SpecNeRF: **Neural Radiance Field Driven Wireless Coverage Mapping for 5G Networks**

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ABSTRACT

Neural Radiance Fields (NeRF) have emerged as a powerful technique for synthesizing novel views of complex 3D scenes from a sparse set of images. The advances in NeRF has shown prominence in the field of wireless networks as well. This paper explores the application of NeRF in the domain of spectrum sensing, proposing a novel approach that leverages the capabilities of RF based NeRF and extend it to enhance the accuracy and efficiency of spectrum sensing in wireless communication networks. Our proposed solution SpecNeRF is evaluated through extensive experiments, demonstrating significant improvements in terms of scalability, robustness to environmental changes, and adaptability to varying signal conditions. SpecNeRF not only provides a viable solution for current spectrum sensing challenges but also paves the way for innovative applications in future wireless networks, including cognitive radio and 6G technologies.

CCS CONCEPTS

• **Networks** → **Wireless access points, base stations and infrastructure**; *Network performance evaluation*; • **Human-centered computing** → Ubiquitous and mobile devices.

KEYWORDS

Radio Environment Mapping, Neural Radiance Fields, Spectrum Sensing

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1 INTRODUCTION

With the recent advances in wireless communication, there is a growing demand for efficient deployment and management of network resources to provide optimal user experience. The surge in network demands is expected to increase even further with the new generation of data hungry applications targeted towards high throughput networks like 6G and beyond.

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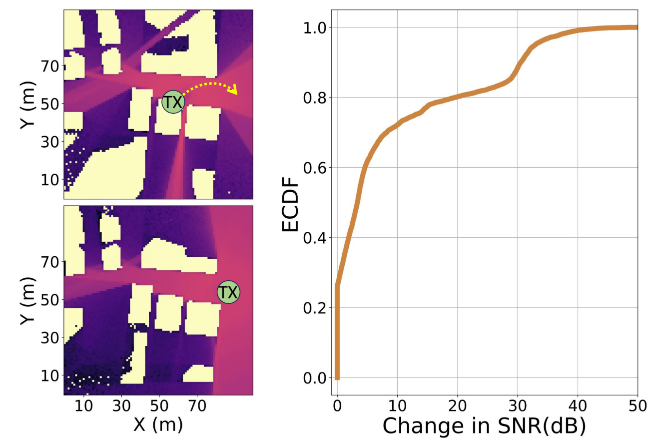


Figure 1: An illustration of the change in REM along with the pixel wise absolute error ECDF for a change in transmitter location (≈ 12m). The median change in is ≈ 8dB for an area of 75×75m.

A crucial tool for planning such deployments is the Radio Environment Map (REM), which represents the spatial distribution of signal parameters. For example, an REM can depict the signal-to-noise ratio (SNR) or received signal strength (RSS) across a given geographical area. REMs are effective in identifying zones with strong coverage, weak coverage, and areas completely cut off from signal access. Analyzing REMs is vital for triggering mechanisms that dynamically adjust network capacity across the coverage area. These mechanisms may include beamforming to enhance signal strength in targeted zones, optimizing the directionality of transmit power, or even relocating base stations to improve overall coverage. Therefore, having access to an accurate and up-to-date REM is crucial for effective network deployment and optimization.

Efficiently estimating REMs remains a significant challenge. Broadly, two approaches are employed: analytical propagation models [5, 16, 17] and data-driven methods. Analytical models are effective for long-range transmissions at relatively lower frequency bands (e.g., VHF or lower UHF bands) but are susceptible to errors [1, 2]. In contrast, data-driven methods, often combined with analytical models, are preferred when the REM requires high degree of detail and good accuracy. Cellular ISPs frequently conduct measurement campaigns, commonly referred to as *wardriving* [14], to validate their coverage areas. While such wardriving significantly enhances REM accuracy, it is also an expensive and resource-intensive process.

Scalability Challenges: While wardriving has inherent costs, the challenge intensifies when network conditions change. For instance, as illustrated in Fig. 1, relocating the transmitter by just 12 m from its original position causes significant alterations in the REM, with a median change of approximately 8 dB. Such shifts render the pre-existing REM obsolete, necessitating new measurements to update it accurately. Even minor adjustments, such as altering the antenna's azimuth, can lead to substantial changes in the REM that are difficult to predict due to complex terrain characteristics. Furthermore, when capacity requirements fluctuate across a coverage area, modifications to the deployment infrastructure must be executed with precision to meet these demands. In all these scenarios, it is evident that wardriving-based solutions lack scalability—each time the network undergoes or requires changes, it is impractical to recollect measurements.

In this paper, we propose SpecNeRF (Spectrum Neural Radiance Field), a framework designed to scale up REM estimation by minimizing the reliance on wardriving. SpecNeRF estimates the obstacles within the channel and predicts propagation loss for a given transmitter configuration. Our approach leverages a state-of-the-art computer vision technique for 3D reconstruction called Neural Radiance Fields (NeRF), which achieves high-fidelity reconstructions from minimal 2D images [12, 13]. NeRF has recently been adapted for the wireless domain to map signal strengths across spatial zones [11, 24]. Unlike traditional methods that merely interpolate observed samples, these techniques use location-tagged signal measurements to estimate the *wireless propagation environment* (e.g., buildings, foliage, obstacles). The propagation environment is encoded as a neural network which can predict the REM at any arbitrary resolution. For instance, when the transmitter location changes, this neural network can be queried to infer signal strength at any receiver location. SpecNeRF significantly scales up REM estimation, making it feasible where traditional wardriving would be prohibitively expensive or impractical, as it would require re-estimating the entire REM from scratch. Our key contribution in this paper is leveraging NeRF-based techniques to efficiently maintain up-to-date REMs or spectrum occupancy maps with minimal additional measurements, even when network configurations change. SpecNeRF has the potential to help network operators significantly reduce wardriving costs.

2 SCALING REM ESTIMATION

In the following, we provide some background on Radio Environment Maps as well as the challenges involved in estimating them.

2.1 Radio Environment Maps (REMs)

The REM of a region is predominately dependent on the location, height, direction (azimuth) and transmit power of the antenna along with the environmental factors especially, terrain that affect signal propagation.

Classical Approaches. A naive approach for REM estimation is to exhaustively collect samples through *wardriving* and interpolate them over the region of interest. Some of the widely used interpolation techniques are - Inverse Distance Weighting (IDW) [9], Radial basis Function (RBF) [8], Gaussian Process Regression or Kriging [4]. More advance interpolation technique utilizes graph structures [18, 20] to represent spatial locations, achieving significantly smoother interpolation values. The method leverages both local neighborhood relationships and global known values, ensuring a more accurate and refined interpolation outcome. Such practice is often prohibitive due to budget constraints and lack of scalability [2, 14]. Analytical approaches such as wireless propagation loss models [5, 16] are often used in conjunction with such wardriving data [1]. However, analytical models have limited accuracy and may not be very reliable when capacity demands are stringent.

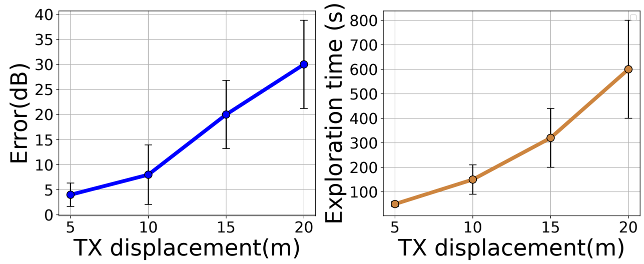


Figure 2: The error incurred for REM estimation for a region of dimension 75m×75m. *Left*: For displacement in transmitter position, and *Right*: Cost incurred (interpolation time) to recover the error.

Recent Learning-Based Approaches. Recent approaches involve sophisticated deep learning based (DL) techniques to predict REMs that utilizes trained models to estimate the REM from sparse or noisy measurement (e.g., crowdsourced [2]) data. With the sampled measurements and a given transmitter location, a neural network model estimates the path-loss that the signal incurs while transmission. This approach is further divided into - *offline* and *online* phases based on the training mode. In offline mode, the training process is conducted only once over an exhaustive dataset. While in online mode, the model continuously trains to adapt within the environment, resulting in a more detailed REM. Although the accuracy can be high in cases, the trained models are often not easily generalize to other terrains.

2.2 Challenges on Network Configuration Updates

Although the existing techniques are in practice since long, the problem of REM estimation is still unresolved. There are various factors that contributes to the problem. Among the various contributing elements, we emphasize two of the major factors that significantly impacts the problem –

First, the accuracy of both interpolation and DL is largely dependent upon the collected data samples. Complex geographical region limit the amount of collected data, resulting in significant differences between the estimated REM using interpolation and the original one. While ML models offers to reduce this discrepancy, training such models is itself a challenging task. This reduces the efficacy of REM estimation significantly, particularly in scenarios that requires rapid transmitter deployment.

Second, the problem of scalability remains unresolved in both the approaches. This problem becomes even more pronounced in the context of 5G, where the location of small cells changes rapidly based on the number of users. In fig. 2, we illustrate one such example of the exploration cost associated with the IDW technique using the same region as shown in fig. 1, where the transmitter location is gradually moved by a specific distance. The exploration cost increases exponentially, highlighting significant scalability challenges and a substantial rise in operational expenses. Additionally, other existing techniques show only a marginal change in exploration cost, further underscoring the persistent scalability challenges.

We therefore ask the question whether we can build a scalable solution for REM estimation that reduces the exploration overhead without compromising on the accuracy? In [24], the existing NeRF technique is translated from the visual to RF domain. We propose to extend it further to capture the RF propagation in outdoor environment for a given set of transmitter position. While existing techniques learn the RSS changes over a region, SpecNeRF identifies the underlying factors responsible for the RSS changes. This enables SpecNeRF to estimate REM for any given transmitter location, thereby enhancing its robustness in dynamically changing environments. SpecNeRF target towards rapid ad-hoc REM estimation of unknown regions. Compared to existing DL techniques, SpecNeRF gives an additional advantage of reduce training samples requirements, making it more adaptable and efficient in diverse scenarios. Furthermore, SpecNeRF is designed to operate efficiently on relatively low-end device with a single GPU. This combination of reduce data requirements along with hardware efficiency makes SpecNeRF as a highly practical and sustainable solution for real-time applications in dynamic and resource-constrained environments.

3 OVERVIEW OF SpecNeRF

3.1 In a nutshell

SpecNeRF is a real-time solution that is easy to deploy and run on any GPU powered system. There are two major components of SpecNeRF–

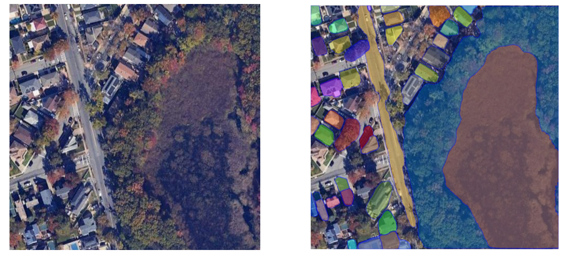
Optimized war driving: A path planning algorithm designed to cover key components critical to understand the region within the constraints of the exploration budget. The algorithm assigns a cost to each key component based on its proximity to the deployed transmitters and generates an optimal trajectory to cover all components at minimal cost.

NeRF based REM estimation: A Multi-Layer Perceptron (MLP) or more specifically a NeRF model that essentially reduces the loss between the original and predicted signal strength. Unlike the existing techniques, we train and run the MLP locally on a low end device. This provides significant improvement in terms of latency, hardware requirements and energy consumption.

3.2 Optimized war driving

One of the major challenge that we aim to optimize is to collect data samples and learn the RF propagation inside the region efficiently without exhaustive manual *war driving*. The design aims to collect the maximum possible data samples from key components responsible for RF propagation loss while minimizing the exploration cost.

To understand the key components responsible for the RF propagation, we take a satellite footage of the given region and run the Segment Anything Model (SAM) [7] on it. The segmented footage (shown in fig. 3) highlights the key locations that needs to be visited to understand different RF propagation phenomenon



(a) Original Satellite Footage (b) Segmented Footage

Figure 3: (a) Original satellite footage (b) Segmented footage generated using Segment Anything Model (SAM).

such as shadowing, diffraction, etc., more efficiently. We denote the segments with $S = \{S_1, S_2, S_3...S_K\}$, where K denotes the number of obstacles.

Algorithm 1 SpecNeRF TRAJECTORY PLANNER

Input: Segments$\rightarrow \{S_1, \ldots, S_n\}$ Centroids $\rightarrow \{G_1, \ldots, G_n\}$
Output: Optimal tour with minimal cost covering all segments
procedure OPTIMALTOUR(Segments, Centroids)
    $N \leftarrow$ number of segments
    Initialize $dp[2^N][N] \leftarrow \infty$
    for $i \leftarrow 0$ to $N-1$ **do**
        $dp[1 \ll i][i] \leftarrow C(S_i)$ ▷ Initialize starting costs
    for $M \leftarrow 1$ to $2^N - 1$ **do**
        for $i \leftarrow 0$ to $N-1$ **do**
            if $M\&(1 \ll i)$ **then**
                for $j \leftarrow 0$ to $N-1$ **do**
                    if $i \neq j$ and $M\&(1 \ll j)$ **then**
                        $dp[M][i] \leftarrow \min(dp[M][i], dp[M\& \sim (1 \ll i)][j] + \text{dist}(j, i))$
    OPTIMAL_ROUTE $\leftarrow \infty$
    for $i \leftarrow 0$ to $N-1$ **do**
        OPTIMAL_ROUTE $\leftarrow$ min(OPTIMAL_ROUTE, $dp[(1 \ll N) - 1][i]$)
    return OPTIMAL_ROUTE

The task is to cover all segments in S while keeping the traversal cost at minimal. We frame the problem as a TRAVELING SALESMAN PROBLEM (TSP) and solve it using dynamic programming approach. We calculate the reward or cost associated with each segment by computing the cumulative distance between the centroid of the segment from each respective transmitter location i.e.,

$$C(S_i) = \sum_{j=1}^{n} \text{dist}(G_{S_i}, T_j) \tag{1}$$

Where G_{S_i} and $C(S_i)$ denotes the centroid and cost associated with the segment S_i. In algorithm 1, we denote the subset of segments using a binary mask M. A higher value of T_j signifies an increased reward, indicating segments that are likely to experience substantial variations in signal strength. These variations are primarily attributed due to the corresponding distance between the transmitter and the segment. The algorithm evaluates the minimal cost of adding a segment to the path by comparing the costs of reaching

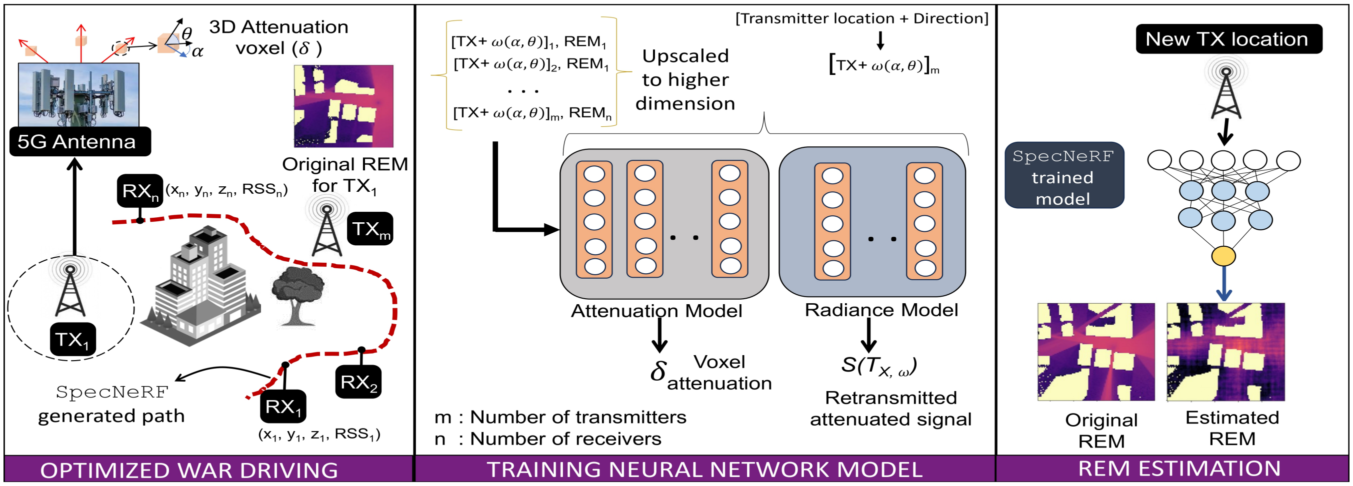


Figure 4: Schematic illustration of the SpecNeRF flow, detailing steps of data collection, training the neural network and the final RSS prediction for a new/change transmitter location.

that segment from all previously visited segments. By iterating over all possible segments combinations, the algorithm computes the minimum cost to traverse all segments.

TSP problem is a well known NP Complete problem. Specifically, the time complexity of solving TSP is O(n*2^n) while the space complexity is O(n^2), where n is the number of segments. However, in practical applications where the number of segments rarely exceeds a single order of magnitude, computational requirements remain manageable.

3.3 NeRF based REM estimation

Neural Radiance Field (NeRF) is a novel deep learning based framework used for scene reconstruction and view synthesis. Given a set of images taken from different view angles, a NeRF model trains a Multi Layer Perceptron (MLP) to reduce the loss between the estimated and original radiance and density values of the image pixels. Consequently by reducing the loss, the NeRF model is able to predict the radiance and density values of image pixels from different view angles i.e, perform view synthesis.

The advances in NeRF open a new direction to understand the RF propagation inside an indoor environment. The study demonstrates promising results for RSS estimation; however, its application is currently limited to indoor environments. SpecNeRF takes inspiration from the work [11, 24] and proposes to extend it a step further for REM estimation. At its core, the RF based NeRF replaces the visual input with the RF signal and estimates the signal strength at any given location.

To formulate the problem in NeRF, consider the region divided into 3D voxels represented by X=(x, y, z). The signal strength received at any location depends on the transmitter location (TX) along with the transmission direction $\omega = (\alpha, \theta)$, where α and θ denotes the azimuthal and elevation angles. Each voxel attenuates the signal by a factor δ, determined by the specific material properties of the voxel. Moreover, each voxel functions as a potential virtual transmitter that transmits the attenuated signal further through the medium. We therefore formulate the NeRF equation as –

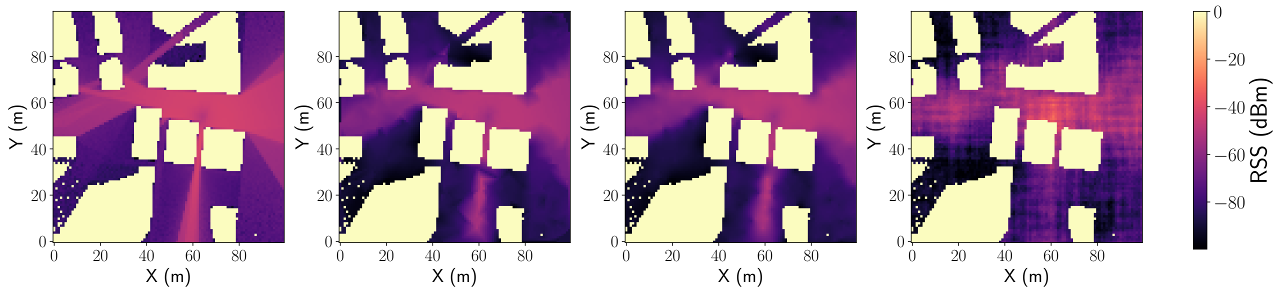
$$F_\Theta : (TX, T_X, \omega) \rightarrow (\delta_x, S(T_{X,\omega})) \quad (2)$$

Here $S(T_{X,\omega})$ denotes the attenuated signal transmitted from a voxel at location T_X and Θ are the learnable weights from the neural network. The NeRF model takes in input two 3D location coordinates (*transmitter and receiver position*) along with one 2D direction coordinate (*transmitter direction*) for the training purpose. The input is up-scaled to a higher dimension by an appropriate encoding scheme. A detailed illustration of the involved steps is shown in fig. 4. Essentially, we train two MLP models - Attenuation and Radiance. The attenuation model estimates the material specific attenuation δ of a voxel for any given transmitter location (TX), while the radiance model estimates the signal retransmitted from the given voxel. Given the constraint of training on a relatively low-end device, we limit the voxel size to 50 cm. To achieve a higher degree of estimation refinement, it is feasible to decrease the voxel dimension further, albeit at the expense of increased training and computational demands. For more descriptive understanding of the RF based NeRF, we recommend the readers to refer the work in [11, 24].

Unlike the existing RF-NeRF where the receivers are anchored to predefined location with mobile transmitter, SpecNeRF considers every voxel as a receiver. For each transmitter location, we capture the signal strength for every possible location in the trajectory. Like any other DL techniques, the performance of SpecNeRF improves with more training samples. We use interpolation technique (RBF) to estimate missing values in the neighborhood of sampled location. Note, we use interpolation only as a medium for Data Augmentation rather than the complete REM estimation. Despite the significant increase in the number of potential receivers, the voxel size, combined with the limited number of transmitters, ensures that the training time does not exceed 20-30 minutes.

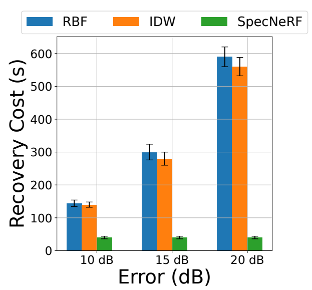
4 RESULTS

We deploy in SpecNeRF inside simulated environments generated using Sionna-RT [6] platform and Open Street Maps [15]. The

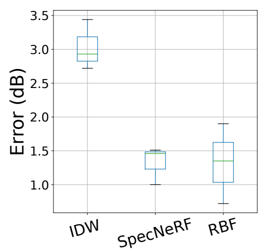


(a) ORIGINAL (b) IDW (c) RBF (d) SpecNeRF

Figure 5: Comparative analysis of the original vs estimated REM generated by : IDW, RBF and SpecNeRF**. Notably, to achieve the targeted accuracy (below $\approx$ 3 dB), 60-70% of data samples are required by interpolation techniques for a new transmitter location. Conversely,** SpecNeRF **leverages existing data to estimate the same efficiently.**

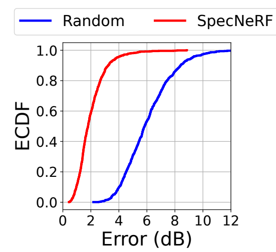


(a) Recovery cost (in terms of exploration time) for transmitter displacement for IDW, RBF and SpecNeRF**.**

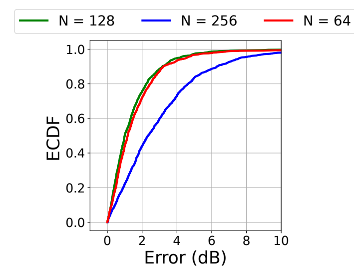


(b) Median and standard deviation of Root Mean Square Error (RMSE) for IDW, RBF and SpecNeRF **generated REMs.**

Figure 6: Comparative study of scalability and reconstruction accuracy of SpecNeRF**.**



(a) ECDF of incurred error for random and SpecNeRF **generated trajectories.**



(b) Comparative study of incurred error for different training batch sizes (N= 64,128, 256).

Figure 7: Performance analysis of SpecNeRF**: (a) Error comparison between random and** SpecNeRF **generated trajectories. (b) Impact of varying batch sizes on performance.**

deployment is done in urban set-up where the obstacle material is mostly concrete. We run all the computation on a device equipped with a GPU of 8GB memory. To assess scalability, we compare SpecNeRF under various setups ranging from urban to semi-urban regions. The NeRF model is trained with a batch size of 128 samples. A ablation study is shown for the same. For ray tracing, we limit both the azimuth and polar angle resolution at 10° i.e., total 36x9 rays are used for the ray tracing.

4.1 Scalability

Scalability is one of the major objective which we resolve using SpecNeRF. We conduct a comparative study to demonstrate the cost reduction achieved with SpecNeRF compared to other existing techniques. Additionally, we illustrate the relative stability in the variance of reconstructed REM by SpecNeRF as compared to other techniques. Since the accuracy of DL driven reconstruction model is governed by the training samples, we show the comparative study with respect to the existing popular interpolation techniques, namely IDW and RBF. As shown in fig. 5, the reconstructed REM by SpecNeRF closely aligns to that of the IDW, RBF methods. This alignment is particularly noteworthy given that these traditional interpolation techniques utilize 60-70% of the data samples for a new transmitter location. On the contrary, SpecNeRF leverages existing data to achieve comparable accuracy, thereby highlighting its efficiency and precision in estimation. In fig. 6a, we show a similar efficacy of SpecNeRF compared to the existing techniques in terms of exploration cost (exploration time in seconds). Since there is no additional exploration overhead for SpecNeRF, we use the REM estimation time as the only cost for comparison. Also, in fig. 6b, we show the relative stability of the reconstruction. Note that to measure the error, we find the pixel-wise Root Mean Square Error (RMSE) of the actual and reconstructed REM. Although existing interpolation techniques exhibit marginally lower errors, their variance is noticeably higher compared to SpecNeRF. Consequently, SpecNeRF emerges as a more robust and reliable tool for REM estimation, especially in regions where the variability needs to be at minimum.

4.2 Random vs SpecNeRF generated trajectory

The trajectory plays a key role in determining SpecNeRF overall accuracy. As discussed earlier, SpecNeRF learns the RF propagation inside the region itself for REM reconstruction. A random trajectory fails to provide a comprehensive coverage of the region. Consequently, a random trajectory results in suboptimal learning of the region compared to a meticulously planned one. We present the same in fig. 7a as an ECDF.

4.3 Ablation study of SpecNeRF Neural Network

To optimize the neural network's performance, we conducted a series of experiments to train SpecNeRF using different batch sizes. A large batch size will decrease training loss at the cost of test accuracy and generalization. Whereas a small batch size will lead to a poor convergence. Fig. 7b illustrates the incurred error during training with varying batch sizes (N = 64, 128, 256) presented as an ECDF. Although a batch size of N=64 shows a similar training loss to that of N=128, it loses in terms of generalization. Hence, we use a batch size of 128 to achieve optimal performance while preserving the regularization. For regularization and reduce the chances of over-fitting, we use a weight decay of 5 x 10^{-5}.

5 RELATED WORKS

REM estimation has been a long-standing challenge, primarily due to scalability issues. Early approaches relied on simulation models like log-path loss and ray tracing [19], but these models often fail to capture region-specific properties essential for accurate spectrum sensing. Existing REM estimation techniques can be broadly categorized into two subcategories:

Interpolation Approach : Common interpolation techniques like Inverse Distance Weighting (IDW)[9], Radial Basis Function (RBF)[8], and Kriging [4] estimate unknown values using weighted samples from neighboring locations. More advanced methods utilize graph-based structures [18, 20] to incorporate both local and global information for improved accuracy. Matrix completion methods, such as in [21], use low-rank approximations to estimate REM from sparse data, albeit requiring extensive parameter tuning, which limits their practicality in dynamic environments.

Machine/ Deep Learning (ML/DL) Approach : Interpolation accuracy is often constrained by data sample availability. Recent ML/DL techniques mitigate this by using data-driven models like Convolutional Neural Networks (CNNs)[10], Graph Neural Networks (GNNs)[3], and Generative Adversarial Networks (GANs)[23] for more robust REM estimation. Auto-encoders[22] are also popular for their efficient data representation learning. However, these approaches require large datasets and substantial computing power, limiting real-world applications.

■ **Discussion** SpecNeRF is a scalable REM estimation solution with promising results in simulation environments, however large-scale real- world deployment is yet to be accomplished. Currently, SpecNeRF requires ≈20 minutes for training that could be further decreased (≈ 4 minutes) by incorporating techniques like `InstantNGP` [13]. With the advancements in edge devices, there is also a possibility to offload the training process to lower-end devices. We anticipate exploring this as part of our future work.

6 CONCLUSION

In conclusion, SpecNeRF represents a significant advancement in the field of Radio Frequency (RF) technology by leveraging the innovative principles of Neural Radiance Fields (NeRF). By extending NeRF's capabilities to outdoor setups, SpecNeRF offers a scalable and efficient solution for Radio Environment Map (REM) estimation. This approach not only enhances the accuracy and reliability of RF mapping in diverse and complex outdoor environments but also paves the way for more advanced applications in wireless communications, autonomous vehicles, and smart city infrastructure. The integration of SpecNeRF into these domains holds the potential to revolutionize how we understand and interact with RF environments, making it a pivotal contribution to the ongoing development of next-generation RF technologies.

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