Generalizable Indoor Path Loss Prediction

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***Abstract*—This paper is presented in the context of the First Indoor Pathloss Radio Map Prediction Challenge at IEEE ICASSP 2025. We propose a deep learning approach using a customized ResUNet architecture with physics-informed features for predicting radio maps in indoor environments. Our architecture progressively adapts to handle increasing task complexity, incorporating dual-stream processing for frequency generalization and specialized antenna gain processing with dilated convolutions. Experimental results demonstrate effective generalization across unknown indoor scenes, frequencies, and antenna patterns while maintaining computational efficiency.**

***Index Terms*—Radio map prediction, deep learning, indoor propagation, path loss prediction**

I. Introduction

Accurate radio map prediction in indoor environments is crucial for wireless network planning and optimization. While ray-tracing methods provide high accuracy, their computational cost limits practical application, particularly in dynamic network environments requiring real-time adaptations [1]. Recent advances in deep learning have shown promising results in radio map prediction, offering a balance between accuracy and computational efficiency [2]. Several approaches have been proposed, ranging from UNet-based architectures [2] to transformer-based solutions [3]. While outdoor scenarios have received significant attention [4], indoor environments present unique challenges due to complex wave propagation phenomena and material interactions. Recent work by Bakirtzis et al. [5] demonstrated the effectiveness of UNet architectures with atrous convolutions for indoor scenarios.

The emergence of deep learning methods for radio map prediction has led to various architectural innovations. Convolutional Neural Networks (CNNs) have shown particular promise due to their ability to capture spatial relationships in propagation patterns [6], while attention mechanisms have improved the modeling of long-range dependencies in signal propagation [7]. However, most existing solutions focus on single aspects of the prediction problem, such as fixed frequency bands or specific antenna configurations.

This paper presents our solution to the Indoor Pathloss Radio Map Prediction Challenge at IEEE ICASSP 2025 [8], addressing three progressive tasks: base scenario prediction, frequency generalization, and antenna pattern integration. Our approach combines physics-informed features with an evolving neural architecture to achieve accurate predictions while maintaining computational efficiency. Unlike previous works that focus on single-frequency or fixed antenna patterns [9], [10], our solution demonstrates effective generalization across these variables while maintaining millisecond-scale inference times, making it suitable for real-world deployment in dynamic indoor environments.

II. Methodology

A. Data Processing Pipeline

Our pipeline integrates environmental and physics-based features. Environmental features comprise building layouts multiplied by frequency before normalization. Physics-based features include euclidean distance map in meter, frequency-dependent free-space path loss (FSPL) map, and comprehensive antenna gain patterns. For antenna characteristics, we generate circular-masked gain maps, relative directivity patterns (computed as normalized deviations from mean gain), gradient magnitude maps using image gradients, edge contour maps derived from gradient thresholds, and normalized angular orientation features. Distance maps follow euclidean principles, while FSPL maps incorporate frequency-dependent propagation characteristics. Each feature is carefully designed to preserve the underlying physics of radio wave propagation while ensuring consistency across different scenarios. Data augmentation plays a crucial role in improving model generalization. We implement physically consistent transformations including random rotations (90° increments) and flips. Random padding and cropping are included for more diverse spatial antenna locations, while frequency interpolation generates synthetic path loss data for intermediate frequencies using FSPL scaling principles. Antenna gain patterns undergo additive perturbations with corresponding one-to-one adjustments in path loss maps to maintain physical consistency. The pipeline prioritizes practical applicability through efficient feature generation. While Non-Line-of-Sight (NLOS) features were found to be beneficial, they were excluded due to their significant computational overhead, maintaining a balance between performance and efficiency.

B. Model Architecture Evolution

Our solution employs a progressively enhanced ResUNet architecture processing input-output pairs of size 384x384 across three tasks. The base architecture (Task 1) processes input features through an encoder-decoder structure with skip connections, scaling feature width from 32 to 512 channels through residual blocks with batch normalization. For Task 2, we introduced dual-stream processing to separate environmental and physics-based features, enabling better frequency generalization while maintaining the core structure. Task 3's architecture introduces several innovations to handle multiple antenna patterns. We implemented dilated convolutions in the decoder pathway and replaced batch normalization with instance normalization. A key addition is the NESwish activation function, defined as $f(x) = x\sigma(x) - \alpha e^{-\beta x^2}$ with trainable parameters, which is proposed as a novel contribution in this work. This activation function is combined with a specialized antenna gain processing branch that integrates gain features at multiple scales through adaptive stride control. This architecture maintains consistent spatial resolution throughout the processing pipeline, ensuring precise path loss predictions.

C. Training Strategy

Our training approach employs a multi-component loss function combining L2, structural similarity (SSIM), gradient, and edge losses:

$$\mathcal{L} = \alpha\mathcal{L}_{L2} + \beta\mathcal{L}_{SSIM} + \gamma\mathcal{L}_{grad} + \delta\mathcal{L}_{edge} \tag{1}$$

The gradient loss ($\mathcal{L}grad$) measures the L1 difference between horizontal and vertical image gradients of predicted and ground truth images, while the edge loss ($\mathcal{L}edge$) computes the mean absolute difference between Sobel edge maps. Both losses use TensorFlow's built-in gradient operators. The weights were tuned to balance structural accuracy and edge preservation, while data augmentation techniques (rotation, flipping, scaling) are applied with controlled probability parameters. The loss components are computed using a binary mask for valid path loss regions, ensuring the network learns only from meaningful areas. The implementation was done using TensorFlow, with the Adam optimizer and a one-cycle learning rate schedule. Model evaluation uses RMSE (Root Mean Square Error), Mean Error (ME), and Standard Deviation (STD) metrics to assess prediction quality comprehensively. Both training and testing have been done on NVIDIA A40 GPUs.

III. Results and Discussion

Our approach showed strong performance across all tasks, as summarized in Table I. The RMSE values reflect the increasing complexity of the tasks. In Task 1, the model achieves 9.66 dB, showing strong accuracy for the base scenario. Task 2 introduces frequency generalization, increasing RMSE to 10.62 dB. This demonstrates the dual-stream architecture's effectiveness in adapting predictions across varying frequencies. Task 3, involving complex antenna patterns, results in an RMSE of 12.53 dB, highlighting the challenge of handling diverse radiation effects. However, the specialized antenna gain processing and dilated convolutions allow the model to capture detailed propagation patterns. Qualitative results confirm its ability to generalize while maintaining physical consistency. The inference time of our models on GPU goes from 0.087 seconds for Task 1 to 0.26 seconds for the most complex model in Task 3. Note that the features construction time is less than 1 millisecond.

TABLE I
PERFORMANCE METRICS ACROSS TASKS

Metric	Task 1	Task 2	Task 3
Test RMSE (dB)	9.66	10.62	12.53

IV. Conclusion

This paper introduced a deep learning approach for indoor radio map prediction, achieving strong generalization across tasks of increasing complexity. Key contributions include a customized ResUNet with physics-informed features, dual-stream processing, and specialized antenna handling. Performance metrics and qualitative results demonstrate its effectiveness in adapting to varying frequencies and antenna patterns. Future work could focus on larger, more diverse datasets to enhance real-world applicability and explore hybrid approaches for improved accuracy in complex environments.

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