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Compressive sensing in wireless mobile communication system at high data rate transmission

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Abstract— **In this paper, the use of compressive sensing in a mobile communication system is proposed in order to increase the data rates. The objective is to increase the data rates of current and possibly future generation mobile systems. In the proposed system the speech signal is sampled below the Nyquist rate by using compressive sensing. The compressed spectrum is then transmitted over the wireless system and successfully reconstructed at the receiver without losing any significant information. In theproposed communication system, first the speech signal is modelled in such a way that theinput signal is sparse enough before applying compressive sensing. The sparse signal ismultiplied by the predefined measurement matrix. The output of the compressive sensingmodule is then transmitted to the receiver.**

Index Terms— **Laplacian distribution, analysis and processing, the threshold spectrum, Impedance characteristics.**

I. Introduction

Compressive Sensing in Mobile Communication SystemThe purpose of this research effort is to implement compressive sensing in a mobile system. By using compressive sensing techniques, the speech signal is preceded at thetransmitter side which is being sent to the receiver through a wireless channel. As aresult, a small number of samples are being transmitted, and this will increase thetransmission data rates when compared to the current communication systems.

The following list points out some of the future work that needs to be done which will improve the advancement of mobile communication systems.

- Implementing compressive sensing in 3G and LTE mobile communication systems
- Parameters like noise, multipath effects and shadowing needed to be considered while measuring the output
- Different transformations need to be tested in order to find the most efficient one for this application
- Design a measurement matrix that will be optimum for speech signals.

At the receiver, the signal is perfectlyreconstructed from a significant small number of measurements by using differentoptimization techniques such as l-norm or convex optimization. The basic block diagramof the proposed systems are shown in Figure 1.

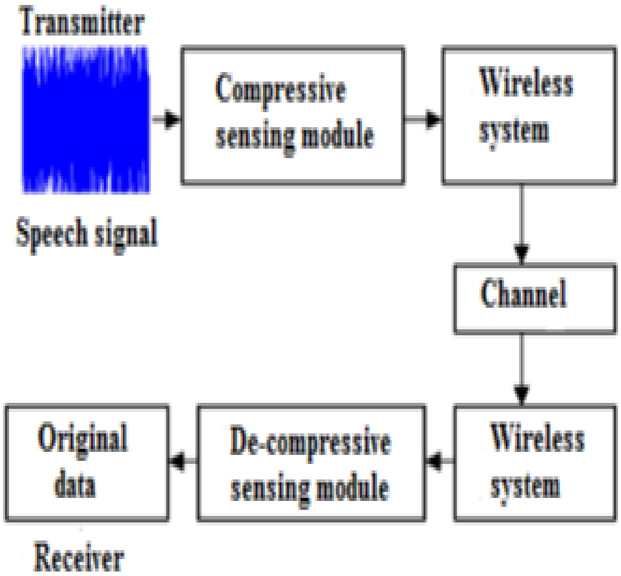

Figure 1. Compressive sensing in a mobile communication system

In the first stageof the project, a speech signal was modelled using a Laplace random number generator shown in Figure 2. It was decided to use a Laplace number generator to model the speech signal, because these types of signals typically have a Laplacian distribution [5]. Themodelled speech signal was mapped into the discrete frequency domain using the FFT.The results obtained from this transformation are shown in Figure 3. In the second stage, before compressive sensing was applied to the signal, a threshold window was used toeliminate the coefficients that are significant to the signal. In other words, all thecoefficients with small amplitude were multiplied by zero. In Figure 4 it can be seen howthe FFT spectrum looks after the threshold has been applied. The purpose of the thresholdis to ensure that the FFT spectrum is sparse.

II. Spectrum Analysis

In the third stage, the threshold spectrum was multiplied by the measurementmatrix, which is a matrix composed of random numbers. The output of the compressivesensing algorithm is converted into a digital signal using an Analog-to-Digital converterin order to be transmitted by the mobile system.

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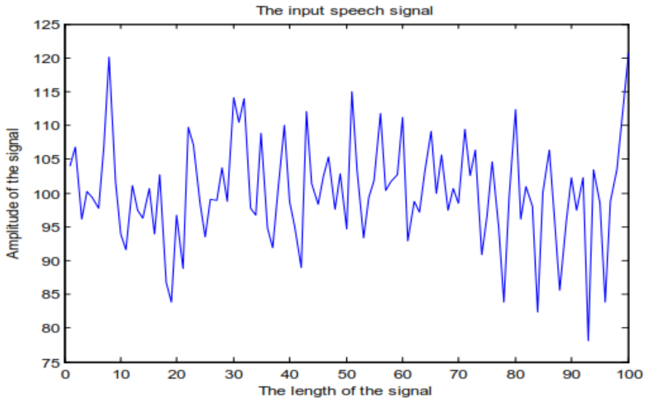

Figure 2. Input speech signal

At the receiver section, an initial guesswas made using the measurement matrix and the observation vector (vector signal),which is close to the input speech signal. Finally, the speech signal was reconstructedfrom a significant small number of observations by using one of the optimizationtechniques available.

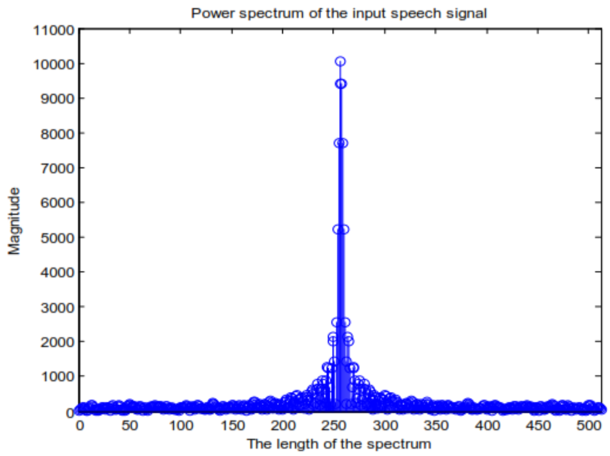

Figure 3. Power spectrum of the input speech signal

The reconstructed signal at the output of the optimization module isshown in Figure 8. The difference between the actual signal and the reconstructed signalwas calculated in order to observe the error between both signals. This error is shown inFigure 6.

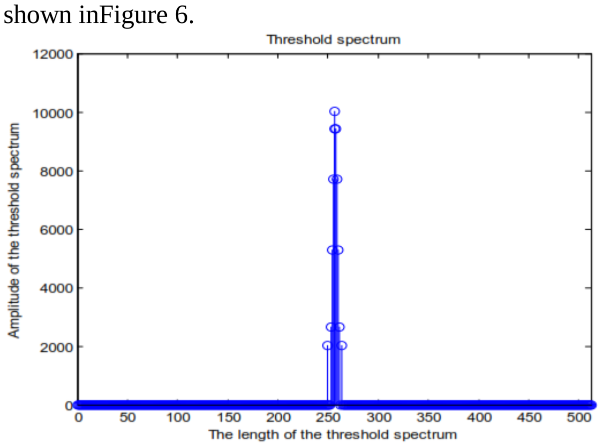

Figure 4. Threshold spectrum of FFT spectrum

The FFT was a revolutionary algorithm that made Fourier analysis and processingof digital signals fairly easy. The FFT algorithm employs a few tricks and can compute log ( )NN operations [6]. There are twofactors that need to be considered when the FFT is implemented in MATLAB the Fourier transform of a discrete signal in2

- FFT uses complexes numbers and
- It computes both positive and negative frequencies.

This is where it becomes difficult to implement FFT in compressive sensing.

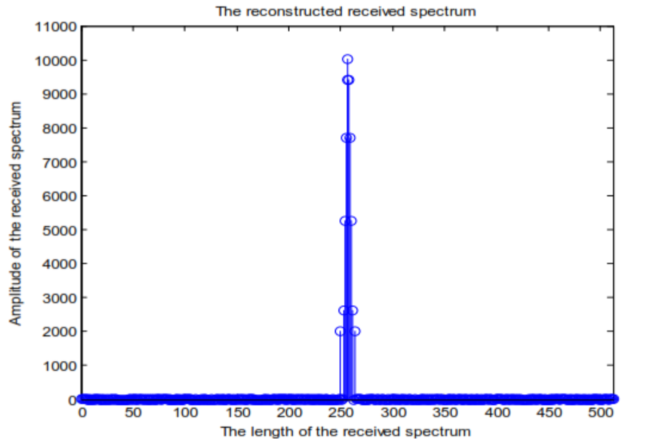

Figure 5. Reconstructed FFT spectrum using l1-minimization

III. ERROR DETECTION AND RECONSTRUNTION

The mainproblem is that applying compressive sensing to a complex number is a tedious andcomplex process, and is being researched at Michigan State University using a hybridcompressive sensing model (Complex and Real) [7]. In order to overcome caused by the FFT, instead a Discrete Cosine Transform(DCT) is implemented. The DCT is conceptually the same as DFT except that it does a better job in concentrating the energy into lower order coefficients than the DFT.

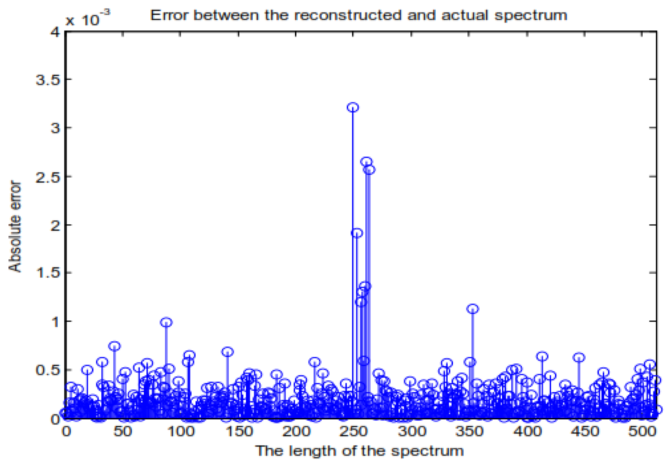

Figure 6. Error between the reconstructed and the actual spectrum

Anotherimportant property of the DCT is that all the spectral coefficients are purely real.Assuming that the input signal is periodic, the magnitude of the DFT is spatially invariant(phase of the input does not matter) which is not true for DCT. The DCT does notintroduce discontinuities while imposing periodicity into the time signal, whereas in theDFT, the time signal is truncated and assumed to be periodic. As a result, discontinuitiesare introduced in the time domain and corresponding artefacts are introduced into thefrequency domain. However, as an even symmetry is assumed while truncating the timesignal, no discontinuities or related artefacts are introduced in the DCT. The comparisonbetween the FFT and the DCT is shown in Figure 10 [8].

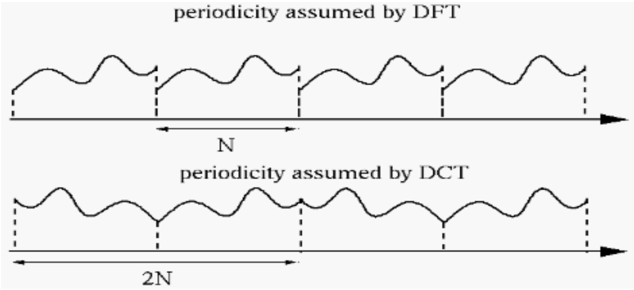

Figure 7. Periodicity comparison of DFT and DCT [8]

In order to test the algorithm on a real speech signal, a wave recorder was used torecord a short piece of speech. The MATLAB function “wavrecord” allows the user torecord n samples of an audio signal at a specific sample rate. For instance, Figure 8,shows a speech signal recorded using the “wavrecord” function composed of 2000samples. The recorded speech signal then goes through the DCT which transforms asequence of real data points into its real spectrum. The transformed speech signal is shown in Figure 9. Before compressive sensing is applied to the DCT spectrum athreshold window is used to eliminate the small coefficients.

Table 1. Amount of compression by varying signal parameter.

Length of Signal (L)	Threshold window (Th) UL	Threshold window (Th) LL	Compressed samples (K)	Error (err)	Compression (%) (K/L)
2000	0.04	-0.06	1000	1.5×10^{-5}	50
2000	0.04	-0.06	900	1.8×10^{-5}	55
2000	0.04	-0.06	800	7×10^{-5}	60
2000	0.04	-0.06	700	0.7	65
2000	0.04	-0.06	600	0.18	70
2000	0.04	-0.06	500	0. 3	75

IV. SPEECH SIGNAL VARIATION

The rationale under thisprocess is that the small coefficient does not contribute to the overall signal compared tothe large coefficient. This is used to ensure that the DCT spectrum is sparse beforeapplying compressive sensing. The result from this process is shown in Figure 7.Thethreshold spectrum is then multiplied by the measurement matrix which in this case iscomposed of randomly generated numbers which is shown in Figure 11.

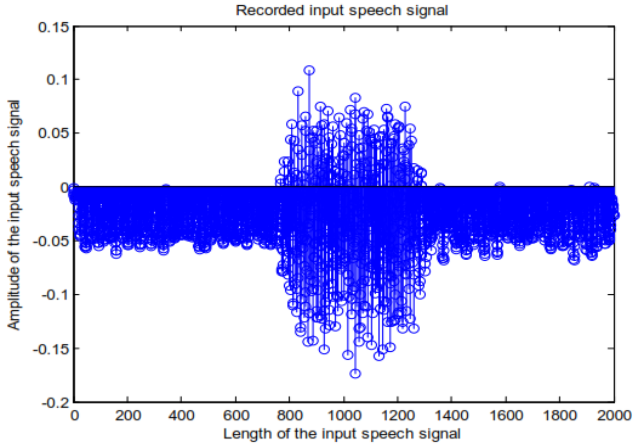

Figure 8. Recorded input speech signal

The output of compressive sensing is the observation vector which is sent to themobile communication module in order to be transmitted which is shown in Figure 12. Atthe receiver the compressed DCT coefficient is decompressed and reconstructed from asignificant small numbers of observations using one of the different optimizationtechniques such as the l normalization shown in Figure 16.

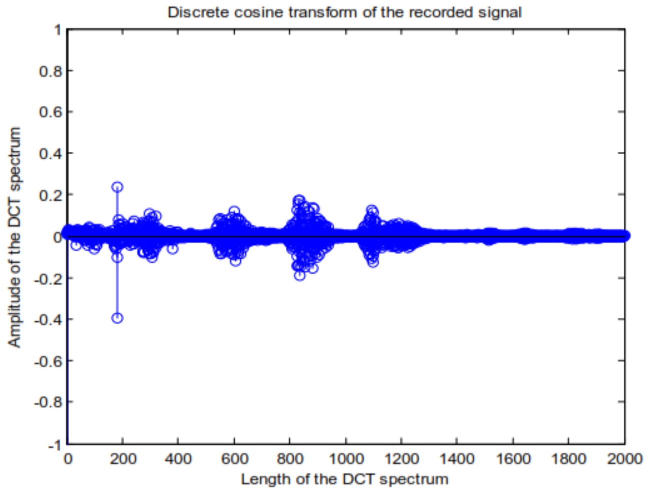

Figure 9. DCT of recorded speech signal

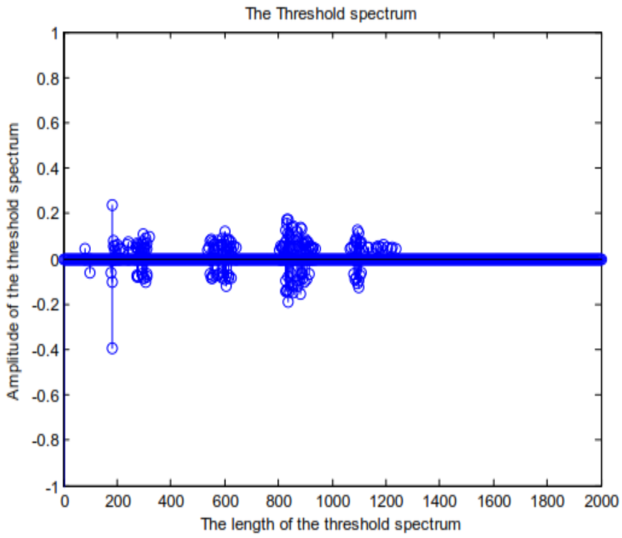

Figure 10. Threshold spectrum

In this research the design of a new mobile communication system using compressive sensing has been studied. The proposed system should fulfil the following specifications:

- Low power consumption
- Accurate reconstruction of the speech signal
- Increased data rates

During the design process, this module went through different tests and analysis in order to find the most adequate optimization technique to reconstruct the speech signal withfew random measurements without losing the information. For simulation purposes, code was created in order to compress and transmit the speech signal below the Nyquist rate by taking only a few measurements of the signal. The result shows that by keeping the length of the signal (L) and threshold window (Th) constant one can achieve the desired compression of the signal by making the signal sparse (K) to a certain amount which in turn increases the data rates.

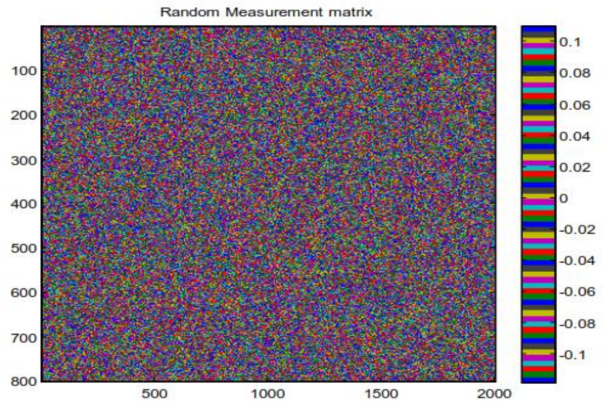

Figure 11. Random measurement matrix

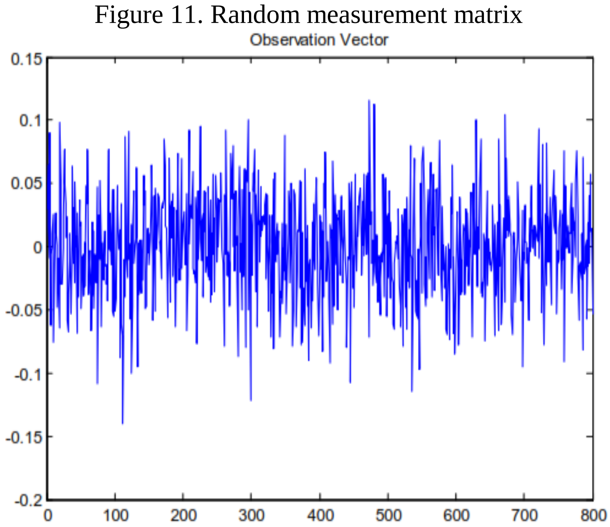

Figure 12. Observation vector

The error is calculated bytaking the difference between the received and the transmitted threshold spectrum, which is shown in Figure 14. Finally, the received reconstructed spectrum is passed through theIDCT in order to recover the speech signal. The recovered speech signal can be observed in Figure 15. 1During the design of the proposed system multiple tests were performed in orderto analyze the efficiency of this system.

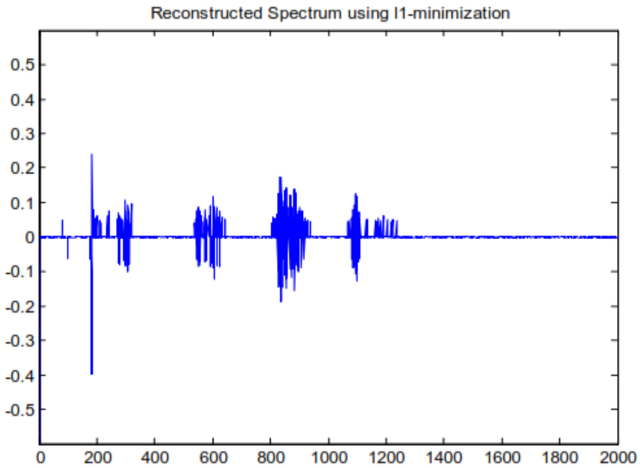

Figure 13. Reconstructed spectrum using l

Table 1 shows how the length of the signal, the threshold value and the sparsity of the signal affect the compression rates. It is also observed that by keeping the length of the signal (L) constant and by varying the Threshold window (Th) it is plausible to achieve a desired compression. This is becauseby modifying the threshold window the compressed sample (K) is also modified

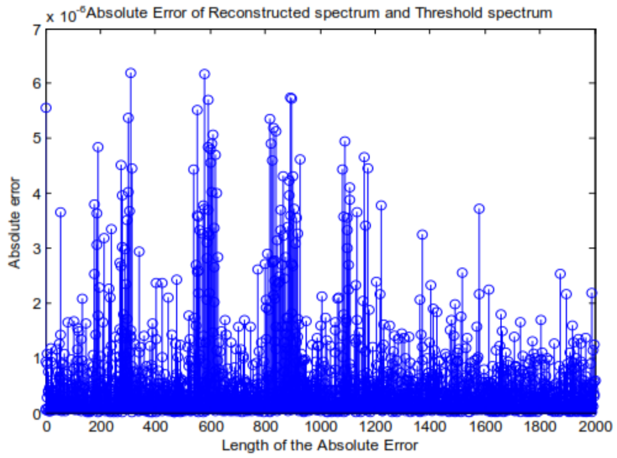

Figure 14. Absolute error between the received reconstructed spectrum and original Spectrum

V. Conclusion

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. However, the system is still not perfect and more research still required. 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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