

Overcoming the Channel Estimation Barrier in Massive MIMO Communication Systems

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Abstract—A new wave of wireless services, including virtual reality, autonomous driving and internet of things, is driving the design of new generations of wireless systems to deliver ultra-high data rates, massive number of connected devices and ultra low latency. Massive multiple-input multiple-output (MIMO) is one of the critical underlying technologies that allow future wireless networks to meet these service needs. This article discusses the application of deep learning (DL) for massive MIMO channel estimation in wireless networks by integrating the underlying characteristics of channels in future high speed cellular deployment. We develop important insights derived from the physical radio frequency (RF) channel properties and present a comprehensive overview on the application of DL for accurately estimating channel state information (CSI) with low overhead. We provide examples of successful DL application in CSI estimation for massive MIMO wireless systems and highlight several promising directions for future research.

Index Terms—Massive MIMO, channel estimation, FDD, 5G cellular, deep learning.

I. INTRODUCTION

Current and future generations of wireless networks must cope with the continuous and rapid growth of applications and data traffic to deliver ultra-high data rate over wide coverage area for massive number of connected devices and to support short-latency and low energy applications. One of the most important technical advances at the radio frequency (RF) physical layer is the emergence of massive multiple-input multiple-output (MIMO) transceivers.

By exploiting spatial diversity and multiplexing gains, massive MIMO can help improve spectrum efficiency and robustness of wireless communication systems under limited bandwidth and channel fading. To fully utilize their potential gains, massive MIMO transmitters require sufficiently accurate channel state information (CSI) on the forwardlink. However, the large number of antennas and the wide bandwidth in high rate links significantly increases CSI dimensionality that poses serious challenges to traditional channel estimation and feedback techniques.

On the one hand, owing to the large number of antennas in massive MIMO systems, channel estimation suffers from high signal acquisition cost and large training overhead. On the

other hand, different uplink and downlink frequency bands in frequency division duplex (FDD) leads to weaker reciprocity between the two channels. Consequently, gNB (or gNodeB) transmitters in FDD networks would require user equipment (UE) to provide downlink CSI feedback frequently. Because of the larger antenna number and broader downlink bandwidth, traditional approaches for CSI feedback may consume staggering amount of uplink channel capacity. Accordingly, the need for accurate downlink CSI constitutes a serious barrier in future high speed wireless communication systems.

Although the problem of downlink CSI estimation and feedback under massive MIMO appears to be insurmountable, the physical traits of the RF channels can provide insights on how to overcome this barrier. Specifically, MIMO channels exhibit a number of important physical characteristics including spatial coherence, spectral coherence and temporal coherence. By exploiting these inherent channel correlation characteristics, we can substantially improve the efficiency of CSI estimation and feedback in practical massive MIMO applications. Thus, learning and effectively utilizing such channel characteristics naturally constitute vital parts of our practical solution to downlink CSI acquisition in massive MIMO systems.

To overcome challenges in massive MIMO systems challenges, compressive sensing (CS) has been studied for channel estimation and channel feedback. CS-based approaches exploit the spatial coherence and channel sparsity that stem from the limited scattering characteristics of signal propagation, and can formulate a compressed representation of CSI matrices. However, there are also limitations. For example, most CS-based approaches impose the strong channel sparsity condition in some domain which may not hold exactly. Additionally, the sparsity of CSI matrix is not exactly on the channel sampling grid, which may lead to degraded performance due to the power leakage effect around the recovered discrete CSI samples. Furthermore, CS-based approaches are often iterative, which can cause additional computation delay.

Recently, deep learning (DL) has emerged as a powerful tool for learning the underlying structures from large measurement of data. DL has achieved notable success in areas including computer vision, natural language processing and decision making. Although still in a nascent stage, DL has recently found several interesting applications in the physical layer of wireless communications [1], including signal detection, channel estimation, low rate CSI feedback, among others. However, how to effectively apply DL techniques to exploit RF channel properties remains an open research issue, as many existing DL based works do not explicitly utilize the physical RF characteristics and provide insufficient physical insights

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despite apparent successes.

In this work, we emphasize the importance of physical insights in applying DL for downlink CSI estimation and feedback of massive MIMO wireless links. In wireless communications, there exists a wealth of expert knowledge on various channel models for designing and achieving fast and reliable data links. Integrating DL with domain knowledge of RF channels acquired over decades of intense research in wireless networks, such as spatial correlation, temporal correlation, and spectral coherence, can provide important insights to clear the CSI barrier for massive MIMO systems.

In typical cellular systems, uplink and downlink channels form a bi-directional RF link with characteristics depending on physical attributes such as bandwidth, wavelength, multipaths and scatters. These physical characteristics lead to CSI correlations often captured in three domains:

- **Spatial and spectral correlation:** Since RF channels of adjacent sub-carriers or adjacent antenna elements exhibit similar propagation characteristics, MIMO CSI should be spatially and spectrally correlated. For example, the downlink channel responses are dependent of the propagation gains and the angles associated with primary reflectors and scatters. Such intrinsic channel coherence can simplify CSI estimation in massive MIMO to require fewer observations and less feedback. Through supervised learning, DL algorithms can acquire such spatial and spectral coherences for effective estimation of downlink CSI from partial pilots or compressed CSI feedbacks from user equipment (UE).
- **Temporal correlation:** It is well known that even for mobile environment under severe Doppler effect, RF channel responses are temporally correlated in typical massive MIMO configurations. As a result, temporal correlation of massive MIMO channels can be exploited to reduce the amount of pilots and UE feedback in downlink CSI estimation.
- **Bi-directional correlation:** Traditionally in TDD systems, an uplink MIMO CSI can approximate its corresponding downlink CSI based on channel reciprocity. For FDD systems, however, such channel reciprocity weakens because uplink and downlink frequency bands differ. Still, FDD uplink and downlink channels experience the same RF environment. In fact, existing works have demonstrated bi-directional correlation between the two channels in terms of directionality [2], shadowing effects [3], multipath delays [4], channel covariance [5], etc. Hence, bi-directional CSI correlation allows us to exploit uplink CSI at gNB to improve downlink CSI estimate by reducing UE feedback of downlink CSI estimate.

Based on these special characteristics of physical wireless channels, appropriately designed DL architectures and algorithms can potentially help reduce the amount of UE feedback for CSI estimation in massive MIMO links. Clearly, how to configure, adapt, and improve such tools for accurate CSI estimation by massive MIMO gNB represents an important technical barrier, as well as an exciting and promising research issue. In this article, we present an overview on the integration

of DL in massive MIMO systems, highlight some promising results, and outline some future research directions.

II. CURRENT WORKS ON DL FOR CSI ESTIMATION

In this section, we introduce the basics of several relevant DL neural networks in wireless communications.

A. Fully Connected Deep Neural Network

Fully connected deep neural networks can extract appropriate features for classification and regression, as shown in Fig. 1(a). Starting by sending measurement data to the input layer, each successive layer attempts feature extraction from the input data, gradually accentuating features that affect decision making while suppressing irrelevant features. Through optimization of network parameters, DL can be trained to capture underlying data structures and models despite outliers and noises.

B. Convolutional Neural Networks (CNNs)

CNNs have been widely applied in problems such as image analysis. As shown in Fig. 1(b), CNNs specialize in processing data with grid-like structures and include special layers for functions such as convolution and pooling. By stacking convolutional and pooling layers alternately, CNN can progressively learn complex models.

Considering the correlation in spatial, temporal, or spectral domains, CSI matrices of massive MIMO systems can often be viewed as two-dimensional images. CNNs have strong potentials for success in massive MIMO channel estimation.

C. Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM)

RNN is a class of neural networks that exploit sequential information by using earlier outputs as part of inputs in later time. Unlike traditional neural networks, RNNs use internal state (memory) to store information that has been calculated. An RNN consisting of LSTM units is often known as an LSTM network. LSTM networks can handle exploding and vanishing gradients in traditional RNNs, and work well in classification and decision-making according to time series data.

Exploiting the temporal correlation of CSI, RNN and LSTM can further improve the accuracy of CSI estimates.

D. Autoencoder

An autoencoder is a neural network trained to efficiently regenerate its input. Shown with the structure of Fig. 1(d), modern autoencoders have generalized the idea of an encoder and a decoder beyond deterministic functions to stochastic mappings. An autoencoder can acquire compressed but robust representations of its input and can be highly effective and efficient in dimension reduction or feature learning.

From a DL perspective, CSI feedback within a wireless communication system can be viewed as a particular type of autoencoder, which aims to recover the downlink CSI at the gNB side based on its received CSI that was compressed by the UE and sent in the UE feedback.

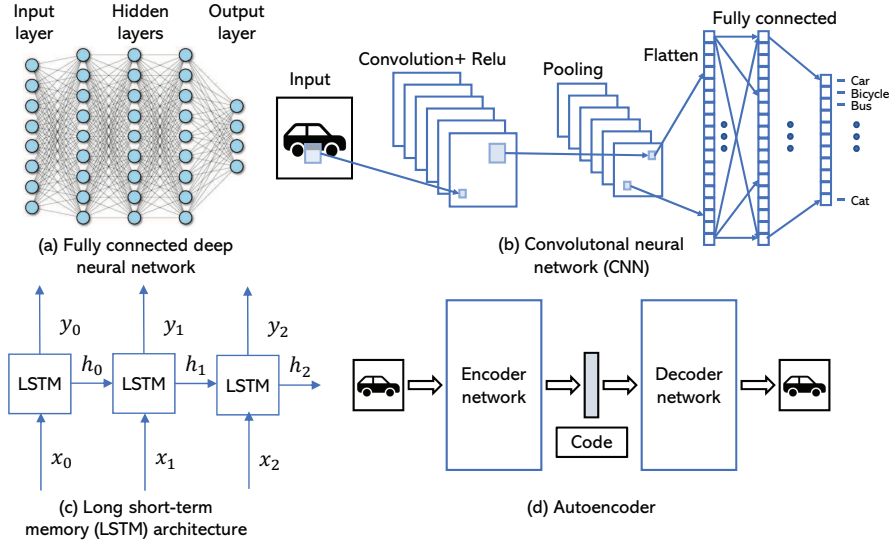


Fig. 1. Commonly utilized deep learning architectures.

III. EXPLOITING WIRELESS CSI CORRELATIONS

Learning and exploiting CSI correlations in massive MIMO can substantially benefit CSI compression and recovery for massive MIMO. In our recent work [6], we have presented two DL-based CSI feedback solutions for massive MIMO wireless communications. We achieved high efficiency by exploiting the underlying CSI correlation between uplink and downlink. Stimulated by this and other preliminary successes, we investigate the hidden CSI data structure in terms of spatial and spectral correlation, temporal correlation, and bi-directional correlation of CSI for dimension reduction in massive MIMO wireless applications.

A. Spatial and Spectral Correlation

Spatial and spectral correlation of CSI have been characteristics commonly exploited in CS-based feedback and CSI estimation. Physical RF propagation elements such as multipaths and scatters provide the foundation of spatial and spectral correlations. For a given gNB, channels are governed by cell specific attributes such as the buildings, ground and vehicles. Multipath propagation channels and scatters between gNB and UE describe how RF signals navigate the path among potential obstacles between transmitter and receiver.

Spatial correlation has been experimentally verified [7]. Smaller antenna separation leads to higher spatial correlation in massive MIMO. Since the physical size of antenna arrays at gNB is small compared to path distance, paths between different gNB-UE antenna pairs share some common properties [8]. On the other hand, spectral coherence measures channel similarity across frequency. For sub-carriers within channel coherence bandwidth, their channels exhibit strong correlation.

Unlike the traditional approaches that often require reasonably accurate correlation models, DL can learn and exploit the underlying channel correlation structure. In CSI estimation, DL algorithms can uncover the inherent but complex CSI relationship in massive MIMO systems and can effectively estimate the CSI of many antennas and sub-carriers based

on small number of channel sounding pilots. For feedback efficiency, DL can also compress high-dimensional CSI to improve the feedback efficiency.

B. Temporal Correlation

RF channels of mobile UEs are governed by physical scatters, multipaths, bandwidth, and Doppler effect. For most practical cases, CSI varies slowly in many massive MIMO systems. For mobile users, coherence time measures temporal channel variations and describes the Doppler effect caused by UE mobility.

Since gNB and UE can store their previous CSI estimates, UE can encode and feed back the CSI variations, instead of the full CSI. The gNB can combine the new feedback with its previously estimated CSI within coherence time for subsequent CSI reconstruction. The temporal correlation feature is a good match with the capabilities of RNN and LSTM that are effective in sequential data processing.

C. Bi-directional Correlation in TDD and FDD

Historically, the uplink-downlink channel reciprocity has predominantly been utilized by TDD gNB to infer downlink CSI from its own uplink CSI estimate. For FDD systems, however, RF components that positively superimpose in one frequency band may cancel each other in another. Hence, FDD uplink-downlink channels do not exhibit direct reciprocity. Nevertheless, because of the shared propagation environment, correlation still exists between the two. For example, the angles of arrival of signals in the uplink transmission are almost the same as the angles of departure of signals in the downlink transmission. When the band gap between uplink and downlink channels is moderate, both links should share similar propagation characteristics including scattering effects. Such correlation can be exploited by gNB for CSI estimation in massive MIMO.

Existing works have demonstrated certain level of correlation between bi-directional channels for FDD systems. The

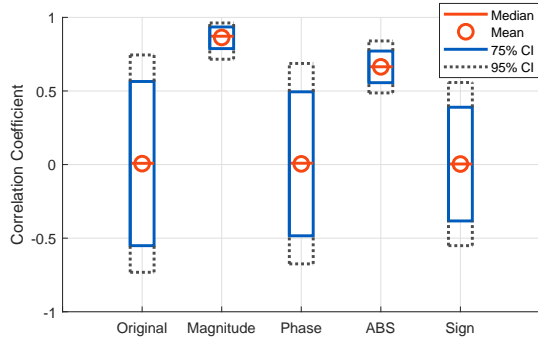


Fig. 2. Distribution of correlation coefficient between uplink and downlink CSI at various levels of Confidence Interval (CI).

directional properties of uplink and downlink FDD channels have been shown as correlated [2]. In [3], the correlation of shadowing effects between FDD channels has also been established. In fact, downlink channel covariance estimation can also benefit from the observed uplink covariance [5]. Similarly, although channel responses could vary for different downlink and uplink frequency bands, their multipath delays remain physically the same [4]. Thus, to utilize the bi-directional channel correlation, channel response matrix from frequency domain should be transformed to delay domain using inverse Fourier transform. Compared with the CSI in frequency domain, the reciprocity in delay domain is evident and strong owing to the shared multipath delays.

To demonstrate bi-directional correlation, we illustrate the correlation coefficient between uplink and downlink FDD channels obtained through numerical tests in Fig. 2. We used a pair of transmitter and receiver in COST 2100 channel model [9] to generate 5.1 GHz uplink and 5.3 GHz downlink channel responses. As shown in Fig. 2, the correlation coefficients between uplink CSI and downlink CSI using the “original” (real/imaginary) format are quite erratic. Since the CSI is complex-valued, their real part and imaginary part correlations are evaluated. This test results appear to show weak correlation between corresponding downlink-uplink channel responses.

A closer examination of the physics reveals that in FDD, CSIs of two carriers of different frequencies may have uncorrelated phases. However, based on FDD multipath channel models, the CSI magnitudes in delay domain should exhibit much stronger correlation. To confirm, we transform the CSI elements into polar coordinate to separately consider their magnitude and phase correlations. Fig. 2 shows that the corresponding magnitude correlation between uplink and downlink CSIs exhibit strong correlation whereas their corresponding phases show very weak correlation. In fact, even by removing the signs from the CSI’s real and imaginary parts, Fig. 2 shows that the absolute values (ABS) of uplink and downlink CSI coefficients are also strongly correlated. However, their signs show little correlation.

These results demonstrate some shared characteristics between uplink and downlink channels in the delay domain. This observation provides the basic principle for utilizing magnitude correlation between uplink and downlink channels in delay domain for estimating CSI of massive MIMO systems.

To better understand the correlation between uplink and

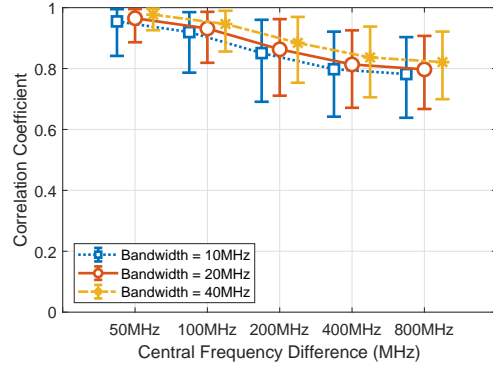


Fig. 3. Influence of band gap and bandwidth on channel magnitude correlation within 95% CI.

downlink CSI, we evaluated the effect of band gap and bandwidth on bi-directional CSI correlation. To show the influence of band gap, we keep the central downlink frequency at 5.3 GHz, while increasing the central frequency difference between downlink and uplink from 50 MHz to 800 MHz. As expected, the results in Fig. 3 show that the bi-directional CSI correlation weakens with growing band gap. To demonstrate the effect of bandwidth on bi-directional CSI correlation, we increase the channel bandwidth from 10 MHz to 20 MHz and 40 MHz, respectively, for different band gaps. As Fig. 3 shows, the bi-directional CSI correlation strengthens for larger channel bandwidth. Consequently, decreasing the band gap between uplink and downlink and increasing the FDD channel bandwidth are two ways to strengthen bi-directional CSI correlations.

IV. DL-BASED CSI ESTIMATION IN FDD NETWORKS

In this section, we discuss the applications of underlying channel characteristics in designing and improving DL-based channel estimation and feedback systems.

A. Channel Estimation

Massive MIMO utilizes large transmit antenna arrays to achieve high data rates and multi-user coverage. It has been viewed as an important technique for future wireless system. Channel estimation for massive MIMO system is highly challenging, especially when the antenna array is large and the number of transceiver RF chains is small.

To overcome the channel estimation challenge in massive MIMO systems, a learned denoising-based AMP (LDAMP) estimation method has been proposed for the beamspace mmWave massive MIMO system with the help spatial and spectral correlation in [10]. LDAMP incorporates a denoising CNN into the AMP algorithm for CSI estimation by regarding the CSI matrix as a 2D natural image. LDAMP leverages compressive signal recovery model and utilizes DL network in iterative signal recovery. This network implicitly makes use of spatial and spectral correlation by learning the CSI structure from a large number of training data. LDAMP network was shown to outperform compressive sensing algorithms even when the receiver only has a small number of RF chains.

Another key challenge of CSI estimation in massive MIMO systems is pilot contamination, which stems from interference of pilot symbols utilized by the users in neighboring cells. In [11], a DL-based channel estimation method was proposed for multi-cell interference-limited massive MIMO systems. The proposed estimator employs a deep image prior CNN, designed for image denoising and inpainting, to denoise the received signal first. A conventional least-squares (LS) estimation is then utilized for CSI estimation. Simulation results show that this deep CSI estimator outperforms traditional LS and minimum mean square error (MMSE) estimators which are unaware of pilot contamination. By testing against uncorrelated Rayleigh fading channel for each subcarrier, the deep CSI estimator no longer performs well, which shows that its performance gain is from exploiting CSI correlations.

In massive MIMO, the hardware cost and power consumption from radio frequency (RF) chains are also challenging. To achieve the tradeoff between the cost and the performance, mixed analog-to-digital converters (ADCs) massive MIMO have also been investigated where a portion of antennas are equipped with high-resolution ADCs while others employ low-resolution ADCs. In [12], with help of spatial and spectral correlation, DL networks are developed to map the CSI from the channels using high-resolution ADCs to those using low-resolution ADCs. Numerical results show that DL-based CSI estimation in mixed-resolution ADCs massive MIMO outperforms linear minimum mean-squared error (LMMSE) methods and expectation maximization (EM) algorithms based on generalized approximate message passing, especially when using mixed one-bit ADCs.

CSI estimation is more difficult in high-speed applications due to the fast time-varying and non-stationary channel characteristics. In [13], a DL network is proposed to tackle the weaknesses of traditional channel estimation methods in high-speed mobile scenarios. Specifically, CNN is used to extract channel response feature vectors, followed by a RNN for CSI estimation. Its simulation results show that the proposed CSI estimation method can achieve significant performance improvement over least squares and LMMSE methods in high-speed mobile scenarios.

B. Channel Feedback

In FDD systems, there often exists a weaker reciprocity between uplink and downlink channels in different frequency bands. Consequently, UE feedbacks are often required to report downlink CSI. For massive MIMO, such feedback data can be substantial because of the large antenna number and wide bandwidth. Moreover, in rapidly changing environment, UEs have to feed back CSI frequently. Thus, conventional methods based on UE feedback face several challenges, including inaccurate channel model and high bandwidth consumption for UE feedback.

To preserve feedback bandwidth and improve CSI recovery accuracy, channel properties including spatial, spectral, temporal correlation and bi-directional channel correlation may be integrated together with DL-based UE feedback. These works have shown substantial performance improvement for down-

link CSI estimation in FDD systems with limited feedback resources on uplink.

The authors of [14] proposed a DL-based CsiNet, as illustrated in Fig. 4(a), to reduce UE feedback overhead in massive MIMO systems. CsiNet mainly utilizes an autoencoder architecture that uses an encoder for CSI compression and a decoder for CSI reconstruction. CNN is used in both encoder and decoder to exploit the spatial and spectral correlation of CSI matrices, in a way similar to image processing. The CSI matrices are separated to real and imaginary parts, which correspond to the two sets of input in this neural network. CsiNet shows substantial performance gain and efficiency over some compressive sensing methods.

The authors of [15] adopted LSTM networks to exploit temporal channel correlation and lower feedback overhead by designing CsiNet-LSTM for time-varying massive MIMO channels. As shown in Fig. 4(b), CSI feedback in CsiNet-LSTM uses a sequence within the coherence time. Compared with CsiNet, the LSTM network in CsiNet-LSTM is adopted at processing sequence data to extract the temporal relationship therein. For CsiNet-LSTM, only the first MIMO CSI matrix of the time sequence is compressed under a moderate compression ratio (CR) and reconstructed by CsiNet. The ensuing CSI matrices are encoded at a high compression ratio by exploiting the temporal correlation. In this way, the authors achieved a better compression ratio and reduced average feedback payload.

In [6], we proposed a DL-based CSI feedback framework to exploit bi-directional channel correlation characteristics. Unlike CsiNet and CsiNet-LSTM, the DualNet in [6] exploits the available uplink CSI at gNB to help estimate the downlink CSI from low rate UE feedback in massive MIMO systems. We designed two DL architectures, DualNet-MAG and DualNet-ABS, to significantly reduce the UE feedback payload. Both DualNet-MAG and DualNet-ABS can utilize the bi-directional channel correlation of the magnitude and the absolute value of the CSI coefficients, respectively. As shown in Fig. 4(c), the decoder in DualNet-MAG reconstructs the downlink CSI magnitudes based on the uplink CSI magnitudes and its received UE feedback codewords. We further developed a magnitude-dependent phase quantization method to reduce the UE phase feedback overhead. Our work in [6] shows significant performance gain by DualNet over other DL architectures relying only on UE feedback.

V. OPEN ISSUES

We have demonstrated the benefits of integrating DL to exploit inherent channel correlations for downlink CSI estimation in massive MIMO wireless communications. We now discuss several future research directions to further improve DL-based CSI estimation for future wireless networks.

A. DL under Different System Settings

In wireless communications, various system parameters can potentially affect the efficacy of DL-based CSI methods. As DL techniques are poised to play a bigger role in future

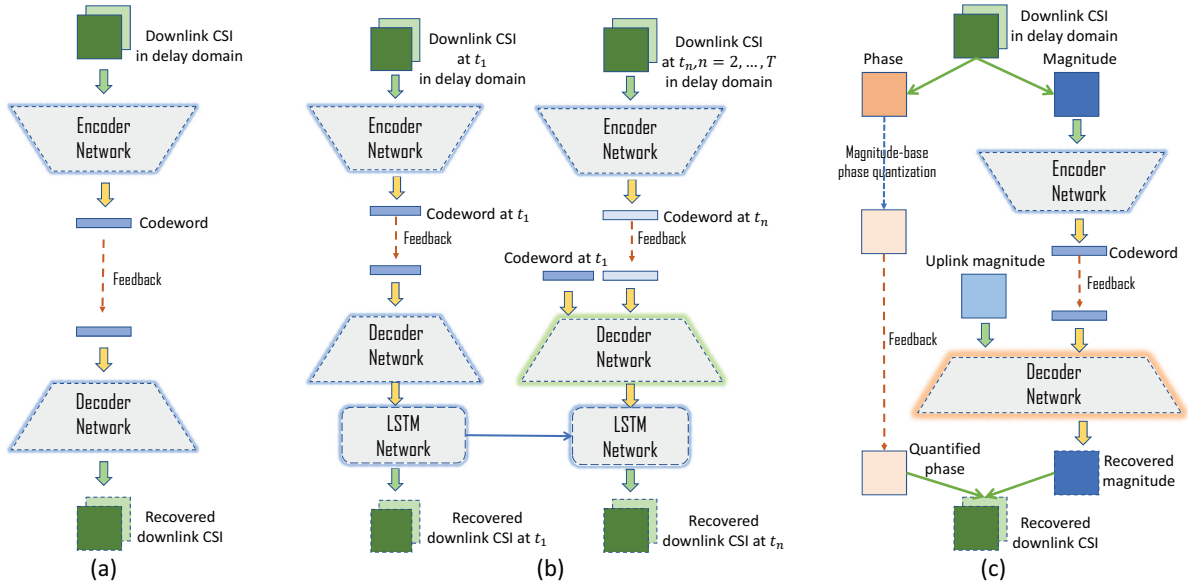


Fig. 4. CSI feedback architectures. (a) Architecture of CsiNet in [14]. (b) Architecture of CsiNet-LSTM in [15]. (c) Architecture of DualNet-MAG in [6].

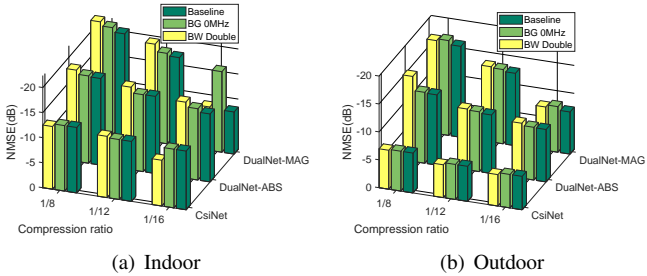


Fig. 5. CSI feedback performance in the influence of band gap (BG) and bandwidth (BW).

wireless systems, one important work is to assess how effective DL-based architectures can be under different network settings. Investigating the impact of system parameters on DL-based solutions can provide better design insights for future development.

We can further investigate the influence of bi-directional channel band gap and RF channel bandwidth on the performance of DL-based CSI estimation in FDD systems. In Section III.C, we have shown that lower bandgap and larger bandwidth lead to stronger bi-directional correlation. One naturally wonders whether they can improve the performance of CSI estimation. We can test the performance of CsiNet, DualNet-MAG, and DualNet-ABS in different bandwidths and bandgaps. The central downlink frequencies are set to 5.3 GHz and 930 MHz for indoor and outdoor scenarios, respectively. For indoor scenario, the bandgap of 180 MHz and bandwidth of 20 MHz are selected as the baselines for comparison. For outdoor scenario, the bandgap of 75 MHz and bandwidth of 5 MHz are set as the baseline. We compare the downlink CSI estimates under feedback compression ratios of 1/8, 1/12, and 1/16. Smaller ratio implies higher compression in CSI feedback and is more efficient.

To test the bandwidth effect, we double the channel bandwidth by maintaining the same bandgap and test the CSI

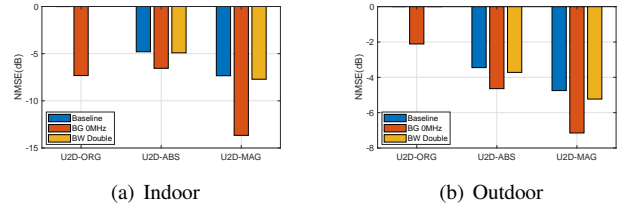


Fig. 6. Performance comparison for different bandgap (BG) and bandwidth (BW).

performance. To test the bandgap effect, we reduce the band gap to 0 without changing the bandwidth. From Fig. 5, both DualNet-ABS and DualNet-MAG can improve the downlink CSI recovery accuracy by reducing the bandgap and/or increasing the bandwidth. The performance of CsiNet remains unchanged for different bandgap values, since uplink CSI is not used in this method. On the other hand, increasing channel bandwidth can worsen the CsiNet performance in some cases. One possible reason is that wider bandwidth leads to more uniform CSI distribution, thereby requiring larger feedback to achieve the same performance.

B. Specialized DL Models Combined With Channel Features

More specialized DL architectures for wireless communications are still under study and should be developed to incorporate wireless channel features and other domain knowledges. Most existing DL networks in physical layer of wireless communications directly adopt known DL architecture or algorithms. Application specific architectures for wireless networks would depend on channel models, signal features, redundancy, and other domain specific knowledge.

As an example for combining bi-directional CSI correlation to infer the downlink CSI using uplink CSI, three architectures are tested¹. Unlike DualNet-ABS and DualNet-MAG, U2D-

¹Details and related codes are provided on: <https://ieeecollabratec.ieee.org/app/workspaces/6247/activities>

ABS and U2D-MAG respectively recover the absolute values and magnitudes of downlink CSI from the corresponding uplink CSI directly without feedback. U2D-ORG divides the downlink CSI into real and imaginary parts without separating their signs as the DL network input. Using the same data set of Section V.A, we consider perfect knowledge of phases and signs of downlink CSI at gNB. The performance of Fig. 6 shows improved downlink CSI accuracy from U2D-ABS and U2D-MAG for reduced bandgap and increased bandwidth. U2D-MAG is superior in all cases. By reducing the feedback payload, U2D-ABS and U2D-MAG show greater promise for better downlink CSI estimation efficiency.

C. Low Complexity and Distributed DL in Wireless Nodes

Although DL is a powerful tool in CSI estimation, its computation burden is significant if running on individual UE node. Considering the battery capacity of mobile devices and wireless sensors in age of ubiquitous connections, it is vital to reduce the complexity of DL algorithms for wireless communications. An important alternative is to distribute the DL computation load among multiple cooperative nodes. In wireless communication systems, learning tasks can be potentially carried out distributively. Distributed DL implementation brings a host of unique challenges such as task scheduling, node coordination, communications for data exchange and result transfer, and robustness, among others.

D. Tradeoff between Performance and Training Efficiency

Existing works and designs have showcased the power of data-driven models in CSI estimation for massive MIMO communications. Even though a universal transmitter/receiver can be optimized in the end-to-end learning-based design, the training process may take very long since results from many communication system blocks are merged. For practical applications, we need to carefully design DL networks and develop algorithms to achieve good tradeoff between the training efficiency and overall performance. In order to improve high training efficiency and achieve good CSI estimation, subsets of communication blocks may be pre-calibrated and model-driven DL methods can be considered.

E. Transfer Learning Based Approaches

Transfer learning allows knowledge learned from one task to be transferred to another similar task. By avoiding model learning from scratch for each new massive MIMO configuration (e.g., antenna number, bandwidth, and mobility), transfer learning can shorten the training process in new configuration and allows DL networks to achieve good CSI estimates even without access or time to use too much training data. Practically, there are many active UEs and gNBs in wireless networks. Therefore, transfer learning is a potential direction for the practical implementation of DL models in wireless communication networks by leveraging prior knowledges.

VI. CONCLUSION

DL has been recently emerged as an exciting design tool in developing future wireless communication systems. In this paper, we introduce the basic principles of applying DL for improving RF wireless network performance through the integration of underlying physical channel characteristics in practical massive MIMO deployment. We provide important insights on how DL benefits from physical RF channel properties and present a comprehensive overview on the application of DL for accurately estimating CSI in massive MIMO communications. We provide examples of successful DL application in CSI estimation and feedback for massive MIMO wireless systems and outline several promising directions for future research.

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