EXACT RECONSTRUCTION OF UNDERSAMPLED AND NON-UNIFORMLY SAMPLED SIGNAL USING MATCHING PURSUIT

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ABSTRACT

In this paper includes the information about the orthogonal matching pursuit. Matching pursuit is a sparse approximation algorithm which finds the best matching projections of multidimensional data onto the span of a redundant. This algorithm challenge to approximate a compressible signal from noisy samples. In OMP error decreases monotonically and it satisfied the condition of energy conservation equation for each value of the samples.

Keywords- *compressive signal, orthogonal matching pursuit, sparse signal, sampling signal, signal reconstruction.*

I. INTRODUCTION

Sampling is a process of converting a continuous signal into discrete time signal.The value or set of values at a point in a time and space area called as samples. The average number of samples obtained per second is called as sampling frequency or sampling rate (fs).The sampling theorem states that “A continuous time signal can be represented in its samples and can be recovered or reconstructed back when sampling frequency is greater than or twice that of highest frequency of message signal” the different types of sampling are oversampling, under sampling and nyquist sampling rate. Under sampling is the condition where the sampling frequency is less than twice that of highest frequency in message signal. The signal can also be reconstructed even if it does not satisfy nyquist rate. Compressed sensing is one of the signal processing technique use to reconstruct the signal by finding solutions to underdetermined linear systems. It is also called as compressive sensing or sparse sampling. The general meaning of the sparse is very few. Sparse signal consists of very few non zero co-efficient in any domain usually sparse signal will be in frequency domain. By using the concept of sparsity a large signal can be reconstructed by selecting very few samples from the original signal.To achieve the recovery of the signal it has to satisfy two conditions they are: Sparsity and Incoherence where in sparsity condition the signal should be in some sparse domain and incoherence is that condition which will be applied through isometric property which is sufficient for sparse signals.There are different algorithms which are developed to reconstruct the sparse signals. Among that one of the algorithm is Orthogonal Matching Pursuit algorithm.

In the present paper we are using matching pursuit algorithm in order to recovery sparse signal.Using this algorithm it has been found that exact signal can be recovered in iterations .By using this algorithm the recovery

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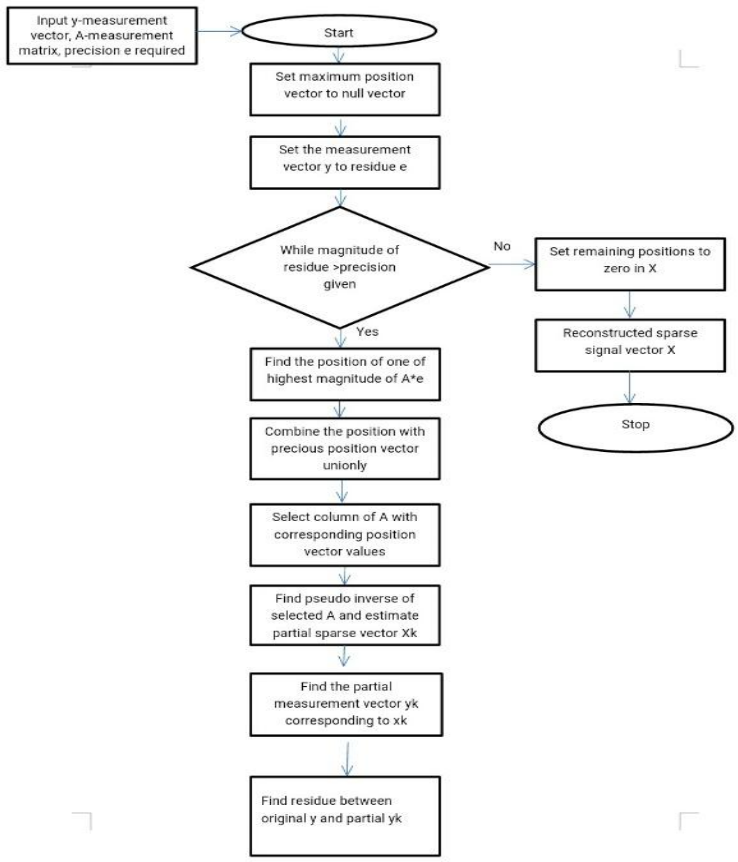
rate is high when it runs for more iterations. In this algorithm after each and every step the extracted coefficients are updated by computing the orthogonal projection of the signal onto the subspace spanned by the set of selected atoms so far. It can give us better result in the reconstruction of the signal but it will require more computation.

II. FLOW CHART



III. METHODOLOGY

The main equation for generation of sparse signal is

$$AX=Y$$

Where, A is the measurements matrix generated using IDFT.

Y is the measurement vector. Measurement vector is the random samples taken from the matrix generated from certain equation as per the requirements

X is the sparse signal that is to be generated.

Here, the sparse signal is generated using OMP algorithm.

Step1: Consider an empty Matrix K. K is used to store the positions of nonzero values in sparse signal.

Step 2: Take a duplicate of measurement matrix in e.

$$e=Y.$$

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Step 3: Take €=0.01

Step 4: Do multiple iterations until the residue, r value becomes less than £.

Step 5: To find the residue value

Let b1, b2...bn be the columns of the measurement matrix A.

multiply b1,b2...bn with Y separately.

We get Xk= X1,X2....Xn

Where X1=b1*Y

X2=b2*Y

Xn=bn*Y

In MATLAB Xk can be calculated using, Xk=pinv(A)*Y.

Assume that X1 has the highest value (neglecting negative), it gives maximum contribution to Y.

Now calculate the residue

r=Y-X1*b1

If the residue is greater than £, continue for second interaction taking b2 and b3 and so on.

Step 6: During the iteration, the position contributing the maximum value is stored in matrix K.

Step 7: Generate a Nx1 matrix X with all zero in it.

Step 8: Put X=0, for positions not in K

X=Xk, for positions in K

IV. APPLICATIONS

This concept is used for signal representation, ECG/MEG, Speech coding, image reconstruction, Radar (ISAR) Signal Processing, Sparse channel equalization, Compressive Sampling**.**

V. RESULT

The matching pursuit algorithm is coded in MATLAB and the result is shown in the following fig 1 to fig 2.

The figure 1 represents the

1. Original signal x(n) for reference.
   This signal is uniformly sampled with N=64 samples. The signal is plotted time versus magnitude (Time domain).
2. Under sampled signal y(n) measured signal.
   A random 16 samples are considered in this signal. The signal is plotted time versus magnitude (Time domain).
3. Spectrum of original signal x(n) for reference.
   Applying inverse DFT for measurement matrix A corresponding to the samples defined in time domain and this signal is obtained. The signal is plotted frequency versus magnitude (Frequency domain).

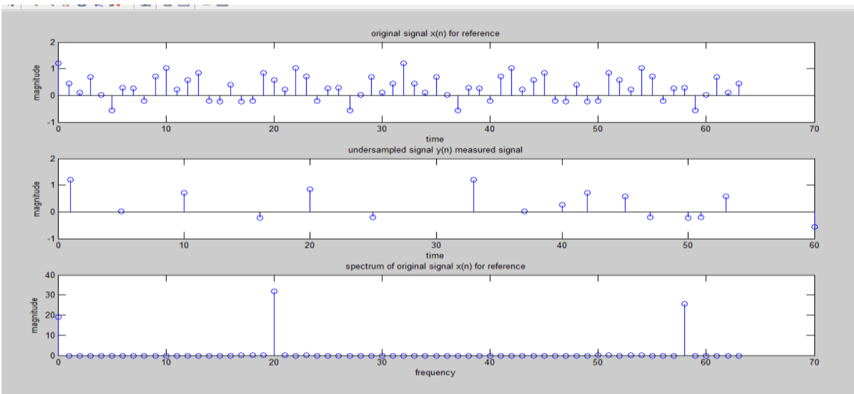

Fig1: The original signal

The Figure 2 represents the

1. Spectrum of reconstructed signal/sparse signal.

   The matching pursuit algorithm is used to get the reconstructed signal. The reconstructed signal is exactly same as original signal.

2. Spectrum of reconstructed signal x_hat.

   The reconstructed signal of original signal (reference) is also obtained here.

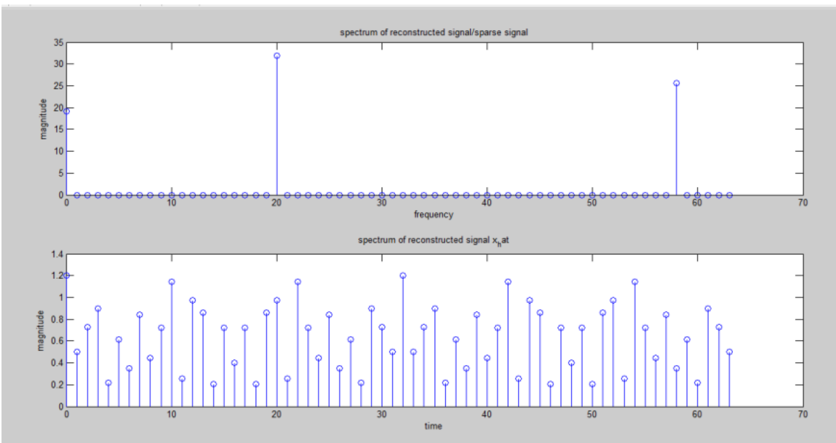

Fig 2: Reconstructed Signal

VI. CONCLUSION

In this paper represent the basic introduction to reconstruction of under sampled and non-uniformly sampled signal. The condition to reconstruct the signal is discussed here. And proved using matching pursuit algorithm and the result is showed in fig 1 to fig 2.

VII. ACKNOWLEDGEMENT

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