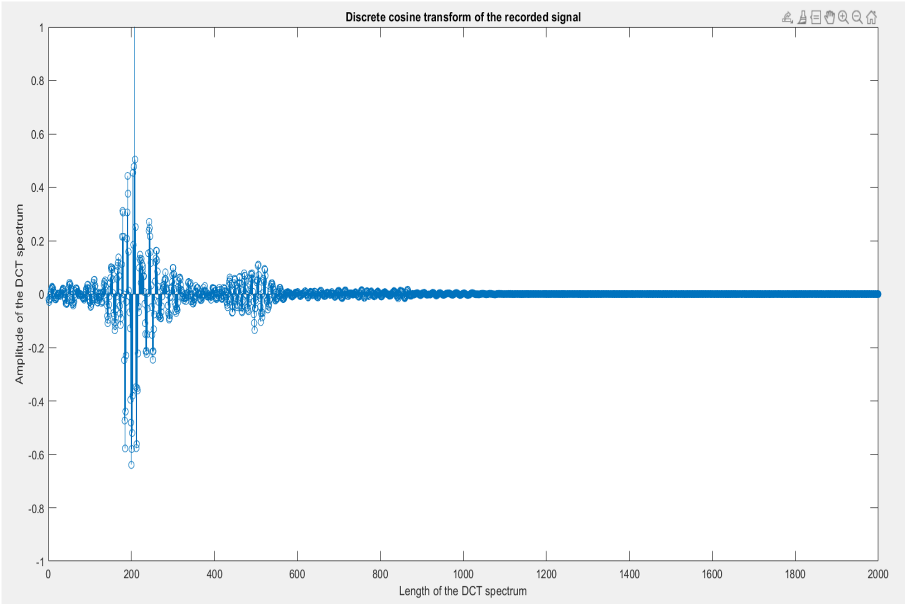

Figure 6.11: L1 Norm[DCT]

The above plot shows the Discrete Coseine Transform using L1 Norm.

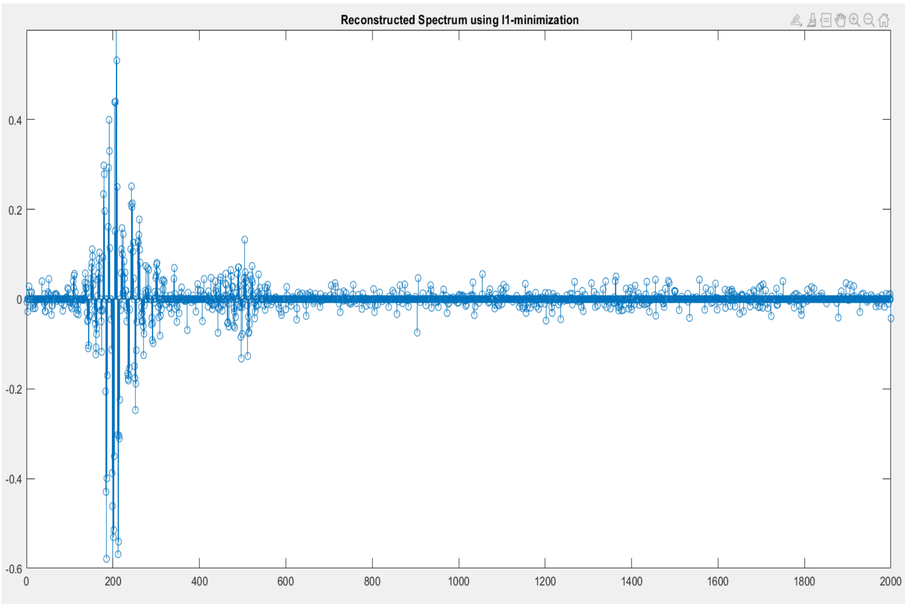

Figure 6.12: L1 Norm Reconstructed signal [DCT]

The above plot shows the Reconstructed signal using L1 Norm in discrete cosine transform

Output plots Using L1 norm code i.e without CVX [**DST**]**:**

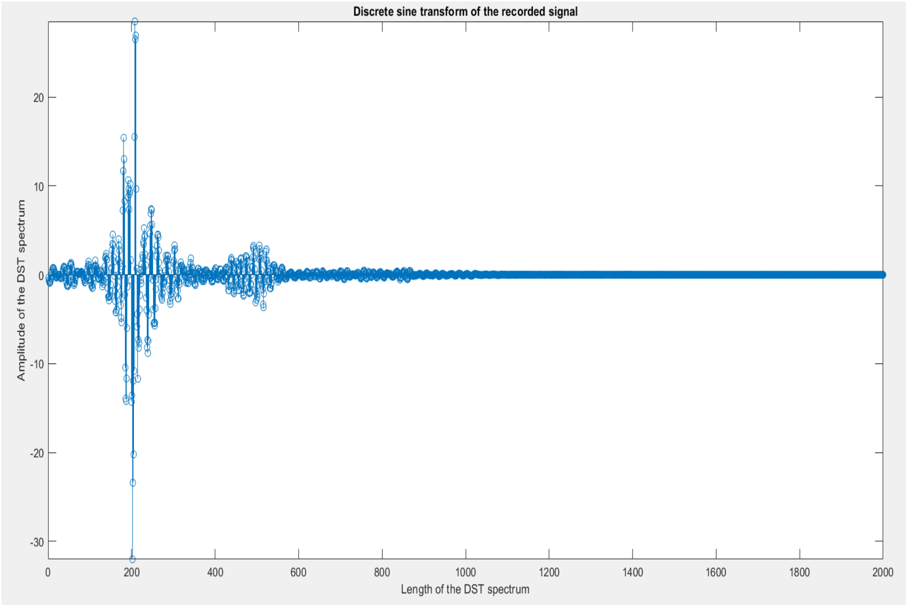

Figure 6.13: L1 Norm [DST]

The output when discrete sine transform is utilized for the code using l1 norm without employing the CVX software.

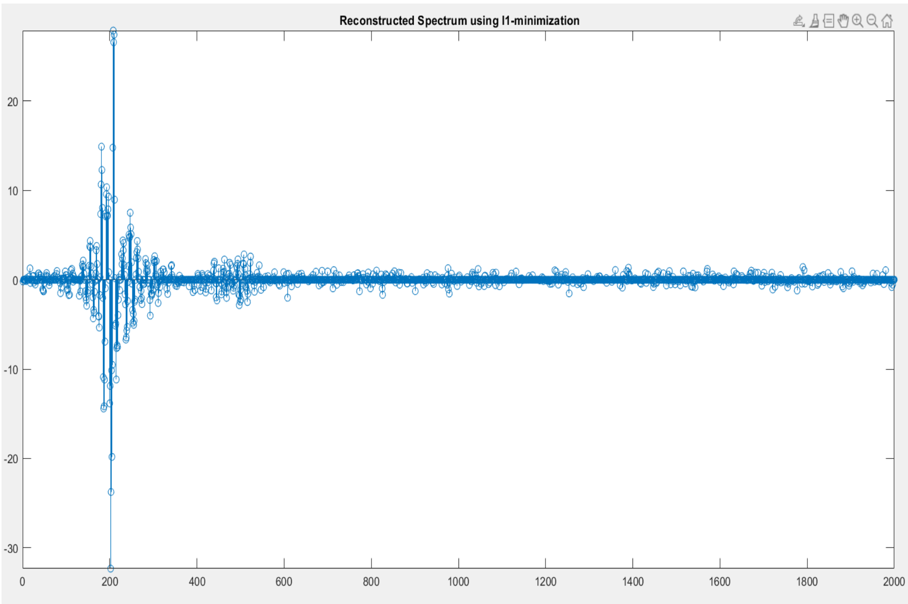

Figure 6.14: L1 Norm Reconstructed signal [DST]

The above plot shows the Reconstructed signal without the CVX software as a result of the iterations of the code employing L1 norm minimization

Output plots Using L1 Norm[FFT]:

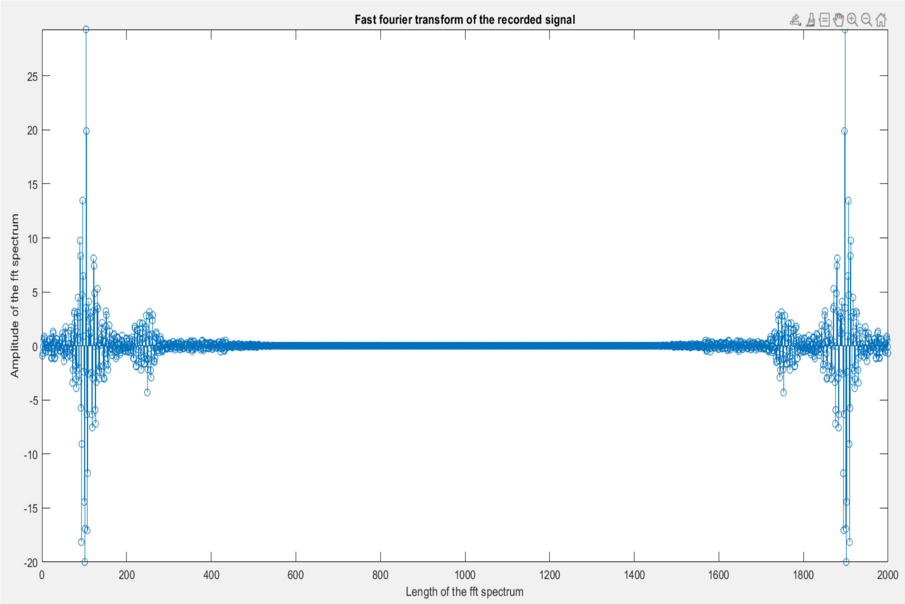

Figure 6.15: L1 norm[FFT]

The above plot shows Fast Fourier Transform using L1 Norm.

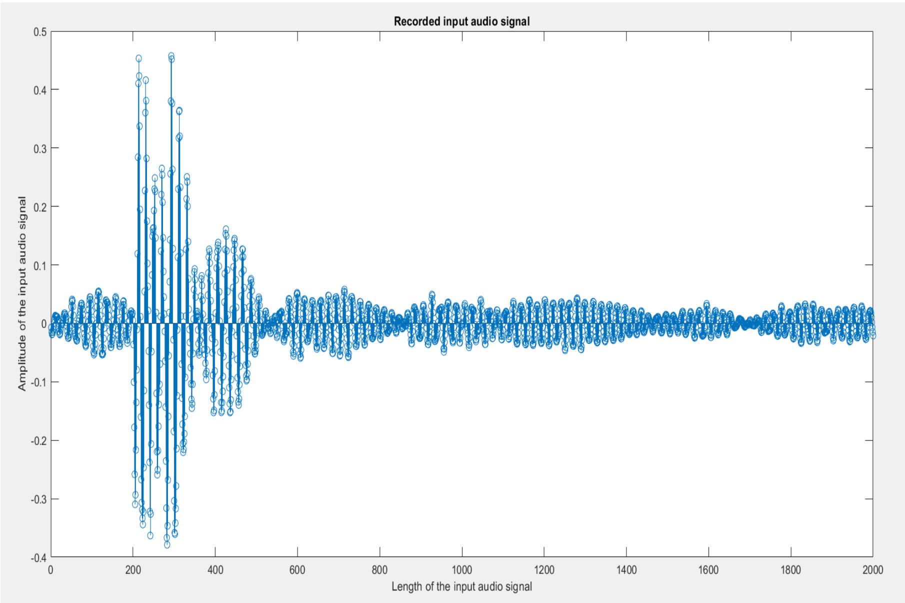

Figure 6.16: L1 norm Reconstructed signal [FFT]

The above plot shows Reconstructed signal using fast fourier transform in L1 norm.

Output plots Using Basis Pursuit[DCT]:

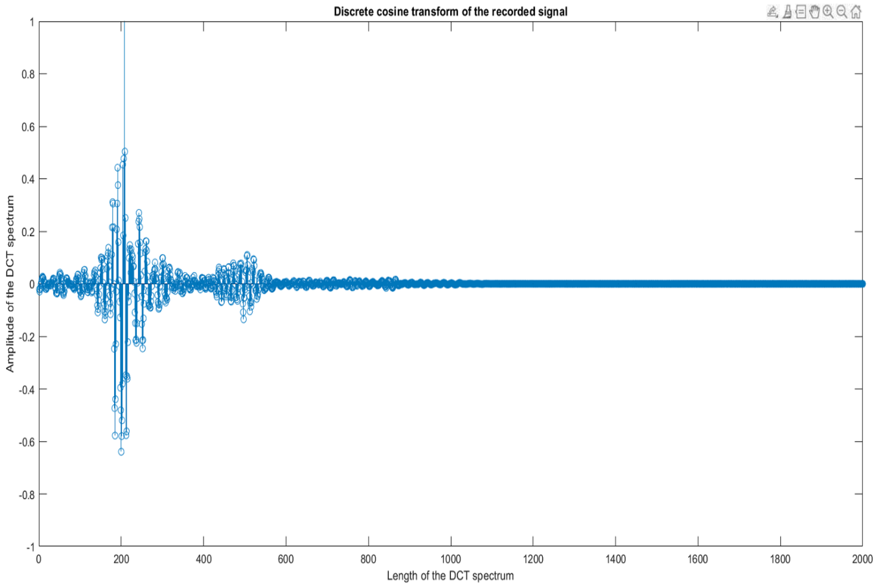

Figure 6.17: BP [DCT]

The above plot shows the Discrete Cosine Transform of input signal in Basis Pursuit.

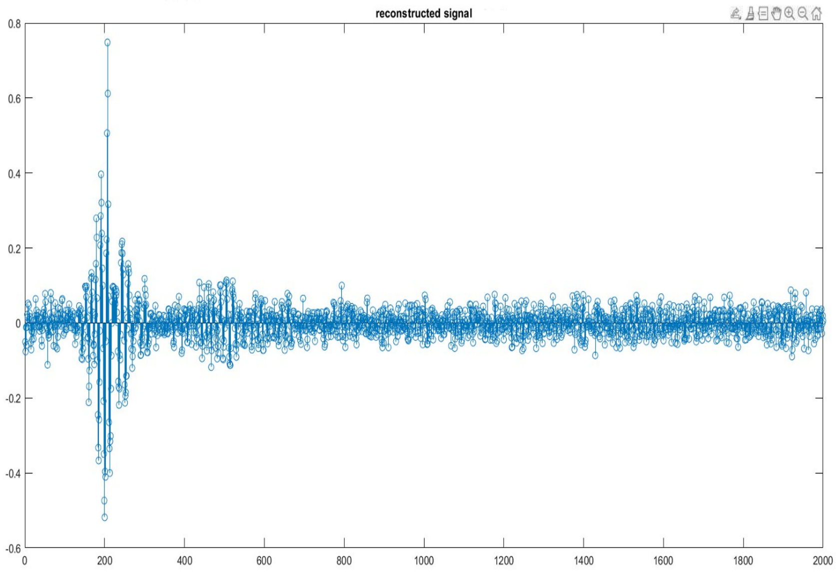

Figure 6.18: BP Reconstructed signal [DCT]

The above plot shows Reconstructed signal using discrete cosine transform in Basis Pursuit.

Output plots using Basis Pursuit[DST]:

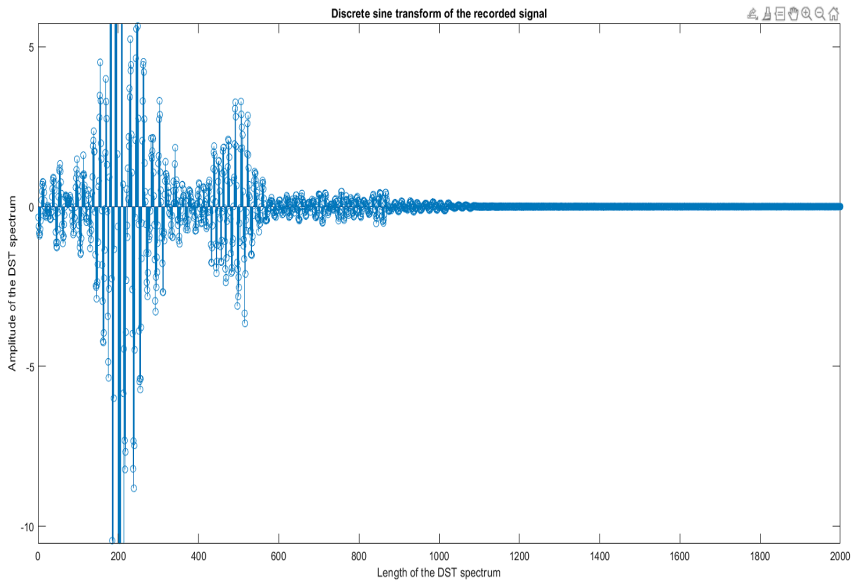

Figure 6.19: BP [DST]

The above plot shows the Discrete Sine Transform of input signal in Basis Pursuit.

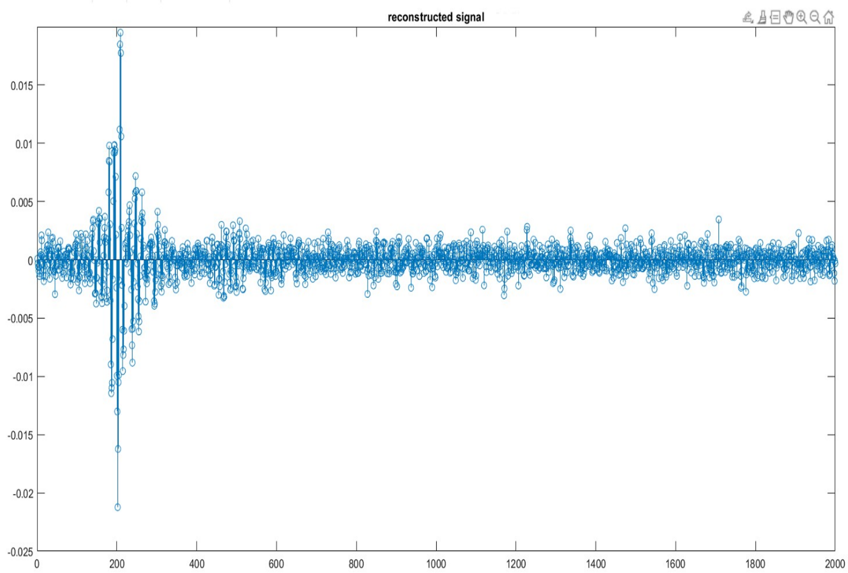

Figure 6.20: BP Reconstructed signal [DST]

The above plot shows Reconstructed signal using discrete sine transform in Basis Pursuit.

Chapter 7

Conclusion and Future Scope

7.1 Conclusion

This project report throws light upon the fundamental concepts of CS in Chapter1, starting with a brief introduction and the background, followed by the scope, pros and cons, applications and the objectives of our project. This is followed by the literature survey in Chapter2. With the objectives in mind, we then put across the Problem Definition and the various requirements of our project in Chapter3. We also put forward the working of the Conceptual Models, based on which the practical models are designed. Consequently, the System Design is described with the Algorithms that have been used, along with the Data design and Logic design of the models in Chapter4. Upon analysis of the System Design and meeting all of our requirements, we then illustrate how the concept is implemented and tested into practicality in Chapter5. Subsequently, the approaches for implementing and testing, along with the coding details are mentioned and explained. Finally, the Result plots and SIMULINK models are illustrated in Chapter6. Also, the comparison of errors for different audio signal durations and different reconstruction approaches is tabulated.

This successfully concludes our project- Development of a Compressive Sensing Model for Data Compression and Reconstruction.

7.2 Future Scope

- Simulink models can be implemented on hardware using FPGA (Field Programmable Gate Array) or DSP (Digital Signal Processor) and their performances can be compared.

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