ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijareeie.com

Vol. 6, Issue 6, June 2017

A Novel Approach to Compress and Reconstruct an Audio Signal

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ABSTRACT: Compressive sensing is a newly emerged technology in which the main aim is to have more efficiency in terms of storage and also in terms of transmission and receiving of data. Proposed methodology is to compress the audio signal for purposes mentioned above and later the compressed audio signal has to be reconstructed with any of the reconstruction algorithm. During Compressive Sensing the number of samples are reduced using transform and is called as sparse matrix, then measurement matrix A is defined with help of both, original audio signal and sparse matrix. When measurement matrix is multiplied with the Sparse matrix, a compressed audio signal is obtained. There are number of reconstruction algorithms to reconstruct the compressed signal, here Compressive Sampling Matching Pursuit (CoSaMp) algorithm is used to reconstruct the compressed audio signal. The CoSaMp gives the reconstructed audio signal with same number of samples as that of input audio signal with less computation effort compare to other reconstructed algorithms. Further it can be applied to videos also.

KEY WORDS: Compressive Sensing, Measurement Matrix, Sparse Matrix, Compressive Sampling Matching Pursuit,

I.INTRODUCTION

According to the Shannon/Nyquist sampling theorem, in order to reconstruct a band limited signal perfectly the sampling rate should be at least two times that of the signal bandwidth B. The quantity $2B$ is called the Nyquist rate. The sufficient condition for signal to be perfectly reconstructed from an infinite sequence of samples is the sample rate f_s should be larger than $2B$. If f_s is less than $2B$, aliasing will be introduced after reconstruction.

While in reality, this sampling rate is still so high that too many samples should be achieved. Especially in the medical imaging modality, we need to reduce the time of the patients exposure in the electromagnetic radiation. So it is desirable to take as few samples as possible without losing essential information.

In traditional data acquisition, the first step is to acquire the full N-sample signal x; then compute the coefficients via and only keep the K largest while discarding the others. The values and locations of the K largest should be encoded. This traditional signal acquisition processing divides the sampling and compression into two separate processes which samples a lot of unnecessary information. This inefficiency is more obvious when the number of samples N is large compared to K.

The energy issue has been the main motivating research challenge in data processing. In order to reduce energy consumption, data compression scheme solves this issue through reducing the amount of data to be transmitted. Traditional data compression approach measure environment, is to uniformly sample and then compress data. It is effective of traditional data compression before transmitting data to reduce total power consumption, but this method waste sensing resources, time and storage. With the emerge of Compressed Sensing (CS), CS becomes the focus of present researches in data compression. Compressed sensing is a method to skip the sampling step by directly acquiring the compressed signal representation to overcome these inefficiencies.

CS combines steps of sampling and compressing with interesting properties, and only storage and transmit a few non-zero coefficients, and nonlinear optimization can then enable recovery of such signals from very few number of

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measurements. Greatly reduce the time of data acquisition, storage and the amount of data needed to be transmitted. It is the prominent advantage of CS. CS has the advantages of excellent compression performance, non-adaptive coding, independent of encoding and decoding**.**

Compressive sensing is a very simple, efficient, non adaptive and parallelizable compressed data acquisition protocol that provides both sampling and compression along with encryption of source information simultaneously. The theory of compressive sensing was developed by Candes *et al* and Donoho in 200iv. This method is different from traditional method as it sampled the signal below the Nyquist rate and it permits to exploit the sparse property.

at the signal acquisition stage of compression. In this method the signal is first transformed into a sparse domain and then the signal is reconstructed using numerical optimization technique using small number of linear measurements. Implementation of Compressive sensing Theory in specific application reduced sampling rates, or reduced use of Analog to Digital converter Compressive sensing is a new paradigm of acquiring signals, fundamentally different from uniform rate digitization followed by compression, often used for transmission or storage. Compressive sensing can be used in image compression, radar system, A to D converter, Medical Imaging, speech compression etc.

In the proposed approach, a speech signal was recorded and compressively sampled using a measurement matrix. The output of the compressive sensing algorithm is the observation vector which is transmitted to the receiver. At the receiver section signal is reconstructed from a significant small numbers of samples by using different optimization techniques such as OMP, CoSaMp etc.

II. (a) COMPRESSIVE SENSING

Compressive sensing is a radical new way of sampling signals at a sub-Nyquist rate. The Shannon/Nyquist sampling theorem states that an analogue signal can be reconstructed perfectly from its samples, if it was sampled at a rate at least twice the highest frequency present in the signal (Nyquist 1928; Shannon 19iv9). This rate is known as the Nyquist or Shannon rate of that signal, and for many signals, such as audio or images, the Nyquist rate can be very high. This may result in acquiring a very large number of samples, which must be compressed in order to store or transmit them, as well as placing a high requirement on the equipment needed to sample the signal. Compressive Sensing (also referred to as compressed sensing or CS) is a recently introduced method that can reduce the number of measurements required; in some ways it can be regarded as automatically compressing the signal. Compressive sensing is a technique that enables us to fully reconstruct particular classes of signals if the original signal is sampled at a rate well below the Nyquist rate.

In particular, compressive sensing works with sparse signals. In many applications the signal of interest is primarily zero, that is, the signal has a representation in some pre-determined basis in which most of the coefficients are 0. Traditionally measurement techniques heavily over sample the signal. Compressive sensing avoids excessive oversampling by using linear sampling operators – a combination of sampling and compression, giving rise to its name.

The goal of compressive sensing is to design the matrix Φ and a reconstruction algorithm so that for k-sparse signals we require only a "small" number of measurements, i.e. $m \approx k$ or slightly larger. This does not violate the Shannon-Nyquist sampling theorem as we are not able to reconstruct all signals, only sparse signals.

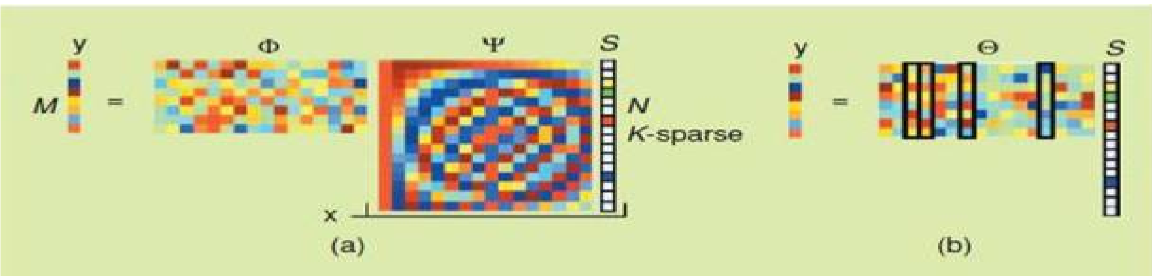

Fig2.1: a)Compressive sensing measurement process with random measurement matrix Φ and DCT matrix $\boldsymbol{\psi}$ the vector of coefficients s is sparse with $\boldsymbol{K = 4}$**.** b) Measurement process with $\Theta = \Phi\psi$**.** There are four columns that corresponds to nonzero s_i coefficients; the measurement vector y is a linear combination of these columns.

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Vol. 6, Issue 6, June 2017

II. (b) MEASUREMENT MATRIX

The measurement matrix Φ must allow the reconstruction of the length- N signal $\boldsymbol{x}$ from $M * N$ measurements (the vector $\boldsymbol{y}$). Since $M < N$, this problem appears ill-conditioned. If, however, $\boldsymbol{x}$ is K-sparse and the K locations of the nonzero coefficients in $\boldsymbol{s}$ are known, then the problem can be solved provided $M \geq K$. A necessary and sufficient condition for this simplified problem to be well conditioned is that, for any vector $\boldsymbol{v}$ sharing the same K nonzero entries as $\boldsymbol{s}$ and for some $\epsilon > 0$.

Significance of measurement matrix:

1. The specific designing of the sensitive matrix will improve the speed of the compressive sensing.

2. It should be designed in such a way that the matrix which is designed should not destroy any information contained in the original signal.

3. A reconstruction algorithm should recover the signal from only M ≈K measurements.

III.METHODOLOGY

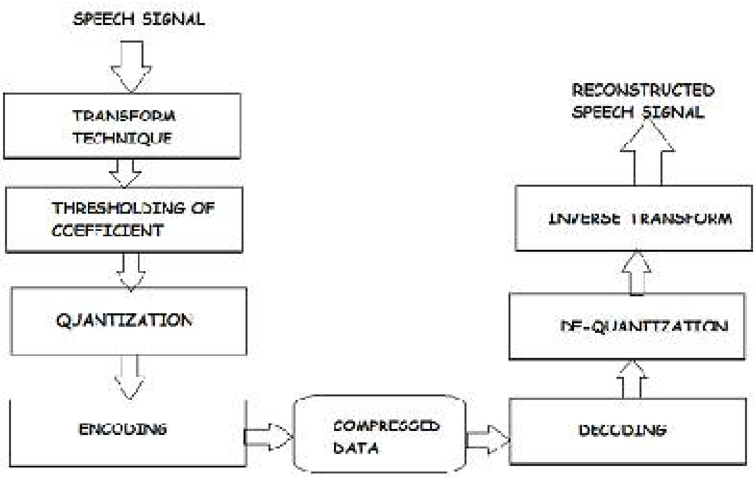

Fig 3.1: Block diagram for compressive sensing

Speech compression is performed in the following steps.

- Transform technique
- Thresholding of transformed coefficients
- Quantization
- Encoding
- **Transform Technique**

DCT and DWT methods are used on speech signal. Using DCT, reconstruction of signal can be done very accurately; this property of DCT is used for data compression. Localization feature of wavelet along with time frequency resolution property makes DWT very suitable for speech compression. In our project we have used the DCT transform technique.

- **Thresholding** After the coefficients are received from different transforms, thresholding is done. Very few DCT coefficients represent 99% of signal energy; hence Thresholding is calculated and applied to the coefficients. Coefficients having values less than threshold values are removed.

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- **Quantization**

It is a process of mapping a set of continuous valued data to a set of discrete valued data. The aim of quantization is to reduce the information found in threshold coefficients. This process makes sure that it produces minimum errors. We basically perform uniform quantization process.

- **Encoding**

We use different encoding techniques like Run Length Encoding and Huffmann Encoding. Encoding method is used to remove data that are repetitively occurring. In encoding we can also reduce the number of coefficients by removing the redundant data. Encoding can use any of the two compression techniques, lossless or lossy. This helps in reducing the bandwidth of the signal hence compression can be achieved. The compressed speech signal can be reconstructed to form the original signal by DECODING followed by DEQUANTIZATION and then performing the INVERSE-TRANSFORM methods. This would reproduce the original signal.
Audio signal has the characteristics of short-term stability. In the real world, some audio signals also have the characteristics of time-varying, some special audio signals are a non-stationary stochastic process, and these signals are usually not sparse and have many non-zero components in whatever basis could be used in reconstruction. As a whole, the essential characteristics of the parameters in some audio signals are changing with time, but there are some especial audio signals whose essential characteristics of the parameters are almost the same in a short time (generally considered to be 10-30 ms), which is the so-called short-term stability. Due to some special audio signals has the characteristics of short-term stability in the real world, these signals could be processed using compressed sensing method. These long-time signals are divided into several short-time signals, each short-time signal is called a frame, and frame length is generally 10-30 ms. After each frame is compressed and transmitted with CS method. Then the approximate audio signals are recovered completely from very few measurements. The compressed sensing framework for Audio signals with short-term stability is provided in Fig iv.1. After all nodes capture their readings, each frames is processed with compressed sensing theory, then all nodes send the observation values to the sink, where the original signals are reconstructed.
In the proposed system, the original sampled signal is composed of 92iv9 samples. The intent is to reconstruct the signal using only 800 samples. In time domain representation of signal it is difficult to select only 800 samples from 92iv9 samples, by applying compressive sensing to the frequency representation of the signal it is possible to perfectly reconstruct it from a significant small number of samples. In order to achieve this goal it is necessary to implement an optimization techniques. Here the DCT technique is used to optimize the signal.
Once the signal is represented in the frequency domain, the sparse signal can be obtained by that signal, which contains 800 samples. This signal will be having corresponding matrix, which is called as Sparse matrix. In order to compress the signal, the random measurement matrix should be obtained. The random measurement matrix should be multiplied with the sparse matrix which will give the compressed signal.

Reconstruction of compressed signal
Practical signal reconstruction algorithm should have all of the following properties.

- It should accept samples from a variety of sampling schemes.
- It should succeed using a minimal number of samples.
- It should be robust when samples are contaminated with noise.
- It should provide optimal error guarantees for every target signal.
- It should offer provably efficient resource usage.

In proposed system in order to reconstruct the compressed signal, the compressive sampling matching pursuit reconstruction algorithm is used. The algorithm is called CoSaMP, from the acrostic compressive sampling matching pursuit. As the name suggests, this new method is ultimately based on orthogonal matching pursuit (OMP), but it incorporates several other ideas from the literature to accelerate the algorithm and to provide strong guarantees that OMP cannot.

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Compressive sampling matching pursuit (CoSaMP) algorithm is one of matching pursuit algorithms used for compressed sensing image reconstruction, which is proposed by D. Needell in 2008. When identifying signal supported set, the CoSaMP uses the inner product of each column vector of the measurement matrix and residual vector as an identification indicator. CoSaMP, the algorithm described in this paper, is at heart a greedy pursuit. It also incorporates ideas from the combinatorial algorithms to guarantee speed and to provide rigorous error bounds.

The CoSaMP Algorithm

The CoSaMP algorithm is, at heart, a greedy iterative method for reconstructing a signal from compressive samples.This section provides an overview of the algorithm and its implementation. We also explain the basic idea behind the analysis of the algorithm, which demonstrates that each iteration reduces the error in the current signal approximation.

Description of algorithm

The input to the algorithm consists of (access to) the sampling operator Φ, the samples $\boldsymbol{u}$, the target sparsity level s, and a halting criterion:

- The sparsity level s is fixed, and the $m \times N$ sampling operator Φ has restricted isometry constant $\delta_4 \leq 0.1$.

- The signal $\boldsymbol{x} \in C^N$ is arbitrary, except where noted. The noise vector $\boldsymbol{e} \in C^m$ is also arbitrary.

The vector of samples $\boldsymbol{u} = \Phi \boldsymbol{x} + \boldsymbol{e}$.

The algorithm is initialized with a trivial signal estimate, meaning that the initial residual is the entire unknown target signal. Each iteration then consists of five major steps.

Identification: Using the current samples, the algorithm computes a vector that is highly correlated with the signal, called the signal proxy. From the proxy, components of the signal that carry a lot of energy are located.

Support Merger: The set of newly identified components is united with the set of components that appear in the current approximation.

Estimation: The algorithm solves a least-squares problem to approximate the target signal on the merged set of components.

Pruning: The algorithm produces a new approximation by retaining only the largest entries in this least squares signal approximation.

Sample Update: Finally, the samples are updated so that they reflect the residual, the part of the signal that has not been approximated. These five steps are repeated until the halting criterion is satisfied. In our analysis, we assume that the method uses a fixed number of iterations.

IV.RESULTS

In a proposed system an audio sample is considered and applied the compressive sensing technique to compress the signal, with the help of different reconstruction algorithm got back the same signal. To reconstruct the compressed audio signal the Matching pursuit algorithms like Orthogonal matching pursuit(OMP) and Compressive Sampling Matching Pursuit(CoSaMP), out of both the algorithms the CoSaMP will show better results when simulated with Matlab. In the proposed system the compressive sensing on audio signal and its reconstruction is performed in the *Matlab version 2007* and the results of the simulation are as shown below.

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The original signal having length N= 92iv9 is considered. The intent is to reconstruct the signal using only 800 samples. Fig4.1 shows the original signal having 92iv9 samples. In time domain representation of signal, it is difficult to select only 800 samples from 92iv9 samples. By applying compressive sensing to the frequency representation of the signal it is possible to perfectly reconstruct it from a significant small number of samples. In order to achieve this goal it is necessary to implement an optimization techniques. Here DCT technique is used to optimize the original signal and the obtained result is as shown in the fig 4.2.

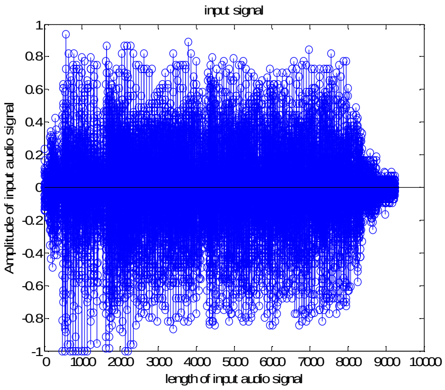

Fig 4.1: Input signal

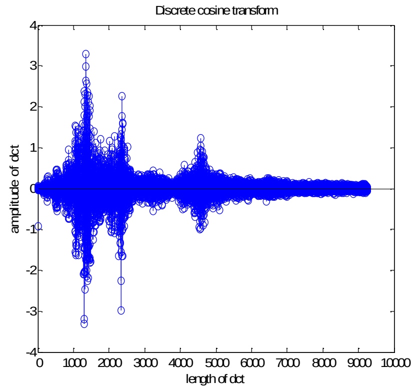

Fig 4.2.: Discrete cosine transform of audio signal

Once the signal is represented in the frequency domain, the sparse signal can be obtained by applying the upper threshold limit and lower threshold limit to the signal obtained by the discrete cosine transform. The samples which are having the amplitudes lower than the lower threshold limit are discarded. Then that signal, which contains k=800 samples is obtained which is called as the sparse matrix as shown in the fig 4.3.

In order to compress the signal, the random measurement matrix should be obtained for the signal. The random measurement matrix should be multiplied with the sparse matrix which will give the compressed signal. The random measurement matrix is as shown in the fig 4.4 and the compressed signal is represented in the fig 4.5.

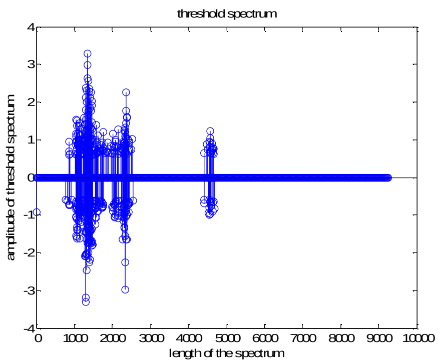

Fig 4.3: Threshold spectrum

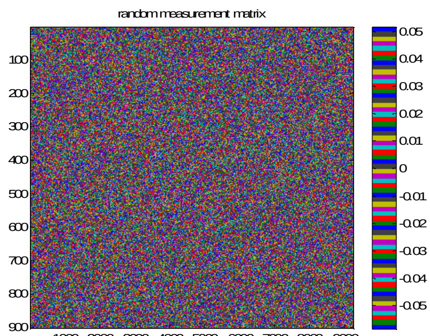

Fig 4.4: Random measurement matrix

The signal obtained by multiplying the measurement matrix with the sparse matrix will give the compressed signal which is called as the observation vector (Y).

Once the observation vector is obtained, the reconstruction algorithm is applied in order to get the reconstructed signal. In the proposed system the reconstruction algorithm CoSaMp is used. The signal obtained after appliying the CoSaMp is as shown in the fig 4.6.

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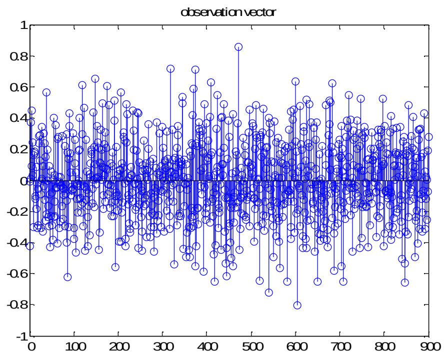

Fig 4.5: Observation vector

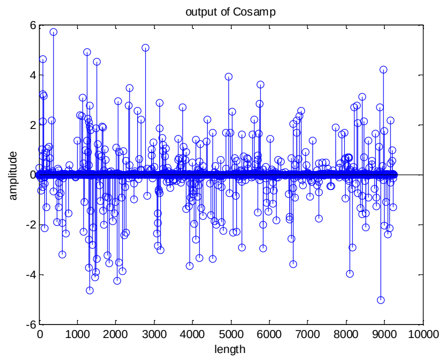

Fig 4.6: Output of CoSaMP

Once the output of the CoSaMP is obtained, it is applied to the inverse of discrete cosine transform in order to get the reconstructed signal as shown in the fig 4.7.
When the reconstructed signal is obtained, it is compared with the observation vector and the error signal is calculated as shown in the fig 4.8.

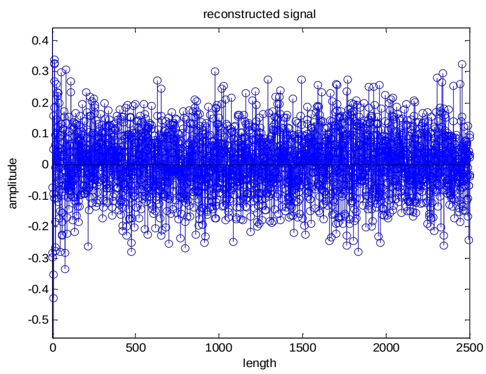

Fig 4.6: Reconstructed signal

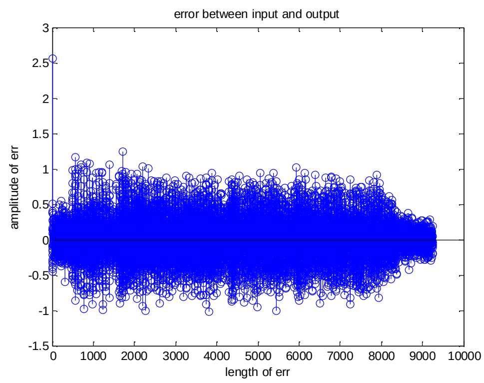

Fig 4.7: Error between input and output audio signal

When the reconstructed signal is obtained, then the error is calculated for the particular value of upper and lower threshold limits. For that particular sensing matrix. Once the error is calculated, the threshold limits are changed and corresponding error is noted and the procedure is repeated to get the different set of values and the difference in the value of error is observed for the particular sensing matrix and these values are tabulated as shown in the Table 4.1.

Sl.No	Threshold	K (Sparsity)	Length of signal(N)	Error
1.	0.3 to -0.3	800	92iv9	1.5983
2.	0.iv to -0.iv	800	92iv9	2.9268
3.	0.5 to -0.5	800	92iv9	2.8562
iv.	0.7 to -0.7	800	92iv9	2.616

Table 4.1 Variation of threshold for particular sensing matrix

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In the next set of results the length of the measurement matrix is varied for the particular threshold values and four sets of results are obtained for each threshold limit as shown in the below tabulation columns

Threshold: 0.3 to -0.3

Sl.No	Sparsity(K)	Length(N)	Error
1.	600	92iv9	3.3809
2.	300	92iv9	3.2260
3.	200	92iv9	2.2709
iv.	100	92iv9	1.5983

Table 4.2 Variation of measurement matrix size for a particular threshold

Threshold: 0.iv to -0.iv

Sl.No	Sparsity(K)	Length(N)	Error
1.	600	92iv9	3.27iv1
2.	300	92iv9	3.2526
3.	200	92iv9	2.3639
iv.	100	92iv9	1.6377

Table 4.2 Variation of measurement matrix size for a particular threshold

The reconstruction of the compressed signal is done with the matching pursuit algorithms such as the orthogonal matching pursuit(OMP) and compressive sampling matching pursuit algorithm (CoSaMP) and the results are tabulated as shown in the below table. The results shows that the error obtained from the CoSaMP are less compare to OMP. Hence more accurate reconstruction of the signal can be obtained. Time required for the reconstruction is less with CoSaMP compared to OMP and other reconstruction algorithms.

V.CONCLUSION

In the proposed system, the signal of $N \times 1$ is considered and DCT of the signal is calculated in order to bring it in the frequency domain, once the DCT of the signal is obtained the threshold limits are applied to the signal the amplitudes of the samples having less lower threshold are eliminated and got the sparse matrix. The measurement matrix A is obtained, the measurement matrix is multiplied with the sparse matrix to get the compressed signal. The reconstruction of the compressed signal is done with two types of matching pursuit algorithms such as Orthogonal matching pursuit(OMP) and Compressive Sampling matching pursuit (CoSaMP) algorithm. With reference to the results obtained by both the algorithms it can be concluded that the accuracy of the CoSaMP is more compared with OMP. Time required for the reconstruction with CoSaMP is less compared with OMP. The proposed system should fulfill the following specifications

- Accurate reconstruction of the speech signal
- Increased data rates

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Vol. 6, Issue 6, June 2017

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 with few 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. Random measurement matrix was 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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