Efficient Channel Estimation in mm Wave Massive MIMO Using Hybrid Beamforming

Neha, Naresh Kumar, and Aarti Kochhar

Abstract Beamforming with MIMO (Multiple-Input Multiple-Output) system is only solution to maximize high data rate and extended cell coverage with satisfying quality of Service (QoS) for fifth generation (5G) cellular networks. In hybrid millimeter-wave (mmWave) massive MIMO systems, estimation of information about Channel State is difficult due to the large channel and small number of RF chains. The present paper accomplishes millimeter-wave-based massive MIMO for hybrid beamforming based on Sparse Estimation. The proposed iterative hybrid algorithms accomplish the low rank and beamforming sparsity properties in massive MIMO to gain full data recovery with minimal error for small time duration. The proposed work model is an mmWave-based beamforming system with imperfect channel state information (CSI) to minimize channel estimation errors. Experimental section highlights the efficiency of our proposed method over traditional methods for the sake of simulation with accounting its improved temporal efficiency, fast convergence, and tolerance to abnormality channel information.

Keywords Beamforming · 5G · MIMO · Hybrid beamforming

1 Introduction

Frequency resource shortage problem in wireless communication can be unraveled using Millimeter wave communications. Wireless communication requires large bandwidth for 5G; thus, millimeter Wave waveband satisfy highly demanding data rate requirements for 5G and beyond, broadband wireless networks [1]. MIMO system with mmWave communications is fulfilling the goal of high-speed data communication with greater than 1 GB per user in urban areas also, hence mmWave-based MIMO system becomes milestone in the development of 5G wireless system.

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Sufficient antenna array gain with MIMO will resolve the significant transmission losses of mm Wavesignal [2].

However, for large antenna array gain, the development of beamforming matrix uses mmWave radio frequency (RF) chains which is costly. Digital beamformer requires the use of an antenna part inside an RF chain which increases energy consumption and equipment costs, hence such type of traditional digital beamformer requires large implementation and maintenance cost. Recently, to fulfill the higher data rate requirements, the 5G New Radio technology [1] may help Composite Beam Forming [3] for a maximum of four spatial sources for wireless transmission. These innovations exploit digital as well as analog signal processing to empower an enormous number of radio wave components to be associated with a small number of RF chains. Thus, minimizing the total implementation and maintenance cost.

In mm Wave massive MIMO frameworks, CSI is required for improvement in Data rate. For all intents and purposes, it appears to be difficult due to high channel inconsistency and enormous numbers of transceiver antenna elements [4]. In most of the available literature, Channel State Information estimation is formulated as an issue having solution in compressive sensing [5], where the Orthogonal Matching Pursuit framework [6] is used to estimate transmitted Data with maximum likelihood. However, the efficiency with which these channel estimation strategies work is satisfactory practically. Large array antenna gains are needed at both uplink and downlink side to minimize the extreme isotropic path loss caused by mmWave frequencies. But mmWave frequencies require little carrier wavelength which make it feasible for large antenna arrays to exhibit in a little structure, with the end goal of beamforming providing a significant increase in antenna gain.Implementation of quick and precise mmWave steerable beamforming is not an easy approach. One major issue is that the Traditional digital transceiver architecture having antenna element equipped with one RF chain is troublesome due to implementation cost, power utilization and dissemination Analog-to-digital and digital-to-analog converters, up-down conversion mixers, filters, power amplifiers, with low-noise amplifiers are all part of an RF chain. The fundamental issue in mmWave transceiver architecture is to keep the number of RF chains much lower than the number of antenna array components. Consequently, hybrid digital (HD) beamforming model, the concatenation of digital and analog beamforming has been widely considered. The main purpose of HD beamforming would be to improve the multi-user system throughput while minimizing cost of hardware, complexity, including power performance.

2 Literature Review

Elbir et al. [7] studied Machine learning for hybrid beamforming using centralized machine learning (CML) techniques and presented a united learning-based structure for hybrid beamforming, where gathering the gradients from the users at BS model training is accomplished. Song et al. [8] investigate the performance of two common designs that might be regarded as exceptional examples, namely, the totally associated and the one-stream-per-subarray structures. The method Song et al. [9] have proposed comprises a strong and highly adjustable artificial learning system that uses low-rank channel recuperation for an array-based massive MIMO framework. The system contains a standard feature extraction module as well as an adaptive recuperation module. Huang et al. [10] proposed an extraordinary learning machine system to mutually improve transmitting and receiving beamformers. This structure is fundamentally expanding the heartiness of beamformers.

To provide the telecommunications industry with an edge, Salh et al. [11] assess and work to increase the energy efficiency and to increase the unpredictability of hybrid-precoding algorithms to benefit the lowering of the number of radio frequency chains within the base station. It also incorporates high-resolution phase shifters specifically for the downlink multi-user mmwave architecture. Kaushik et al. [12] proposed novel design with a structure that progressively actuates the ideal number of radio frequency chains used to execute hybrid beamforming in a millimeter-wave MIMO framework. Chen et al. [13] explore the consolidated effects of quantized phase shifters, channel non-correspondence, and channel estimation errors on the spectral efficiency of a hybrid beamforming MIMO framework working in time-division duplex (TDD) mode.

There are two difficulties in acknowledging hybrid beamforming, and present potential arrangements can handle these difficulties.

(1) Low-Complexity Precoder and Combiner Designs:

The fundamental problem for analog beamformers originates from the low-resolution phase requirements. The ideal exhaustive search algorithm has exponential intricacy in the number of antenna element and is unquestionably illogical for practical implementation.

(2) Channel Estimation with Hybrid Beamforming:

The hybrid precoder and combiner configuration requires full information on channel state, which is hard to be gotten in mmWave MIMO frameworks since the channel is interlaced with analog beamformers and the baseband has no immediate access to the channel matrix. Because of the particular meager quality of mm Wave channels in the angle domain, compressed sensing-based methodologies are regularly utilized to execute productive channel estimation by investigating the channel sparsity in mmWave framework.

3 Methodology

Problem

The following are some insights from the discussion: Array were represented by lowercase characters and matrix using uppercase. The Hermitian, complex conjugate

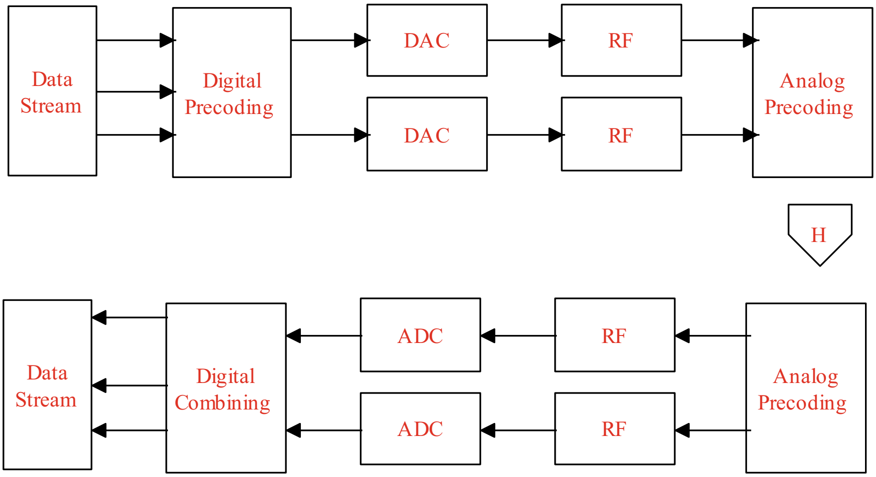

Fig. 1 Architecture of hybrid beamforming for mmWave multi-user massive MIMO system

form, and the matrix transpose, are noted by (•) H, (.)*, (•) T separately; N × N is Identity matrix indicated by N. Re, Im denote real and imaginary parts of the data.

However, MIMO frameworks with transmitting Antenna M and receiving antennas N and N > M is shown in Fig. 1. For discovery, Encoder ought to be known to receiver. Let us expect the channel to be quasi-static Rayleigh channel of order N × M complex channel framework indicated by H. Denoting the complex got information by Y. AWGN (Additive White Gaussian Noise) is introduced by C, having zero mean and one variance with some noise power. On the off chance that encoder produces nsb symbol and span of it is lns, at that point utilizing nsb symbol it makes block matrix of and this can be composed as [13].

$$B_d(S) = \sum_{k=1}^{n} (\mathrm{A}_k R_e(S_k) + A_{k+n} I_m(S_k)) \tag{1}$$

The following are the characteristics of energy regularization:

$$\delta = \mu\left[\left(\frac{B_d(s).B_d(s)'}{1_{ns}}\right)\right] \tag{2}$$

$$B(s) = \frac{B_d(s)}{\sqrt{\delta}} \tag{3}$$

The obtained frame function is given as follows by [14]

$$\mathbf{Y_i} = \mathbf{H}\mathrm{B(s)} + \mathbf{C_i} \tag{4}$$

Additive noise is indicated by term C. The objective is to make an approximation H from Yi. H would be modeled by [15]

$$H = \frac{1}{\sqrt{1_c}} * \mathrm{U} * V^{1/2} * W \tag{5}$$

Unitary matrix with full rank is indicated by W which have dimension of MXM.

Diagonal array has real values id indicated by v of dimension MXM. U is NXM matrix.

The significance of W must be defined in order to approximate the direction and retrieve the transmitted symbol. There is really no knowledge at the receiver's hand in a blindness sense. W could be evaluated through optimizing numerical autonomy by calculating its Kurtosis, defined by K [15].

$$\mathbf{W} = \left\{ \min \mathrm{J(W)} = \sum_{\mathrm{k}=1}^{\mathrm{n}} \mathrm{K} \begin{pmatrix} \hat{}\,(\mathrm{i}) \\ \mathrm{S_k} \end{pmatrix} \right\} \ldots (6) \tag{6}$$

Subject to $\mathrm{WW^H} = \mathrm{I_{nt}}$. Cost function with real number is indicated by J(w). Gradient cost function J(w) is $M \times M$ matrix

$$\tau_{\mathrm{W}} = \frac{\mathrm{dJ(W)}}{\mathrm{dW^*}} \tag{7}$$

$$\frac{\mathrm{dJ(W)}}{\mathrm{dW^*}} = \left(\frac{\mathrm{dJ(W)}}{\mathrm{2dR_e(W)}} + \frac{\mathrm{dJ(W)}}{\mathrm{2dI_m(W)}} \right) \tag{8}$$

Now, model the descent gradient [15]

$$Z = -\tau_W \tag{9}$$

$$W_g = W + Z\mu \tag{10}$$

Where $\mu = 1$

$$W_{new} = Wg * \left(W_g^H * W_g \right)^{-\frac{1}{2}} \tag{11}$$

The recommended methodology combines a primal–dual interior point methodology with a unique preconditioned to provide nonzero sparse signal recovery using the l1-norm normalized least square estimate.

We'd want to restore a missing signal. From its linear observation [16].

$$b = Ax + n \in r^M \tag{12}$$

Exemplary least square technique requires abundant estimation

$$\mathrm{M} > N\,and\,A\,has\,full\,rank$$

$$x^{*} = (A^{\tau}A)^{-1}A^{\tau}b$$

Current compressive detection methods can reconstruct x from either a large number of less estimates because signal is sparse by exploiting the proceeding basis pursuits dimensionality reduction issue:

$$\min_{xe^{N}}\frac{1}{2}\|Ax-b\|^{2}+\tau\|x\|_{1}$$

Algorithm Primal Dual Preconditioned PDP Framework

Inputs: choose $\left(x^{0}, s^{0}\right) > 0$ from Sect. 2.1, stop accuracy ϵ (e.g. 1e–6),

And maximum iteration number k_{max}.

for $k = 1, 2, \ldots.., k_{\max}$ do.

Perform Prediction Step: set $\sigma \leftarrow 0.001$
$(x^{k}, s^{k}, \alpha_{p}, \alpha_{d}) = UPDATE\ (x^{\mathrm{k-1}}, s^{\mathrm{k-1}}, \sigma)$
if $\mu_{k} \leq \epsilon h\left(x^{k}\right)$ and $\|r_{d}^{k}\|$ then.

Break.

Output:x^{k}

Function $UPDATE\left(x^{k-1}, s^{k-1}, \sigma\right)$

Compute Δx, Δs with σ, x^{k-1}, s^{k-1}
Compute α_{p}, α_{d} with x^{k-1}, s^{k-1}, Δx, Δs

4 Channel Estimation Problem

A difficulty with the channel computation is determining the maximum CSI H that can be obtained from low-rank data Y. There are two well-known frameworks; one of them is known as LS and the other is known as CS. The LS technology incorporates a set of L to obtain analog beamformers. The channel coherence interval is initiated with the introduction of W, which is used to gather the required predictions C, and then the complete CSI is retrieved [8]. By taking care of an optimization problem, the CS strategy will obtain low-rank observations from arbitrarily projected sparse signals and reconstruct the input signals precisely.

5 Experiment and Results

In this part, simulation model is undertaken to give more information and insights into sparse channel estimation, which proves the benefits and downsides of that method.

The proposed method is compared with the well-known state of the art of the methods in Table 1. First one is the hybrid beamforming using centralized machine learning (CML) techniques [7]. An alternative is a novel and successful convolutional neural network dependent low-rank channel recovery technology that is specifically built for an array-based massive MIMO framework, and integrates a conventional feature extraction mechanism as well as the adaptable recuperation module shown in Fig. 2 [9]. Third one used for comparison is an extraordinary learning machine system to mutually improve transmitting and receiving beamformers in Fig. 3 [10]. Last one is hybrid-precoding algorithm to empower the decrease of reduction of radio frequency chains inside the base station in Fig. 4 [11].

Table 1 Throughput comparison

SNR	Proposed	CML [7]	LRCR [9]	ELM [10]	HPA [11]
−5	0.88	0.86	0.82	0.76	0.71
0	0.88	0.87	0.83	0.78	0.73
5	0.89	0.88	0.85	0.80	0.76
10	0.90	0.89	0.86	0.82	0.79
15	0.91	0.90	0.88	0.85	0.83

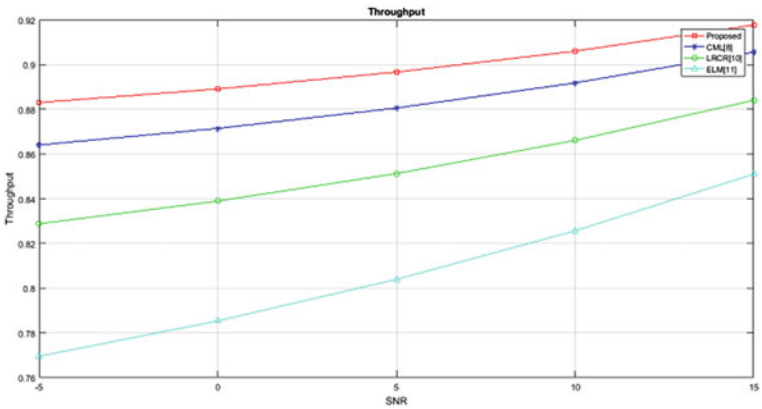

Fig. 2 Comparison of throughput between proposed and reference method

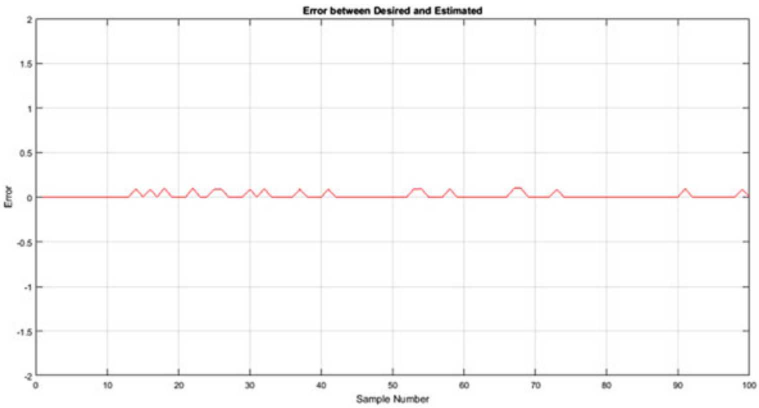

Fig. 3 Error between Tx and Rx signal

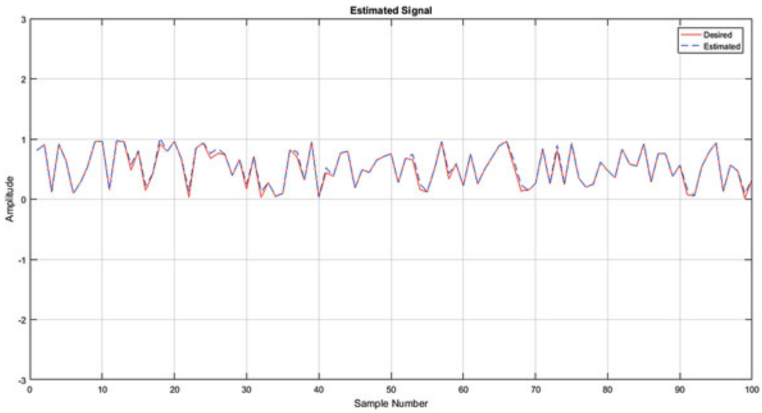

Fig. 4 Transmitted and estimates signal

6 Conclusion

Future mmWave MIMO communication systems may rely heavily on hybrid precoding as well as linking. For this mmwave hybrid beamforming framework, the suggested scheme overcomes design problems and explores approximated approaches of precoder/combiner design and channel approximation. In this paper, we provide an efficient and scalable Sparsed-based method to the low-rank channel recovery issue in mmWave large MIMO systems, where we use a hybrid array structure. Simulation results showed that the optimization model performs better in terms of MSE for channel estimation with shorter frame lengths [17].

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