

Research on the Application of Multilayer Perceptron in Improving Massive MIMO Channel Estimation

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Abstract – Massive MIMO applications hold significant potential in 6th generation mobile communication systems due to their ability to optimize transmission space utilization. The conversion of real-world physical channel matrices into spatially discrete channel models has been studied. For this channel model, the concept of a virtual channel matrix emerged. Algorithms OMP (Orthogonal Matching Pursue) to find channel matrices exist. However, the accuracy of evaluating the coefficients of these channel matrices is not high depending on matrix computation. Furthermore, the OMP applies to each virtual path, so the computational complexity is high. This paper uses the Multilayer Perceptron (MLP) estimation algorithm to determine a virtual channel matrix with higher accuracy using received signals as input. Furthermore, the algorithm's complexity is significantly reduced compared to the OMP algorithm.

Keywords – Beamforming, OMP, MLP, Virtual Channel Matrix.

I. INTRODUCTION

Due to the increasing use of GHz frequencies for current mobile networks, research on millimeter waves has become urgent. Millimeter waves allow for smaller antenna sizes, leading to Massive MIMO having a large number of antenna elements. Traditional Massive MIMO systems use a connection of one RF chain to one antenna element, so the number of RF chains equals the number of antennas. As the number of antennas increases, so does the number of RF chains, making the cost of these hardware components expensive. Therefore, Massive MIMO systems have used a hybrid precoder in the RF transmission section, with 1 RF chain connected to multiple antennas through a beam matrix with weights adjusted through channel estimation. The directional characteristics of millimeter waves are large, so accurate channel information is needed to adjust the weights to correctly direction the beams [1].

The spatial characteristics of the channel are of interest due to its time invariance [2]. This paper describes how to estimate the channel spatial parameters in the channel matrix such as the Angle of Departure (AoD), the Angle of Arrival (AoA) and the physical paths with the greatest gains. Several papers are interested in estimating the spatial sparseness of the channel matrix, which is related to reducing the complexity of the channel matrix such as [3, 4].

The papers [5] investigated the spatial parameter estimation of the signal based on rotation invariance techniques through the ESPRIT algorithm or [6] when estimating the angle fine-tuning through the SAGE algorithm, spectral estimation in [7].

The orthogonal matching pursuit algorithm has been used to estimate the sparseness property of the channel matrix space and reduce the pilot cost due to the spatial invariance of this matrix [8].

For hybrid beam shaping with analog transmission, a hierarchical codebook containing multiple layers is pro-

-posed, each layer having beam weights increasing from top to bottom. The higher the beam weights, the narrower the beam width and the greater the number of beams. When using this codebook, the large number of antennas in a full-dimensional massive MIMO system leads to complex beam training costs. Fortunately, in the Massive MIMO system using mm Wave, a sparse channel matrix based on a compression sensor matrix – CS – based CE is proposed to reduce costs [9, 10]. The paper [10] estimated this matrix by collecting the received signal through a redundant dictionary in which a grid of non-quantized arrival angles AoA and departure angles AoD is used to improve overhead performance.

Several papers have focused on studying this algorithm [1, 8, 10]. Some papers show the application of OMP in some underwater acoustic communication systems [11] or orthogonal frequency division multiplexing [12].

However, in a physical environment with many scatterers, applying OMP (Orthogonal Matching Pursue) becomes difficult because this environment lacks sparseness, and applying OMP to each physical path is challenging. This paper proposes a virtual channel model to represent the real-world model, then applies the OMP algorithm to find the virtual channel matrix. Furthermore, from this virtual channel model, the paper introduces a MLP (Multilayer Perceptron) to predict the virtual channel matrix when the real channel matrix changes with the angle of travel of the physical path.

II. MODEL

A. Practical Massive MIMO Model

The transmitter has a precoding F through a phase matrix:

$$Y = FS \tag{1}$$

Where:

Y is the received signal matrix of size $N_T \times N_p$. N_S is the number of transmitted symbol streams with each stream having N_p pilot channel symbol.

S is the transmitted pilot symbol matrix in which there is a size of $N_S \times N_p$.

F is the precoding set in the transmitter of size $N_T \times N_S$.

Further analysis: The elements of row i and column j of the transmitted RF matrix have the following calculation expressions: $[F]_{i,j} = \frac{1}{\sqrt{N_T}} e^{j\theta_{i,j}}$.

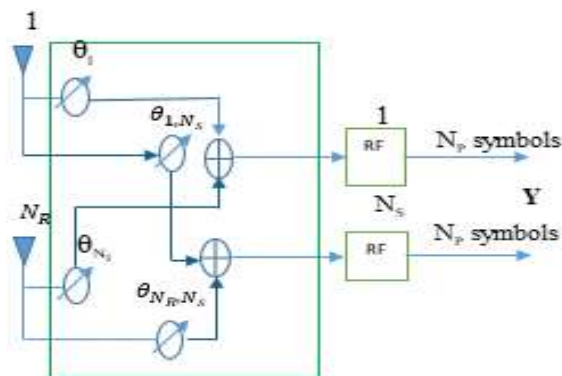


Fig. 1. Massive MIMO transmitter using hybrid beamforming.

For the receiver:

$$Y = W^H H X + W^H N \quad (2)$$

Where:

Y is the received signal matrix of size $N_S \times N_P$.

X is the received signal matrix of size $N_T \times N_P$.

W is the combiner at the receiver of size is the number of character streams that can be transmitted.

We present the elements of row i , column j of the received RF matrix as follows: $[W]_{i,j} = \frac{1}{\sqrt{N_R}} e^{j\theta_{i,j}}$.

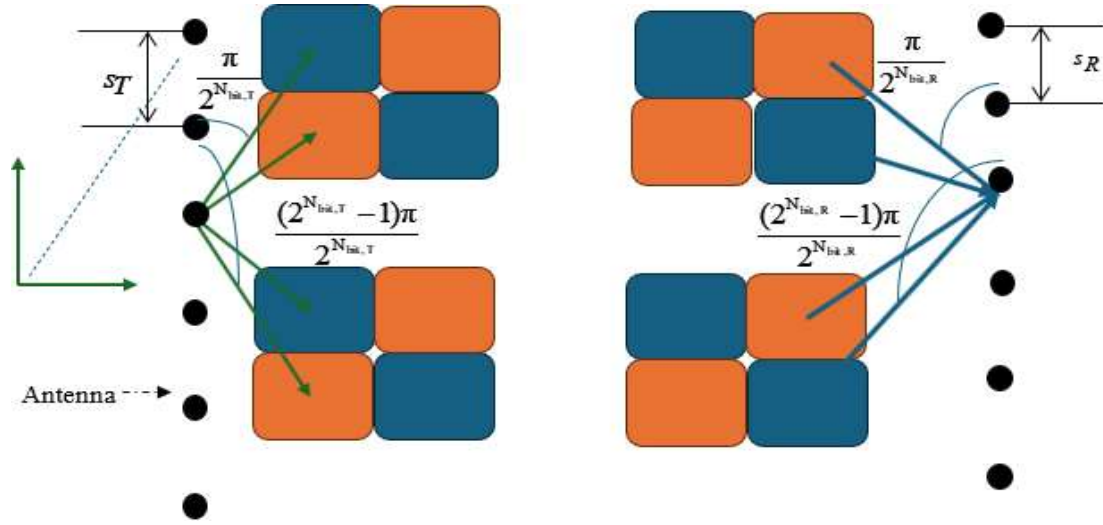


Fig. 3. Channel model in which angles are quantized.

B. Constructing the Virtual Channel Matrix

To reduce overhead costs and computational complexity, we have a virtual channel model as shown in Figure 3.

$$H = A_R H_v A_T^H \quad (3)$$

Matrix A_t and A_r are written: $A_R = [\mathbf{a}_R(\theta_1^r), \mathbf{a}_R(\theta_2^r), \dots, \mathbf{a}_R(\theta_L^r)]$

Where

$$\mathbf{a}(\theta_i^r) = \left[1, e^{-j\frac{2\pi}{\lambda}s_R \cos(\theta_i^r)}, \dots, e^{-j\frac{2\pi}{\lambda}(N_r-1)s_R \cos(\theta_i^r)} \right]^T$$

$$A_T = [\mathbf{a}_T(\theta_1^t), \mathbf{a}_T(\theta_2^t), \dots, \mathbf{a}_T(\theta_L^t)]$$

Where

$$\mathbf{a}(\theta_i^t) = \left[1, e^{-j\frac{2\pi}{\lambda}s_T \cos(\theta_i^t)}, \dots, e^{-j\frac{2\pi}{\lambda}(N_T-1)s_T \cos(\theta_i^t)} \right]^T$$

Each element of (size is) is a complex Gaussian random variable with similar and independent i.i.d distribution, each element has a mean of 0 and variance of σ^2 . N_P is the number of pilot channel symbols with the assumption that this is a block-shaped flat fading model, in which the channel matrix does not change.

Calculate the virtual channel matrix when quantizing the angles:

$$H_v = \sqrt{\frac{N_T N_R}{L}} \text{diag}(\alpha_1, \dots, \alpha_L) \quad (4)$$

With the following model related to channel virtualization we use $\bar{\theta}_g^t = \bar{\theta}_g^r = \frac{(g-1)\pi}{2^{N_{bit,T}}}$ with $g = 1 \rightarrow G = 2^{N_{bit,T}}$

$$\bar{A}_R = [\bar{a}_R(\theta_1^r), \bar{a}_R(\theta_2^r), \dots, \bar{a}_R(\theta_G^r)]$$

$$\text{In which } \bar{a}(\bar{\theta}_g^r) = \left[1, e^{-j\frac{2\pi}{\lambda} s_R \cos(\bar{\theta}_g^r)}, \dots, e^{-j\frac{2\pi}{\lambda} (N_R-1) s_R \cos(\bar{\theta}_g^r)} \right]^T$$

$$\bar{A}_T = [\bar{a}_T(\theta_1^t), \bar{a}_T(\theta_2^t), \dots, \bar{a}_T(\theta_G^t)]$$

$$\text{In which } \bar{a}(\bar{\theta}_g^t) = \left[1, e^{-j\frac{2\pi}{\lambda} s_T \cos(\bar{\theta}_g^t)}, \dots, e^{-j\frac{2\pi}{\lambda} (N_T-1) s_T \cos(\bar{\theta}_g^t)} \right]^T$$

The main purpose of communication is to find or from equation (1). According to LS estimation, we have the channel matrix calculated as follows: $\bar{h} = \text{vec}(H) = \frac{1}{\sqrt{P}} (Q^H Q)^{-1} Q^H \text{vec}(Y)$ in which

$$Q = F^T \otimes W^H \quad (5)$$

III. OMP ALGORITHM

Estimating mm Wave channels based on OMP:

1. Requirements: Received matrix $\bar{Q} = (F^T \bar{A}_T^* \otimes W^H \bar{A}_R)$, measurement vector $\bar{y} = \sqrt{P} \bar{Q} \text{vec}(\bar{H}_a) + \bar{e} + \bar{n}$ and threshold level δ .
2. We assume is the empty set, the rest $r_{-1} = 0, r_0 = \bar{y}$ and iteratet = 1
3. $j = \arg \max_{i=1, \dots, G^2} |\bar{Q}(i)^H r_{t-1}|$ Find AoD and AoA
4. $I_t = I_{t-1} \cup \{j\}$ Update AoD/AoA
5. $h_t = \arg \min_h \|\bar{y} - \sqrt{P} \bar{Q}_{I_t} h\|_2$ Estimate channel gain
6. $r_t = \bar{y} - \sqrt{P} \bar{Q}_{I_t} h_t$ Update the rest
7. $t = t + 1$
8. When $\|r_{t-1}\|_2^2 - \|r_{t-2}\|_2^2 \leq \delta$ then stop.
9. $\hat{h}_a(i) = h_{t-1}(i)$ with $i \in I_{t-1}$ and $\hat{h}_a(i) = 0$ in the rest case
10. Return the result $\bar{H}_a^{CS} = \text{vec}^{-1}(\hat{h}_a)$

Here we assume there is only one receiving antenna, then the system becomes SIMO for simplicity. Also we assume there is only one RF sequence connected to the receiving antennas, then becomes the radiation weight vector (for analog radiation).

IV. MLP ALGORITHM

The main challenge in acquiring channel matrices is separating them from the receive signals.

DNN architecture consists of an encoder and a decoder, where the encoder extracts feature vectors from complex radiation patterns, and the decoder is responsible for recovering the radiation patterns from the acquired feature vectors.

Steps to implement MLP:



Fig. 4. Implementation diagram for encoding and decoding Massive MIMO using DNN.

Direct training phase of the encoder: In this phase, we need to train the MLP to convert the received signals and represent them as matrices.

Online training phase of the decoder: During this phase, the received signal is converted into a matrix.

V. SIMULATION

When using OMP, the error is quite large with different channel matrix patterns:

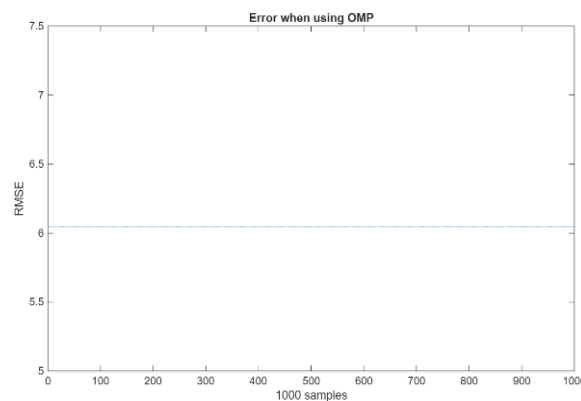


Fig. 5. Estimation error for virtual channel matrix using OMP.

When using MLP, we can see that after 1500 iterations, we can accurately predict H_a when the channel matrix changes.

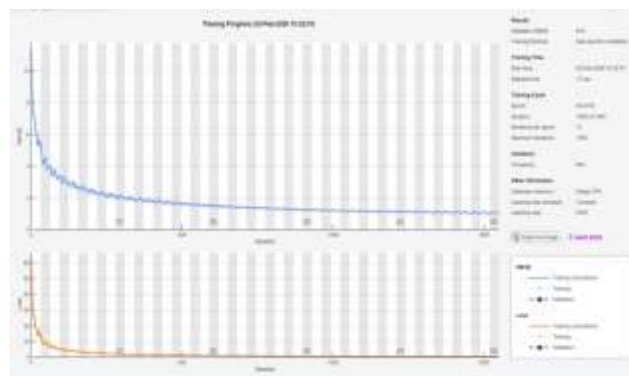


Fig. 6. RMSE and Loss value using Multilayer Perceptron (MPL) to predict the virtual channel matrix.

While MLP implementation may take time to train, it is done offline (requiring a large dataset and long training time), whereas OMP is applied directly at the receiver. However, when MLP is implemented online at receivers, it has a simpler structure, lower computational complexity, and much higher accuracy compared to OMP [10].

VI. CONCLUSION

This paper presents the application of the MLP algorithm in predicting the values of the virtual channel matrix coefficients when receiving signals at the receiver. Predicting the virtual channel matrix is more accurate than the orthogonal matching (OMP) algorithm, while also having lower computational complexity.

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AUTHOR'S PROFILE



Hoai Trung Tran, got Bachelor degree in University of Transport and Communications (UTC) in 1997 and hold the post of lecturer at the University. He then got a Master degree from Hanoi University of Science and Technology (HUST) in 2000. In the period 2003 to 2008, he had concentrated on researching in the field of Telecommunication engineering and got his PhD at University of Technology, Sydney (UTS) in Australia. He is currently an lecturer at the UTC in Vietnam. His main research interests are digital signal processing (DSP), applied information theory, radio propagation, MIMO antenna techniques and advanced wireless transceiver and circuit design.