OPTIMIZED DEEP LEARNING MODEL BASED CHANNEL ESTIMATION FOR MASSIVE MIMO WITH HYBRID TRANSCEIVERS: A META-HEURISTIC APPROACH

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Abstract—**At present in the field of wireless communication, artificial intelligence technology is an effective way to all levels of the wireless communication system. In 5G mobile technology, to achieve high spectrum utilization and link reliability large-scale Multiple Input Multiple Output technology is used. In this paper, the proposed HAD massive MIMO systems optimized Deep Convolutional Neural Network is used for uplink channel estimation. For enhance the channel estimation capability inside each neural network, the region-specific measurement matrix and channel estimator are jointly optimized. The network parameters are selected with an Improved Election-based Optimization Algorithm. The HAD architecture is designed for the proposed approach is reduce the hardware cost and circuit energy consumption.**

Keywords—Multiple Input Multiple Output, Deep convolutional neural network, Hybrid analog-digital, Channel estimation

I.INTRODUCTION

Massive multiple-input multiple-output (MIMO) is significant in terms of spectral and energy efficiency and enabling technologies in the fifth generation of wireless communication systems [1, 2]. In 5G mobile communication systems, high spectrum utilization and link reliability is achieved with large-scale Multiple Input Multiple Output (MIMO) technology. The problems faced by massive MIMO systems are increasing the number of antennas configured at the transceiver end of the MIMO system and the signal processing process at the receiving end of the communication system becomes more complex[3, 4]. So designing signal detection algorithms with low computational complexity and high detection performance is difficult for massive MIMO systems [5].

In time-division duplex (TDD) systems, only the uplink channel needs to be estimated, but in frequency-division duplex (FDD) systems, the downlink CSI needs to be estimated and fed back to the base station (BS) by the users. This downlink training and uplink feedback increases the number of antennas at the BS and can deteriorate the system efficiency [21][22][23] [24][25]. Since the problem comes from the large number of antennas, dimension reduction is important.

The traditional method uses compressive sensing (CS) algorithms like S-VBI [17], which, however, is not suitable for the power leakage, thereby decreasing the sparsity level of signal .CS algorithms the true AoAs of uplink channel paths at the BS do not exactly match the discrete angle grids find out by the shift-version DFT matrix [7]. In the case of low sparsity level signals, CS algorithms often fail to achieve satisfactory performance. For the above problems, algorithms with less dependency on signal sparsity and better performance-complexity, we propose a DL-based HAD massive MIMO channel estimation approach.

III.LITERATURE REVIEW

In [7], a spatial BEM has been proposed to transform the problem of estimating channel impulse responses to that of estimating spatial basis function weights, which are sparse due to the physical scattering characteristics. The spatial and frequency wideband effects are considered in [8], where the channel sparsity in the angle and the delay domains is exploited, and angular and delay rotations are used to further enhance the sparsity level. Although more computationally efficient, the BEM methods inevitably introduce approximation error to channel estimation due to the imperfect model. A comprehensive overview of low-rank channel estimation methods for massive MIMO systems can be found in [9].

In conventional massive MIMO systems, each antenna is equipped with a dedicated radiofrequency (RF) chain, which leads to high hardware and energy cost when the number of antennas is large. To tackle this issue, the so-called hybrid analog-digital (HAD) architecture has been proposed, where the multi-antenna array is connected to only a limited number of RF chains through phase shifters in the analog domain [10, 11]. However, the channel estimation problem becomes more difficult in the context of HAD since now the received signals at the BS are not the original signals at antennas, but only a few of their linear combinations. In this situation, the conventional least-square (LS) estimator becomes inefficient with dramatically increased overhead [12].

In [13], the complete channels are obtained by LS in the preamble stage and directions-ofarrival (DoAs) of channel paths are estimated first. Since the DoAs change slowly and can be used for a relatively long period, only channel gains of each path need to be re-estimated. Usually, the number of paths is much smaller than that of antennas in millimeter wave systems, therefore greatly reducing the estimation overhead. An alternative method is to adopt the compressive sensing (CS) methods to directly recover the sparse channels all at once, such as orthogonal matching pursuit (OMP) [14], sparse Bayesian learning (SBL) [15], etc. Through embedding the structural characteristics of channel sparsity, several improved CS algorithms have been further proposed, including structured SBL [16] and structured variational Bayesian inference (S-VBI) [17].

The aforementioned methods either suffer from unsatisfactory performance or high complexity, hence channel estimation algorithms with better performance-complexity tradeoffs are urgently required for practical HAD massive MIMO systems. Recently, deep learning (DL) has been successfully applied to many areas in wireless communication [18–20], including spectrum sensing [21], resource management [22] [24], beamforming [25] [27], signal detection [20], and channel estimation.

III.PROPOSED MODEL

Massive multiple-input multiple-output (MIMO) in practical applications faces one of the critical challenge i.e,accurate and efficient estimation of high dimensional channels. In the hybrid analog digital (HAD) transceivers, channel estimation becomes more complicated because of information loss caused by limited radio-frequency chains. The traditional compressive sensing (CS) algorithm has some drawbacks due to unsatisfactory performance and high computational complexity. Therefore, in this research work, a two-stage optimized deep learning-based channel estimation framework will be proposed. The framework includes three stages, namely network segmentation, network training, and online network selection.

In the first stage, the entire angular space is segmented into many small angular regions, then for each region, the neural network containing a measurement matrix and a channel estimator is trained with a large amount of channel data collected from users in the given region.

Then the second stage, two types of data are sent to the BS by the user. The GPS information is sent regularly to help BS select a suitable network for the user. The azimuth angle of the user can be calculated based on the received position coordinates from which a pair of region-specific measurement matrix and channel estimator can be extracted. Second, all antennas at the user transmit orthogonal pilot sequences to the BS simultaneously during the pilot training phase. Then the analog and digital combining matrices received baseband signal processed by the channel estimator can be used to estimate the user's channels.

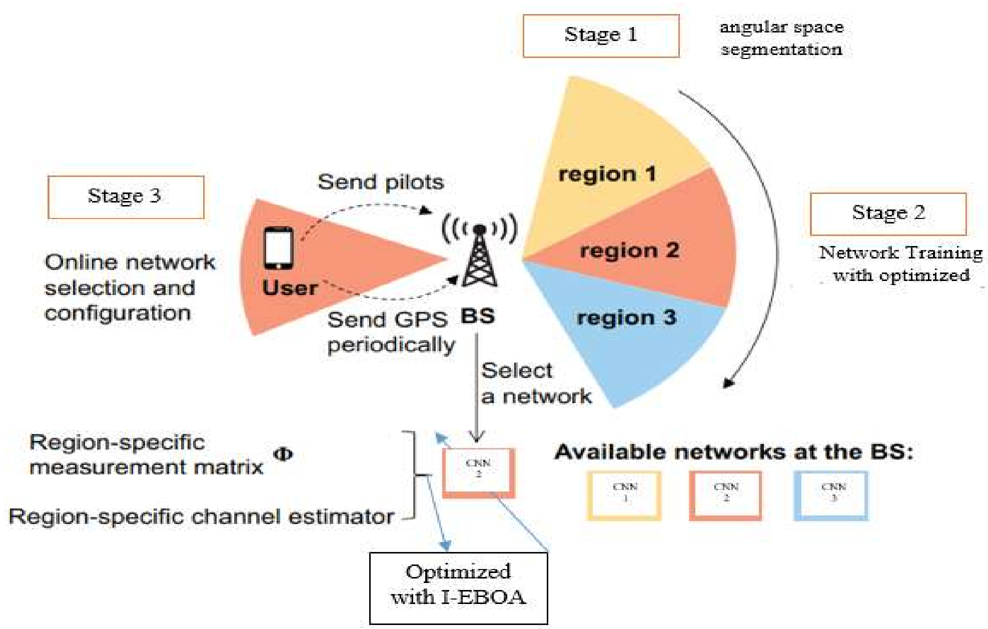


Fig.1 Proposed Two-stage optimized deep learning-based channel estimation framework

Network segmentation:

Initially,the entire angular space is segmented into many small regions with a novel angular space segmentation method**.** This helps to better exploit the sparsity structure of channels in the angular domain.

Network training:

A dedicated optimized Deep Convolutional Neural Network (DCNN)is trained for each region (i.e. segments). DCNN will be trained with the large amount of channel data collected from users in the angular region.Inside each DCNN, theregion-specific measurement matrix and channel estimator are optimally selected with Improved Election-based Optimization Algorithm (I-EBOA), which not only improves the signal measurement efficiency, but also enhances the channel estimation capability.This I-EBOA model will assist in optimizing the network parameters (weight) of DCNN. Moreover, I-EBOA will be an improved version of standard Election-based Optimization Algorithm (EBOA). In fact, the standard EBOA model has been developed with the inspiration acquired from voting process to select the leader.

Network selection and configuration:

In the network selection phase, two kinds of data are sent to the Base Station (BS) by the user. First, the GPS information is sent periodically to help BS select a suitable network for the user. Specifically, based on the received position coordinates, the azimuth angle of the user can be calculated, and the network whose corresponding angular region contains the azimuth angle is selected, from which a pair of region-specific measurement matrix and channel estimator can be extracted. Second, all antennas at the user transmit orthogonal pilot sequences to the BS simultaneously during the pilot training phase. Then, based on the received baseband signal processed by the analog and digital combining matrices, the channel estimator can be used to estimate the user's channels.

Algorithm for the offline networks training, online network selection and configuration processes

Step 1: % Initialization

Step 2: Initialize the width of angular regions β, the maximal azimuth angle error $\triangle\theta_{az}$, the angular spread of uplink channel $\triangle\theta$, dataset $\mathcal{D}$, required data number D, data number counter d = 0, the start angle $\theta_{start} = 0$, and the lower bound of the end angle $\theta_{elb} = \pi/2$

Step 3: % Offline multiple networks training

Step 4: while $\theta_s < \theta_{elb}$ do

Step 5: while d < D do

Step 6: Compute the end angle $\theta_{end} = \theta_{start} + \beta$, uniformly sample an azimuth angle of the user θaz in the angular region $[\theta_{start} - \triangle\theta_{az}, \theta_{end} + \triangle\theta_{az}]$

Step 7: Uniformly sample AoAs of channel paths at the BS in the AoA range $[\theta az - \triangle\theta, \theta az + \triangle\theta]$, uniformly sample AoDs of channel paths at the user in the AoD range $[0, 2\pi]$, randomly generate gains of channel paths according to Then, generate a channel label H_d according to $\mathcal{CN}(0, 1)$ and obtain the data Hˆ d by adding noise on the label

Step 8: Append $\mathcal{D}$ with M $(\hat{h}_d, h_d)$ pairs, where $\hat{h}_d$ and hd are columns of $\hat{H}_d$ and H_d, respectively

Step 9: d = d + 1

Step 10: end while

Step 11: Train a neural network to convergence with $\mathcal{D}$, save the network model and record the θ_{start} and θ_{end} corresponding to this network. Then, empty $\mathcal{D}$

Step 12: Update $\theta_{start} = \theta_{end}$ for the next angular region

Step 13: end while

Step 14: % Online network selection

Step 15: Compute the azimuth angle of the user θaz based on the position coordinates of the BS and the user, which can be obtained by GPS information

Step 16: If $0 \leq \theta_{az} \leq \pi/2$, select the network that satisfies $\theta_{start} \leq \theta_{az} \leq \theta_{end}$. If $\pi/2 \leq \theta_{az} \leq \pi$, select the network corresponding to the azimuth angle with the same sine value. If $\pi \leq \theta_{az} \leq 2\pi$, select the network corresponding to the azimuth angle with the opposite sine value

Step 17: % Measurement matrix configuration and channel estimation

Step 18: Extract the analog and digital measurement matrices W_{RF} and W_{BB}, and the channel estimator from the selected network

Step 19: Configure the phase shifters according to W_{RF}

Step 20: Measure the signals and process the baseband signal with W_{BB}, then do channel estimation with the channel estimator

IV.RESULTS AND DISCUSSION

Simulation results of the proposed DL-based channel estimation approach and validate its superiority is presented here. The normalized MSE (NMSE) as the performance metric, which is defined by

$$\mathrm{NMSE} = \frac{\left\| \hat{\boldsymbol{H}} - \boldsymbol{H} \right\|^2}{\|\boldsymbol{H}\|^2}$$

where Hˆ denotes the estimated channel matrix. Therefore, the NMSEs of the original channels and the angular domain channels are the same. The parameters used in the simulation experiments are summarized in Table I

The energy distributions of its columns and the elements of the average angular domain channel vector are explained in Fig. 2

TABLE I. Simulation Parameters

Parameter	Value
N	64
M	4
R	16
N_p	20
$\triangle\theta$	$5°$
$\triangle\theta_{az}$	$1°$
β	$5°$
SNR	20 dB

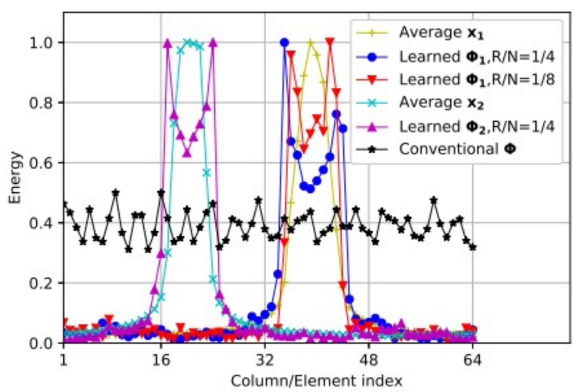


Fig. 2 Energy distributions of different Φ’s columns and the average of x’s elements.

The impact of angular spread, △θ, is explained in Fig. 3

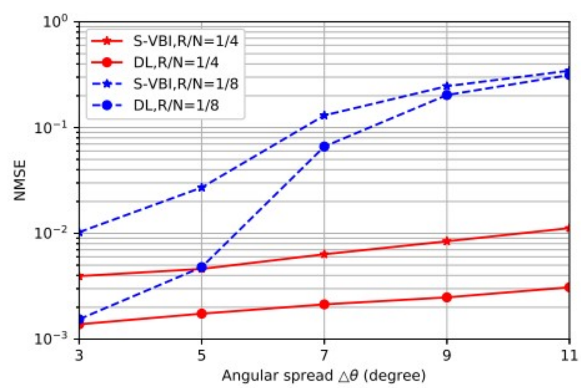


Fig.3 The impact of angular spread

TABLE II. The impact of angular space segmentation granularity

β	N_{net}	NMSE of DL	NMSE of S-VBI
$3°$	30	0.00165	0.00456
$5°$	18	0.00172	0.00461
$10°$	9	0.00216	0.00503
$15°$	6	0.00251	0.00564

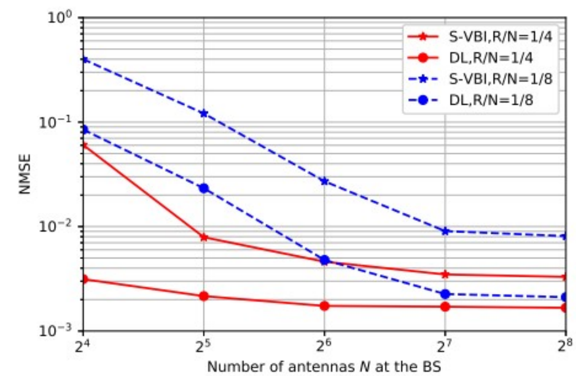
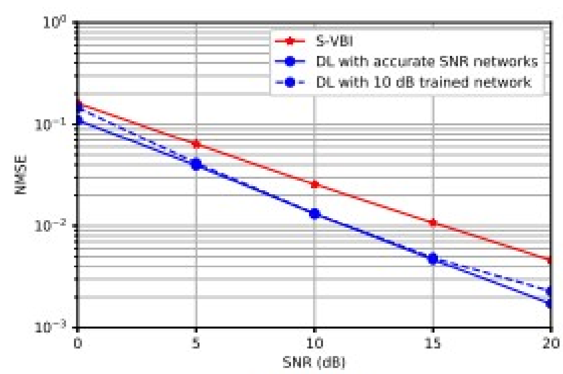
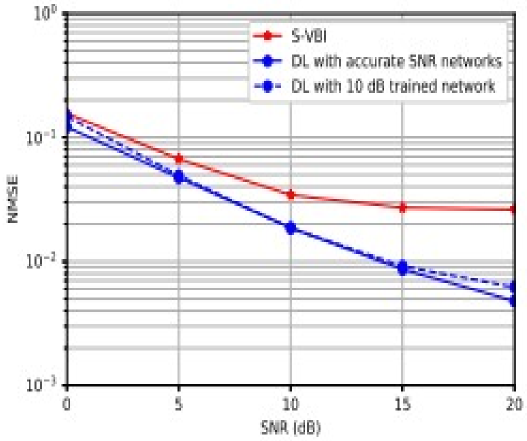


Fig. 4The impact of antenna number

The impact of SNR is explained in Fig. 5. It is shows that higher SNR results in better performance because of reduced noise effects. However, with 1/8 RF chains, the NMSE of S-VBI meets SNR increases above 15 dB, where the error is controlled by the limited ability of reversing the compression effects. Then, the NMSE of DL-based approach continues to decrease smoothly, which indicates its superiority and the generalization to different testing SNRs are investigated properly.



(a) R/N=1/4



(b) R/N=1/8

Fig..5The impact of SNR.

V.CONCLUSION

The proposed approach can be particularly appealing in scenarios where energy saving is critical, such as IoT communications, since much better performance can be achieved without any extra energy cost of channel estimation. Simulation results show that the proposed DL-based approach is superior to the state-of-the-art CS algorithms and the conventional measurement matrix in terms of both NMSE performance and computational complexity, providing a promising real-time solution for HAD massive MIMO systems . The HAD architecture adopted here is reduces the hardware cost and circuit energy consumption.

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