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BEAM SQUINT EFFECT AND CHANNEL ESTIMATION FOR MASSIVE MIMO IN MMWAVE SYSTEM BASED ON MULTILAYER PERCEPTRONE

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Abstract: As the number of users in communication system increases occurs the rise of millimetre wave (mmwave) communication, which offers high data transmission for 5G system. In Multiple input Multiple output (MIMO) system, there are large no of antennas for data transmission, while number of antennas are much more for massive MIMO. Here the wide band signal will be proportional to spatial wide band effect, where spatial wide band effect is the physical propagation delay of the transmitted wide band signal. The orthogonal frequency division multiplexing (OFDM) with different subcarriers will see the same path with different angles for arrival (AoAs), termed as beam squint. The spatial wide band effect gives rise for beam squint as they are proportional to each. Uplink and downlink channel estimations are done by extracting the frequency sensitive as complex channel gain and frequency insensitive parameters as delay and AoA, using pilot signals, by compressive sensing-based approach. This paper proposes channel estimation techniques based on neural network, which has a set of data to understand the relationship using algorithms. Here uses Multi-Layer Perceptrone (MLP) and Convolutional neural network (CNN) methods, with data collection, channel estimation and the error calculation of detected channel. MLP utilizing supervised learning based on back propagation algorithm with sequence, hidden and classification layers. For CNN the process is based on image input, CNN ReLU and regression layers. Mathematical and graphical results show the relevance of the proposed system over the conventional for mmwave communication under general system configuration.

Keywords: Spatial Wideband Effect, Beam Squint Effect, Mmwave, Massive MIMO.

1. Introduction

Wireless communication technology is widely used in the present decade, with wide frequency bands mmWave communications is more reliable. Wireless networks [1] enables unique gigabits-per-second data transmission and rapidly growing demand of wireless traffic can be satisfied. In mmWave [2] bands radio signals suffer from small path loss and weak diffractive ability, hard to bypass obstacles. The literature discusses techniques which have been proposed to solve these issues and achieve high system capacities. Among them Massive multiple-input multiple-output (MIMO) technology is applied where spectral and energy efficiencies can be improved. MIMO techniques can greatly increase the capacity of wireless systems without requiring any extra bandwidth. MIMO systems can offer, an accurate channel state information (CSI) which is required at the transmitter and/or receiver. A key role in MIMO communications is played by an accurate channel estimation, most wide and popular used approach to the MIMO channel estimation is to employ training sequences [3] (also referred as pilot signals), then estimate the channel based on the received data and the knowledge of training sequence. For high data rate and quality in digital communication systems, recently there has been an increasing interest in orthogonal frequency division multiplexing (OFDM). Here transmits the information on each of sub carriers, utilizing multi carrier modulation technique by dividing the total signal bandwidth into the number of sub carriers. Band efficiency, multipath immunity, resistance to inter symbol interference, high-rate data transmission is some of the advantages of OFDM systems. However, different antennas may receive different time-domain symbols from the same physical path in a system with large-scale antenna arrays. These symbols are received at the same sampling time due to the large propagation delay of electromagnetic waves which travels across the whole antenna array. This propagation delay that occurs, even the wave transmission starts together is termed as the spatial-wideband effect. Here, phase difference is been considered by ignoring the delay difference among the received signals at different antennas the massive MIMO channel model, where delay difference are not applicable any more.

In this case, distinct angles of arrival (AoAs), angle made with the vertical line by wave at the point of arrival, for the same path will be seen for different subcarriers in an OFDM system. This results from spatial-wideband effect, which is termed as beam squint. By analysing the relationship between beam squint and the spatial wide band effect with gain, angle of arrival and delay here proposes a channel estimation technique, for frequency-division duplex (FDD) in mmWave massive MIMO-OFDM systems based on both analog and digital precoding considering beam squint effect. The level of the beam squint effect spatial-wideband effect are in proportionality, where spatial-wideband effect causes beam squint in the frequency domain. Hence, in large-scale antenna arrays and/or broadband transmission it will become remarkable and non-negligible. Initially beam squint effect has been investigated in array signal processing and radarsystems,because radarsare the earliest systems that deploy large-scale antenna arrays.Beam squint


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renders theactually fixed physical angles of arrival (AoAs) and anglesof departure (AoDs) frequency-dependent on the perspectiveof BS in massive MIMO communications. Channel estimation based on pilot data signals is the approach, in which training sequence consist of known data symbols (pilots). Here pilots are continuously transmitted at the beginning of a session, the initial channel parameters estimation is done using the received pilot signals. Channel estimation technique based on Pilot signals have better performance than blind techniques where fading and varying channels occurs. Least square (LS) and minimum mean square error (MMSE) algorithms are used in pilot-based channel estimation. Implementation of LS algorithm is quite easy, where in the case of time varying channel this algorithm shows a poor performance. Both frequency andtime selectivity of fading channel can be also combated by MMSE algorithm. However, channels matrix inverse, correlation computation and noise information are needed in MMSE in order to acquire channel state information. Accordingly, MMSE algorithm, better mean.

In this paper, multilayered perceptrons (MLP) [4] a class of neural network with backpropagation (BP) learning algorithm is proposed for channel estimation in OFDM systems. Artificial neural networks are information processing patterns which are inspired by biological nervous system. Here, have a large number of highly interconnected processing elements which are known as neurons. It uses Adaptive Learning where, customized resources for unique needs are provided. In this work, developed a MLP based Neural network for estimating channel with supervised learning in 3 layers as, input, hidden and output. This estimator works on the basis of BP algorithm which modifies synaptic weight of hidden layer where mapping error can be propagated into hidden layer. MLP has two stages as training stage, the collection of input output values that are used to train the network and testing stage, trained values are used for accessing network performance.

The rest of this paper is as follows: Section 2 proposes the wideband massive MIMO-OFDM systems with spatial wideband effect and beam squint. Section 3 introduces the system model considering beam squint. Section 4 extracts channel parameters derive. Section 5 derives LS, MMSE and MLP with the supervised learning by back propagation algorithm. Section 6 gives the simulation results and Section 7 concludes this paper.

2. Spatial Wideband Effect and Beam Squint Wideband Massive Mimo System

Consider a base station (BS) and A number of single-antenna users randomly distributed throughout the cell in a mmWave massive MIMO-OFDM system[5]. Here L-antenna uniform linear array (ULA) and the antenna spacing s is equipped with a BS. Multipath delay spread in orthogonal frequency-division multiplexing (OFDM) is combated with S_c subcarriers. Consider B as the transmission bandwidth for this OFDM system, with subcarrier spacing as $\eta = B/Sc$. Combating of the maximum multipath delay plus the maximum propagation delay of electromagnetic waves travelling across the whole antenna array is done by the long enough cyclic prefix (CP).

The ath user has $I_k$incident paths from to the BS. Time delay can be denoted as $\tau_{a,i,l}$as the ith path from the ath user to the lth antenna of the BS and denote $T_{a,i} \triangleq T_{a,i,1}$ for the simplicity ,where the value $l \in \{1, . . . ,L\}$ and $a \in \{1, . . . , A\}$, $a \in \{1, . . . , I_k\}$. AoA of the ith path from the ath user is $\vartheta_{a,i}$and define normalized AoA as$\psi_{a,i} \triangleq \frac{s \sin \vartheta_{a,i}}{\lambda_c}$, where carrier wavelength is λ_c. The antenna array sizes are much smaller than the distance between the transmitter and the receiver according to the far-field assumption.

$$T_{a,,i,l} = T_{a,l} + (l\text{-}1)\frac{s \sin \vartheta_{a,i}}{g} = T_{a,i} + (l\text{-}1)\frac{\vartheta_{a,i}}{f_c} \qquad (1)$$

Where $f_c = \frac{h}{\lambda_c}$ is the carrier frequency and c is the speed of light. The complex channel gain, $\alpha_{a,i}$ of the ith path from the ath user. Then, the expression for impulse response of the uplink channel between the ath user and the lth antenna at the BS can be as:

$$h^T_{a,l} = \sum_{i=1}^{Ik} \alpha_{a,i} e^{-j2\pi(l-1)\psi_{a,i}} \delta(t - T_{a,i,l}) \qquad (2)$$

Consider the Fourier transform of (2), the frequency response at the BS between the ith antenna and the ath user can be as:

$$h^F_{a,m}(f) = \sum_{l=1}^{Ik} \alpha_{a,m} e^{-j2\pi(M-1)\psi_{a,i}(1+\frac{f}{f_c})} e^{-j2\pi f T_{a,i}} \qquad (3)$$

Discrete Fourier transform (DFT) transforms to virtual angle domain for obtaining the following theorem, which shows a wideband mmWave massive MIMO-OFDM systems considering the beam squint effect. Stacking all $h^F_k(f)$'s into a vectoryields from different antennas:

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$$h_k^F(f) \triangleq \sum_{l=1}^{L_k} \alpha_{k,l} a(\Xi_{k,l}(f)) e^{-j2\pi f T_{k,l}} \quad (4)$$

It gives the spatial-domain steering vector. The wideband massive MIMO-OFDM channel accurately depicted by the proposed model. Different from the widely-used mmWave models, by considering the steering vectors which is frequency dependent, which is referred to as the beam squint effect. The channel of the ath user can be arranged by a matrix by mathematical manipulations as:

$$H_a^F(f) = \sum_{l=1}^{Ik} \alpha_{a,i}\ a(\ \Xi_{a,i}(f)) a_U^H(\ \Xi_{U,a,i}(f)) e^{-j2\pi f T_{a,i}} \quad (5)$$

By taking beam squint over OFDM subcarriers, the channel between the ath user at the yth subcarrier and BS can be:

$$h_{a,y} \triangleq \sum_{i=1}^{Ik} \alpha_{a,i}\ a(\ \Xi_{a,i}((y\text{-}1)\eta))\ e^{-j2\pi(y-1)\eta T_{a,i}} \quad (6)$$

Theorem 1: Each path in angle domain to squint along with subcarrier indices is induced by the spatial-wideband effect. Along the angular indices the maximum squint, approximately the propagation delay that occurs across the antenna array in the sample periods. The squint over all subcarriers for ith path can be expressed as:

$$|v_{1,}S_c - v_{i,1}| = L[\psi_{a,i}\frac{(S_c-1)\eta}{f_c} = (L\frac{s\sin v_{a,i}}{\lambda_c f_c})B \cong \frac{T_{a,i}^{prop}}{T_s} \quad (7)$$

The relationship between the beam squint effect and the spatial-wideband effect is clarified by theorem 1, and indicates that can use the propagation delay in samples, $T_{k,l}^{prop}$, where the beam squint level is determined. One-path channel in virtual angle domains in different subcarriers, where different angles of a certain path at different subcarriers are seen in the BS. Theorem 1 can be applied for multi-dimensional setups,to each dimension that can observe the beam squint level of each dimension. The beam squint effect is not commonly discussed and difficult to be observed in the conventional small MIMO communication systems, where the spatial-wideband effect cannot be considered because the propagation delay across antennas is small.

3. System Model Based on Spatial Wideband Effect

By considering the spatial wide band effect derived the wideband mmWave massive MIMO channel model with, the manifestation in frequency domain is known as the beam squint effect. This model is related to the irrelevance to the architecture and the array manifold. Hence, the hybrid analog/digital precoding and the full-digital systems share the same channel model. Consider the mmWave systems under the phase shifter-based hybrid architecture, as in mmWave communications it is much more practical.

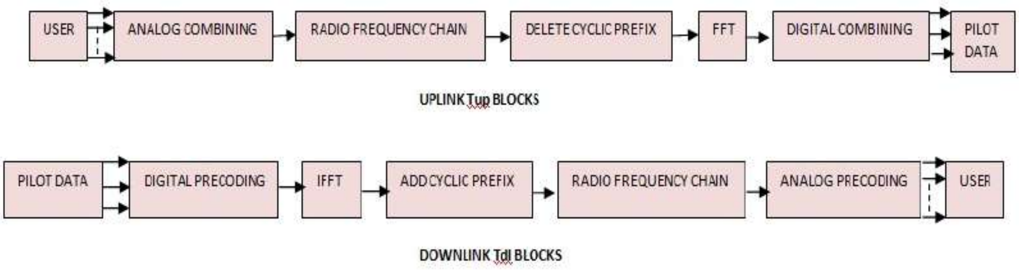

Fig 1. Block diagram of uplink and downlink with user and base station

Assume the BS to have N_{RF} radio frequency (RF) chains. Employ successive OFDM blocks for uplink channel estimation as Tup. For the yth subcarrier and the dth block the hybrid precoder at the BS can then be denoted as **W** y,d= **W**RF, d **W**BB ,y,d∈$C^{L\times NRF}$, where **W**RF, d ∈CL×N_{RF} is the phase shifters implemented analog combiner by at the d th block and **W**BB,y,d is the digital baseband combiner at the y th subcarrier and the b th block. Here each user assigned with P of Sc subcarriers as pilots and the pilot subcarrier indices set for the thea th user, the received signal vector at the BS in the y th subcarrier at L antennas can be expressed as:

$$Z_{a,y,d} = B^{H}_{a,d} x_{a,y,d} + W^{H}_{a,d} n_{a,y,d} \quad (8)$$

Here, $x_{a,y,d}$ implies the pilot symbol from ath user at yth subcarrier in the dth block with a Gaussian noise where each element is independently distributed. The pilot symbols[6] are known for both users and base station

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$$y_{k,q} \triangleq \left[\frac{1}{x_{k,q,l}} y^T_{k,q,1} \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \frac{1}{x_{k,q,l,T_{up}}}\right]$$
$$= W_q^H h_{k,q} + W_q^H Z_{k,q} \qquad (9)$$

Then

$$W_q \triangleq [W_{q,1}, \ldots\ldots\ldots W_{q,T_{up}}] \in \mathbb{C}^{M \times N_{RF}\ T_{up}}$$

$$y_k \triangleq [y^T_{k,p_k,1}, \ldots\ldots\ldots\ldots, y^T_{k,p_k,k}]^T = W^H h_k + n_k$$

$$W \triangleq \begin{bmatrix} W_{p_k,1} & 0 & \cdots & 0 \\ 0 & W_{p_k,2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & W_{p_k,T_{up}} \end{bmatrix} \in \mathbb{C}^{MP \times N_{RF} PT_{up}} \qquad (10)$$

$$h_k = P_k(\psi_k, T_k)\alpha_k \qquad (11)$$

4. Channel Parameter Extraction and Uplink Channel Estimation

A sparse representation is given by h_k which is of the basis above that considers the beam squint effect [7]. By using AoA-delay reciprocity covariance matrix of downlink channel can be reconstructed with the parameters (physical) of the uplink channel.During initial uplink channel parameter extraction, the channel state information and the user locations are unknown to the BS at the beginning and hence orthogonal trainings have to be applied to reduce inter-user interference and pilot degrading at the BS. In this situation, it operates within the users with the frequency orthogonality among different user. At the initial parameter extraction phase, each path's initial AoA, time delay, and complex gain for all user's estimation is done. A parameter extraction algorithm is introduced for this stage, where for the subsequent multi-user uplink and downlink channel estimations is sufficed. The uplink pilot's transmission process for the a th user is

$$ya = B^H P_a(\psi_a.\tau_a)\alpha_a + n_a. \qquad (12)$$

The aim over here is to extract these physical parameters, $\{\psi_a, \tau_a, \alpha^a\}$, from ya. The compressive sensing algorithm, could be a powerful tool where the number of the parameters is fewer than the dimension of ya, i.e., $3Ia <<< N_{RF}PTup$, thus parameter extraction problem can be solved. Proposes a compressive sensing-based off-grid approach for obtaining the physical parameters, instead where the dictionary remains unknown during the iterative parameter extraction and not pre-defined. Here the number of paths for channel is initialized to a large value, as $I_L(\geq I_a)$. The problem formulation can be as:

$$\min_{\psi,\tau,\beta} ||\beta||_0$$
$$||z_a - B^H P_a(\psi,\tau)\beta||_2 \leq \xi \qquad (13)$$

Here the number of nonzero entries of vector β, $||\beta||_0$ and it's a small positive number, the error tolerance is controlled by ξ, which is related to the noise statistics. Initial physical parameters are obtained, then with a small amount of training uplink and downlink channels can be estimated. It depends on three facts given:

Coherence times of delays and angles are longer than the channel gains, mobile's physical location changes much slower than the channel variation. AoAs and path delays of a user obtained during initial parameter extraction phase depending on its moving speed, remain unchanged for a relatively long time. Hence need to re-estimate or update only the channel gains for the coherent time of new coming channel. Next, if different AoAs and path delays are possessed by two user, then same time-frequency band can be used for training as the asymptotical angle-delay orthogonality, is the criteria for the BS to distinguish them, which further reduces the training overhead. Finally, AoAs and path delays are the frequency-insensitive parameters which can be directly applied in downlink channel estimation. Hence,for reconstructing the downlink channel only the channel gains need to be fed back to the BS to and then significantly reduce the user feedback. As first proposes a criterion for uplink user scheduling and grouping for channel estimation of the uplink. Where the asymptotical angle-delay orthogonality is been considered, has two asymptotically orthogonal non-identical paths.

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$$D_u(h_{a_1}, h_{a_{21}}) \triangleq \min_{i_1,i_2}\left[\left\|\left[L\ (\psi_{a1,i1,})P\eta\tau_{a_1i_1}\right]^T\left[I\ (\psi_{a2,i2,})P\eta\tau_{a_2i_2}\right]^T\right\|_2\right] \quad (14)$$

Then user a_1 and user a_2 assigned into the same group of uplink training, $Id_u(h_{a1,}h_{a2}) \geq \Omega_u$, here Ω_u is been termed as the guard interval. For channel estimation among channels of different users in the same training group in terms of the asymptotical orthogonality, the LS estimate can be as:

$$\widehat{\alpha}_{a,LS}=(B_g^H P_a)^{\dagger} z_g= (P_a^H B_g B_g^H P_a)^{-1} P_a^H B_g z_g \quad (15)$$

As for all N_c subcarriers channel basis, define $[\widetilde{\mathbf{P}}_a = \widetilde{\mathbf{P}}(\psi_{a,i}\tau_{a,i})\ldots\ldots\ldots\ldots\widetilde{\mathbf{P}}(\psi_a\, l_{a,}\tau_{a,} l_{a,})]$ a users uplink channel on all subcarriers can be reconstructed as:

$$h_{a,LS}=\widetilde{\mathbf{P}}_a\widetilde{\boldsymbol{\alpha}}_{a,LS} \approx \widetilde{\mathbf{P}}_a\alpha_{a,LS} \quad (16)$$

Long-term average is required for the acquisition of channel statistical information. Here construction of the channel covariance matrix is enlightened in terms of the physical channel parameters, such as AoAs, path delays, and Λk, in an efficient way. Calculation of Λkcan be done from previous averages with fewer samples than required in the construction of conventional covariance matrix. During the initial parameter extraction phase, obtain a single estimate of complex gains which can replaceΛk. When compared with the true ones, such covariance matrices perform favourably in channel estimation. Considering different users in the same group the asymptotical orthogonality among them, the MSE values can be estimated as

$$\tilde{h}_{a,MMSE}=\widetilde{P}_a\Lambda_a P_a^H B_g\left(B_g^H \textstyle\sum_{r\epsilon\mathcal{G}_g} R_r B_g + \sigma_n^2 C_{n_g}\right)^{-1} \quad (17)$$

5. Downlink Channel Estimation

Downlink channel can be immediately obtained for time-division duplex (TDD) systems, by reciprocity between uplink and downlink, not for FDD systems. A novel downlink channel estimation strategy is designed for FDD system, which has less user feedback and low training overhead. Here beam squint effect is carefully considered while exploiting the sparsity and the AoA-delay reciprocity of mmWave massive MIMO [8] channels. In conventional cases for each multipath component, without the consideration of beam squint, can simply use a single RF chain inorder to generate a beam pointing towards the specified direction. After considering the beam squint effect, frequency-dependent beam-steering vectors over different subcarriers should generate a beam, which cannot be achieved with a single RF chain since the analog precoders are generally constant during single OFDM [9],[10] block. Ignoring beam squint will prevent the signals from reaching the specified users in certain frequencies.

A. Downlink Channel Model and User Grouping

Here the downlink carrier frequency is f_c^O and wavelength is $\lambda_c^O = 1/ f_c^O$. Then downlink channel as:

$$h_a^O= BP_a(\psi_a^O, \tau_a)\alpha_a^O \quad (18)$$

From the uplink version extracted in initial parameter extraction phase ψ_k^D can directly computed as:

$$\psi_{k,l}^D= \frac{d\sin\vartheta_{k,l}}{\lambda_C^D}=\frac{f_C^D}{f_c} = \frac{d\sin\vartheta_{k,l}}{\lambda_c}=\frac{f_C^D}{f_c}\psi_{k,l} \quad (19)$$

Hence path delays are not known by the users and does not synchronize with each other, terms ofAoAs is been proposed to group users only. Here by stacking all steering vectors in Aorth into a matrix designing of the analog precoder, **F**RF $\in$C $^{L\times|Aorth|}$ is done, matrix with each column being one steering vector in Aorth. The **F**BB,g which is the digital precoder [11] at the gth subcarrier, is a diagonal matrix as:

$$\mathrm{Diag}(F_{BB,q}) = F_{RF}^{\dagger}\left(\textstyle\sum_{k\epsilon\mathcal{G}_g^D} B_{k,q}\right)c_q \quad (20)$$

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B. Downlink Channel Estimation with LS or MMSE estimator

Let za≜ $[z_a,1, . . ., z_p,P]^H \in C^{P\times 1}$ and pilot subcarriers are all 1's as assumed for simplicity. In the same group by using the asymptotical orthogonality between different user channels, the of downlink complex gains of LS estimate can be obtained as:

$$\tilde{\alpha}_{a,LS} = (C^H)^{\dagger} g_a \quad (21)$$

The downlink channel covariance matrix can be constructed by considering **P**a (ψa,**τ**a) replaced by **P**a($\psi^D{}_a$**τ** $_a$) and from the average of previous estimated gains **Λ**acan be calculated . The downlink complex gains MMSE estimate can be determined as:

$$\tilde{\alpha}_{a,MMSE} = \Lambda_a (P_a^O)^H \Sigma_m (\Sigma_m^H R_a^O \Sigma_m + \sigma_n^2 T_{oi} I_P)^{-1} z_a \quad (22)$$

C. Mlp Neural Network with Back Propagation for Channel Estimation

The backpropagation (BP) algorithm is based on nonlinear LS optimization method. Here O(w) is the objective function [12], the aim is to minimize O(w).

$$O(w) = ½ \sum_{l=1}^{u} (Ei - Vi)^2 \quad (23)$$

Where pth expected output as Ei, pth obtained output as Vi and number of output points as u. Updates the weight of network as
Δw = input * η * O(w) (24)

Here the learning rate which changes the weight so as to obtain the correct output represented as η. Learning rate plays an important role in this process for determining the efficiency of the network. The objective function changes the learning rate parameter accordingly. As the learning rate is higher network is trained faster. But here system may diverge as oscillations are produced. Contrary, lesser learning rate takes more time to train the network. 0.05 is the value of learning rate used. The BP algorithm trains MLP NN[13]. An MLP has 3 layers as input, output and hidden layer where number of hidden layers can be large values. Backpropogation is done through these hidden layers where the weight is been adjusted to get the desired result.

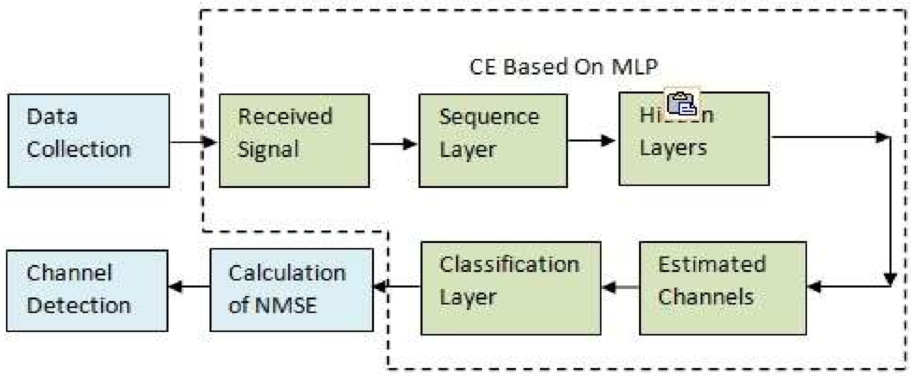

Fig 2. Block Diagram for Channel Estimation Using MLP

ANN channel estimator consists of three layers. these layers are namely the input layer, hidden layer and output layer where hidden layer consisting of P2 neurons and input and output with P1 neurons. The complex OFDM [14] signals are splitted into real and imaginary parts as NN requires only real signals. Working process includes the followings: tangent sigmoid activation function is applied after the input signal and weights are multiplied. The activation function is
$net_j = \sum_{i=0}^{P1} Si\, Wij$ (25)
Where the weight between input, $W_{ij}$and hidden layer at jth node together with P1 denotes number of input neurons [15]:

$$N_j = f(netj) = (e^{netj}-1)\,(e^{netj}+1) \quad (26)$$

The output layer's activation function is given by

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$Net_k=\sum_{j=1}^{P2} Nj\,Wjk$ (27)
$N_k = f\,(net_k)$

Where Wjk is weight between hidden layer and output layer at kth node and P2 denotes number of hidden layer nodes. The output of the neural network estimator is given by

$$N_k=f(net_k)f(\sum_{j=0}^{P2} Wjk\ \ f\,(\sum_{i=0}^{P1} Wij\ \ f(Siwij))) \qquad (28)$$

6. Stimulation Results

This section demonstrates the necessity of carefully treating the beam squint effect by presenting the numerical results and proposed approaches under practical mmWave massive MIMO system configurations are validated. ULA is equipped here in the base station where antenna spacing is about half the wave length of carrier signal. The uplink carrier frequency is 26GHz and downlink carrier frequency is 28GHz. The AMSE, absolute mean squared error and NMSE, normalized mean squared error is been employed as the performance indicators.

In fig 3 and fig 4, as the value of squint level increases the error rate is obtained more for the conventional LS and MMSE methods and for proposed MLP error rate is less. By analyzing the frequency sensitive parameter complex channel gain in LS, NMSE is gradually increasing as squint increases, remains almost constant for MMSE, and much lesser and constant for proposed MLP. AMSE of the frequency sensitive parameters AoAS and delay are considered, here the AMSE value increases in LS and almost constant for MMSE and MLP, where numerical value for AMSE is lesser for MLP.

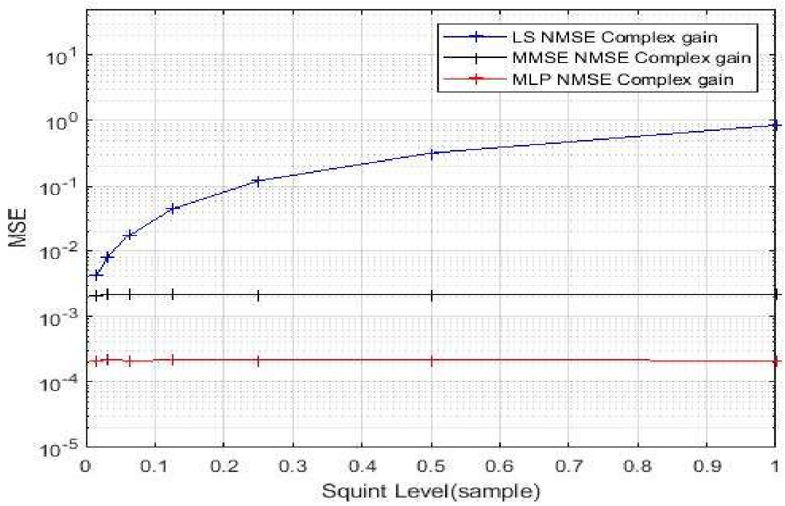

Fig 3. Initial Channel Parameter Extraction, Frequency Sensitive Versus Squint Levels

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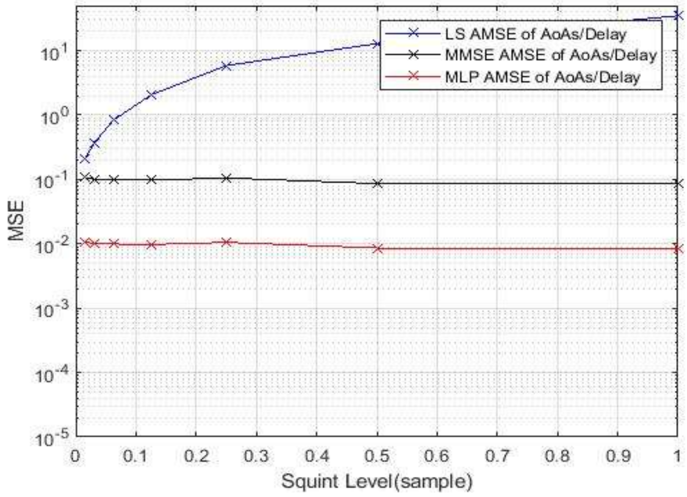

Fig 4. Initial Channel Parameter Extraction, Frequency Insensitive Versus Squint Levels

For Fig 5 to 9 NMSE of the channel and SNR, signal to noise ratio is considered as the performance indicators. In Fig. 5 and Fig. 6, the different frequency sensitive and insensitive parameters as complex gain and AoAS and delay respectively are analyzed based on these indicators. Here the effect of beam squint is illustrated by single user scenario with 12 pilot subcarriers, 4 as number of RF chains and OFDM blocks as 12. In Fig.5 the value of complex gain is considered by SNR and NMSE,error rate is more for the conventional methods when compared with our proposed MLP method. For Fig. 6 the value of frequency insensitive parameters is considered and by analyzing, the value of error is minimum for the MLP proposed method than the conventional LS and MMSE.

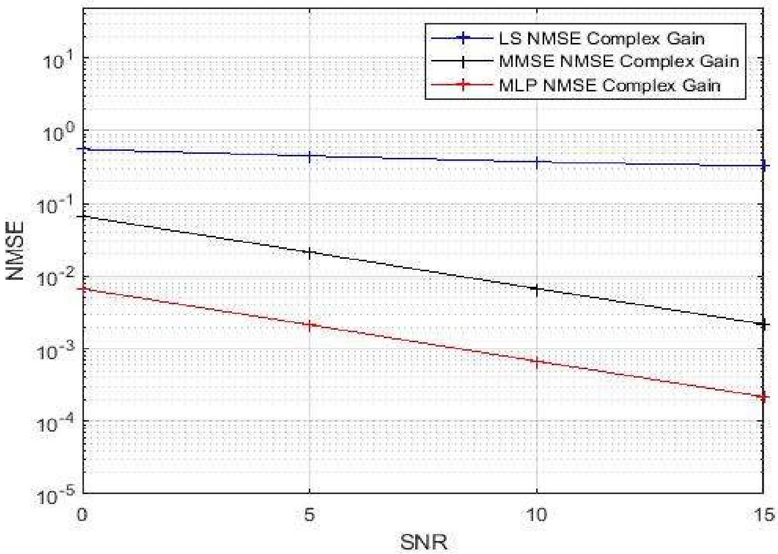

Fig 5. Initial Channel Parameter Extraction, Frequency sensitive Versus SNR

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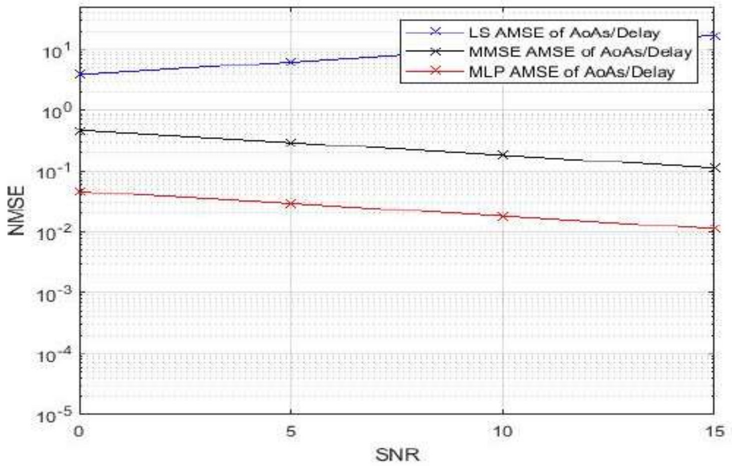

Fig 6. Initial Channel Parameter Extraction, Frequency Insensitive Versus SNR

For Fig. 7 no of OFDM blocks and radio frequency chains (RF Chains) employed in the system is varied and given the values as 3 and 6 respectively. With increase in the number of RF chains and OFDM blocks better estimation is provided by the proposed method with less error flow. For conventional method estimation is not much due to the significantly high error rate.

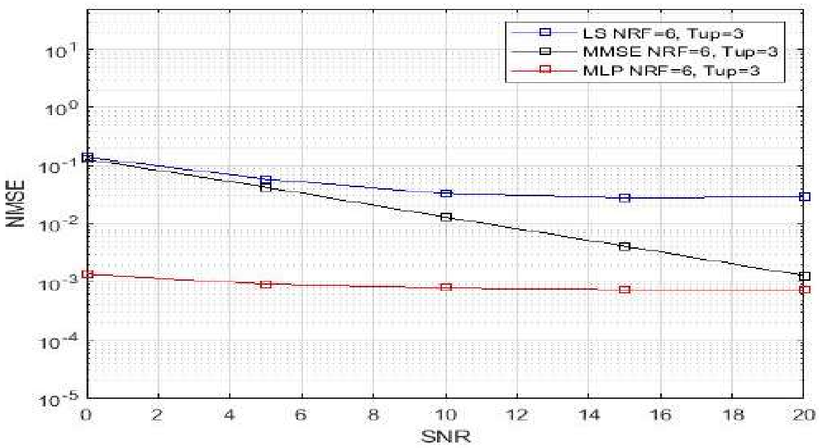

Fig 7. Varying No. of RF Chains and OFDM Blocks for NMSE of uplink channel versus SNR

Fig. 8 and fig.9 shows users receives the same power when number of antennas are varied where the received power at user side is normalized for it. For fig.8 the number of antennas are set as 32 for LS,MMSE and MLP estimations. Error NMSE value is less for MLP and increases as for MMSE and LS methods respectively. In fig. 9 64 is the number of antennas with this value also error is less for the proposed MLP which gives an accurate system. As the number of antennas,L increases the error rate is more for conventional methods and lesser for proposed while considering NMSE and SNR.


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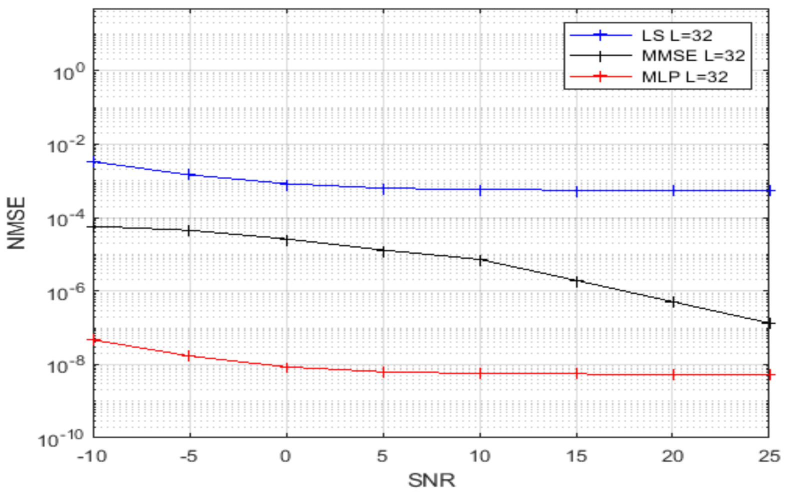

Fig 8. Base Station Antennas no set as 32 for NMSE versus SNR

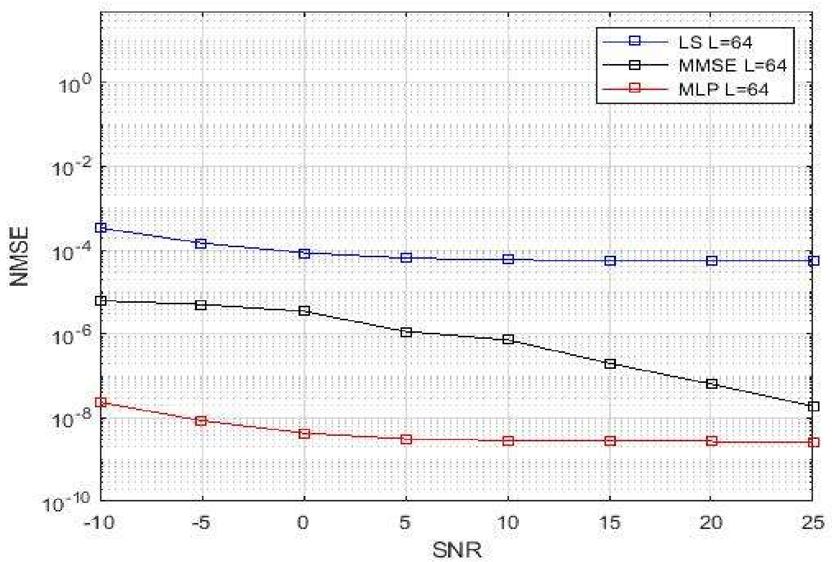

Fig 9. Base Station Antennas no set as 64 for NMSE versus SNR

7.Conclusion

This paper investigates the beam squint effect and propose a wideband channel estimation strategy for FDD mmWave massive MIMO systems with multilayer perceptrone. channel impulse responses are obtained by an assistance of pilot symbols, The networks are trained using these responses. The trained networks are utilized as a channel estimator here. Performance of MMSE and NN using BP algorithm estimation technique is compared. MLP, a class of neural network estimator shows performance as good as the transmission case also with perfect channel impulse responses. Finally, the superiority of the proposed channel model and channel estimation strategies over algorithms based on the conventional MIMO models under general mmWave system configurations are demonstrated by numerical results.

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