MIMO – OFDM CHANNEL ESTIMATION BASED ON A SPARSE RECOVERY-NAMP ALGORITHM

[1]Masthan-E-Shahina Shaik, [2]A.Madhusudhanarao, [3]G.Parnesh, [4]A.V.Ramanaiah, [5]K.Sreenivasulu
[1]Asst. Professor, [2,3,4,5] Final Year, B .Tech
[1]Electronics and Communications Engineering
[2,3,4,5] Geethanjali Institute of Science and Technology, Nellore, India

Abstract: Due to the influence of the wireless generation environment in the transmission operation, there are different academic degrees of fading and delay, which results in the distortion of the symbols for the MIMO-OFDM system. For purpose of effectively overcoming the interference and distortion, the receiver needs to achieve accurate channel characteristics and also wireless channel has to exhibit sparse characteristics. so accurate and fast channel estimation is the core part of the stable wireless communication system. Therefore, the main disadvantage of existing SAMP algorithm is to obtain sparsity level of the signal and get priori knowledge because of changeable environment. So to increase the accuracy and reduce the time of channel approximation we proposed a new adaptive matching pursuit (NAMP) algorithm. The main aim of this algorithm is to select the atoms with a stable step size and remove the components of small energy by Singular Entropy order determination (SEOD) in the sparse solutions. First, NAMP does not require any priori-knowledge of the sparseness level. Second, to increase the efficiency of signal recovery we have to determine the fixed step size of the signal. Finally our proposed NAMP algorithm provides less computational complexity and achieves more stable performance than the existing SAMP algorithm.

***IndexTerms* - MIMO-OFDM, New Adaptive Matching Pursuit, SAMP, Compressed sensing, Singular Entropy Order Mechanism.**

I. INTRODUCTION

In present generation communication systems plays a vital role in the transmission of data from any place to any place or from any other individuals. For transmitting the exact transmission of data, we need some protocols and algorithms for the designing of communication systems and also while transmitting the data in channel of MIMO-OFDM systems there are some losses occur because of different degrees of fading, distortion, inter symbol interference and absorption of the signal in the channel. To avoid this problems in the MIMO-OFDM system, we have to estimate the characteristics of the channel parameters. There are different methods for channel estimation they are least square(LS),minimum mean square error(MMSE)[3],orthogonal matching pursuit(OMP)[4],compressive sampling matching pursuit(CoSAMP) [5] ,sampling matching pursuit (SAMP) algorithms are used. The Least Square (LS) and Minimum Mean Square Error(MMSE) algorithms are based on Shannon sampling therom, by using these algorithms we can reconstruct the exact signal but the spectrum is not efficiently utilized. To improve the efficient utilization of spectrum, Orthogonal Matching Pursuit(OMP) algorithm is used but the sparsness of the channel is not estimated. To reduce the problem in OMP algorithm, we go for Compressive Sampling Matching Pursuit CoSAMP) algorithm is used, the effectiveness of sparse channel estimation is verified by simulation results. The main disadvantage of the algorithms is required to obtain the sparsity level of the signal. But, the priori-knowledge is difficult to be acquired because of the unstable environment. To no longer rely on the sparsity level, a sparse signal estimation method referred to as the sparsity adaptive matching pursuit (SAMP) algorithm puts forward a stage-wise approach, which further increase the accuracy of signal estimation, but the performance of there construction is poor under low signal-to noise ratio(SNR) and algorithm complexity is high. With the development of CS[6] theory, how to use the technique for channel estimation has become the hot spot of current research. In order to optimize the accuracy and reduce the time of channel estimation, this paper introduces a new adaptive matching pursuit (NAMP) reconstruction algorithm for sparse multipath channel estimation, which does not need to get the knowledge of channel sparsity level as well. First, NAMP algorithm adopts the fixed step size similar to the CoSaMP algorithm, for purpose of improving the efficiency of signal recovery.

Next, a real-time elimination mechanism known as the SEOD method is adopted in the iteration process to prevent the less relevant atoms from being introduced, which can resist the noise interference so as to improve the robustness of the algorithm and be beneficial to forecast the sparsity.The experimental results demonstrate that the proposed SAMP algorithm achieves better performance than SAMP, whatever the accuracy of wireless channel estimation or computational complexity.

II. SYSTEMMODEL

The block diagram of the NAMP MIMO-OFDM system is given below

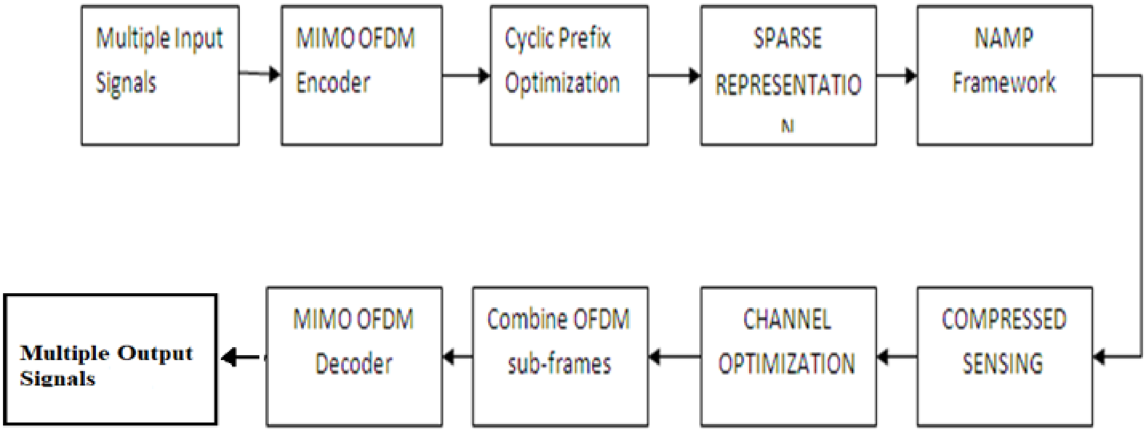

Fig 2.1:Schematic Block Overview of the proposed system.

In this block diagram multiple signals is given as input to the MIMO-OFDM encoder, here modulation of signals is done. Those modulated signal is given as input to the cyclic prefix optimizer. In this block those modulated signals is spited into positive and negative halves. From those halves the sparse matrix is generated by performing DFT on it. Those matrices are given to the NAMP algorithm for estimating the channel parameters and reconstructing the original signal. The redundancy of the signal is compressed by using compressed sensing algorithms. In MIMO-OFDM decoder, decoding of signal is done. The detailed analysis of the estimating the channel parameters are given below.

Consider a system with L number of Multi paths. The CIR can be given as

$$h(\tau,t)=\sum_{q=1}^{L} \alpha_q(t)\delta(\tau-\tau_q(t)) \qquad (1)$$

Where $\tau_q(t) \in \mathbb{R}$ and $\alpha_q(t) \in \mathbb{C}$ are real-valued delay spread and complex-valued magnitude for path q, in turn. Assuming block-fading channel where each block has channel parameters are persistent and also neglecting the symbol synchroniety, CIR in discrete form is given by

$$h(\tau,t)=\sum_{q=1}^{L} \alpha_q(t)\delta((\tau-\tau_q)T_q) \qquad (2)$$

Where $_{\alpha}$ is the sampling interval must be minimum compared to the maximum DS(Delay Spread) in a high data rate systems,(2) results in a channel with comparatively more number of zero taps and few nonzero taps. Let L be the total channel taps and Q of them nonzero (Q<<P) and it is called Q- sparse channel.

Let us consider OFDM system of N subcarriers, we select Np subcarriers as pilots with position $t_1,t_2,\ldots\ldots t_{Np}$ ($1\leq t_1<t_2<\ldots.<t_{Np} \leq N$) and N_D ($N_D = N - Np$) used as data subcarriers. $X(t_1),X(t_2),\ldots\ldots.,X(t_{Np})$and $Y(t_1),Y(t_2),\ldots\ldots.Y(t_{Np})$ represent the transmitted symbols and the received symbols at pilot locations. In frequency domain the estimated transfer function on pilot subcarriersis

$$\hat{H}(k)= \frac{Y(k)}{X(k)} \quad k= t_1, t_2, \ldots ,t_{Np} \qquad (3)$$

The channel transfer function in frequency domain using(DFT) discrete fourier transform $\hat{H}(k)$ (k = 1,2, ,N) can be obtained by taking pilot subcarriers and interpolating as shown in equation 3. If we take channel sparsity into account , the problem can be expressed as

$$y = X . F_{Np\times L}.h +n_0 \qquad (4)$$

Where $h=[h(1),h(2),\ldots.,h(L)]^T$ $X=diag\{X(t_1),X(t_2),\ldots\ldots.,X(t_{Np})\}$and =[n(1),n(2)…… (Np)] are the CIR, the diagonal matrix and the noise vector which is AWGN in nature,respectively. $Y=[Y(t_1),Y(t_2),----Y(t_{Np})]$

$$F_{N_p\times L} = \frac{1}{\sqrt{N}}\begin{bmatrix} 1 & w^{t_1} & \cdots & w^{t_1(L-1)} \\ 1 & w^{t_2} & \cdots & w^{t_2(L-1)} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & w^{t_{N_p}} & \cdots & w^{t_{N_p}(L-1)} \end{bmatrix}$$

Where w= In fact is a DFT submatrix chosen by column indices [0,1,….,L-1] and row indices [$t_1,t_2,\ldots\ldots t_{Np}$] from a regular NxN Fourier matrix. Further we can adopt and get

$$\mathbf{y} = \mathbf{A_d}.\ \mathbf{h} + \boldsymbol{n_0} \qquad \textbf{(5)}$$

To estimate the channel we have to obtain h from y and A_d. If columns of A_d is less than its rows (L<Np), equation (5) can be viewed as regular LS problem and solution to the problem is given by

$$\hat{\mathbf{h}}_{\mathbf{ls}} = (A_d^H A_d)^{-1} A_d^H . \mathbf{y} \qquad \textbf{(6)}$$

Evidently, we are more concerned in this case when the channel coefficients are more than the pilots (Np>L). It significantly help in decreasing pilots and therefore spectral efficiency is increases. Ideally, for sparse recovery problem there is a feasible solution if most components of vector h are zero (Q<<L).

III. COMPRESSED SENSING ALGORITHM

Compressed sensing algorithm reconstructs the signal based on the necessary fact that more number of signals can be categorized with only a few non-zero coefficients in appropriate basis. The recovery of signals can then be enabled by using few measurements of non-linear optimization. A Q-sparse vector can be reconstructed from equation (5) with purposefully considered A_d by resolving l_0- norm minimization problem

$$\mathbf{min}_{h \epsilon \mathbb{R}^L} \|h\|_0 \ \ s.t. \|y - A_d.h\|_2 \le \sigma_n \qquad \textbf{(7)}$$

Where ||h|| is the total number of non zero components of h and α is the variance of noise vector n is given by αn .However convex optimization problem can replace this problem.

$$\mathbf{min}_{h \epsilon \mathbb{R}^L} \|h\|_1 \ \ s.t. \|y - A_d.h\|\_2 \le \sigma_n \qquad \textbf{(8)}$$

There are techniques which would solve these kinds of problem shown in (7) and (8). They are divided into classes unevenly, containing convex optimization and greedy algorithms. Greedy algorithms are mainly used due to their low complexity.

Calculation of best non-linear approximation to a signal in a complete, redundant dictionary is attained by the proposed method which is a basic greedy algorithm. Proposed algorithm forms a series of sparse approximations to the signal stepwise that shapes a linear combination of matrix columns closest to the signal [7]. The measurement matrix do not have orthogonality between the atoms in the proposed non-orthogonal (or basic) matching pursuit algorithm. If we keep on removing succeeding residuals from the previous one can literally reestablish components that are not orthogonal to the span of the previously included atoms. Therefore, MP is revised as OMP. Here, for the next repetition, residue's orthogonal component can only be considered [8]. This means one can't choose the same atom twice and outcomes in convergence for a r-dimensional vector after at most r steps. The complexity is decreased compared to traditional LS method. Compared to other greedy algorithms like SP and CoSAMP, computational time complexity of orthogonal matching pursuit (OMP) is more. This is because at each step only one atom is selected. The total computational time of orthogonal matching pursuit (OMP) is given by O(m.N.K) where m.N is the total number of repetitions and K is the sparsity. Subspace Pursuit(SP) is another type of greedy algorithm which has less computational time and better BER performance. So instead of choosing one column at each step we choose S columns from the measurement matrix iteratively through LS method until preventing criteria is met. SP select S columns not like choosing single column in MP and OMP. The main drawback of SP is that we must have prior knowledge of S before we start the algorithm. Hence it is necessary to extend SP to the occurrence where the sparsity is not known. The total computational time of orthogonal matching pursuit (OMP) is given by O(m.N.log(K)).We can see that compared to OMP computational time complexity of SP is decreased because we are doing group selection instead of one.

Algorithm 1. NAMP Based Channel Estimation

Input: received symbol at pilot subcarriers $\mathbf{R}$, sensing matrix $\widehat{\boldsymbol{\Theta}} = \mathbf{SF}$, step size factor D, threshold parameter γ, threshold parameter ζ

Initialize: $\check{\mathbf{h}} \leftarrow \mathbf{0}_{N\times 1}$, $\hat{\mathbf{r}}_0 \leftarrow \mathbf{R}$, $\bar{\boldsymbol{\Gamma}} \leftarrow \emptyset$, $i \leftarrow 1$

For $i \leftarrow 1$ to WQ_R do

1: Identification: $\boldsymbol{\Gamma}_i \leftarrow supp(|\widehat{\boldsymbol{\Theta}}^H \cdot \hat{\mathbf{r}}_{i-1}|, D)$, $\bar{\boldsymbol{\Gamma}}_i \leftarrow \bar{\boldsymbol{\Gamma}}_{i-1} \cup \boldsymbol{\Gamma}_i$

2: Channel estimation: $\mathbf{h}_i \leftarrow \widehat{\boldsymbol{\Theta}}^{\dagger}_{\bar{\boldsymbol{\Gamma}}_i} \cdot \mathbf{R}$

3: Pruning: Via eq **9** find the position P_{se} when $E_{P_{se}} \geq \gamma$

4: Via eq. **10** update channel estimation $\check{\mathbf{h}}_i$

5: Update index set: $\bar{\boldsymbol{\Gamma}}_i = \bar{\boldsymbol{\Gamma}}_i(pos(1{:}P_{se}))$

6: Update residual: $\hat{\mathbf{r}}_i = \mathbf{R} - \widehat{\boldsymbol{\Theta}}_{\bar{\Gamma}_i} \cdot \check{\mathbf{h}}_i$

7: **end for** $(||\hat{\mathbf{r}}_i||_2 \leq \zeta)$

Output: $\check{\mathbf{h}} = \widehat{\boldsymbol{\Theta}}^{\dagger}_{\bar{\boldsymbol{\Gamma}}_i} \cdot \mathbf{R}$

Those equation 9 and 10 are used for calculating the singular entropy order and updating the channel parameters

$$E_{P_{se}} = \sum_{j'=0}^{P_{se}} \triangle \hat{E}_{j'}, E_{P_{se}} \subset (0,1],$$

$$\check{\mathbf{h}}_i = \mathbf{U}_{iD\times P}\widehat{\boldsymbol{\Lambda}}_{P\times P}\mathbf{V}^T_{P\times 1},$$

IV. SIMULATION RESULTS

We considered Rayleigh channel with three channel taps. The number of OFDM subcarriers used is 128. Out of which 12 are used as pilot subcarriers. NAMP algorithm are used to estimate the channel characteristics. The pilots are arranged according to the RIP(Restricted Isometric Property) among all OFDM subcarriers. In order to reduce channel estimation problem, we employ frequency orthogonal pilot placement.

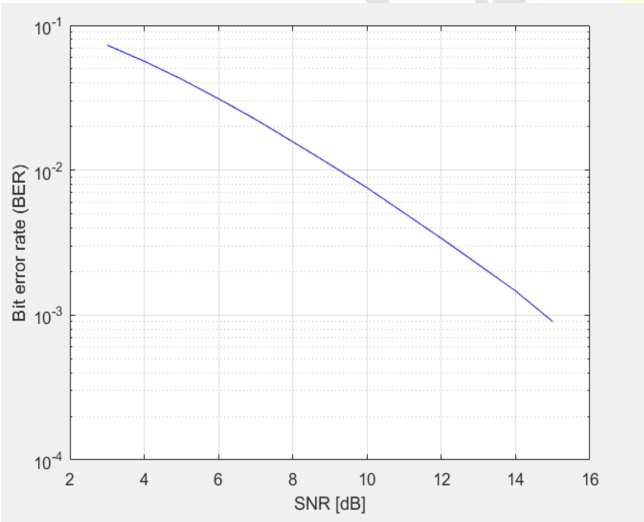

Fig.4.1 Bit error rate to Signal to Noise ratio

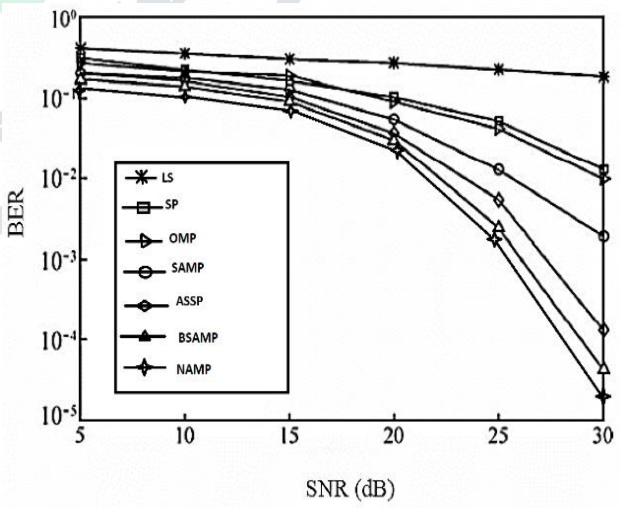

Fig.4.2 Graph of BER to SNR of different algorithms

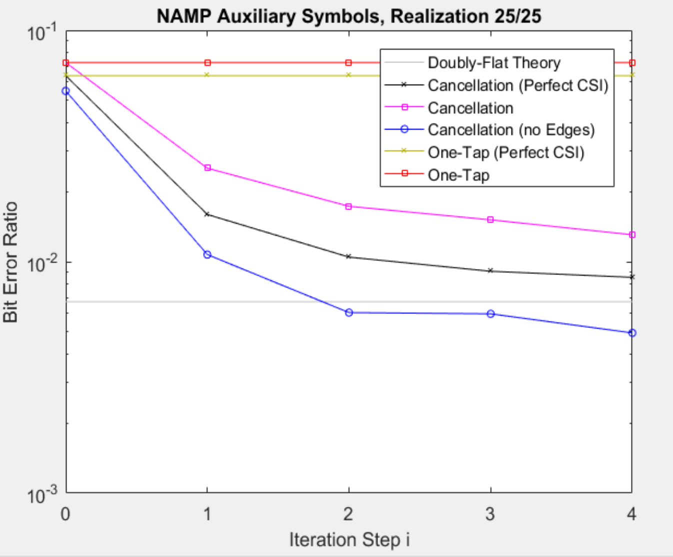

Fig.4.3 NAMP auxiliary symbols realization

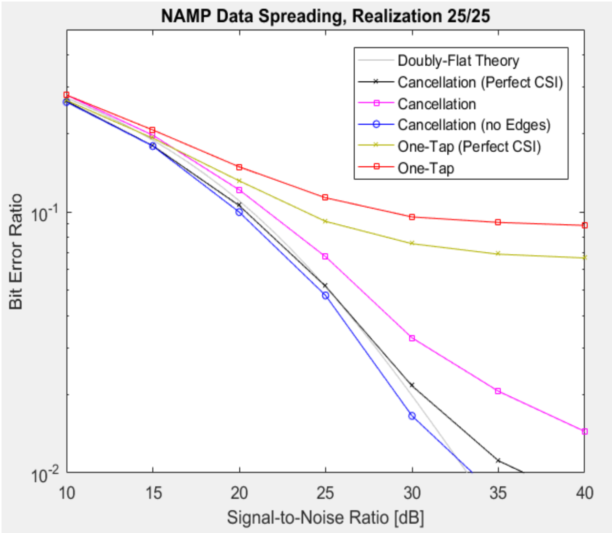

Fig 4.4 NAMP Data spreading Realization

For example, we place 12 pilots among 128 subcarriers. Fig 4.1 gives the relation between BER and SNR, here BER is inversely proportional to the SNR form this graph we conclude that the BER is decreased by increasing the SNR. Fig 4.2 shows the comparison of different algorithms used for Channel estimation from this graph we conclude that the BER is less and SNR is high for NAMP algorithm compared to the others algorithms .Fig 4.3 and 4.4 is the NAMP frame work of theoretical and Practical approach upto25 iterations from this graph we conclude that the BER is reduced and SNR is increased for each stage this shows that the time delay of the system is less because time delay is inversely proportional to SNR. As shown in the below table, we conclude that the complexity of our proposed NAMP algorithm is less compared to the other algorithm.

Step	NAMP	SAMP	CoSaMP	OMP
Identification	3.11×10^{-4}	3.12×10^{-4}	2.17×10^{-4}	9.92×10^{-5}
Estimation	7.43×10^{-5}	1.03×10^{-4}	1.26×10^{-4}	6.27×10^{-5}
Pruning	3.25×10^{-5}	1.46×10^{-5}	1.51×10^{-5}	--*
Sample Update	2.81×10^{-5}	4.88×10^{-5}	2.93×10^{-5}	3.25×10^{-5}

TABLE 4.1 COMPARISION OF NAMP WITH OTHER ALGORITHMS

V. CONCLUSION

This paper gives the report about the sparse recovery algorithms for pilot assisted OFDM channel estimation, where NAMP algorithm is proved to be better than OMP and SAMP. By using this algorithm we get the signal better than the signal getting from SAMP, CoSAMP algorithms and also the time delay and occurrence of noise is less compared to the previous algorithms.

VI. REFERENCES

[1] LaSorte, Nick; et al. (2008). *The history of orthogonal frequency division multiplexing* (PDF). IEEE GLOBECOM 2008 Conference. doi:10.1109/GLOCOM.2008.ECP.690.

[2] G.Gui, L. Dai, S. Kumagai, F. Adachi, "Variable earns profit: Improved adaptive channel estimation using sparse VSS-NLMS algorithms", *Proc. IEEE Int. Conf. on Commun*, pp. 4390-4394, Jun. 2014.

[3] Johnson, D. "Minimum Mean Squared Error Estimators". Connexions. Archived from Minimum Mean Squared Error Estimators the original

[4] A. J. Tropp, A. C. Gilbert, "Signal recovery from random measurements via orthogonal matching pursuit", *IEEE Trans. Inf. Theory*,vol. ,no. 12, pp. 4655-4666, 2007.

[5] D. Needell, J. A. Tropp, "CoSaMP: Iterative signal recovery from incomplete and inaccurate samples", *Appl. Comput. Harmon. Anal.*, vol. 26, no. 3, pp. 301-321, May 2009.

[6] E. Candès, J. Romberg, and T. Tao, "Robust uncertainty principles: Exact signal reconstruction from highly incomplete frequency information," IEEE Trans. on Information Theory, vol. 52, pp. 489 - 509, Feb. 2006.

[7] S. G. Mallat and Z. Zhang, "Matching Pursuits With Time- Frequency Dictionaries," *IEEE Trans. Sig. Proc.*, vol. 41, no. 12, pp. 3397–3415, Dec.1993.

[8] J. A. Tropp and A. C. Gilbert, "Signal Recovery From Random Measurements via Orthogonal Matching Pursuit," *IEEE Trans. Inf. Theory*, vol. 53, no. 12, pp. 4655– 4666, Dec.2007.