LoRAT: Low Rank Adaptation and Transfer for Multi-environment Channel Estimations

Qi Wang*, Xubo Li*, Yong Xiao*†‡
*School of Elect. Inform. & Commun., Huazhong Univ. of Sci. & Tech., Wuhan, China
†Peng Cheng Laboratory, Shenzhen, China
‡Pazhou Laboratory (Huangpu), Guangzhou, China

***Abstract*—Data-driven AI models, particularly deep learning-based wireless channel estimation solutions, have exhibited promising potentials in modeling the intricate, non-linear relationships between environmental conditions and wireless channel characteristics. However, multi-environment model training requires high computational and communication resource costs. Also, each AI model has limited generality and cannot be directly adopted to new and unknown environments that have different channel conditions, compared to its training dataset. To address these limitations, this paper proposes LoRAT, a low-rank model adaptation and transfer framework for efficient multi-environment channel estimation model development. In LoRAT, a number of foundation models are first trained for a limited number of known environments, and then a simple low-rank model transfer approach is proposed to enable quick and efficient transfer of these foundation models to new unknown environments. We consider the uplink-based downink channel state information (CSI) estimation problem for an FDD wireless system as an example to describe the implementation details and evaluate performance of LoRAT. In this case, we train a set of attention-based diffusion models as foundation models for downlink CSI estimations in the known environments and we show that transferring the low-rank parts of these foundation models is capable of constructing environment-specific CSI estimation models for any new unknown environment. Our proposed LoRAT does not require any labeled datasets in the unknown environments and, since the model transfer only requires to calculate the low-rank part of the model parameters, the computational and communication cost is much lower than the traditional AI model-based solutions, especially for wireless systems across a large number of different environments. Extensive experiments have been conducted to compare the performance of LoRAT with state-of-the-art solutions. Our experimental results suggest that LoRAT provides up to 15% and 265% improvement in accuracy of multi-environment channel estimation, compared to FIRE and codebook-based solution, respectively.**

***Index Terms*—Low-rank adaptation, channel estimation.**

I. Introduction

Accurate and timely estimation of wireless channels is critical for wireless systems and services, especially for B5G and 6G systems that require unprecedented levels of reliability, ultra-low latency, and high data rates for supporting a wide range of emerging applications including high-reliability, low-latency, and reliable communication (HLLRC) and immersive communication [1]. For example, in vehicular networking networks, precise channel state information is vital for ensuring reliable communication for safety-critical tasks like collision avoidance, where even a slight delay or error could have catastrophic. Similarly, e-healthcare applications such as remote surgery and patient monitoring demand highly reliable and low-latency data transmission, making robust channel estimation essential for patient safety. Furthermore, immersive communications, including the metaverse, extended reality (XR), virtual reality (VR), and augmented reality (AR), require extremely high data fidelity and minimal latency to provide a seamless user experience, which is only possible with a consistently accurate understanding of the wireless channel [2].

Unfortunately, the high randomness and environment-specific nature of wireless channels makes accurate channel estimation across multiple environments an extremely challenging task. The traditional methods such as the close-form mathematical model-based solutions and pilot preamble-based approaches are known to be difficult to capture the complexity and non-linearity of wireless channels, especially for environments with high dynamics and complex reflections and scattering path propagation. Recently, the data-drive AI model, especially the deep learning-based channel estimation solutions have attracted significant interest from both industry and academia due to their capability to learn the complex, non-linear relationships between environmental conditions and channel characteristics.

While AI model-based solution can outperform traditional methods, they often require pre-training channel estimation models before use and both training and real-time estimation demand much more computational and communication resources. Also, a major limitation of AI model-based solutions is their limited generality, as these models often struggle to adapt to the significant variations in wireless channel conditions that often arise across different times and locations [3]. This has led to two primary research directions: one-model-fits-all and small environment-specific model developments. The former approach requires to pre-train a large general-purpose model that provides relatively satisfactory performance for a range of environments. The later approaches requires to develop a large number of models to cover various environments and use scenarios which is difficult to scale. Also, even training small models requires a certain amount of computational resources that may not available for some small devices.

Motivated by the above limitations, in this paper, we propose LoRAT, a low-rank model adaptation and transfer framework for quick and efficient multi-environment channel estimation model developments. In LoRAT, a number of foundation models are pre-trained for a limited number of known environments, and a simple low-rank model transfer approach is developed to allow quick and efficient transfer of these foundation models to new unknown environments. LoRAT is composed of three major steps to achieve environment-specific model adaptation and transfer, including low-rank model adaptation, data-to-model mapping, and low-rank model transfer. More specifically, the channel estimation models in the known environments have been first partitioned into two parts: a major part of the model parameters has been pre-trained and shared among different environments to learn the common features of multi-environment wireless channels, and a small part of model parameters has been adapted to capture the unique features of each individual environment. Then, we propose a data-to-model mapping approach that output the difference between the channel estimation models of different environments by evaluating the divergence between the probability distribution of datasets collected in different environments. Finally, we apply the proposed data-to-model mapping approach to transfer the low-rank part of the foundation models pre-trained in the known environments to the new unknown environments by evaluating their divergence of data distributions. Note that our proposed approach does not require any labeled data samples in the unknown environments as data-to-model mapping only requires to evaluate the divergence of data distribution of unlabeled data samples across different environments. We consider the uplink-based downink channel state information (CSI) estimation problem for an FDD wireless system as an example to describe the implementation details and evaluate the performance of LoRAT. We show that the attention-based diffusion models can be developed to effectively capture the intricate relationships between uplink and downlink CSIs. We present the detailed procedures of implementing LoRAT for multi-environment channel estimations and conduct extensive experiments to compare the performance of LoRAT with the state-of-the-art solutions. Our experimental results suggest that LoRAT provides up to 15% and 265% improvement in accuracy of multi-environment channel estimation, compared to FIRE and codebook, respectively.

II. System Model and Problem Formulation

A. System Model

We consider the general channel estimation problem in a multi-environment wireless network system. Each environment is defined by a specific environmental state consisting of a range of variables that may affect the channel state information (CSI) between a specific transmitter-receiver pair. In this paper, we focus on a MIMO-OFDM system in which the transmitter and receiver are equipped with N_t and N_r antennas, respectively, and utilize K subcarriers. The environmental state in this case includes the values of N_t, N_r, and K, the environmental layout between and surround the transmitter and receiver, the transmit and receive parameters such as antenna gains, transmit power, etc. Suppose that each transmitter-receiver pair is associated with a specific environmental state. We use i to label the i-th transmitter-receiver pair in the environmental state e_i. We consider a finite set of environments and use $\mathcal{E}$ to denote the set of corresponding environmental states, i.e., $e_i \in \mathcal{E}$. We can write the signal obtained by the receiver in the kth subcarrier at environmental state e_i as [4]:

$$\mathbf{Y}_{e_i}[k] = \mathbf{H}_{e_i}[k]\mathbf{X}[k] + \mathbf{N}_{e_i}[k] \tag{1}$$

where $\mathbf{H}_{e_i}[k]$ is the complex channel matrix given by

$$\mathbf{H}_{e_i}[k] = \sum_{p\in\mathcal{P}_{e_i}} a_{e_i,p} e^{\frac{-j2\pi f_k d_{e_i,p}}{c} + j\phi_{e_i,p}}, \tag{2}$$

where $\mathcal{P}_{e_i}$ is the set of signal propagation paths between the transmitter and receiver, and environmental state e_i includes the path attenuation factor $a_{e_i,p}$, transmission distance $d_{e_i,p}$, and phase shift $\phi_{e_i,p}$ for each path $p \in \mathcal{P}_{e_i}$, i.e., $e_i = \langle a_{e_i,p}, d_{e_i,p}, \phi_{e_i,p}\rangle_{p\in\mathcal{P}_{e_i}}$. $\mathbf{X}[k] \in \mathbb{C}^{N_t\times 1}$ is the transmit signal vector and $\mathbf{N}_{e_i}[k] \in \mathbb{C}^{N_r\times 1}$ is the additive noise vector at the receiver.

Generally speaking, transmitters cannot know the complete information of the environmental state or the specific values of the channel matrix. They can however obtain an estimated version of the channel matrix $\hat{\mathbf{H}}_{e_i}[k]$ through some other information. In the blind and semi-blind channel estimation scenario, the transmitter estimates the channel matrix based on some seemly unrelated information. For example, in an uplink-based downlink channel estimation of an FDD cellular system, a base station (BS) estimates the downlink (from BS to UE) channel matrix connecting to a UE based on the signal received from the uplink (from UE to BS) channel from the same UE in another subcarrier. More formally, we can define this problem in environment state e_i as follows:

$$\hat{\mathbf{H}}^{\mathrm{dl}}_{e_i} = f_{\boldsymbol{\omega}_{e_i}}\left(\mathbf{H}^{\mathrm{ul}}_{e_i}\right) \tag{3}$$

where $f_{\boldsymbol{\omega}_{e_i}}(\cdot)$ is the (semi-blind) channel estimation function with optimization variable $\boldsymbol{\omega}_{e_i}$, and $\hat{\mathbf{H}}^{\mathrm{dl}}_{e_i}$ and $\mathbf{H}^{\mathrm{ul}}_{e_i}$ are the estimated downlink channel matrix and uplink channel matrix, respectively, of the same BS and UE pair, defined as follows:

$$\mathbf{H}^{\mathrm{ul}}_{e_i} = \left[\mathbf{H}_{e_i}[1], \mathbf{H}_{e_i}[2], ..., \mathbf{H}_{e_i}[K]\right] \in \mathbb{C}^{K\times N_r\times N_t},$$
$$\hat{\mathbf{H}}^{\mathrm{dl}}_{e_i} = \left[\hat{\mathbf{H}}_{e_i}[1'], \hat{\mathbf{H}}_{e_i}[2'], ..., \hat{\mathbf{H}}_{e_i}[K']\right] \in \mathbb{C}^{K\times N_r\times N_t},$$

where k and k' are the labels of the uplink and downlink subcarriers, respectively. Note that the channel estimation function can either be a mathematical expression derived based on the physical law of the wireless propagation, in this case $\boldsymbol{\omega}_{e_i}$ is the optimization variable, or an AI model with model hyperparameter $\boldsymbol{\omega}_{e_i}$. In the latter case, if the model is trained by a given training dataset $\mathcal{D}_{e_i}$, we can abuse the notation and use $f_{\boldsymbol{\omega}_{e_i}, \mathcal{D}_{e_i}}(\cdot)$ to denote the channel estimation function.

In the rest of this paper, we use uplink-based downlink channel estimation problem as an example to show that it is possible to develop a simple model transfer approach to quickly transfer a limited set of pre-trained models into any new and unknown environments.

B. Problem Formulation

We consider the AI model-based channel estimation approach. Since different environments generally require different channel estimation models, it is generally impossible to develop an individual model for each environment, especially for those new and unknown environments. A simple and efficient solution is to first pre-train a limit number of foundation models and then develop a simple and efficient model transfer solution that allows quick transfer of the pre-trained models into new and unknown environments.

More formally, suppose a set of foundation models have already been pre-trained in a set of environmental states $\mathcal{E}_S$ with corresponding model parameters denoted by $\boldsymbol{\omega}_S = \langle \boldsymbol{\omega}_{e_i} \rangle_{e_i \in \mathcal{E}_S}$. Suppose each model $\boldsymbol{\omega}_{e_i}$ is pre-trained by dataset $\mathcal{H}_{e_i}$. We also assume the wireless channel between a given pair of BS and UE in a given state e_i follows a fixed probability distribution Ψ_{e_i}. The main objective is to efficiently construct a new environment-specific model in a new unknown environmental state based on one or multiple foundation models, i.e., for a new environmental state $e_j \notin \mathcal{E}_S$, the newly constructed model can be written as $\boldsymbol{\omega}_{e_j} = \mathcal{T}(\boldsymbol{\omega}_S)$ where $\mathcal{T}(\cdot)$ is the model construction function that maps the parameters of available foundation models to a new target environment e_j. The above problem can be formulated as follows:

$$\min_{\boldsymbol{\omega}_{e_j} = \mathcal{T}(\boldsymbol{\omega}_S)} \mathcal{L}_{e_j}(\boldsymbol{\omega}_{e_j}) = \mathbb{E}_{h_{e_j,n} \sim \Psi_{e_j}} \left[\ell(\boldsymbol{\omega}_{e_j}; h_{e_j,n}) \right], \quad (4)$$

$$\text{s.t.} \quad \hat{h}^{\mathrm{dl}}_{e_j,n} = f_{\boldsymbol{\omega}_{e_j}}(h^{\mathrm{ul}}_{e_j,n}),$$

where $h_{e_j,n} = \langle h^{\mathrm{ul}}_{e_j,n}, h^{\mathrm{dl}}_{e_j,n} \rangle \in \mathcal{D}_{e_i}$ is the nth training data sample, $\ell(\boldsymbol{\omega}_{e_j}; h_{e_j,n})$ is the loss function that quantifies the discrepancy between the predicted and true channel matrices.

III. Model Adaptation and Transfer

A. Architecture Overview

Let us now introduce LoRAT, a novel model adaptation and transfer framework, that allows quick and efficient transfer of a finite set of known environment models to any new and unknown environments. Suppose the set $\mathcal{E}$ of considered environments can be divided into two subsets: known environment subset, denoted as $\mathcal{E}^S$ and unknown environment subset, denoted as $\mathcal{E}^T$, for $\mathcal{E}^S \cup \mathcal{E}^T = \mathcal{E}$. In each known environment

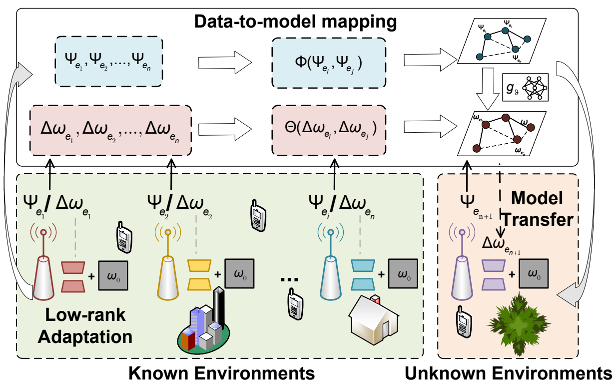

Fig. 1: LoRAT architecture.

$e_i \in \mathcal{E}^S$, we assume a training dataset $\mathcal{D}_{e_i}$ is available and a channel estimation model $\boldsymbol{\omega}_{e_i}$ has already been pre-trained. The main objective is then to construct a new environment-specific model for each unknown environmental state.

LoRAT is composed of three major components: low-rank adaptation, data-to-model mapping, and model transfer modules as illustrated in Fig. 1. Before we describe the details of each individual modules, let us now first discuss the operation procedures of the LoRAT. **Low-rank adaptation of known environment models:** Motivated by LoRA, an efficient model fine-tuning framework that freezes a major part of the pre-trained model parameters and focuses on fine-tuning a small number of model parameters for each task and scenario, we assume that the channel estimation models in the known environments are also sharing a major part of their parameters and each environment only maintains a small portion of model parameters to capture its environment-specific feature. In this way, we only need to focus on transferring and fine-tuning the environment-specific parts of models for each new and unknown environment to save the model transfer and adaptation cost.

Data-to-model mapping: It is known that each AI model is trained to capture the underlying patterns of its given dataset. When two models are trained on distinct datasets, the learned parameters and resulting behaviors will differ in a manner that directly reflects the statistical dissimilarity between the distributions of their respective datasets. Motivated by this observation, in this paper we follow our previous work [5] to develop a novel data distribution-based model adaptation, we referred to as the data-to-model mapping, framework to quantify the differences between different channel estimation models in different environments by measuring the divergence between their local data distributions.

Unknown environment model transfer: Finally, for each unknown environment, it will first evaluate the divergence between its local channel estimation data and each dataset in the known environment and then use the data-to-model mapping model to calculate the model differences, which can be eventually used to construct environment-specific model for the unknown

Algorithm 1 Model Adaptation and Transfer

Input: A shared pretrained foundational model $\boldsymbol{\omega}_0$; known environment set $\mathcal{E}^S$ with datasets $\{\mathcal{D}_{e_i}\}_{e_i \in \mathcal{E}^S}$;
Output: Environment-specific model $\boldsymbol{\omega}_{e_j}$ for unknown environment e_j
Step 1: Low-rank Adaptation
for each $e_i \in \mathcal{E}^S$ **in parallel do**
    Initialize environment-specific model: $\boldsymbol{\omega}_{e_i} \leftarrow \boldsymbol{\omega}_0 + \Delta\boldsymbol{\omega}_{e_i}$;
    Train $\Delta\boldsymbol{\omega}_{e_i}$ on $\mathcal{D}_{e_i}$ via SGD while keep $\boldsymbol{\omega}_0$ frozen;
end for
Step 2: Data-to-model Mapping
for $e_i \in \mathcal{E}^S$ **do**
    for $e_{i'} \in \mathcal{E}^S, e_{i'} \neq e_i$ **do**
        Compute data distribution divergence $\Phi(\Psi_{e_i}, \Psi_{e_{i'}})$;
        Compute model correlation $\Theta(\Delta\boldsymbol{\omega}_{e_i}, \Delta\boldsymbol{\omega}_{e_{i'}})$;
    end for
end for
Train the mapping function g_ϑ by using (7).
Step 3: Model Transfer
for $e_i \in \mathcal{E}^S$ **do**
    Calculate data distribution divergence $\Phi(\Psi_{e_i}, \Psi_{e_j})$;
    Obtain model correlation $\lambda_{e_i e_j} = g_{\vartheta^*}(\Phi(\Psi_{e_i}, \Psi_{e_j}))$;
end for
Construct the transferred model: $\boldsymbol{\omega}_{e_j} \leftarrow \boldsymbol{\omega}_0 + \sum_{e_i \in \mathcal{E}^S} \frac{\lambda_{e_i e_j}}{\sum_{e_i \in \mathcal{E}_S} \lambda_{e_i e_j}} \Delta\boldsymbol{\omega}_{e_i}$.

environment based on the models of the known environments.

Let us now give a more formal description of each of the above components as follows. The detailed algorithm is presented in Algorithm 1.

B. Low-rank Adaptation

In this paper, we follow the commonly adopted LoRA approach [6] to construct environment-specific models by finetuning low-rank adapters of a shared pre-trained foundational model $\boldsymbol{\omega}_0$ for different known environments. Specifically, each environment-specific model is constructed by $\boldsymbol{\omega}_{e_i} = \boldsymbol{\omega}_0 + \Delta\boldsymbol{\omega}_{e_i} = \boldsymbol{\omega}_0 + \mathbf{B}_{e_i}\mathbf{A}_{e_i}$, where $\Delta\boldsymbol{\omega}_{e_i}$ denotes the low-rank adapter that corresponds to the environmental state e_i. Here, $\mathbf{B}_{e_i} \in \mathbb{R}^{d\times r}$ and $\mathbf{A}_{e_i} \in \mathbb{R}^{r\times m}$ are trainable parameters with rank $r \ll \min(d, m)$, while the foundational model parameters $\boldsymbol{\omega}_0$ remain frozen during adaptation.

Since we focus on the uplink-based downlink channel estimation problem, the foundational model $\boldsymbol{\omega}_0$ is instantiated as an attention-based diffusion model [7], as illustrated in Fig. 2. In this architecture, the uplink channel matrices serve as the conditional input and the model outputs an estimate of the corresponding downlink channel matrices. Note that the core component of the diffusion model is the self-attention

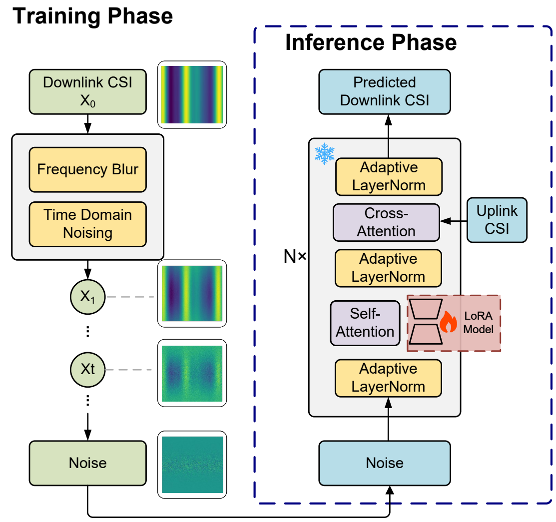

Fig. 2: Low-rank adaptation of foundation model

block, which is utilized to restore the downlink channel matrices from noise. Thus, we restrict finetuning to this self-attention block only for computational efficiency. We denote this block as $\mathbf{W}_0 = \langle \mathbf{W}_0^Q, \mathbf{W}_0^K, \mathbf{W}_0^V \rangle$, where $\mathbf{W}_0^Q, \mathbf{W}_0^K, \mathbf{W}_0^V$ represent the query, key and value weight matrices within each self-attention layer, respectively. The LoRA model $\Delta\boldsymbol{\omega}_{e_i}$ also contains the self-attention block consisting of three matrices, i.e, $\Delta\mathbf{W}_{e_i} = \langle \Delta\mathbf{W}_{e_i}^Q, \Delta\mathbf{W}_{e_i}^K, \Delta\mathbf{W}_{e_i}^V \rangle$. During finetuning, the foundational parameters $\mathbf{W}_0$ are frozen, and only the low-rank matrices $\Delta\mathbf{W}_{e_i}$ are updated via gradient descent.

Finally, the environment-specific model for environment $e_i \in \mathcal{E}^S$ is constructed by combing the foundational model with its low-rank adaptation:

$$\boldsymbol{\omega}_{e_i} = \boldsymbol{\omega}_{e_0} + \Delta\boldsymbol{\omega}_{e_i}, \tag{5}$$

where the self-attention parameters are given by

$$\begin{aligned} \mathbf{W}_{e_i}^Q &\leftarrow \Delta\mathbf{W}_0^Q + \mathbf{B}_{e_i}^Q \mathbf{A}_{e_i}^Q, \\ \mathbf{W}_{e_i}^K &\leftarrow \Delta\mathbf{W}_{e_i}^K + \mathbf{B}_{e_i}^K \mathbf{A}_{e_i}^K, \\ \mathbf{W}_{e_i}^V &\leftarrow \Delta\mathbf{W}_{e_i}^V + \mathbf{B}_{e_i}^V \mathbf{A}_{e_i}^V. \end{aligned} \tag{6}$$

This formulation enables efficient adaptation while preserving the pre-trained knowledge encoded in $\boldsymbol{\omega}_0$.

C. Data-to-model mapping

In this section, we develop a mapping function that maps the data distribution dependency to model correlation. Let $\Phi(\Psi_{e_i}, \Psi_{e_j})$ represent the measure of the divergence between the distribution of wireless channel in two distinct environments e_i and e_j, which can be Kullback-Leibler (KL) divergence, Jensen-Shannon (JS) divergence, or Wasserstein-1 distance, etc. Let $\Theta(\Delta\mathbf{W}_{e_i}, \Delta\mathbf{W}_{e_j})$ denote the measure of the correlation between the corresponding LoRA adapters, which can be normalized L1 distance, L2 distance, or cosine similarity, etc. Our objective is to develop the nonlinear mapping relationship from distribution dependency to model correlation through a neural network $g_\vartheta : \Phi(\Psi_{e_i}, \Psi_{e_j}) \rightarrow \Theta(\Delta \mathbf{W}_{e_i}, \Delta \mathbf{W}_{e_j})$ parameterized by ϑ. To train this mapping function, we minimize the following regression loss over all pairs of distinct known environments:

$$\min_{\vartheta} \ \mathcal{L}_{\text{map}}(\vartheta) = \sum_{\substack{\forall e_i, e_j \in \mathcal{E}^S, \\ i \neq j}} \| g_\vartheta(\Phi(\Psi_{e_i}, \Psi_{e_j})) - \Theta(\Delta \mathbf{W}_{e_i}, \Delta \mathbf{W}_{e_j}) \|^2. \quad (7)$$

The optimized mapping function g_{ϑ^*}, obtained by minimizing $\mathcal{L}_{\text{map}}$, enables the estimation of model correlation from distributional divergence, establishing a principled basis for model transfer to unknown environments.

D. Low-rank model transfer to unknown environments

Let us now develop the model transfer framework that maps the environment-specific models developed in known environments to unknown environments. The detailed procedures consists of three key steps. First, for an unknown environment $e_j \in \mathcal{E}^T$, we will calculate the divergence between its data distribution and that of each known environment $e_i \in \mathcal{E}^S$ by using the previously defined divergence measure $\Phi(\cdot, \cdot)$. Note that this step does not require any labeled channel matrices, making it suitable for unsupervised domain adaptation. Second, the computed distribution divergences are fed into the previously trained mapping neural network g_{ϑ^*}, which outputs the model correlation coefficients, denoted as $\lambda_{e_i e_j}$. Finally, the transfer is performed. To enhance transfer efficiency, each known environment shares the low-rank decomposition of its self-attention block $\Delta \mathbf{W}_{e_i}$ with the target environment, while one of the known environments additionally transfers the shared pre-trained foundational model $\boldsymbol{\omega}_0$. Specifically, we adopt a linear aggregation strategy such that the self-attention block of the unknown environment is given by:

$$\mathbf{W}_{e_j} = \mathbf{W}_0 + \sum_{e_i \in \mathcal{E}^S} \frac{\lambda_{e_i e_j}}{\sum_{e_i \in \mathcal{E}^S} \lambda_{e_i e_j}} \Delta \mathbf{W}_{e_i}. \quad (8)$$

IV. Performance Evaluation

A. Experimental Setup

Dataset: We conduct experiments based on Argos [8], a dataset consisting of real-world MIMO channel measurements across more than 20 environments including both Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) scenarios. In each environment, a BS equipped with 96 antennas communicates with one UE over 52 subcarriers, thus the recorded CSI is of the shape 5026 frames $\times$ 96 antennas $\times$ 52 subcarriers. We set the first 26 subcarriers for the uplink channel and allocate the remaining 26 for the downlink channel.

Model: The restoration network in our diffusion model is composed of 24 attention layers stacked together. The CSI data are first mapped into embeddings of dimension 128 through the embedding layer, and then are fed as a condition into the 8-head cross-attention layer to guide the denoising process. The total denoise steps are set to 200. The data-to-model mapping model consists of four linear layers, each of which is followed by a ReLU activation function. For model transfer, Our LoRA models of rank 8 are injected into all the query, key and value matrices of attention layers. Throughout the training and fine-tuning process, AdamW optimizer is utilized with learning rate set to 1e-4.

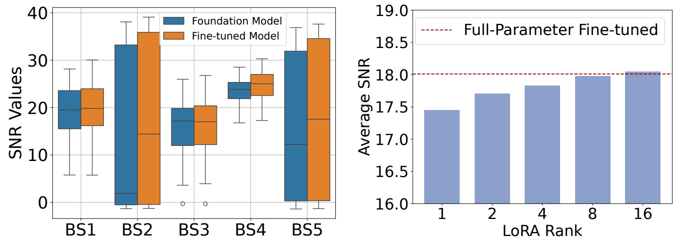

Fig. 3: Performance of low-rank adaptation: (a) comparison of the foundation model and LoRA-based fine-tuned models; (b) comparison of different rank of LoRA models.

Metric: The Signal-to-Noise Ratio (SNR) metric is employed to assess the accuracy of downlink channel estimation in comparison with the ground truth. Specifically, SNR measures the error between the estimated downlink channel $\hat{h}^{\text{dl}}$ and the actual channel state h^{dl}. This is quantified using the formula $\text{SNR} = -10 \log_{10} \left(\frac{\|\hat{h}^{\text{dl}} - h^{\text{dl}}\|^2}{\|h^{\text{dl}}\|^2} \right)$. A higher positive SNR indicates a closer match between the predicted channel and the true channel state, reflecting better estimation accuracy.

B. Experimental Results

1) Performance of low-rank adaptation: We first evaluate the performance of low-rank adaptation. We collect CSI data from BSs deployed across 5 different environments, and deploy the foundation model on five BSs in a non-fine-tuning and LoRA-based fine-tuning manner respectively to assess the accuracy of channel estimation. As shown in Fig. 3(a), the LoRA-fine-tuned model achieves consistently higher SNR than the original foundation model across all base stations, with a particularly notable improvement at BS2. This demonstrates that even lightweight, parameter-efficient fine-tuning can significantly enhance model adaptability to real-world channel conditions. In Fig. 3(b), we compare the performance of LoRA modules with varying ranks against full-parameter fine-tuning. The results reveal that once the LoRA rank exceeds a certain threshold, the model performance approaches, and in some cases even surpasses, that of the fully fine-tuned counterpart. Specifically, the results show that with LoRA rank greater than 8, the performance of the model approaches the full-parameter fine-tuned model. This highlights the efficiency and effectiveness of LoRA in achieving competitive performance with significantly reduced

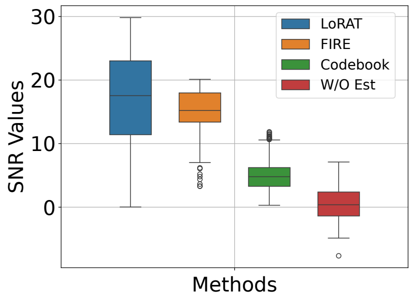

Fig. 4: Comparison of different transfer method

parameter overhead, making it a promising approach for on-site deployment in dynamic wireless environments.

2) Performance of model transfer: To evaluate the performance of our proposed LoRAT, we collect CSI data from BSs deployed across 6 different environments, five of which are used as source domain and the other as target domain. For a comprehensive evaluation, we compare the estimation accuracy of our transfer method with other methods as follows:

- **Without estimation:** In this case, we directly use uplink CSI as downlink CSI.
- **Codebook [9]:** It is a classical channel estimation method used in the 3GPP physical channel standard. users measure the channel and choose the closest vectors from a predefined codebook, then send the index to the BS.
- **FIRE [10]:** It is a VAE-based method that encodes the uplink CSI into latent representations and then decodes them into downlink CSI.

We can observe that our proposed LoRAT demonstrates significant performance improvements over both the learning-based FIRE and traditional codebook approaches. Specifically, LoRAT achieves a median SNR value around 18 dB, substantially higher than FIRE's median of approximately 15 dB and the codebook's median near 5 dB. This indicates that LoRAT effectively enhances channel estimation performance, offering superior robustness and accuracy compared to FIRE and the conventional codebook method.

3) Comparison of different metrics combination: We compare the performance of model transfer under different model correlation metrics and different data distribution dependence metrics, as shown in TABLE. I. Specifically, we respectively adopt cosine similarity, normalized L1 norm and L2 norm to measure the model correlation, and KL divergence and JS divergence to measure the dependency of data distribution. Across all measures, the model transfer performance are consistent, with slight variations indicating that the choice of metric has limited impact on the overall performance.

V. Conclusion

This paper proposes LoRAT, a low-rank model adaptation and transfer framework for quick and efficient adaptation and transfer of foundation models to new unknown environments.

TABLE I: Model transfer performance under different metrics. Performance is tested by SNR in dB.

Measure	Cosine Similarity	L1 Norm	L2 Norm
KL Divergence	16.36±7.47	**16.45±7.46**	16.29±7.39
JS Divergence	16.37±7.47	**16.45±7.46**	**16.45±7.46**

We consider the uplink-based downink CSI estimation problem for an FDD wireless system as an example to describe the implementation details and evaluate the performance of LoRAT. In this case, we train a set of attention-based diffusion models as foundation models for downlink CSI estimations in the known environments and we show that transferring the low-rank parts of these foundation models is capable of developing new environment-specific CSI estimation models for new unknown environments. Extensive experiments have been conducted. Our experimental results suggest that LoRAT provides up to 15% and 265% improvement in accuracy of multi-environment channel estimation, compared to FIRE and codebook, respectively.

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