

Machine-Learning-Aided Massive Hybrid Analog and Digital MIMO DOA Estimation for Future Wireless Networks

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Abstract. *Due to a high spatial angle resolution and low circuit cost of massive hybrid analog and digital (HAD) multiple-input multiple-output (MIMO), it is viewed as a valuable green communication technology for future wireless networks. Integrating the massive HAD-MIMO with direction of arrival (DOA) will provide an even ultra-high performance of DOA measurement, which can the fully-digital (FD) MIMO. However, phase ambiguity is a challenge issue for a massive HAD-MIMO DOA estimation. In this paper, we consider three parts: detection, estimation, and Cramer-Rao lower bound (CRLB). First, a multi-layer-neural-network (MLNN) detector is proposed to infer the existence of emitters. Then, a two-layer HAD (TLHAD) MIMO structure is proposed to estimate the DOA and eliminate phase ambiguity using only one time block. Simulation results show that the proposed MLNN detector is much better than both the existing generalized likelihood ratio test (GRLT) and the ratio of maximum eigen-value (Max-EV) to minimum eigen-value (R-MaxEV-MinEV) in terms of detection probability. Additionally, the proposed TLHAD structure can achieve the corresponding CRLB.*

Keywords

DOA, hybrid analog and digital, MIMO, green technologies, CRLB, multi-layer-neural-network

1. Introduction

The position of a target of interest can be inferred by using its emitted signal measured at an array of spatially separated nodes, where the positions of nodes are known.

Actually, source localization has been become one of the crucial issues in many research fields such as robot, mobile communications, radar, sonar, wireless sensor networks, satellite communications, human-computer interaction, and marine communications [1–4]. Source localization techniques fall into the main five categories: direction of arrival (DOA) in [5], received signal strength indicator (RSSI) in [6], [7], time of arrival (TOA), time difference of arrival (TDOA), and frequency difference of arrival (FDOA). Different from other methods, RSSI may work in both line-of-sight (LOS) and Non-LOS (NLOS) environments and is insensitive to the availability of multi-paths. In particular, the remaining four techniques are more suitable for the LOS scenario. In the presence of multipaths, their localization accuracies will be degraded substantially.

With the deep integration of artificial intelligence and information, communication, and data technologies (ICDT), some emerging services such as Metaverse and holographic communication have higher demands for end-to-end information processing rates and latency, enabling the integrated sensing and communication (ISAC) one of the leading trends of sixth generation (6G) technology. In recent years, with the emergences of the massive antenna array structure, DOA estimation, as a traditional field, can provide a ultra-high accurate desired signal direction for beamforming and tracking, and achieve a higher signal-to-noise ratio at the receiver with less transmit power compare to conventional small MIMO receiver [8–10]. As one of the key technologies in the beyond fifth generation (B5G) and 6G mobile communication systems [11], DOA estimation will gradually serve in the construction of ISAC, and provide a high energy-efficient green beamforming communication. As the number of antennas tends to large-scale or ultra-large-scale, it is possible to

achieve a localization accuracy of centimeter via DOA. Unluckily, this leads to a high circuit cost like massive antennas, analog-to-digital convertors (ADCs), and radio frequency links, etc. The corresponding computational complexity is significantly increased. Hybrid analog and digital (HAD) MIMO array becomes a natural choice, which can dramatically reduce energy consumption and circuit costs and enable a reliable green wireless communication technology to support future sustainable development of applications such as Metaverse or Web3.0 [8], [12]. Three high-performance DOA estimation methods were proposed in [8] for eliminating phase ambiguity of massive hybrid MIMO systems, and the Cramer-Rao lower bound (CRLB) was derived. In [12], a fast ambiguous phase elimination method was proposed to find the true direction using only two snapshots at the cost of a slight performance loss. The DOA estimation problem of sparse array design with non-circular (NC) signals was investigated in [13]. Furthermore, in [14], the generalized sparse Bayesian learning algorithm was integrated into the 1-bit DOA estimation. Adopting massive MIMO receive array with low-resolution ADC, demonstrated a new DOA estimation scheme in [15].

Due to the adoption of eigenvalue decomposition, the computational complexities of the above matrix-decomposition-based DOA estimators are high. A novel deep-learning framework of achieving super-resolution channel estimation and DOA estimation was proposed in massive MIMO systems in [16]. In [9], a low-complexity deep-learning based DOA estimator with uniform circular arrays (UCA) was proposed for the massive MIMO systems with much lower computational complexity than conventional maximum likelihood (ML) method. Afterwards, in [17], a novel estimating signal parameter via rotational invariance techniques (ESPRIT) method and a machine learning framework were proposed to improve the accuracy of DOA measurements for the HAD structure. Due to its ultra-high precision of angles using a massive or ultra-massive MIMO, the positioning based on the angle of arrival (AOA) can reach a high-performance localization accuracy. For example, in [18], a geometric center AOA localization method was proposed utilize single base station, which can achieve the CRLB. By estimating the DOA was given to achieve the associated CRLB by forming a polygon of intersecting multiple estimated DOA lines. The final source position is the center of this polygon. Aiming at the indoor localization, the paper [19] proposed a fifth generation (5G) signal based localization method by employing the estimates of the AOA and the time of flight, which can achieve a centimeter-level localization accuracy. In [20], the authors presented an improved polarity representation to uniformly use the AOA the localization of a signal source, regardless of whether it is a near or far.

To the best of our knowledge, there is no work about the deep learning based detection. In addition, existed DOA estimation methods for the HAD structure need multi time block to adjusting analog phase shifters. Thus, we integrate

the deep learning into detector and come up with a novel HAD structure to eliminate angle ambiguity. In addition, we propose a multi-layer-neural-network (MLNN) based detector and a two-layer DOA estimator for HAD structure. In addition, we present performance of HAD architecture with low-resolution ADCs.

The remainder of this paper is organized as follows. Section 2 describes the system model of designed heterogeneous hybrid MIMO structure. In Sec. 3, a MLNN based detector is proposed. In addition, We proposed a two-layer DOA estimation method for HAD structure in Sec. 4. Then, the performance is analyzed in Sec. 5. Furthermore, we summarize existing challenging problems in Sec. 6. Finally, we draw conclusions in Sec. 7.

2. System Model

As shown in Fig. 1, a sub-connect HAD structure is considered. The signal is transmitted from a far-field emitter and impinges the uniform linear array (ULA). The ULA is equipped with M antennas, M_s subarrays. Next, every subarray has M_a antennas. Referring to [8], for the m_s th subarray, the signals are added after passing the analog phase shifters. Thus, the received baseband signals can be given by

$$\mathbf{y}(n) = \mathbf{V}_A^H \mathbf{a}(\theta_0) s(n) + \mathbf{w}(n) \quad (1)$$

where $\mathbf{w}(t) \sim \mathcal{CN}(0, \mathbf{I}_M)$ is the independent and identically distributed (i.i.d.) additive white Gaussian noise (AWGN) and $s(t)$ is the signal. $\mathbf{a}(\theta_0)$ is the steering vector

$$\mathbf{a}(\theta_0) = \left[e^{j\Psi_{\theta_0}(1)} \ e^{j\Psi_{\theta_0}(2)} \ \dots \ e^{j\Psi_{\theta_0}(M)} \right]^T \quad (2)$$

where

$$\Psi_{\theta_0}(m) = 2\pi \sin \theta_0 \frac{d_m}{\lambda}, \quad m = 1, 2, \dots, M \quad (3)$$

where λ is the wavelength of the carrier wave, θ_0 is the DOA, d_m is the distance from the m th antenna to the reference point of the array and M is the number of antennas. \mathbf{V}_A is the analog beamforming (AB) matrix, which is expressed as

$$\mathbf{V}_A = \begin{bmatrix} \mathbf{V}_{A,1} & \mathbf{0} & \dots & \mathbf{0} \\ \mathbf{0} & \mathbf{V}_{A,2} & \dots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{V}_{A,M_s} \end{bmatrix} \quad (4)$$

where

$$\mathbf{V}_{A,m_s} = \frac{1}{\sqrt{M_a}} \left[e^{j\omega_{m_s,1}} \ e^{j\omega_{m_s,2}} \ \dots \ e^{j\omega_{m_s,M_a}} \right]^T \quad (5)$$

is the AB vector of the m_s th subarray.

The detection problem can be written as a binary problem

$$\begin{cases} H_0 : & \mathbf{y}(n) = \mathbf{w}(n), \\ H_1 : & \mathbf{y}(n) = \mathbf{V}_A^H \mathbf{a}(\theta_0) s(n) + \mathbf{w}(n). \end{cases} \quad (6)$$

Thus, generalized likelihood ratio test (GLRT) is given by

$$T_{\text{GLRT}} = \frac{p(\mathbf{y}|H_1)}{p(\mathbf{y}|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \gamma_{\text{GLRT}}. \quad (7)$$

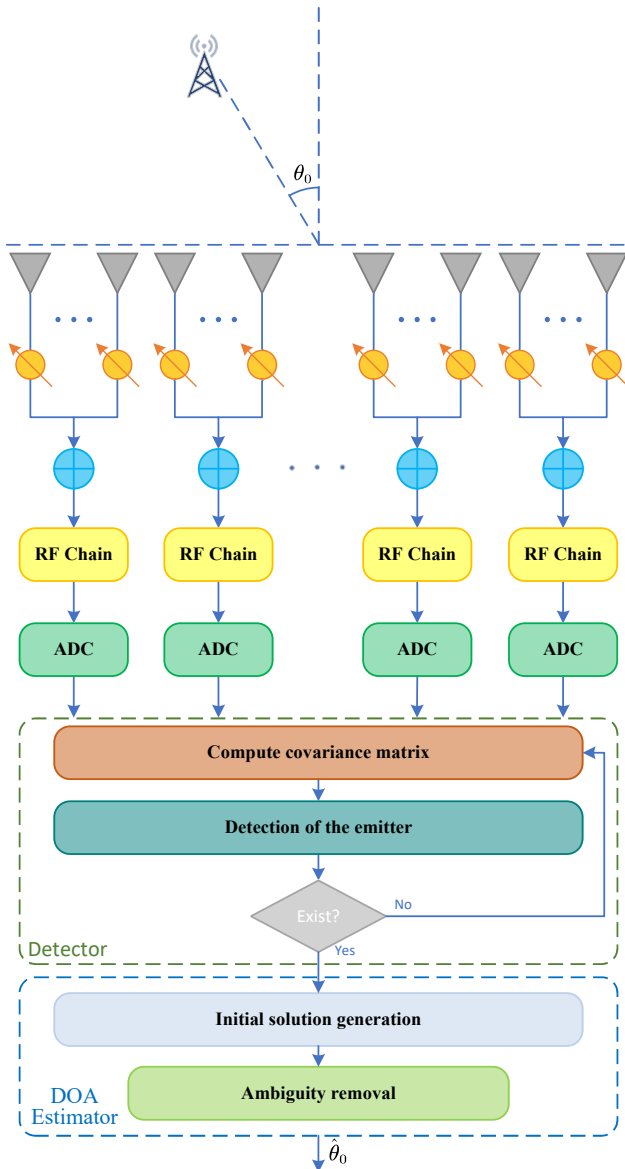


Fig. 1. System model.

3. Proposed Multi-Layer Neural Network Detector for Multi-Emitter

Since the turn of the twentieth century, direction-finding using MIMO receive array has been investigated extensively so far. The research efforts focused mainly on DOA measurement methods, CRLB, and array calibration etc. To the best of our knowledge, there are few research works on passive emitter detection. Similar to radar, an active way of finding direction and range, it is also mandatory for passive direction-finding to infer whether the emitter exists or not before performing DOA estimation operation. For example, when there exists no emitter, a DOA measurement operation is directly conducted. Obviously, this will output the direction angle of a virtual emitter, result in a form of false alarming, and waste the computational amount at MIMO receiver.

To achieve a high detection performance of emitter and trigger the next step: DOA measurements, a high-performance detector was proposed to infer the existence of multi-emitter from the eigen-space of sample covariance matrix of receive signal vector [21]. Here, the sampling covariance of receive signal vector was first computed, and its EVD was performed to extract all its eigenvalues. The test statistic is defined, as the ratio of maximum eigen-value (Max-EV) to minimum eigen-value, called R-MaxEV-MinEV. Their closed-form expressions were presented and the corresponding detection performance was given. As shown in [21], the proposed R-MaxEV-NV method performs much better than the traditional generalized likelihood ratio test (GLRT) method with a fixed false alarm probability in terms of receiver operating characteristic curve (ROC).

To improve the ROC performance, a multi-input single-output (MISO) binary classification of MLNN is proposed in this article. Here, all the eigenvalues of the covariance matrix of the received signal is used as the input signal of the MLNN. A gradient descent algorithm is used to train the neural network. The output of the neural network is a value in the interval $[0,1]$ and an appropriate threshold is determined by the ROC. When the output of the network is less than the threshold, it means that the emitter does not exist and returns to the previous step, and when the output of the network is greater than the threshold, it means that the emitter exists and continues speculation. The training set is constructed by Monte Carlo simulation, and only one neuron is needed for the output layer.

Figure 2 sketches the block diagram of the passive emitter detection system based on MLNN. Firstly, a set of sample vectors is collected within one time block, and the corresponding covariance matrix is estimated. Secondly, an eigen-decomposition (EVD) is made on the estimated covariance matrix to obtain all its eigenvalues, which are used as the input signal of MLNN.

The total MLNN training process is divided into three stages. In the first stage, the training data is used to learn the MLNN activation function, and the activation functions of each layer is optimized, including Sigmoid, Tanh, Rectified linear unit, etc., to explore the optimal activation function configuration. Note that the sigmoid function is adopted in the output layer. In the second stage, the appropriate network depth and the number of neural units in each hidden layer are attained. The main purpose of the hidden layer is to extract channel features, such as clutter and noise co-square matrix. Finally, after determining the network depth and the number of neurons per layer, the random gradient method is applied to minimize the variance and obtain all the weighted coefficients of the MLNN, in order to avoid under fitting and over fitting, the amount of data in the training set is 5–10 times the total number of weighted coefficients. Finally, the above MLNN is directly applied to the massive MIMO receiver to test its false alarm and detection probability performances.

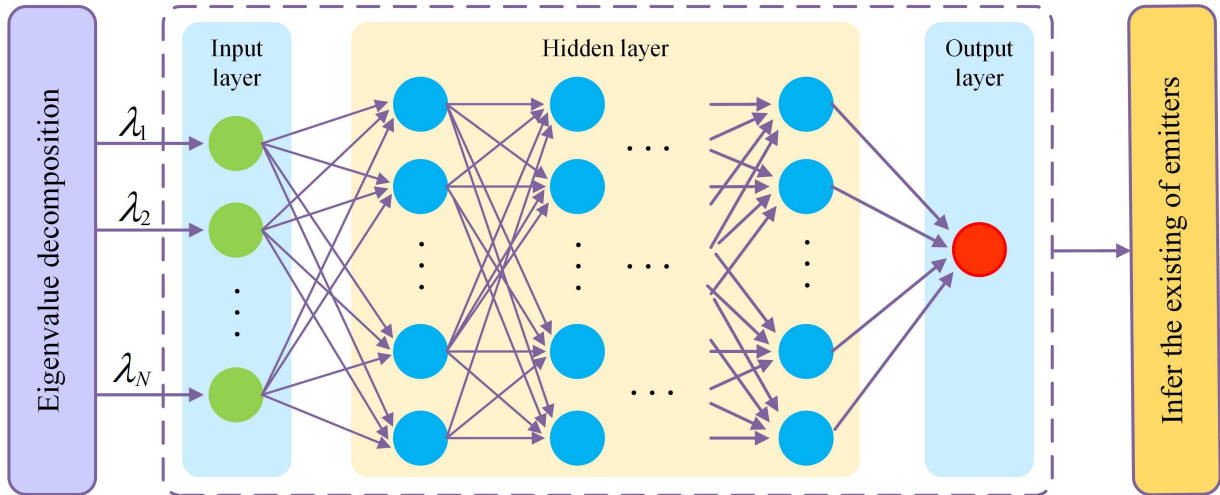


Fig. 2. Proposed MLNN detector.

Below, the practical detection performance simulation is conducted to evaluate the detection probability of the three detection methods. System parameters are shown in Tab. 1. We employ a PC to do simulation, which is equipped with AMD Ryzen 5900X and NVIDIA RTX4070TI. In addition, Python and Tensorflow are adopted to design and process MLNN. The MLNN has one input layer, four hidden layer and one output layer. The number of neurons are 32, 256, 256, 128, 64, and 2, respectively. In addition, the ReLU function is chosen as the activation function in hidden layers. The network is trained offline by employing about 10^6 randomly generated training data. The size of the batch and epoch are respectively set as 500 and 50. Average run time is about 0.0586 second¹.

| Parameters | Values |
|--|--------|
| Number of antennas in the array (M) | 64 |
| Number of antennas in the subarray (M_a) | 4 |
| Signal to noise ratio (SNR) | -20 dB |
| Number of snapshots (N) | 200 |

Tab. 1. Values of simulation parameters.

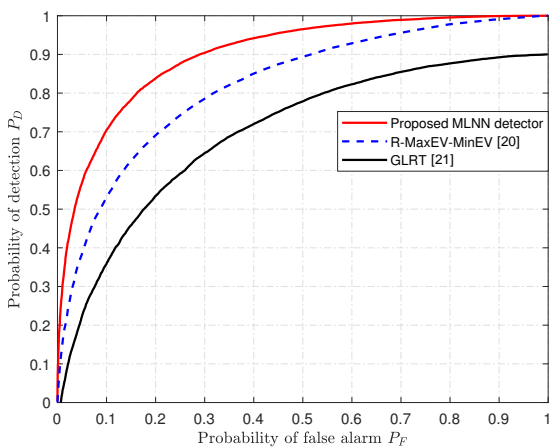


Fig. 3. ROCs under three different detection methods.

Figure 3 plots the ROCs for the proposed MLNN detector with conventional GLRT [22] and R-MaxEV-MinEV as performance benchmarks. It can be seen from Fig. 3 that the detection performance of the proposed MLNN detector for multi-emitter is much better than existing GLRT for a fixed false alarm probability (FAP). Additionally, the R-MaxEV-MinEV is slightly better than GLRT in terms of detection probability given a small FAP.

4. Proposed Two-Layer HAD Structure

A HAD MIMO receiver is very suitable for DOA measurements due to its low circuit cost and power consumption at the expense of some performance loss, especially for large-scale or ultra-large-scale scenario [8], [9]. The major drawback of HAD is that there exists phase ambiguity. This means the DOA measurement method using HAD is made up of two steps: forming a set of candidate solutions by conventional DOA estimators like Root-MUSIC and eliminating spurious solutions in such a set to find the true direction angle in [8], [12]. In [8], three high-performance DOA measurement methods were proposed and the corresponding CRLB was also derived. Among them, the best one is the HAD-Root-MUSIC, which can achieve the hybrid CRLB with a lower-complexity than others. However, they require $M + 1$ snapshots to implement one-time DOA estimate, where M is the number of antennas per subarray. This results in a large processing delay. To reduce this delay, an improved fast HAD-Root-MUSIC method was proposed in [12], where the analogy phase alignment was divided into multiple sub-groups, and the analog beamforming of the sub-arrays of each sub-group was arranged at a candidate angle in a time block to eliminate the ambiguity of the phase. Compared with [8], it needs only two snapshots to find the true direction angle of emitter at the cost of a little performance loss.

¹Parts of the models, data and codes that support the study are available from the corresponding author upon reasonable request.

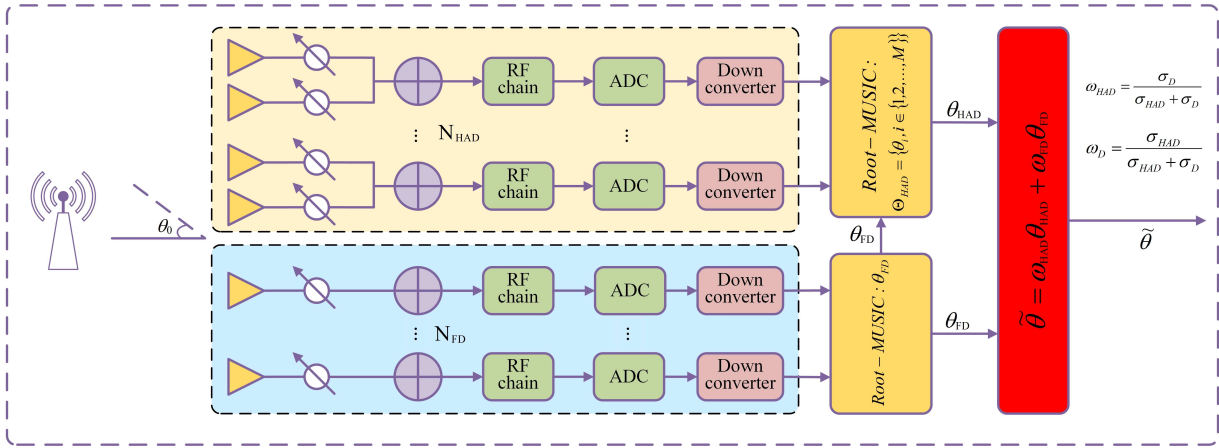


Fig. 4. Proposed two-layer HAD structure.

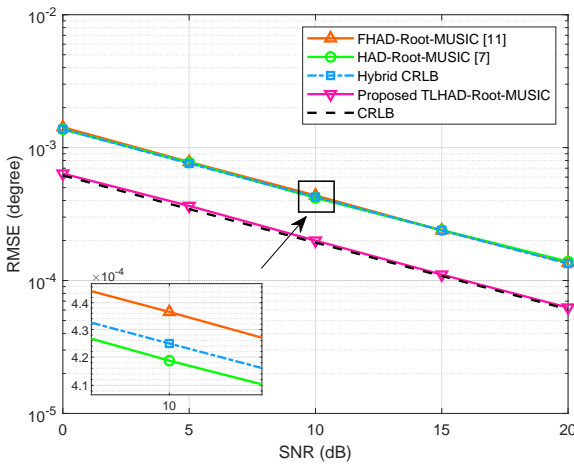


Fig. 5. RMSE versus SNR of the proposed method.

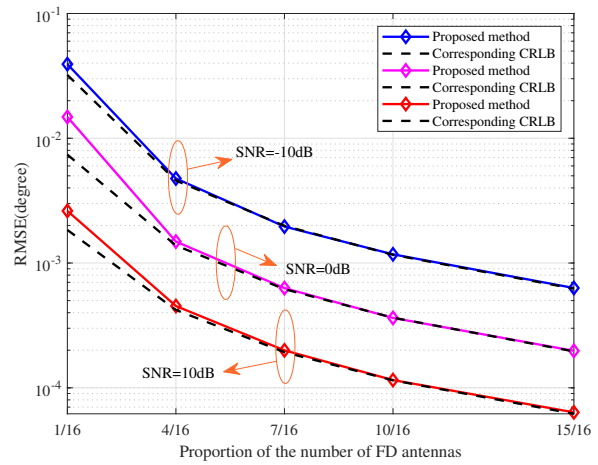


Fig. 6. RMSE versus proportion of FD of the proposed method.

Does it exist an one-snapshot DOA measurement method? To address this problem, a two-layer HAD receive structure is proposed in Fig. 4. The total receiver consists of three parts: a HAD on the left-top corner, a fully-digital (FD) on the left-bottom-left corner, and a combiner on the right side. The first part of HAD is to generate a set of candidate solutions by using some traditional methods like Root-MUSIC, which is shown as

$$\Theta_{HAD} = \{\theta_i, i \in \{1, 2, \dots, M\}\}. \tag{8}$$

The second part of FD is to estimate the true solution, θ_{FD} , which will be adopted to remove the spurious solutions in candidate set. The final part combiner is to combine the two true solutions to output an improved solutions.

$$\tilde{\theta} = \omega_{HAD}\theta_{HAD} + \omega_{FD}\theta_{FD}. \tag{9}$$

The choice of the weight coefficients of this combiner will affect the resulting performance of the two-layer structure. In order to achieve a good performance, they are chosen to be proportional to the corresponding CRLBs, which is given by

$$\omega_{HAD} = \frac{\sigma_D}{\sigma_D + \sigma_{HAD}}, \quad \omega_D = \frac{\sigma_{HAD}}{\sigma_D + \sigma_{HAD}}. \tag{10}$$

Figure 5 plots the curves of RMSE versus SNR of the proposed method with existing method and the CRLB as performance benchmarks. From this figure, it is seen that the proposed method can achieve the corresponding CRLB and performs better than existing methods HAD-Root-MUSIC and FHAD-Root-MUSIC in [8], [12]. This is mainly due to the fact that the proposed structure using a FD sub-structure to replace the corresponding HAD substructure. The proposed structure actually is a mixture of FD and HAD. Obviously, increasing the portion of FD in the total structure will improve the RMSE performance of estimating. Therefore, compare with conventional HAD structure and methods, proposed structure and method are more suitable in most applications.

To evaluate the impact, Figure 6 plots the curves of RMSE versus the proportion of FD of the proposed structure for three different SNRs (-10 dB, 0 dB, and 10 dB) with the corresponding CRLBs as performance benchmarks. Observing this figure, we find that the proposed structure still can achieve the two-layer HAD CRLB for $\eta \geq 25\%$. In addition, the RMSE of proposed methods could approach the corresponding CRLB for all SNR. It means that the appropriate proportion of FD can be selected for the performance requirements of different scenarios.

To sum up, proposed structure and method not only eliminate the phase ambiguity in one time block, but also have better performance.

5. Performance Analysis of HAD-MIMO DOA Measurements with Low-Resolution ADCs

As the number of antennas goes to large-scale in massive MIMO receiver, the number of ADCs increases accordingly. High-resolution ADCs means high cost and energy consumption. Adopting low-resolution ADCs is a promising solution to reduce the circuit cost and power consumption in future wireless communications. Low-resolution structure has attracted many attentions. By resorting to the compressive sensing, the DOA estimation with 1-bit ADCs was solved as a sparse recovery problem. The multiple signal classification (MUSIC) method can be directly utilized to perform DOA estimation with 1-bit ADCs. However, to the best of our knowledge, the performance loss was not derived and analyzed due to the use of low-resolution ADCs. Thus, in [15], the authors proposed a performance loss factor to evaluate the performance loss in massive MIMO systems with low-resolution ADCs. By employing the additive quantization noise mode (AQNM), the closed-form CRLB expression was derived. Based on that, a new performance loss factor was defined. It is shown that the performance loss factor is related to SNR and number of quantization bits. Additionally, it is also verified that all subspace-based methods can be used in low-resolution ADC architecture without any modification.

Figure 7 plots the performance loss versus the number of quantization bits for different SNRs. The simulation parameters are also chosen as Tab. 1. It is obvious that performance loss decreases as the number of quantization bits increases. In addition, the performance loss is a decreasing function of SNR. If we set 1 dB loss as an acceptable loss,

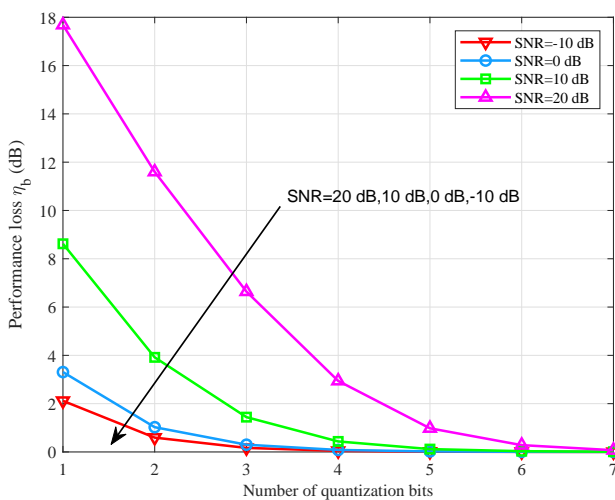


Fig. 7. Performance loss versus number of quantization bits with $N = 32$ and $M = 128$ for different SNRs.

2-bit ADCs are suitable in the low SNR region. However, as the SNR increases, it is better to adopt 3-bit ADCs in the medium SNR region. It is recommended to adopt 4 ~ 5 bit ADCs in the high SNR region. Furthermore, ADCs with $b > 5$ only achieve a trivial performance gain over those with lower-resolution.

In conclusion, adopting low-resolution ADCs could decrease the circuit cost and energy consumption. When recommended quantization bit is selected, the performance loss is negligible according our analysis.

6. Open Challenging Problems

However, there are still several important open problems arising in DOA estimation field using massive HAD-MIMO summarized as follows:

1. As the number N of antennas tends to large-scale or ultra-large-scale, the computational complexities of emitter detections and DOA measurements increase as a function of N^3 . For example, $N = 1000$, its complexity reaches up to 10^9 FLOPs. Thus, there is a large demand for low-complexity emitter detectors and DOA estimators in the case of large-scale.
2. For multi-emitter scenario, only detection is not sufficient. Obviously, a further task is to infer the number of passive emitters using deep learning methods. This will be very helpful for aiding the next step DOA measurement.
3. DOA estimation using ultra-massive MIMO systems could achieve an ultra-high precision of angles, which could pave the way to the AOA localization. How to use multiple estimated AOAs to realize a high-performance and low-complexity localization from geometric aspect? There are two ways: using multiple distributed massive receive MIMO arrays or dividing a ultra-massive array into several subarrays. Each array or subarray makes an independent DOA measurement, and the measured DOAs are used to form several intersection points. The key is how those intersection points are explored to form a high-precision geometric intersection localization method of achieving the corresponding CRLB.

7. Conclusions

In this article, a MLNN-based detector was proposed to improve the emitter detection performance. Subsequently, a DOA estimation algorithm with a TLHAD structure was proposed, which achieves the elimination of phase ambiguity in a single snapshot and makes a significant reduction on a DOA measurement time delay. Furthermore, a low-cost framework of DOA estimation combining low-resolution ADCs and large-scale HAD MIMO system was

also reviewed, which strikes a good balance between performance and circuit cost. Finally, potential challenges of DOA estimation for massive or ultra-massive MIMO systems were discussed, and several new open important issues were presented. Thus, considering its low-cost-circuit and high performance, massive HAD DOA measurement may become a promising green communication technology for many future applications like Metaverse, Web3.0 and the ISAC of beyond 5G/6G, etc.

Acknowledgments

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