

RACNN: Residual Attention Convolutional Neural Network for Near-Field Channel Estimation in 6G Wireless Communications

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Abstract. Near-field channel estimation is a fundamental challenge in sixth-generation (6G) wireless communication, where extremely large antenna arrays (ELAA) enable near-field communication (NFC) but introduce significant signal processing complexity. Traditional model-based methods suffer from high computational costs and limited scalability in large-scale ELAA systems, while existing learning-based approaches often lack robustness across diverse channel conditions. To overcome these limitations, we propose the Residual Attention Convolutional Neural Network (RACNN), which integrates convolutional layers with self-attention mechanisms to enhance feature extraction by focusing on key regions within the CNN feature maps. Experimental results show that RACNN outperforms both traditional and learning-based methods, including XLCNet, across various scenarios, particularly in mixed far-field and near-field conditions. Notably, in these challenging settings, RACNN achieves a normalized mean square error (NMSE) of 4.8×10^{-3} at an SNR of 20dB, making it a promising solution for near-field channel estimation in 6G.

Keywords: Near-field communication (NFC) · 6G · Channel estimation · Deep learning · ELAA

1 Introduction

Sixth-generation technology (6G) is expected to be the next major advancement in telecommunications. The key performance indicators of 6G should be much superior to those of 5G in terms of peak data rate, spectral efficiency, access density, coverage, and latency [7]. To achieve these indicators, 6G requires a significantly increased number of antennas, i.e., thousands of elements, compared to hundreds of elements in 5G. Antenna arrays that meet this requirement are referred to as extremely large antenna arrays (ELAA), distinguishing them from massive multiple-input multiple-output (MIMO) in 5G.

ELAA is not only more complex in design and deployment but also introduces new challenges in signal processing [13], particularly the fundamental transition

in electromagnetic propagation modeling from planar-wave (i.e., far-field communication in 5G) to spherical-wave (i.e., near-field communication in 6G). In detail, the Rayleigh distance is used to determine the boundary where propagation is divided as near-field or far-field. For instance, [1,13] indicate that wireless communication systems operating with ELAA and within the Terahertz frequency range (typically around 300GHz) can extend the Rayleigh distance beyond 200 meters, often covering a significant portion of user equipment (UE) devices. This implies that most UEs will operate within the near-field propagation region. Hence, the near-field communication in 6G (NFC-6G) introduces specifically two major challenges: (i) the substantial computational complexity as the number of ELAA elements reaches thousands; (ii) all existing signal processing techniques used in 5G and earlier generations must be adjusted to work with the near-field channel model. In this study, we focus on the problem of channel estimation.

Channel estimation is an essential problem in wireless communication systems and many studies have been proposed to address this problem in far-field scenarios [3]. These studies can be divided into two groups: (i) traditional model-based methods, such as least squares (LS) and minimum mean square error (MMSE) [8], and (ii) learning-based methods, which have recently gained attention for leveraging machine learning techniques in channel estimation. Methods in the former group are simple to implement in practice. However, their estimation accuracy is affected by noise and interference. Moreover, when the number of ELAA elements grows larger, the matrix inversion required in these methods is computationally challenging. The latter group is further divided into two approaches, i.e., model-driven methods and data-driven methods. The model-driven approach focuses on optimizing the model based on mathematical solutions. For example, in [14], the authors presented LISTA and SDL-LISTA networks, which are neural networks based on the iterative shrinkage and thresholding algorithm (ISTA). In [9], the authors proposed AMP-NET based on the principle of approximate message passing (AMP) for joint activity detection and channel estimation. These methods achieve higher estimation accuracy compared to the original methods with a small number of learning parameters. However, a neural network with a small number of learning parameters also has its own drawbacks. They perform well only under specific channel conditions that match their training data, such as the number of far-field paths, near-field paths, and noise distribution. The data-driven approach can mitigate this limitation by training neural networks with a large number of learning parameters. This enables the networks to learn from a wide range of channel conditions. To illustrate, in [2], the authors proposed XLCNet for channel estimation in NFC-6G systems. Specifically, XLCNet transforms noisy channel vectors into 2-channel images and then uses a convolutional neural network (CNN) to denoise them. Notably, this network supports not only far-field and near-field scenarios but also mixed far-field/near-field scenarios. Moreover, CNN is a widely studied architecture that has been utilized for many years. With recent advancements in learning-based

techniques for image processing and natural language processing, the underlying concept of XLCNet has the potential for further enhancement.

Inspired by [2] and a recent advancement in deep learning (DL) known as the attention mechanism [11], we propose a novel network named the residual attention convolutional neural network (RACNN) for NFC-6G wireless communication.¹ RACNN inherits the idea of estimating noise through a neural network and subtracting the estimated noise from the input at the final stage. RACNN follows the convolutional block structure of XLCNet and incorporates self-attention blocks to enhance the overall performance of noise estimation. Our numerical results show that RACNN outperforms traditional model-based methods (LS and MMSE) and XLCNet in various scenarios, e.g., (i) the testing dataset matches the number of far-field and near-field paths in the training dataset; (ii) only far-/near-field paths exist; and (iii) mixed far-field/near-field paths. The rest of this paper is organized as follows. Section 2 introduces the Rayleigh distance and the channel model in NFC-6G. Section 3 presents our proposed RACNN network for channel estimation. Experiment setups, evaluation methodology, results, and performance analysis are discussed in details in Section 4. Finally, we conclude the paper in Section 5.

2 System Model

2.1 Rayleigh Distance

The Rayleigh distance of an NFC-6G system can be represented as follows

$$D_{\text{Ray}} = \frac{2(M\frac{\lambda}{2})^2}{\lambda} = \frac{1}{2}M^2\lambda, \tag{1}$$

where M is the array dimension and λ is the signal wavelength [10]. In NFC-6G systems, the antenna array can reach thousands of elements, the transmit wavelength is shorter, and the aperture is larger. As a result, the Rayleigh distance D_{Ray} increases, extending to typical operating distances in cellular networks. This shift places UE services within the near-field range [10]. Unlike far-field channels, where signals exhibit planar wavefronts, signals in near-field channels propagate with spherical wavefronts and spread-out patterns, resulting in non-uniform distribution characteristics at the receiver. To understand far-field and near-field physical properties, we analyze them over mathematical channel functions presented in the next subsection.

2.2 Channel Models

We consider an NFC-6G wireless channel with an ELAA consisting of M elements, serving K user equipments. Following the article in [13], the downlink far-field channel is modeled as

$$\mathbf{Y} = \mathbf{H}\mathbf{P}^{\frac{1}{2}}\mathbf{X} + \mathbf{Z}, \tag{2}$$

¹ Simulation codes: <https://github.com/DoHaiSon/RACNN>.

where $\mathbf{H} \in \mathbb{C}^{M \times K}$ represents the channel matrix, $\mathbf{P} = \text{diag}(P_1, P_2, \dots, P_K)$ is the signal amplitude, $\mathbf{X} \in \mathbb{C}^{K \times K}$ is the matrix of data symbols, and $\mathbf{Z} \in \mathbb{C}^{M \times K}$ is an additive white Gaussian noise matrix. We also assume that signal transmission is lossless and signal amplitudes across all antennas are identical, i.e., $P_k = P \forall k$. In NFC-6G systems, the channel matrix \mathbf{H} can be expressed in a unified form for both far-field and near-field cases as follows:

$$\mathbf{H} = \mathbf{A}\mathbf{G}, \quad (3)$$

where $\mathbf{G} \in \mathbb{C}^{M \times L}$ is a gain matrix whose elements are independent identically distributed from $\mathcal{CN}(0, \sigma^2)$, $\mathbf{A} \in \mathbb{C}^{M \times L}$ is the steering matrix (which can be the far-field \mathbf{A}_{far} , near-field \mathbf{A}_{near} , and hybrid $\mathbf{A}_{\text{hybrid}}$), and L is the number of multipaths [13]. Particularly, the steering matrix \mathbf{A}_{far} in far-field cases is given by

$$\mathbf{A}_{\text{far}} = \sqrt{\frac{M}{L}} [\mathbf{a}(\phi_1), \mathbf{a}(\phi_2), \dots, \mathbf{a}(\phi_L)]. \quad (4)$$

Here, each channel vector $\mathbf{a}(\phi_l)$ is expressed as

$$\mathbf{a}(\phi_l) = \frac{1}{\sqrt{M}} \left[e^{-j2\pi \frac{d}{\lambda} \sin(\phi_l)}, \dots, e^{-j2\pi \frac{d}{\lambda} (M-1) \sin(\phi_l)} \right]^\top, \quad (5)$$

where $d = \frac{\lambda}{2}$ denotes the antenna spacing within the ELAA and $\phi_l = [-\frac{\pi}{2}; \frac{\pi}{2}]$ be the steering angle of the l^{th} path. On the other hand, the steering matrix \mathbf{A}_{near} in near-field cases is parameterized by ϕ_l and r_l as follows

$$\mathbf{A}_{\text{near}} = \sqrt{\frac{M}{L}} [\mathbf{a}(\phi_1, r_1), \dots, \mathbf{a}(\phi_L, r_L)], \quad (6)$$

with the steering vector $\mathbf{a}(\phi_l, r_l)$ is defined as

$$\mathbf{a}(\phi_l, r_l) = \frac{1}{\sqrt{M}} \left[e^{-j\frac{2\pi}{\lambda}(r_{l,1}-r_l)}, \dots, e^{-j\frac{2\pi}{\lambda}(r_{l,M}-r_l)} \right]^\top, \quad (7)$$

where r_l represents the distance from the l^{th} -antenna element to the center of the antenna array, while $r_{l,m} = \sqrt{r_l^2 + \delta_m^2 d^2 - 2r_l \delta_m d \sin(\phi_l)}$ is the distance between the l^{th} -scatterer and the n^{th} -antenna element at the base station with $\delta_m = \frac{2n-N-1}{2}$ and $m = 1, 2, \dots, M$.

Consider that the gain \mathbf{G} in NFC-6G systems remains similar when signals propagate among far-field and near-field regions. Accordingly, the hybrid-field channel model $\mathbf{H}_{\text{hybrid}}$ adopts the following form

$$\mathbf{H}_{\text{hybrid}} = \mathbf{A}_{\text{hybrid}}\mathbf{G}, \quad (8)$$

where the steering matrix $\mathbf{A}_{\text{hybrid}}$ is a combination of the far-field and near-field channels

$$\mathbf{A}_{\text{hybrid}} = \sqrt{\frac{M}{L}} [\mathbf{a}(\phi_1), \dots, \mathbf{a}(\phi_{L_o}), \mathbf{a}(\phi_{L_o+1}, r_{L_o+1}), \dots, \mathbf{a}(\phi_L, r_L)]. \quad (9)$$

We refer the readers to [13] for further details on these channel models.

3 Proposed Residual Attention CNN Network

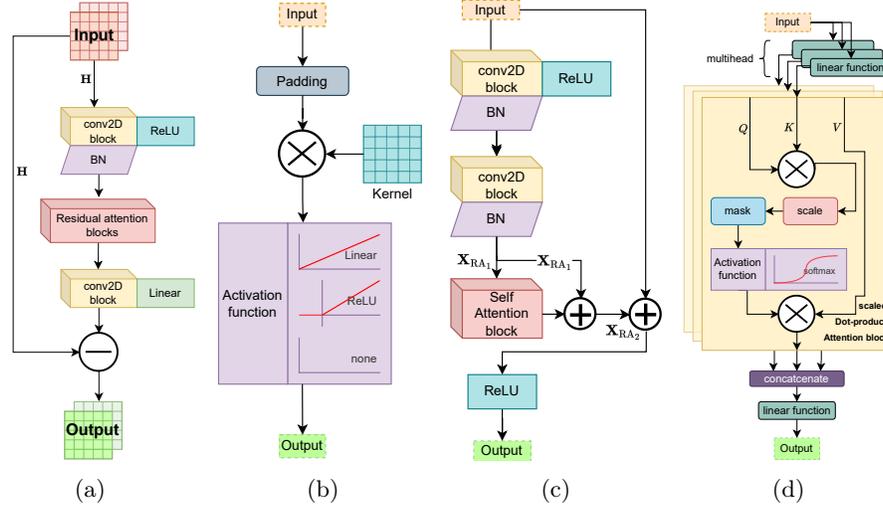


Fig. 1: The proposed RACNN network: a) main workflow; b) conv2D block; c) residual attention block; d) self-attention block.

In this section, we propose a new residual attention CNN (RACNN) architecture to estimate the hybrid-field channel in NFC-6G systems. In particular, RACNN consists of four types of blocks: conv2D, residual attention (RA), rectified linear unit (ReLU), and batch normalization (BN). See Fig. 1 for an illustration of our proposed network.

To simplify the design, we consider a single-user scenario with $K = 1$, reducing the channel matrix \mathbf{H} to a vector representation $\mathbf{h} \in \mathbb{C}^{M \times 1}$. Initially, RACNN transforms this vector into a matrix representation, expressed as $\mathbf{h} \in \mathbb{C}^{M \times 1} \rightarrow \mathbf{X} \in \mathbb{R}^{2 \times N_x \times N_y}$, where $N_x \times N_y = M$. This transformation separates the complex elements of \mathbf{h} into their real and imaginary components, which facilitates more effective training [2]. At this stage, \mathbf{X} is represented as a 2-channel image and serves as the input for the channel estimation process. As illustrated in Fig. 1(a) and Fig. 1(b), RACNN incorporates multiple 2D convolutional (conv2D) blocks which are mathematically expressed as

$$\mathbf{Y}(C_y) = \sum_{k=0}^{C_x-1} \mathbf{W}(C_y, k) \star \mathbf{X}(k) + \text{bias}(C_y). \quad (10)$$

Here, “ \star ” denotes convolution operator, the weight \mathbf{W} is a kernel matrix, $\mathbf{W} \in \mathbb{R}^{r \times r}$ (e.g., $r = 3$), and $\text{bias}(C_y)$ represents the bias to alter the activation function. C_x and C_y are the channel numbers of input \mathbf{X} and output \mathbf{Y} , respectively. In our setting, we use 64 filters in each conv2d block and set the value of C_x to 2.

To reduce overfitting during the training process, the output from certain conv2D blocks passes through a rectified linear unit (ReLU) activation function [5] to introduce nonlinearity. Batch normalization (BN) [6] is also employed to adjust and scale activations, helping reduce the covariate shifting. Specifically, the BN in our network is defined by

$$\mathbf{Y}_{\text{BN}} = \gamma \mathbf{Y}_{\text{conv2d}} + \beta, \quad (11)$$

where γ and β are the scale and shift parameters, $\hat{\mathbf{Y}}_{\text{conv2d}}$ is normalized from the input $\mathbf{Y}_{\text{conv2d}}$ (output of the conv2d layer) as $\hat{\mathbf{Y}}_{\text{conv2d}} = \frac{\mathbf{Y}_{\text{conv2d}} - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}}$, with μ_B and σ_B^2 is the mean and variance of $\mathbf{Y}_{\text{conv2d}}$.

To support the extraction stage in each conv2D, a Residual Attention (RA) block is paired with the network to introduce the attention mechanism. An RA block has two mechanisms: (i) the data attention function refines the features learned by the network, and (ii) the residual connection function helps maintain effective network learning as data progresses deeper [12]. Particularly in our RACNN network, we use the **self-attention mechanism** based on [11]. This layer generates an attention map that highlights the important regions or features of the input using its own weights. Accordingly, RA block helps each output from conv2D blocks retain the original information while incorporating the refined features from the attention mechanism. Fig. 1(c) illustrates the architecture of a Residual Attention block, which follows the following sequence:

(i) The attention layer first calculates the Query, Key, and Value by applying the learned linear transformation to an input matrix \mathbf{X}_{RA_1} , as illustrated in Fig. 1(d). As self-attention takes the same weights from all inputs, this remains consistent across all heads

$$\mathbf{Q} = \mathbf{X}_{\text{RA}_1} \mathbf{W}_{\mathbf{Q}}, \quad \mathbf{K} = \mathbf{X}_{\text{RA}_1} \mathbf{W}_{\mathbf{K}}, \quad \text{and} \quad \mathbf{V} = \mathbf{X}_{\text{RA}_1} \mathbf{W}_{\mathbf{V}}. \quad (12)$$

Here, $\{\mathbf{Q}, \mathbf{K}, \mathbf{V}\}$ represent the query, key, and value matrices, respectively, and $\mathbf{W}_{\mathbf{Q}}, \mathbf{W}_{\mathbf{K}}, \mathbf{W}_{\mathbf{V}}$ denote their attention weight matrices. The attention weights are computed by comparing the query and key vectors. The difference between these two vectors determines how much attention an input element should give to others. This is typically done by calculating the dot product between the query and key vectors:

$$\mathbf{W}_{\text{attention}} = \text{softmax} \left(\frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{D}} \right), \quad (13)$$

where the scaling factor \sqrt{D} is introduced to prevent large values that may cause instability. Then, the output $\mathbf{X}_{\text{attention}}$ of the attention mechanism is obtained by

$$\mathbf{X}_{\text{attention}} = \mathbf{W}_{\text{attention}} \times \mathbf{V}, \quad (14)$$

(ii) The attention details are then combined with the original input to perform a residual connection operation. Similar to the ResNet [4] model, the original input \mathbf{X}_{RA_1} is added to the attention feature map $\mathbf{X}_{\text{attention}}$, resulting in the final output:

$$\mathbf{X}_{\text{RA}_2} = \mathbf{X}_{\text{RA}_1} + \mathbf{X}_{\text{attention}}. \quad (15)$$

Table 1: Simulation parameters of the training process and wireless communications system.

Parameters	Specification	Parameters	Specification
Signal frequency	$f = 30\text{GHz}$	No. training samples	180000
Antenna size	$N = 256$	No. testing samples	60000
Wavelength	$\lambda = 0.01$	No. iterations	200
Antenna distance	$\lambda/2$	Learning rate	0.001
No. far-field paths	$L_f = \mathcal{U}[0; 10]$	Optimizer	Adam
No. near-field paths	$L_n = \mathcal{U}[0; 10]$	Loss function	MSE

4 Numerical Experiments

In this section, we conduct various experiments with different channel configurations to evaluate the performance of RACNN. We also compare RACNN with traditional methods, including LS and MMSE [8], as well as the deep learning method XLCNet [2]. Several channel configurations will be used for validation, including far-field, near-field, and hybrid channels.

4.1 Experiment Setup

For training, both RACNN and XLCNet will use the same channel configuration dataset, similar to work in [2]. Particularly, the experimental parameters are detailed in Table 1. All experiments are conducted on a workstation computer with an Intel Core i9-14900K processor, 128GB of RAM, and an Nvidia RTX 4090.

To evaluate the algorithm’s performance, we use the Normalized Mean Square Error (NMSE) metric to validate the performance over SNR levels, and the Mean Square Error (MSE) to calculate loss over training iterations:

$$\text{NMSE} = \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}, \quad \text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2, \quad (16)$$

where y_i is the observed value, \hat{y}_i is the estimated value, \bar{y} is the mean of the observed values, and n is the total number of observations.

4.2 Experimental Results

Evaluation on Synthetic Datasets: Fig. 2 shows the testing results using the synthetic dataset from Table 1. We can see that RACNN outperforms other methods in most scenarios. Specifically, RACNN demonstrates improved estimation accuracy performance compared to the deep learning model XLCNet (a CNN model) across all scenarios. This difference is particularly noticeable at

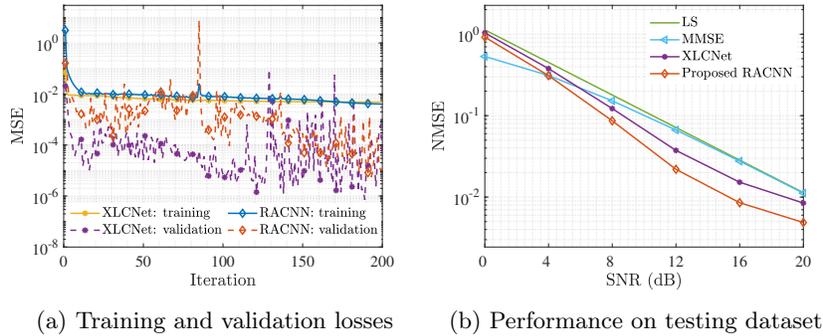


Fig. 2: Performance of training and testing phase.

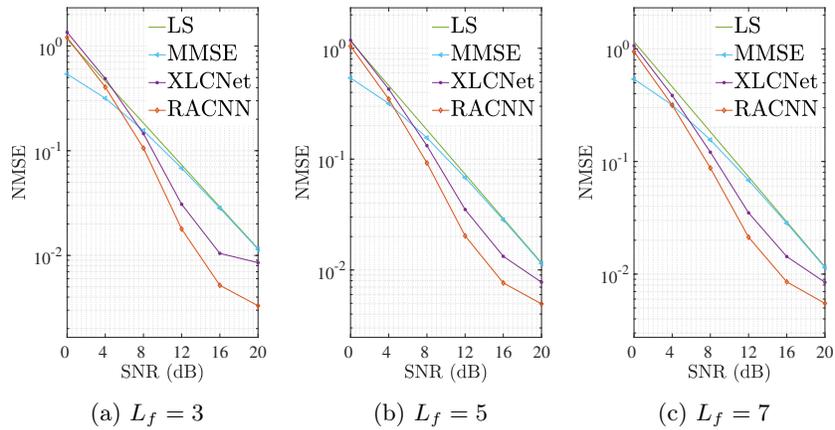


Fig. 3: Performance of estimators for far-field only.

higher SNRs, ranging from 16dB to 20dB, where the error rate gap can be as large as 0.5. However, when considering data extraction speed and training rate, XLCNet has the advantage. As illustrated in Fig. 2(a), RACNN has a slightly slower loss convergence speed compared to XLCNet (as shown by the training loss curve). In terms of validation, the loss during testing on RACNN remains higher for more iterations and only reaches optimal results around 150 iterations. This suggests an increased computational requirement due to the integration of RA blocks.

Far-Field and Near-Field Channel Estimation: In this experiment, we validate the performance of RACNN on near-field channel and far-field channel independently. This is done by modifying the BS transmit path L_f and L_n of each electromagnetic field in a range of constant (3, 5, and 7). The experimental results are shown in Fig. 3 and Fig. 4. They indicate that RACNN

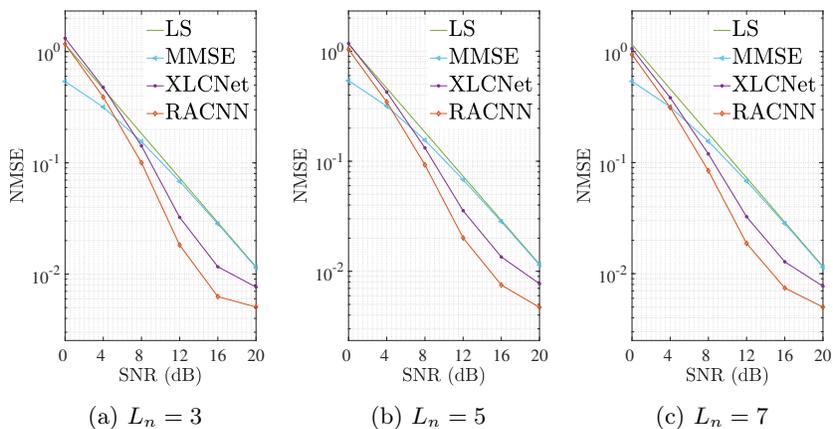


Fig. 4: Performance of estimators for near-field only.

achieves the best estimation accuracy performance in most testing cases. At low SNRs (≤ 4 dB), MMSE performs better, particularly with lower multipath values $L_f = 3$ and $L_n = 3$. However, when the multipath increases, the performance of RACNN begins to improve significantly, as compared to others. Fig. 5 shows the detailed results, investigating channel configurations. We can observe that all methods perform poorly at lower SNR levels. As the SNR increases, a noticeable difference in performance emerges. Looking at the far-field channel, changing in channel configuration have a small impact on impact on XLCNet’s results. In contrast, with RACNN, each line becomes progressively more differentiated as the SNR increases. This behavior differs when the same test is conducted for the near-field channel, where both RACNN and XLCNet exhibit stable performance across all scenarios despite the increasing SNR.

Hybrid-Field Channel Estimation: Similar to the experiments above, we also apply the same validation approach for the hybrid-field channel by mixing different L_f and L_n settings. The test begins with the lowest multipath configuration at $L_f = 3$ and $L_n = 3$, then gradually increases far-field and near-field paths to different values (e.g., 6 or 9) to investigate the impact of system configuration changes on RACNN and its competitors. The experimental results, shown in Fig. 8, indicate that RACNN maintains its position of the best performance on hybrid-field channel except at SNR of 0dB. Consistent with the results of previous experiments, RACNN’s performance improves as SNR increases, outperforming XLCNet at high SNRs. From Fig. 8, we also observe that RACNN is a good option for hybrid-field channel estimation, achieving good performance, especially at high SNRs with fewer multipaths. The difference in RACNN performance is expressed prominently at the high SNR range, especially in the range of 16 to 20dB, where the error between the best and worst result is around 2×10^{-3} . From here, we expect a potential where RACNN capability could be improved

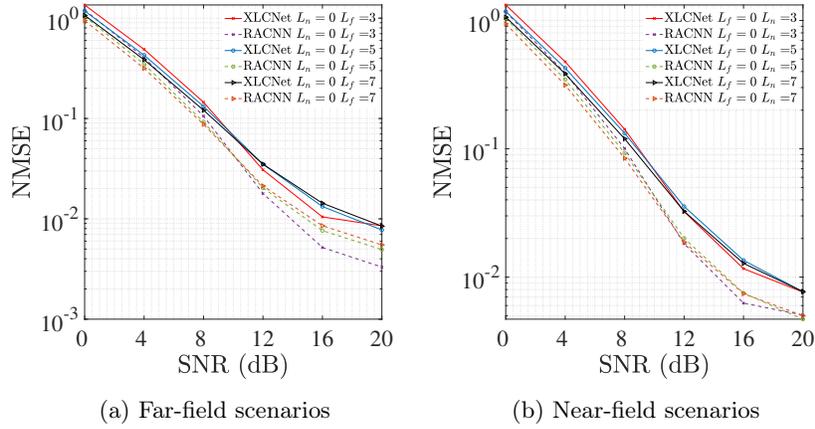


Fig. 5: Performance of estimators in scenerio for far-/near-field only.

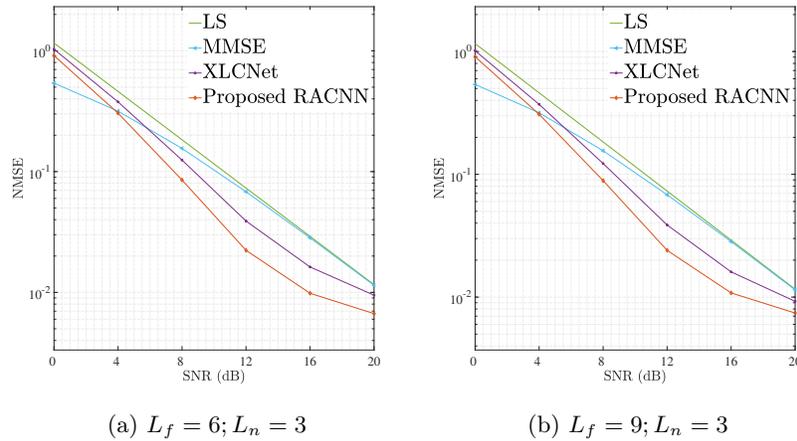


Fig. 6: Performance of hybrid channel model with varying in far-field.

from the current result with a few tweaks in model architecture. Despite the performance differences, an increase in channel paths does not directly lead to noise reduction, as performance ranking remains inconsistent across SNR levels. This is evident in Fig. 8, where we observed the advantage of increased transmitting multipath at lower SNR. However, as SNR rises, channel configurations with higher multipaths begin to pose a drawback. This property applies to both far-field and near-field channels.

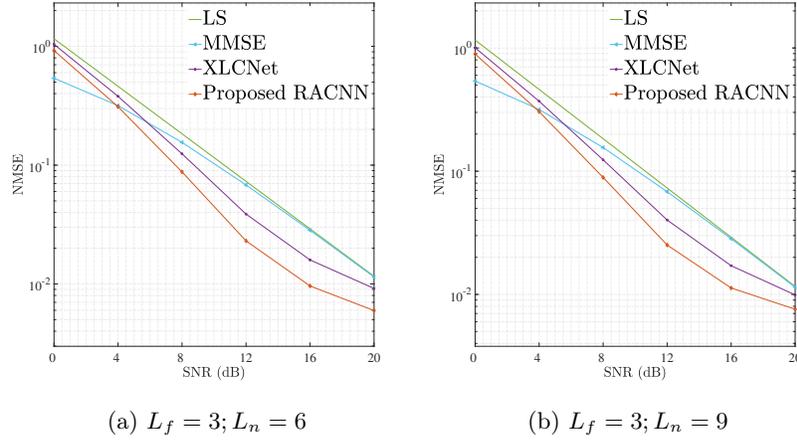


Fig. 7: Performance of hybrid channel model with varying in near-field.

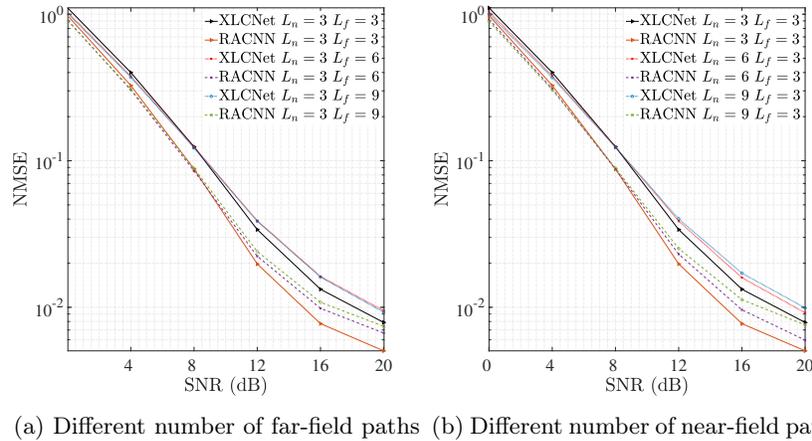


Fig. 8: Performance of RACNN and XLCNet in estimating hybrid channels.

5 Conclusion

In this paper, we proposed the Residual Attention Convolutional Neural Network for near-field channel estimation in 6G wireless communication systems. RACNN integrates convolutional layers with self-attention mechanisms to enhance feature extraction during denoising process. Through various experiments, RACNN consistently outperformed other estimators, i.e., LS, MMSE, and XLCNet. More details, in scenarios with different far-field and near-field path settings, RACNN maintained the best performance across all cases, except at 0dB SNR where MMSE had a slight advantage. The experimental data also indicated that RACNN's performance improved significantly as the number of near-field and far-field paths reduced. Overall, the findings suggest that RACNN is a promis-

ing solution for the complex signal processing demands of ELAA in 6G systems, offering robustness and improved accuracy in near-field channel estimation.

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