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Compressive Sensing For Speech Signals

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ABSTRACT

Compressive sensing signal is generating the sparsity at the strongly relies. The signal of the sparsely is compressively sampled by small range of the signal which include maximum salient information. Some areas like signal processing, photo processing and sonar system. This paper will discuss about the implementation of the compressive sensing. The results in compressive sampling (also known as compressive sensing) provide a new way to reconstruct the original signal having the minimum amount of observations. The paper having the main goal to propose a new method which employs to compress the speech signal at the transmitter and decompress it at the receiver by using one kind of a optimization.

Key words: Sampling, Optimization, Sparsity, Compression, L1-minimization.

1. INTRODUCTION

Generally, most of the people communicate with each other using speech, it's a common way expressing one's thoughts and opinions. Voice communication did become most popular in communication sector now a day, in our day to day uses. Among the applications, transmission delay should be minimum, and the speech is reconstructed with high quality at the receiver end. In our day to day life, we use applications which can be accessible with speech signal as an input and act accordingly, such as modern electronic devices. Basically, storage and transmission of data is rapidly increasing with time to time. In order to achieve these requirements, speech compression procedures are used, which play a major part in storage and transmission of data efficiently. Here we use a strategy named compressive sensing, which is used to obtain the signal with minimum rate better than the nyquist rate. In compressive sensing, an autonomous irregular projection inspects the respected signal. About ten or eleven minimization techniques are used to reconstruct the original signal with the same quality and less disturbances. The first signal is actually reconstructed just in the event is normally meager. In here, the probability of compressive sensing in speech compression is being investigated by an endeavor.

2. BACKGROUND ANALYSIS AND METHODOLOGY

2.1. Compressive Sensing Theory

The compressive sensing theory had been discovered by Candes et al and Donoho. It includes taking arbitrary projections of the signal and recovering it from few estimations utilizing the optimized techniques. In the traditional sampling speculation the signal was tested making use of the Nyquist rate, though the assistance of compressive sensing of the signal had been examined below the Nyquist rate. This is possible that the given signal was changed into a place where it can be sparsely represented. At that point the signal reconstruction is obtained from the examples utilizing the diverse optimization strategies accessible. The block diagram of the compressive sensing system is shown in Figure 1.

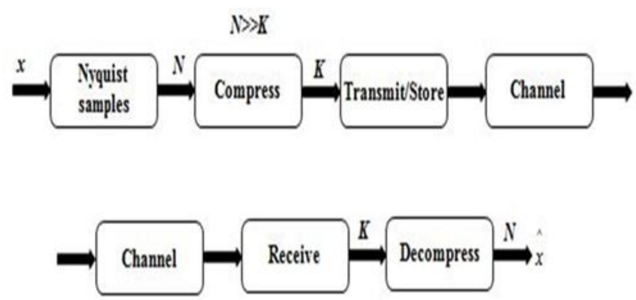

Figure 1: The Block Diagram of the compressive sensing

2.2. Compressive Classification

This section will discuss the classification of compressive sensing based on its application. It deals with the effect of compressive sensing and its performance. The compressive sensing structure is used for a vast range of statistical inference tasks. E.g. In finding the solution to detection and estimation problems in which the original signal is reconstructed from the measurements.

2.3. Classical detector

Classical detector is one of the classifications in sensing. Give us a change to state that there are multiple theories regarding the available signal in the measurement or it isn't. When the classical neyman - pearson is looking against to the threshold γ it represent to estimate the x in the original signal.

2.4. Optimization Techniques

The primary role in signal reconstruction in Compressive sensing is the signal reconstruction is done by basic quantity estimations. The utilization of optimized Techniques it has the feasible to reconstruct the signal without dropping the signals at the authority. There has been a movement of papers related to the theory of signal recovery from particularly divided information.

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3. IMPLEMENTATION TECHNIQUE

3.1. Measurement Matrix

Here we deal with representation of a signal in the basis of incoherence. Now take the process of linear measurement which calculates variable M less than N product between the collection of vectors and variable x.

$$y = \Phi x = \Phi \Psi \alpha$$

Here Φ is described as M order N measurement matrix having φTj as a measurement vector for each row and here α is considered as the coefficient vector having K number of elements excluding zero. It is clear that any count of size matrix can be used in any case, considering the case that they are incoherent having any stable basis Ψ, namely function sin and wavelet, gabor, spikes. The measurement matrix is the process of compressive sensing having K-sparse coefficient.

3.2. Fast Fourier Transform

Fast Fourier Transform is a process that computes discrete Fourier transform. It converts the signal from time domain to the frequency domain. In this we use FFT for the modeling the speech signal.

3.3. L1-minimization

A series of papers have developed a theory of signal reconstruction from very high incomplete information. The results show that the sparse vector is recovered from a few numbers of linear measurements. We can solve the under determined linear equations or sparsely corrupted solutions to an over determined equations using l1-minimization. Recently, l1-minimization is the alternative to the combinational l1-normalization, which counts the no. of non-zero elements in the vector; we use this for creating the signal as a sparse superposition of waveforms.

3.4. Compressed Detector

The theory described will be easily prolonged when the compressive sampler is made by using these measurements. For this section, the subsequent hypothesis is considered:

$$H\,0: y = \varphi n$$

$$H\,1: y = \varphi(x + n)$$

Here n and N refers to a white Gaussian noise with mean zero with a standard variance. It’s very easy to show that the required value is given by co-ordinates y and its respective φ x values.

4. QUALITATIVE ANALYSIS

4.1. Length of the signal

The Length of the signal is taken by considering the samples. In this we have taken 8000 samples which are very less No. of samples when comparison to the Original signal.

4.2. Threshold Window

The threshold window which eliminates the coefficients that is important for the signal. In other words all the small amplitude coefficients should be multiplied with zero. By varying the threshold window we can be able to attain the compression that we want. That is why the compressed sample will also be modified by changing the threshold window.

4.3. Maximum Absolute Error

Absolute error is the error between the reconstructed spectrum and the Threshold spectrum. We calculated the reconstructed spectrum obtained by using L1-minimization and the threshold is obtained from the DCT of the original image

4.4. Comparison with Wavelet Transform

The mathematical tool for wavelet transform is used in lots of regions of technical and engineering, particularly in the fields of audio and facts compression. It is defined as a small region that it is electricity focused in time to provide a device for the analysis of temporary, non-desk bound, or time-varying phenomena A signal regularly can be better analyzed, described, or processed if it's miles expressed as a linear decomposition. We used the wavelet analyzer inside the mat lab for the comparison of the regular compression and the wavelet compression to provide a device for the analysis of temporary, non desk bound.

5. TABLE

Table.1: Comparison of Compressive Sensing and Wavelet Compression

Parameters	Length of the Signal	Threshold Window	No of zeros	Maximum absolute error	Compression %
Compressive sensing	8000	0.0074 to -0.0045	1000	0.0160	50%
Wavelet	8000	0.1188	1000	0.1840	50%

The above table 1 shows the comparison of compression of speech signal using wavelets and compressive sensing using different parameters. Performance of compressive sensing is better when compared to wavelet compression as there is a minimum error with same compression rate using different parameters.

6. RESULTS

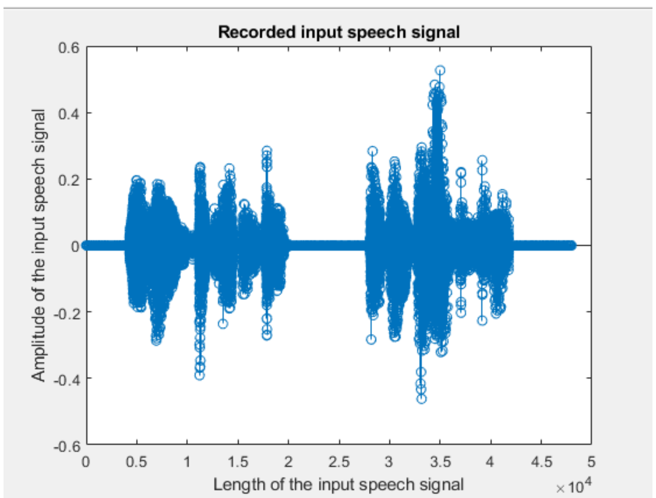

Figure 2: Recorded input speech signal

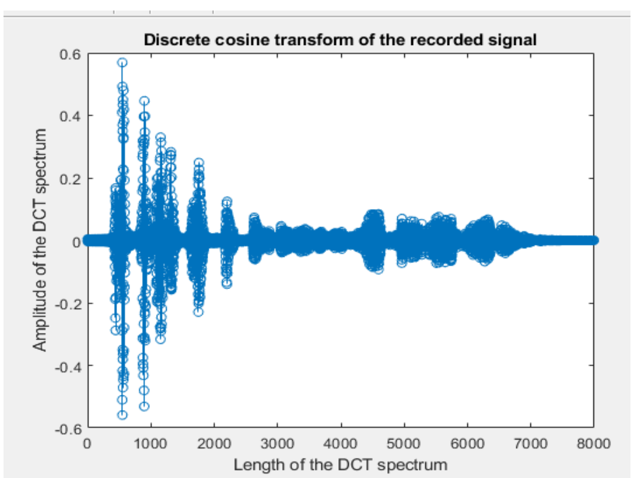

Figure 3: DCT of recorded speech signal

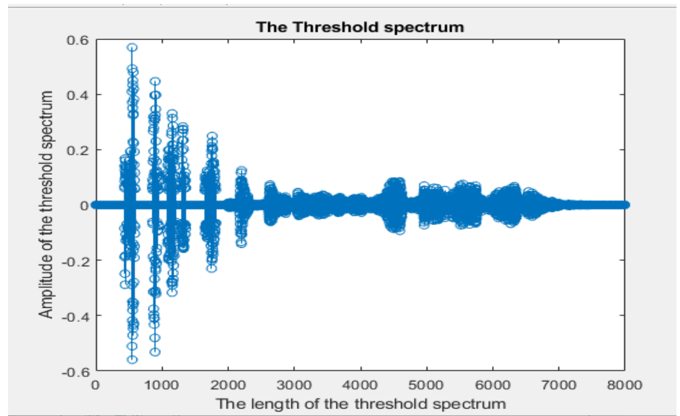

Figure 4: Threshold spectrum

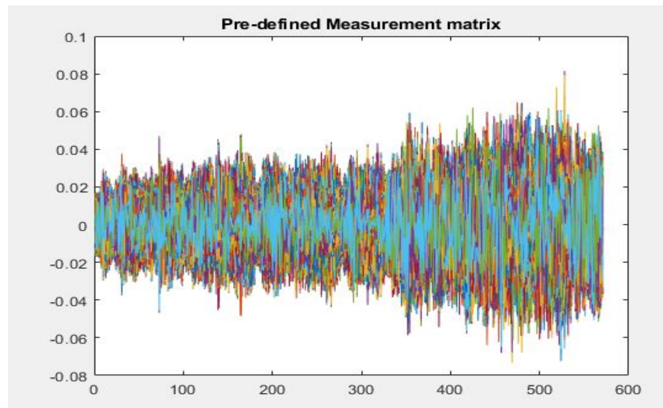

Figure 5: Measurement matrix

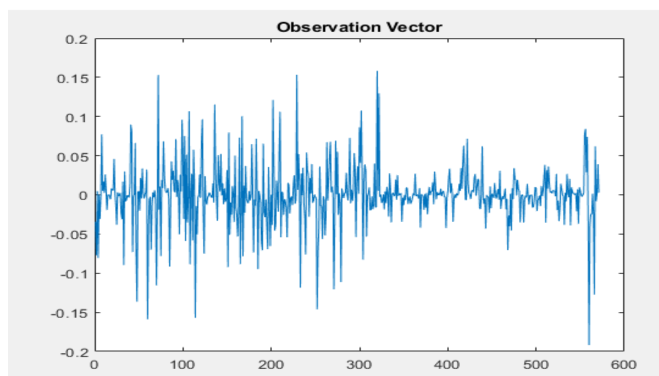

Figure.6: Observation vector

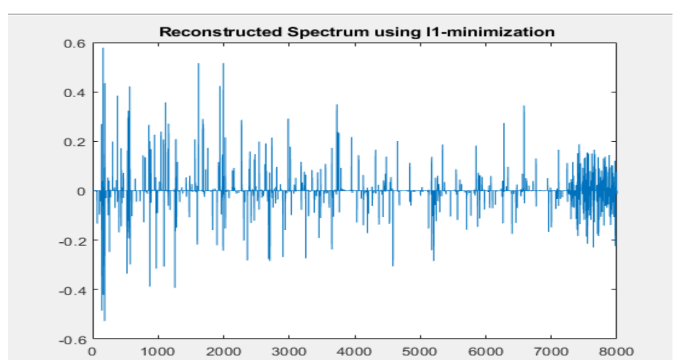

Figure.6: Reconstructed spectrum using l1 minimization

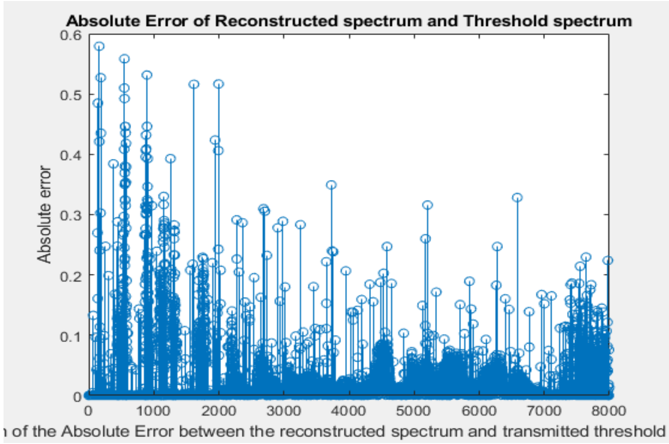

Figure 8: Absolute error between the received reconstructed spectrum and original spectrum

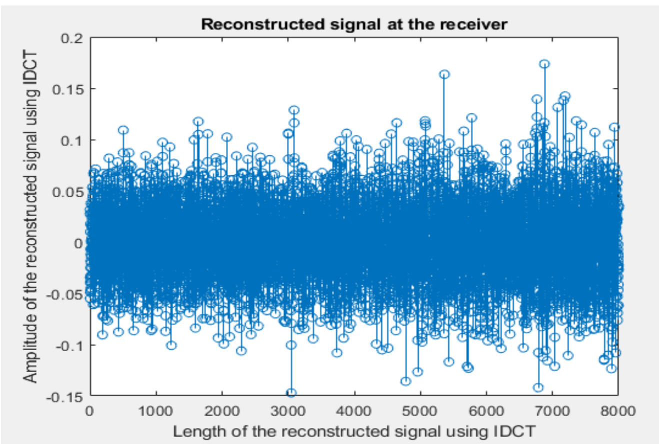

Figure 9: Reconstructed speech signal at the receiver

First We have to recorded a speech signal using MATLAB functions in the Figure 2.we have recorded the signal for n number of 8000 samples. DCT is applied for the recorded signal in Figure 3. so that the real data points can be transformed into its real spectrum. Before applying compressive sensing we apply DCT to the recorded signal, a threshold window s obtained in the Figure 4 which is used to eliminate the small coefficients. In Figure 5 the random measurement matrix (composed of random numbers) is obtained using MATLAB function ('randn'). In Figure 6. the signal is multiplied by several Dirac functions centered at different locations to obtain the observation vector. In Figure 7 the reconstructed spectrum is obtained by using the l1 normalization method,the observation vector and the predefined measurement matrix.In Figure 8. we found the absolute error between the Reconstructed spectrum and the Threshold spectrum.In Figure9 Finally the reconstructed spectrum is obtained by using the compressive sensing.

7. CONCLISION

In this paper the design of a speech signal system using compressive sensing has been done. The proposed system should fulfill the following specifications like Low power consumption, Accurate reconstruction of the speech signal and Increased data rates. During the design process, this module went through different analysis in order to find the most adequate optimization technique to reconstruct the speech signal with few random measurements without losing the information. Two different types of measurement matrices: predefined and random measurement matrices were studied and tested using MATLAB. The speech signal was reconstructed without losing important information in order to achieve an increase in the data rates. After multiple simulations, it was found that the system worked as expected and the speech signal was reconstructed efficiently with a minimum error. Performance of compressive sensing is better when compared to wavelet compression as there is a minimum error with same compression rate using different parameters.

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