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Generative Path Selection Technique for Efficient Ray Tracing Prediction

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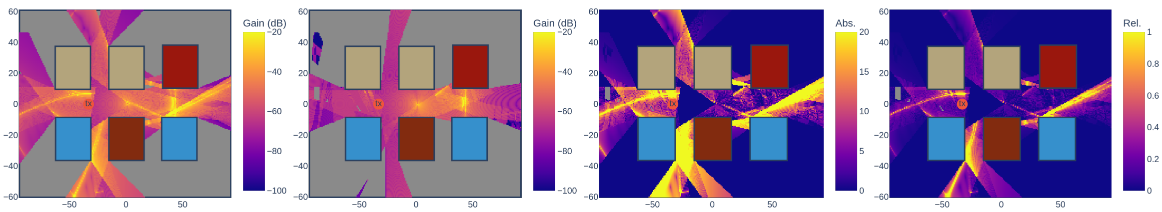
Ray Tracing (RT) is a fundamental technique used to simulate radio wave propagation in wireless communication systems. It accurately models wave interactions with environmental objects, making it essential for predicting signal coverage and interference. However, large-scale environments introduce an exponential increase in potential ray paths, requiring significant computational resources. We build on previous research [1] to address this issue by leveraging Machine Learning (ML) to optimize path sampling, thereby reducing complexity.

Traditionally, RT determines ray paths through exhaustive search, as in image-based RT. This ensures completeness, but suffers from exponential growth in candidate paths as the number of scene objects N or allowed interactions K increases. However, in most propagation scenarios, only a small fraction of candidate paths are valid, as many are blocked by objects like building facades. Instead of evaluating all candidates, we introduce a ML-based generative model to prioritize high-probability ray paths. Unlike standard ML models requiring explicit ground-truth knowledge, our model learns from an implicit "goodness" measure of paths based only on scene geometry. Our approach selectively samples relevant paths, maintaining accuracy while significantly reducing computation.

Our method extends previous work by training a model on first- and second-order reflection paths and applying it to radio coverage map generation. We compare our model's output with exhaustive search results and observe a fair agreement. For first-order reflections, an exhaustive search evaluates up to N paths, and for second-order reflections, $N(N-1) \approx N^2$ paths, whereas our approach achieves comparable results while only simulating P paths per reflection order. This performance gain is valuable for larger scenes or higher-order paths, where tested ray paths grow with $N(N-1)^{K-1}$. As detailed in [1], our model samples path candidates, which are then validated using geometrical optics. A post-processing step removes redundant candidates. Beyond prediction accuracy, our focus is on the novelty of the approach and its efficiency improvements.



(a) Ground truth. **(b)** Prediction. **(c)** Absolute difference. **(d)** Relative difference.

Figure 1. Comparison of the coverage map between the ground truth (Fig. 1a) and the prediction (Fig. 1b) using $P = 20$. Figs. 1c and 1d show the absolute and relative differences (in dB) between the two coverage maps.

Our first results highlight the potential of ML in accelerating RT. While traditional ML-based propagation prediction directly estimates channel parameters, such as received power or delay spread, our approach focuses on learning the multipath pattern. Once paths are determined, propagation characteristics can be computed through closed-form expressions. However, while our model achieves good training accuracy, these results do not always translate into accurate coverage map predictions (see Fig. 1). In our urban street canyon example, the model performs well inside the main canyon but misses some regions outside where coverage should exist. Addressing these discrepancies is a priority for improving suitability for radio propagation. Future work will refine our approach to enhance performance and generalization across diverse environments.

References

[1] J. Eertmans, N. D. Cicco, C. Oestges, L. Jacques, E. M. Vittuci, and V. Degli-Esposti, “Towards Generative Ray Path Sampling for Faster Point-to-Point Ray Tracing,” *arXiv preprint*, Oct. 2024.