MODEL BASED IMPLEMENTATION OF COMPRESSIVE SENSING TECHNIQUES FOR AUDIO

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***Abstract*—Compressive Sensing (CS) or Compressive Sampling is one of the recent breakthroughs in signal processing technology. It is a signal sensing paradigm that samples signals at a sub-Nyquist rate by capitalizing on signal sparsity and compressing the acquired signal at the time of sensing. The reconstruction of the compressive sampled signal gives back the original signal saving significant storage capacity due to the sub- Nyquist sampling. CS comprises of two high-level, salient steps – Data Acquisition and Data Reconstruction. The objective of this paper is to illustrate the implementation of the CS concept through models for data acquisition and reconstruction using MATLAB and SIMULINK, and also illustrate a comparison of some of the ways in which CS has been achieved for different audio signals.**

***Index Terms*- Compressive Sensing, Signal Processing, Sparsity, Acquisition, Reconstruction.**

I. INTRODUCTION

The concept of compressive sensing was introduced in 2004 when Emmanuel Candes, David Donoho, Justin Romberg and Terence Tao proved that a signal can be reconstructed from much fewer samples than the conventional Nyquist sampling theorem [1]. Advancements in applied mathematics, computer science and signal processing have paved a path for this new sensing modality which is essentially a way of reconstructing a high dimensional signal with massively down-sampled measurements, making it one of the most significant and blooming areas of research in signal processing technology. It has become a recent breakthrough that overrides the requirements of the sampling theorem, unlocking a new perspective towards sampling data, which successfully saves significant storage space and enables efficient data sampling. Compressive sensing and the process of reconstruction is done by first acquiring and sensing the data through a certain methodology involving down-sampling and then applying suitable reconstruction techniques to get back the original data through sparse signal recovery .Standard compression still relies on having access to full high-dimensional measurements. The recent advancement of compressive sensing however provides a way of approaching sampling:
instead of collecting high-dimensional data just to compress and discard most of the information, it is instead possible to collect surprisingly few compressed or random measurements and then infer what the sparse representation is in the transformed basis [2].

II. METHODOLOGY

Compressive sensing employs some of the salient techniques in applied mathematics involving linear algebra essentially solving an underdetermined linear equation. The methodology in performing the same comprises of acquiring certain very few samples of the data followed by reconstructing the original signal utilizing appropriate reconstruction algorithms.

A. Acquisition

To acquire and sense certain data points in the signal, firstly ,the conversion the audio signal into its vectored representation of data points by sampling at a certain frequency is done ,then a suitable transformation in the appropriate basis is performed followed by employing a sensing matrix that senses or certain data points of the input by giving us the compressed data.

In order to transform the input vector ’y’ in the appropriate domain we use a universal transform basis represented by matrix ’ψ’ in which the signal is compressible.

$$y = \psi x$$

This results in a sparse representation of the input signal in the transformed domain, x as depicted in fig 1.

By using a sensing matrix certain data points of the audio signal are sensed. Here we incorporate a random orthonormal sensing matrix ’φ’ consisting of orthonormal vectors, that is multiplied with the input signal vector to yield the vector of compressive measurements ’b’. (fig 2)

$$\varphi y = b$$

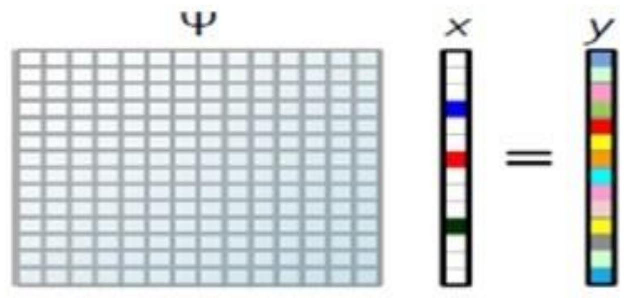

Fig. 1. transforming the input to yield its sparse form

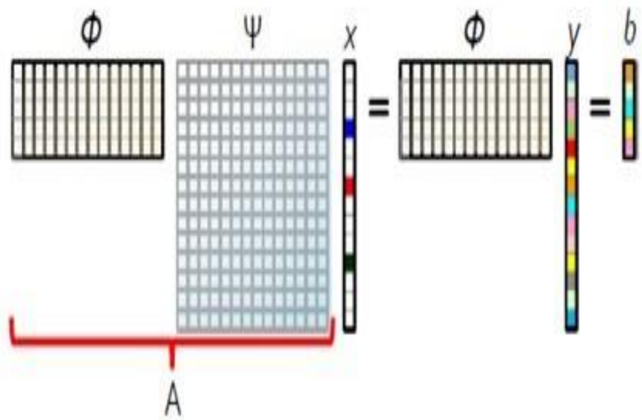

Fig. 2. sensing certain few points using the sensing matrix

B. Reconstruction

Mathematically, compressed sensing exploits the property of sparsity of a signal to achieve complete signal reconstruction from surprisingly few i.e downsampled measurements. Therefore, after sensing the elements of input ’y’ and obtaining the compressive measurements , the next step is to succesfully reconstruct the signal using these measurements in ’b’.

As pictorically represented in the above figure the matrix φ times ψ is rewrittten as a matrix ’A’ resulting in the equation

$$Ax = b$$

The above equation is an underdetermined linear equation as described earlier where the objective of reconstruction is to solve for x thereby recovering the sparse signal.

In order to successfully perform compressive sensing on audio signals methodically as illustrated above we incorporate MATLAB to code some of these essential mathematical equations that entail the aquisition of data samples followed by recontruction , by coding the appropriate reconstruction algorithms . A model for the same is then designed in SIMULINK.

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III. MODEL DESIGN

A. Data Acquisition Model

To begin with, we first need to acquire our data samples from the signal by obtaining the down-sampled set of data points. For this, the data acquisition model is designed. This model essentially deals with the acquisition of samples 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 called the sensing matrix producing very few compressive measurements. We do the following in data acquisition -

- Input audio signal of suitable file format
- sampling the signal with a suitable sampling rate
- formulation of Random matrix

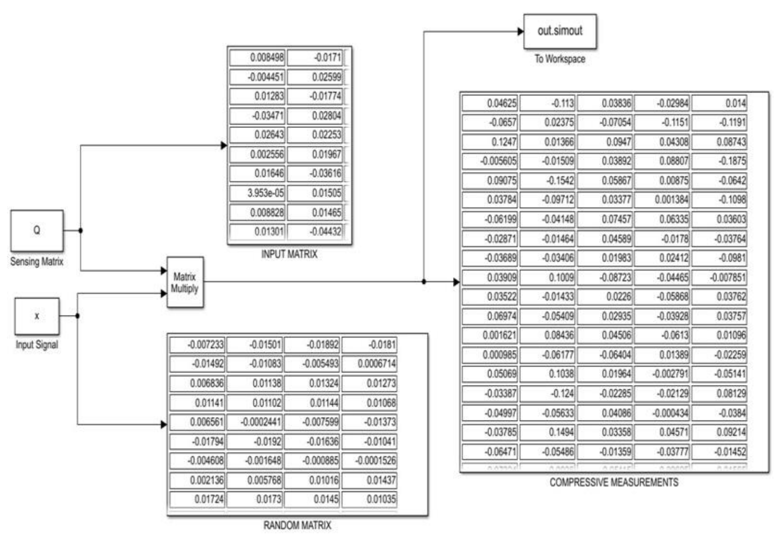

Fig. 3. The Data Acquisition model

Fig 3 depicts the Acquisition model designed, comprising of the input signal block and the sensing matrix block subject to matrix multiplication (as illustrated in fig 2), in order to obtain the vector of compressive measurements.

B .*Reconstruction Model*

The reconstruction model follows the data acquisition where in the obtained down-sampled measurements are used to reconstruct the original signal by employing appropriate reconstruction algorithms governed by the reconstruction matrix.

Some of the parameters considered while designing this are as follows -

- Using suitable reconstruction methodologies like Basis pursuit and to successfully perform sparse signal recovery of the given input audio signal.
- computing the reconstruction matrix based on the above considerations
- Performing suitable inverse transformation on the recovered sparse signal to reconstruct the input signal

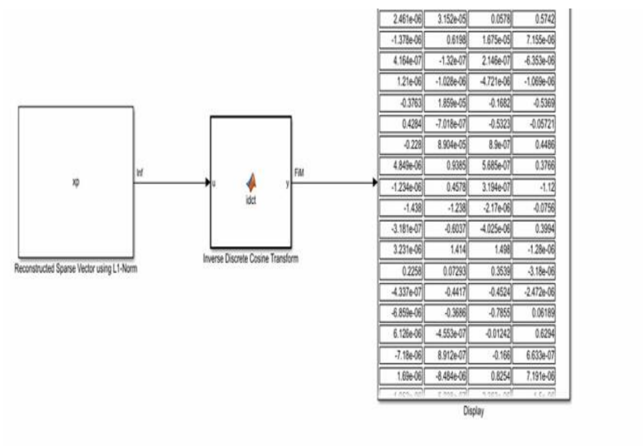

Fig 4. Reconstruction model

C. Reconstruction Algorithm

There exists many reconstruction algorithms for compressive sensing, employing advanced mathematical techniques to successfully reconstruct the data from the sub-Nyquist samples. One of these is the well known basis pursuit algorithm focussing on minimizing the norm subject to the constraint in an underdetermined linear equation. In compressive sensing, we want to search for the sparsest vector consistent with the measured data. The problem can be stated as L0 minimization.

$$\text{minimize } \|x\|_0 \text{ subject to } Ax = b$$

Solving the L0 minimization problem can be shown to be NP hard (Non deterministic polynomial time hardness). However, computationally efficient algorithms are well-developed to solve a relaxed version of the problem. One of these algorithms is basis pursuit, which can be stated as follows.

$$\text{minimize } \|x\|_1 \text{ subject to } Ax = b$$

where the problem is reduced to a convex l1-minimization here, $\|.\|_0$ denotes the 0 pseudo-norm, given by the number of nonzero entries; this is also referred to as the cardinality of x and $\|.\|_1$ denotes the L1 norm.

CVX - A Convex programming approach :

Convex optimization deals with mathematical optimization techniques tackling mathematically complex problems where all the constraints are convex functions i.e the constraints over convex sets.CVX is a mathematical modelling language tackling convex problems. It allows constraints to be implemented through the standard Matlab syntax and essentially supports disciplined convex programming.
For reconstructing the audio, basis pursuit is employed in two different ways - 1) programming it as an l1 minimization function (Without the use of CVX) and 2) programming it as a convex optimization problem using the CVX software.

The results thereby obtained for audio signals of different durations observed, comparing transform bases such as the sine, cosine and fourier transforms subjected to the audio.

IV. RESULTS

For various duration of input audio signals and transform bases (sine , cosine and fourier) the performance of the CS algorithm is tested as seen in the figures below. The below figure shows the input audio signal considered

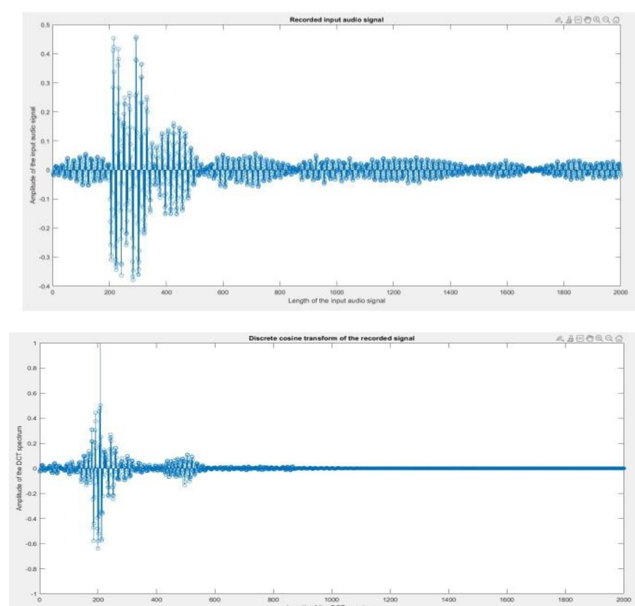

Fig. 6. CVX

The input audio is transormed in a cosine domain and compressed using the orthonormal sensig matrix after which it is reconstructed with and without using CVX represented in fig 6 and fig 7.

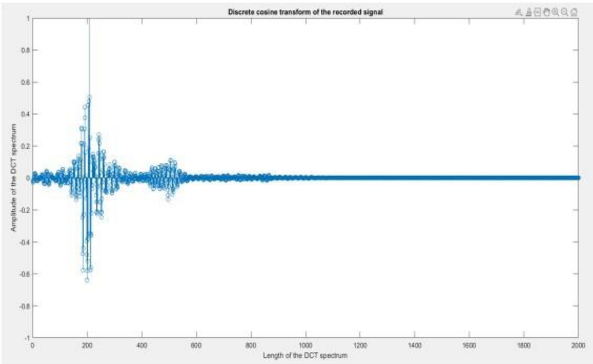

Fig 7. Without CVX

The signal to noise ratio for various audio signals considered is tabulated for both the approaches of CS is performed.

Without CVX			
	0.2 secs	3 secs	5 secs
DCT	0.5666	0.0004	2.0202
DST	0.4767	0.0484	1.4414
FFT	36.663	0.0257	37.7301

Using CVX			
	0.2 secs	3 secs	5 secs
DCT	0.6345	0.05	1.5714
DST	60.5945	60.0371	61.8453
FFT	62.0597	66.0226	61.5987

V. CONCLUSION

The implementation of Compressive sensing on audio signals using two different approaches was done. The algorithm for compressive sensing and sparse signal recovery was tested on different audio samples and the signal to noise ratio is compared.

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