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Sparse Channel Estimation in MM - Wave Hybrid MIMO systems

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Abstract

Millimeter wave (mm-Wave) is emerging as one of the predominant 5G technology at high frequency. In this paper the channel estimation at mm-Wave is formulated as a sparse problem in which the hybrid multiple- input multiple-output (MIMO) precoders and combiners are used as the measurement matrices. The hybrid MIMO system judiciously partitions mm-Wave precoding-combining between analog and digital domain, due to high power consumption and cost of mixed signal devices. Exploiting the sparsity of mm-Wave channels, a (Compressed sensing) CS problem is formulated that estimates the angle of departure/arrival and gain of each corresponding path. Mm-Waves employs the directional beam forming which divides the angle of arrival and the angle of departure space intogrids. A dictionary is created where all the possible angles of arrivals of the received array response vectors corresponding to a particular resolution are placed. Given the RF beamforming matrix using discrete fourier transform (DFT matrix), baseband precoder-combiner matrix (assumed to be unitary), the orthogonal matching pursuit (OMP) algorithm, ORACLE-LS estimator performance is compared in terms of normalized mean square error (NMSE) on a virtual channel model in mm-Wave hybrid MIMO system. The MATLAB simulation results shows the advantage of low complexity OMP estimator which evaluates NMSE using fewer samples compared to ORACLE-LS estimator which requires full training samples, and it's estimation error has shown to approach Cramer Rao lower bound.

Keywords: *mm- Wave, sparse channel estimation, Hybrid MIMO, Compressed sensing, ORACLE-LS estimator, Orthogonal Matching Pursuit.*

I. INTRODUCTION

Of Late the upcoming wireless systems has been empowered by a present day technology known as millimeter wave (mm-Wave). The mm-Wave has been around and is as old as wireless itself (Bose in India 1895 and Lebedew in Russia) [1]. The MIMO communication at mm-Waves is a promising technology and a strong contender for next generation wireless communications [2]. The Technology advances make mm-Waves possible for low cost consumer devices. Mm-Wave is coming to us in huge volumes in HDTV, Wireless LAN etc.

The sparsity of mm-Wave channels is due to the fact that the impulse response is dominant by a few non-zero (significant) paths which are fewer than number of transmitting/receiving antennas [3]. Due to its sparse nature, a hybrid MIMO system with digital baseband precoding along with analog beamforming in radio frequency (RF) domain has been proposed for mm-Wave communications [4]-[6]. In Hybrid MIMO systems, the no. of RF chains depends on the rank of the channel matrix (which is a low rank matrix) and it's implementation will be simpler than conventional systems of MIMO which require RF

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chain per individual antenna and it will be a full rank channel matrix. To efficiently design a mm-Wave hybrid MIMO system, it is an extremely challenging task to estimate channel state information (CSI) in mm-Wave systems, unlike conventional MIMO systems. The main reason for difficulty in estimation of CSI is that the SNR is low before the transmit beamforming and there are large no. of antennas. To boost the SNR, instead of estimating all the channel coefficients of the channel matrix, the angle of departure/arrival of the dominant paths are estimated along with their corresponding channel path gains. The mm-wave signals are susceptible to blockages from buildings,rain and high atmospheric attenuation, hence intelligent beam forming techniques are needed to overcome it.

In a closed loop beam training method to estimate CSI in mm-Wave, beam departure/arrival angles are first estimated and also the gain of each path associated with each angle pair are determined. The closed loop training process which is a multiple-stage procedure avoids an exhaustive beam searching method. In this closed loop method the transmitter (Tx) emits the pilot beam and receiver (Rx) feedback it's decision by selecting the best beam. This method has been adopted in many systems practically [7],[8] but the drawback of this method is that it's performance tends to be restricted by the beam training patterns, and also the training overhead linearly increases with increase in no. of users.

An alternate effective approach for sparse estimation of MIMO channels in mm-Wave is by estimating angle of departure /arrival by using the technology called Compressed sensing (CS)[9]-[11]. In mm-Wave Hybrid MIMO systems, the RF beam formers that are employed yields the directional beams which are correlated with other beams, resulting in increase in SNR of the system. As in conventional CS, the use of i.i.d random pilot vectors is difficult in mm-Wave system.

In this paper, channel estimation in mm-Wave hybrid MIMO systems-a sparse way is presented using the CS approach based on OMP algorithm and compare its performance with Least squares and ORACLE estimator. OMP was initially proposed for channel estimation of multi carrier under water acoustics [12].

The organization of the paper is as follows: In Section IIthe mm-Wave Hybrid MIMO system Model is described, Section III holds the Channel estimation formulation using
LS and ORACLE Estimator, Section IV describes the CS based mm-Wave Hybrid MIMO Sparse Channel Estimation using grid based OMP and in Section V the simulation results using MATLAB is presented showing the advantage of the proposed algorithm. Last Section VI holds the conclusion with future work.

Notations:

Lower case x represent a vector while the upper case X represents a matrix. The given superscripts X^T, X^*, X^{-1}, X^H denotes the transpose, the conjugate, the inverse, the Hermitian (conjugate-transpose) of the matrix X respectively.

II. MM-WAVE HYBRID MIMO SYSTEM MODEL

Consider a mm-Wave system as shown in Fig.1 which consists of a Tx with the number of transmitting antennas (N_{T_X}) communicating N_s data steams to a Rx with receiving antennas(N_{R_X})[2]. Hybrid Analog to Digital precoding and combining architecture is one novel approach that judiciously partitions the MIMO signal processing and communications between the analog and digital domains in mm-wave system, it's a low complexity implementation of MIMO in mm-wave systems.

The incoming data stream consist of number of symbols N_s which are transmitted by employing a small number of RF chains L_t/L_r at the Tx/Rx such that $N_s < L_t < N_{T_X}$ and $N_{R_X} > L_r > N_s$[4],[15]. Consider the downlink transmission from base station to mobile station,assuming that the base station applies an baseband precoder$F_B \in \mathbb{C}^{L_t \, X \, N_s}$ followed by an RF precoder$F_R \in \mathbb{C}^{N_{T_X} \, X \, L_t}$. If $F = F_B F_R$ is $N_{T_X} \, X \, N_s$ matrix, which is a

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combination of precoding matrices at the base station, the signal is transmitted from the base station through a virtual channel.

The implementation of RF precoding / combining can be done by using multiple approaches in analog domain such as phase shifters [13], switches/ lenses [14]. Assume that the channel state information (CSI) is known at both Tx and Rx, and the RF precoder F_R is implemented by using analog phase shifter.

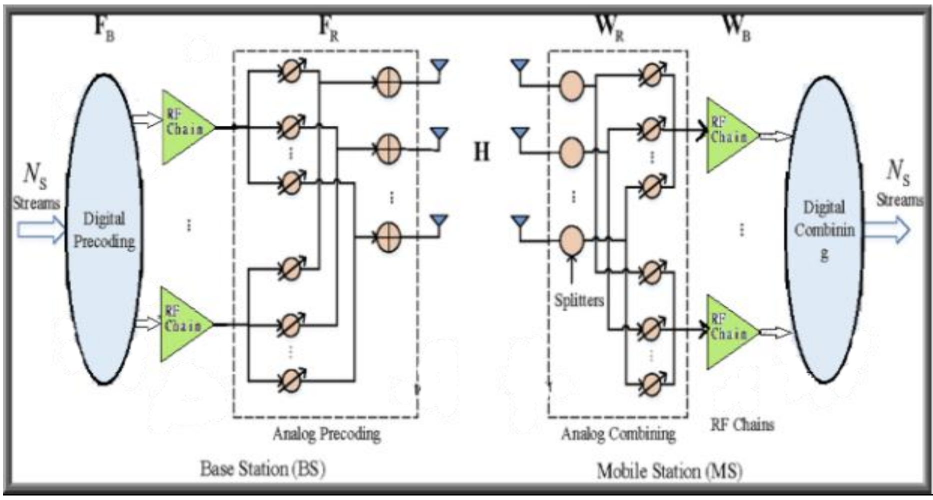

Fig.1: Block diagram of MM-wave MIMO system using Hybrid beamforming

A virtual channel model is adopted where the received signal vector r observed by the mobile station is given by equation (1) as

$$r = H_n F s + n \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where $H_n = N_{R_X}$ X N_{T_X} is the Channel matrix of the mm-Wave channel,

$n \sim \mathcal{N}(0, \sigma^2 I)$ is the Gaussian noise in the channel,

$F = F_B F_R$ is the combination of baseband and RF precoder at basestation and s is the transmitted symbol in N_s data steam.

At the Rx (mobile station), the combiner $W = W_R W_B$ consists of the RF and the baseband combiner which processes the received signal r and results in (2)

$$Y = W^H H_n F s + W^H n \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

The received signal at the mobile station can be given in matrix form Y as (3)

$$Y = \sqrt{\rho}\left(W_B{}^H W_R{}^H H_n F_B F_R\right) + \tilde{N} \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

and the transmitted pilot matrix is $\sqrt{\rho} I$, where ρ is the average power per symboltransmission.

The mm-Waves frequency response can be approximately expressed as equation (4) as given in [2]

$$H(f) = \sum_{l=1}^{N_p} \alpha_l\, b_R\left(\theta_R^l, \phi_R^l\right) b_T^*\left(\theta_T^l, \phi_T^l\right) \ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Where N_p = No. of multipath components

$b_R\left(\theta_R^l, \phi_R^l\right), b_T^*\left(\theta_T^l, \phi_T^l\right)$ are the beam steering vectors are at the Rx/Tx

Θ is the Azimuth angle

$\emptyset$ is the Elevation angle

α_l ,Complex channel gain

$\left(\theta_R^l, \phi_R^l\right)$, $\left(\theta_T^l, \phi_T^l\right)$ are the pair of angles of arrival/ departure.

The mm-wave Channel model [15] can be further described as follows in equation (5),(6) by considering only azimuth angle θ i.e all the scattering is w.r.t horizontal beamforming only and neglecting the elevation angle $\emptyset$

$$H_n = \sqrt{\frac{N_{T_X} N_{R_X}}{L}} \sum_{l=1}^{L} \alpha_l b_R\left(\theta_R^l\right) b_T^H\left(\theta_T^l\right) \ldots\ldots\ldots\ldots\ldots\ldots (5)$$

$$H_n = \sqrt{\frac{N_{T_X} N_{R_X}}{L}}\,[b_R(\theta_R^1) b_R(\theta_R^2) \ldots\ b_R(\theta_R^L)]x \begin{bmatrix} \alpha_1 & \ldots. & 0 \\ : & : & : \\ 0 & \ldots. & \alpha_L \end{bmatrix} \begin{bmatrix} b_T^H(\theta_T^1) \\ b_T^H(\theta_T^2) \\ \vdots \\ : \\ : \\ b_T^H(\theta_T^L) \end{bmatrix} \ldots\ldots\ldots\ldots\ldots\ldots(6)$$

Where H_n is a sparse combination of basis directional array vectors= $b_R(\theta_R^l), b_T^H(\theta_T^l)$ at the Rx/Tx

$L =$ No. of scatterers< minimum(N_{T_X}, N_{R_X})

The Matrix H_n can be expressed in vector form asin (7)

$$H_n = B_R\ H\ B_T^H \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(7)$$

whereH is a L –sparse matrix ,

B_R , B_T are the beam steering vectors.

The beam steering directional Cosine Vectors at the Rx and Tx is given by (8)

$$b_R(\theta_l^r) = \frac{1}{\sqrt{N_{R_X}}} \begin{bmatrix} 1 \\ e^{-j\frac{2\pi}{\lambda} d_r \cos\theta_1^r} \\ : \\ : \\ e^{-j\frac{2\pi}{\lambda}(N_r-1) d_r \cos\theta_l^r} \end{bmatrix};$$

$$b_T(\theta_l^t) = \frac{1}{\sqrt{N_{T_X}}} \begin{bmatrix} 1 \\ e^{-j\frac{2\pi}{\lambda} d_t \cos\theta_1^t} \\ : \\ : \\ e^{-j\frac{2\pi}{\lambda}(N_t-1) d_t \cos\theta_l^t} \end{bmatrix} \ldots\ldots\ldots\ldots\ldots\ldots\ldots(8)$$

In Vector form, the above equation (8) can be expressed as (9)

$$vec(H_n) = \left\{ \begin{matrix} (B_T^* \otimes B_R).vec(H) \\ (B_T^* \odot B_R).vecd(H) \end{matrix} \right| \ldots\ldots\ldots\ldots\ldots\ldots\ldots (9)$$

Where the 1st quantity is vector identity (10)

$$vec(\alpha\beta\gamma) = (\gamma^T \otimes \alpha).vec(\beta) \ldots\ldots\ldots\ldots\ldots\ldots\ldots..(10)$$

And the 2nd equality holds as H as a diagonal matrix and $(B_T^* \odot$ BR ϵ ℂNTXNRXX L……………………………..(11)

Where the Symbol $\otimes$ represents the Kronecker product and $\odot$ denotes Khatri-Rao product.

The column wise matching Kronecker product is the KhatriRao product given by (12)

$$A \odot B = [a_1 \otimes b_1\quad a_2 \otimes b_2\quad a_3 \otimes b_3 \ldots.. a_n \otimes b_n] \ldots\ldots\ldots(12)$$

III. CHANNELESTIMATION FORMULATION USING LS AND ORACLE ESTIMATOR

In order to formulate the problem of channel estimation, the received signal Y is written in vector form denoted by (13)

$$\bar{y} = \sqrt{\rho}\left({F_B}^T {F_R}^T \otimes {W_B}^H {W_R}^H\right).vec(H_n) + vec(\tilde{N}) \ldots(13)$$

Where ρ represents the average power transmitted per symbol, Q represents a sensing matrix in (14)

$$Q = ({F_B}^T {F_R}^T \otimes \text{WBHWRH} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(14)$$

An straightforward approach to LS estimate is given by equation (15)

$$vec(H_{LS}) = \frac{1}{\sqrt{\rho}}(Q^H Q)^{-1} Q^H \bar{y} \ldots\ldots\ldots\ldots\ldots\ldots\ldots(15)$$

But $(Q^H Q)$ sensing matrix has a full rank and estimation problem has large dimensions $(N_{T_X} N_{R_X})$, therefore LS estimate is suitable for conventional channel estimation where channel is assumed to have a rich multipath structure but it is difficult to apply same for mm-wave channel estimation because it is rank deficient, due to its sparse nature.

The ORACLE estimator assumes that the angle of departure/arrival are known. To derive ORACLE estimator, rewriting $\bar{y}$ by substituting $H_n = B_R\ H\ B_T^H$ in above equation (13) and applying vector operator as in (11) we obtain simplified equations from (16)-(22)

$$\bar{y} = \sqrt{\rho}\left((F_B F_R)^T \otimes {W_B}^H {W_R}^H\right)\left((B_T^H)^T \otimes \text{BRvecH+vecN} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(16)\right.$$

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$\bar{y} = \sqrt{\rho}\left((F_B F_R)^T (B_T^H)^T \otimes W_B{}^H W_R{}^H B_R\right) vec(H) + vec(\widetilde{N})$……………………………………………..….(17)

$\bar{y} = \sqrt{\rho}(F_B{}^T F_R{}^T B_T^* \odot W_B{}^H W_R{}^H B_R) vecd(H) + vec(\widetilde{N})$…………………………………………….…….(18)

$\bar{y} = \sqrt{\rho} Q_s . vecd(H) + vec(\widetilde{N})$……………………...(19)

$Q_s \xrightarrow{\Delta} (F_B{}^T F_R{}^T B_T^* \odot WBHWRHBR$………………….....(20)

is an equivalent sensing matrix

The ORACLE estimator also estimates $vecd(H)$ in the LS sense which require full rank, $N_{T_X}^{beam} N_{R_X}^{beam} \geq L$.

$vec(Y) = \bar{y} = \sqrt{\rho} Q_s . vec(H) + vec(\widetilde{N})$…………….(21)

$\bar{y} = \sqrt{\rho} Q_s h + vec(\widetilde{N})$………………………………..(22)

Consider an example $N_{T_X}^{beam} = N_{R_X}^{beam} = 24 N_{T_X}^{beam} N_{R_X}^{beam} = 576$; and $G^2 = 32^2 = 1024$. The size of an equivalent sensing matrix will be

$Q_s = size\ N_{T_X}^{beam} N_{R_X}^{beam}\ X\ G^2 = 576\ X\ 1024$ which means that the system has less rows and more columns, which signifies that there are more unknowns than the number of measurements or the observations, clearly the system is an underdetermined system.

This problem is overcome by using the technology of compressed sensing(CS), where channel estimation problem is formulated as a sparse channel estimation where the number of estimated values of entries are L sparsity level which is very less than dimensions $(N_{T_X} N_{R_X})$.The number of dominant multipath are very less in real time environment.

The ORACLE estimator is helpful in analyzing the lower bound of compressed sensing channel-estimator.

IV. CS BASED MM_WAVE HYBRID MIMO SPARSE CHANNEL ESTIMATION

Compressed sensing(CS) is a path breaking and a revolutionary technology to estimate sparse signals[16]. In CS based mm-Wave Channel Estimation, the channel estimation problem is formulated as a sparse channel estimation where number of non-zero entries or dominant multi-paths are very less compared to conventional rich multipath channel structure. The OMP(Orthogonal Matching Pursuit) Algorithm is used to solve the problem of sparse recovery and estimate the channel[15].

In the OMP algorithm, the angle of arrival and angle of departure space [0 to $\boldsymbol{\pi}$]is partitioned into $\boldsymbol{G}$ grids. A dictionary corresponding to array response vectors of all the possible angles of arrivals/departures is created. Dictionary size depends on individual resolution where all the received array response vectors corresponding to a particular resolution may be placed.

The angle of arrival at receiver is not known but it will be close to one of the angle of arrivals present in dictionary. If the particular angle of arrival/angle of departure is not present in the dictionary then it’s taken as zero. In a mm-wave system, multipath dominant components are very few, the problem is solved on path by path basis which is an efficient way of doing estimation for better accuracy. Only those entries of the matrix will be non-zero, if you have that corresponding angle of arrival and departure active. The Matrix with large number of zeros and only few non-zeros, is a sparse Matrix. The columns contains the angle of arrival/departure pairs. The beam space matrices are similar to DFT matrices.

At each iteration, the algorithm picks up the column of $\boldsymbol{Q_s}$ which has strong correlation with the residual and active column index will be updated. In CS, the sparse channel estimation problem can be mathematically represented as an optimization problem (23)-(25).

$vec(H_{CS}) = arg\,min \|y - \sqrt{\rho} Q_s h\|_2 = \|y - Ah\|_2$…..(23)

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$s.t \|vec(H_{CS})\|o = L$ Where $A = \sqrt{\rho}Q_s$ ………….(24)

As $lo\ norm$ is non-convex, it's hard to obtain its solution. The above difficulty can be replaced by an equivalent optimization problem given by

$min \|h\|_1 \quad s.t\ y = \sqrt{\rho}Q_s h$which is convex………..(25)

The OMP is a class of Greedy algorithm, which is a simple, less complex and iterative algorithm to estimate sparse signals.

Let A matrix consists of columns given by $A = [a_1, a_2, \ldots . a_n]$,can be expressed as (26),(27)

$y = Ah$……………………………………...…..(26)

$y = [a_1, a_2, \ldots . a_n]h$…………………………...……..(27)

At each iteration, the OMP algorithm correlates the maximum projection of each column of A on observations/measurements y, given in (28) and their difference yields a residue (30).

$i_1 = arg\, max \left| \frac{a_j^H}{\|a_j\|} y \right|$

…………………………......(28)

Solve the LS problem given as $min \|y - A_1 h_1\|^2$ and obtain its estimate as h_1 which is given by (29)

$h_{(1)} = (A_1^H A_1)^{-1} A_1^H y$ ……………………………(29)

Residue $r(1) = y - A_1 h_1$ ………………………....(30)

Now that particular column of A is removed and find the maximum projection of correlation of the remaining columns of A with the residue $r(1)$ and repeat the process. By using a proper suitable criteria for stopping OMP algorithm i.e when the difference of the norm of the consecutive residues lies below a certain threshold ε (31) such that

$\|r(n-1) - r(n)\| \leq \varepsilon$……………………………..(31)

The OMP based channel estimate for mm-Wave Hybrid MIMO system is given by (32)

$H_n{}^{CS} = B_R H^{CS} B_T^H$ …………………………………….(32)

Where B_R, B_T are the beam steering vectors, and the sum of square error is given by the Frobenius norm in equation (33)

$\left\| \mathrm{H_n} - \widehat{\mathrm{H_n}}^{\mathrm{CS}} \right\|_{\mathrm{F}}^2$ ...……………………………..…....(33)

The performance metric is the Normalized Mean square error of OMP estimator which is defined by (34)

$10 \log_{10}\left(\mathrm{E}\left[\frac{\left\| \mathrm{H_n} - \widehat{\mathrm{H_n}}^{\mathrm{CS}} \right\|_{\mathrm{F}}^2}{\|\mathrm{H_n}\|_{\mathrm{F}}^2} \right] \right)$……………………………(34)

The Algorithm for mm-Wave channel estimation based on OMP algorithm with inputsQbar sensing matrix, measurement vector $\overline{\mathrm{y}}$ and threshold ε is presented below:

Algorithm : mm-wave Channel Estimation based on OMP
Input: Qbar sensing matrix, measurement vector y and threshold ε
h_b_omp = OMP_mmWave_Est (y,Qbar, ε)
[rq,cq] = size(Qbar); % obtain the number of rows and columns
set_I = zeros(cq,1); % initialize active column index
r_prev = zeros(rq,1); % initialize the previous residue
h_b_omp = zeros(cq,1);
r_curr = y; % initialize the current residue
Qs = []; %initialize sensing matrix
ix1 = 1; % Counter=1
while (abs((norm(r_prev))^2 - (norm(r_curr))^2) >ε) do
% obtain the index of the largest absolute inner

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```
product
[m_val, m_ind] = max (abs (Qbar'*r_curr));
%obtains the angle of departure/arrival pairs
set_I (ix1) = m_ind; %Updates angle of departure/arrival pair set
Qs = [Qs, Qbar (:,m_ind)]; % update the active column set
H_b_ls = pinv(Qs)*y;        % estimate channel
r_prev = r_curr;
r_curr = y - Qs*H_b_ls;     %update residual
ix1 = ix1 + 1;              %increment counter
end while
return h_b_omp(set_I(1:ix1-1)) = H_b_ls;
```

V. SIMULATION RESULTS

To simulate results, MATLAB 2018a (Mathworks) simulator is used.

Consider the Tx and Rx consisting of a uniform linear array with $N_{T_X} = N_{R_X} = 32$, the number of RF chains $N_{RF} = 8$. N-Beam is the number of transmitted pilot beams and L is the sparsity level which is set to 4 i.e the number of dominant paths arriving at the receiver. The angle of arrival and angle of departure space are divided into G grids and a dictionary is created corresponding to array response vectors of all the possible angles of arrivals/departures.

The results shows that lower bound are obtained from ORACLE-LS estimator approaching Cramer Rao Bound and the upper bound is obtained based on the performance of OMP, whose theoretical analysis is derived in [15].

The procedure for sparse way of estimating the channel in mm-Wave Hybrid MIMO system is presented below stepwise:-

Step 1:

Set up the required parameters for mm-Wave channel estimation as shown in Table-1 below:

Step 2:

Initialize the quantized transmit/receive array beam response vectors and generate their dictionary matrix. Here the cosθ values are directly generated not the angles which is given by dirCos=2/G*(I-1)-1,for I=1:G

when I=1, dirCos=-1 and when I=G then dirCos ≈1 (-1,1] and by using its results the vectors of the array response are generated.

TABLE I. SIMULATION PARAMETERS

Simulation Parameters	
N_{T_X}	32
N_{R_X}	32
RF chains	8
N_Beam	24
Grid G	32
ITER	1 : 5
L sparsity	4
dirCos	(-1,1]
SNRdB	10:10:50

Step 3:

Dictionary Matrix creation for RF and Baseband precoder/combiner $F = F_B F_R$.

Create mm-wave dictionary matrix for RF precoder and combiner, where RF precoder/combiner are the DFT matrices where the Baseband matrices of precoder/combiner are unitary block diagonal matrices(for simplicity).

step 4:

Obtain the sensing matrix Q which is the kronecker product of precoder/combiner matrices at the baseband and RF as given in (35)

Q=kron((FB.')*(FR.'),(WB')*(WR'))…… …….(35)

Step 5:

The channel gain is generated and obtain its channel matrix H. The channel noise is generated over the pilot beam array vectors.

The Observation/measurement vector y is obtained.

Step 6:

Computate the Normalized Mean square error for OMP,ORACLE LS along with Cramer Rao

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bound(CRB). CRB gives the lower bound of the NMSE estimate over the SNR.

The NMSE for mm-Wave Hybrid MIMO system using OMP algorithm is estimated using the expression given in equation(34). The Cramer Rao bound (36) over the range of SNR is plotted, which gives the lowest bound of the estimated error as derived in[15] and as shown in Fig.3

$$CRB=tr(inv(Q_s'*Q_s))/(Nt*Nr)\ldots\ldots\ldots\ldots(36)$$

Where $Q_s \overset{\Delta}{\rightarrow} \left(F_B{}^T F_R{}^T B_T^* \odot W_B{}^H W_R{}^H B_R\right)$ is an sensing matrix of the Hybrid MIMO precoder-combiner along with the beam array response vectors.

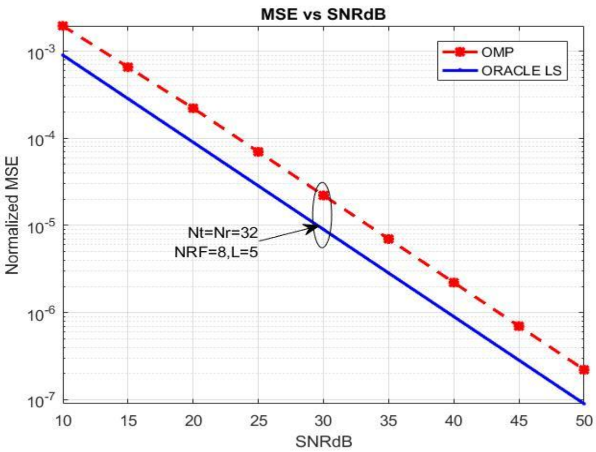

Fig 2. NMSE performnace against SNR for the OMP and ORACLE-LS Estimator when $N_t=N_r=32$, Sparsity- level=5,N_{RF} =8

Fig.2 shows the NMSEs vs SNR performance of the ORACLE LS estimator and OMP when $N_T=N_R=32$ and N_Beam= $N_T{}^{Beam}=N_R{}^{Beam}$ =24. It can be observed that as the SNR varies from 10dB to 50 dB, the NMSE value reduces linearly and the performance of OMP estimator is close to ORACLE LS estimator and the OMP also shows advantage with increase in sparsity. The ORACLE LS estimator shown consistent performance and it gets better with reduction in sparsity level and deteriorates with more sparsity.

Unlike LS estimator which require large number of samples for an efficient estimate, OMP performs the computation with very few number of samples efficiently. When the samples are sparse OMP shows advantage over conventional estimators.

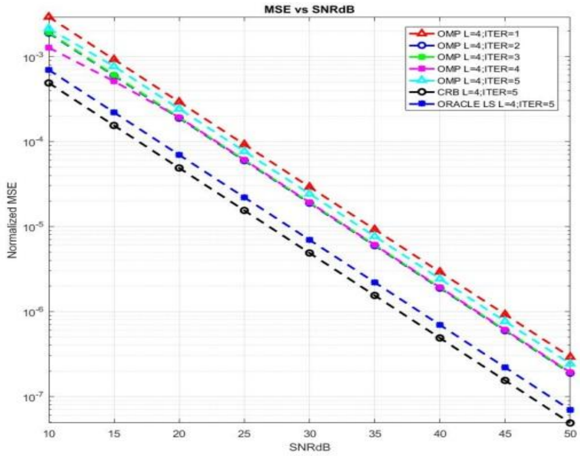

Fig 3. NMSE performance against SNR at different levels of iterations of OMP, ORACLE LS estimators approaching CRB lower bound.

In Fig.3, the performance error NMSE of the proposed OMP algorithm caused due to assumption of the quantized angle of arrival and departures is evaluated. The curves portray the performance of the proposed algorithm at different values of iteration when sparsity level is set to L=4, which can also be varied. As the number of iterations vary in steps from1 to 5 with (ITER=1,L=4), (ITER=2,L=4),(ITER=3,L=4), (ITER=4,L=4),(ITER=5,L=4) the performance gets closer and closer to CRB means that estimation error is minimum. It shows that the performance loss due to quantization assumption is very small in OMP algorithm and has an advantage over conventional LS algorithm.

VI. CONCLUSION

A CS based sparse channel estimator in mm-Wave hybrid MIMO system was proposed, based on a virtual channel model. The OMP algorithm solves the problem by employing a dictionary of array response vectors consisting of quantized angle grids. The computer simulations shows the outperformance of OMP algorithm with sparse data, and also reaches the Cramer Rao lower bound in error estimation with respect to SNR.

Future extension in this area will be to use the Artificial Intelligence(AI)based learning algorithms to enhance its performance further. Also dictionaries of precoders–combiners can be enhanced by using different array response vectors like 2D arrays.

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