Wireless Channel Prediction in Partially Observed Environments

Mingsheng Yin, Yaqi Hu, Tommy Azzino, Seongjoon Kang, Marco Mezzavilla, Sundeep Rangan
NYU Tandon School of Engineering, Brooklyn, NY, USA
e-mail: {my1778, yh2829, ta1731, sk8053, mezzavilla, srangan}@nyu.edu

Abstract—Site-specific radio frequency (RF) propagation prediction increasingly relies on models built from visual data such as cameras and LIDAR sensors. When operating in dynamic settings, the environment may only be partially observed. This paper introduces a method to extract statistical channel models, given partial observations of the surrounding environment. We propose a simple heuristic algorithm that performs ray tracing on the partial environment and then uses machine-learning trained predictors to estimate the channel and its uncertainty from features extracted from the partial ray tracing results. It is shown that the proposed method can interpolate between fully statistical models when no partial information is available and fully deterministic models when the environment is completely observed. The method can also capture the degree of uncertainty of the propagation predictions depending on the amount of region that has been explored. The methodology is demonstrated in a robotic navigation application simulated on a set of indoor maps with detailed models constructed using state-of-the-art navigation, simultaneous localization and mapping (SLAM), and computer vision methods.

Index Terms—Millimeter-wave; ray tracing; multi-modal sensors; machine learning

I. INTRODUCTION

There has been growing interest in combining radio frequency (RF) sensing, such as RADAR, with other sensing modalities such as camera or LIDAR [1], [2]. Camera data have also been proposed to guide communications, such as beamforming at millimeter-wave (mmWave) frequencies [3], [4]. A basic problem in these applications is to predict RF propagation from visual information from cameras or other sources.

One natural approach to this problem is to first build a 3D model of the environment from the camera data. Numerous RGBD and cloud point cameras, along with different view synthesis pipeline algorithms, are now widely commercially available for this purpose [5], [6], [7]. Given a complete 3D model, one can then, in principle, predict the RF propagation between any two points in the environment with standard ray tracing tools or other electro-magnetic (EM) solvers [8].

In this paper, we address a critical problem that may arise in these applications:

How do we predict RF propagation when only a portion of the environment has been observed?

An example scenario for this problem is shown in Fig. 1. A robot agent explores an unknown indoor environment, as may occur in search and rescue operations. Using camera data, it builds a map of the environment through some form of photogrammetry. The particular camera data and partial map shown in Fig. 1 are sample output of a state-of-the-art Active Neural simultaneous localization and mapping (SLAM) module [9] simulated on the Gibson AI dataset [10] that we will discuss in detail below. The agent is also given a hypothetical wireless transmitter (TX) location. If the full environment were known, the agent could determine the true receive (RX) power throughout the environment. For example, the “True RX power” in Fig. 1 was predicted using a commercial ray tracing solver [11], also described in detail below. The problem we address is how to estimate the propagation when only a portion of the map has been reconstructed. Importantly, we wish to estimate the propagation for links where the transmitter (TX) and/or receiver (RX) are outside the environment that has been observed.

Finding good solutions to this problem is tremendously challenging, particularly in the mmWave frequencies range, which is the focus of this work. In addition to the standard challenges of mmWave ray tracing [12], propagation prediction with partial information implicitly requires some model to “fill in” the environment in the regions that have not yet been...
observed. The problem can be seen as an EM “inpainting”, in analogy to the computer vision problem where most state-of-the-art algorithms require extensively trained deep generative models \[13\].

As a starting point to understand the problem, in this work, we consider a simple heuristic solution: We first run ray tracing on the partial map, where the unexplored area is treated as free space. We then train simple machine learning-based estimators to predict link state (LOS, NLOS, or outage) and path gain from features obtained by partial ray tracing.

We show that the proposed methodology has a useful “interpolation property”: On the one hand, when the environment is completely unobserved, the features are sufficient so that the predictor can default to the form of a standard statistical channel model, such as those used by 3GPP \[14\]. On the other hand, as the partial information is built up, the model can increasingly use the partial ray trace to obtain more accurate, site-specific predictions.

II. PROBLEM FORMULATION

A. Environments and Partially Observed Environments

We describe the environment as some function of space, \( F(x) \), where \( x \in \mathbb{R}^d \) denotes the spatial position with \( d = 2 \) or \( d = 3 \) depending on whether we consider 2D or 3D representations. For the purpose of predicting EM propagation, at each \( x \), \( F(x) \) could be a binary variable indicating whether or not a location is occupied or a discrete variable with one of a finite set of values if there are multiple types of material. In addition, \( F(x) \) may indicate the permittivity of any surfaces and objects in the environment.

Given such an environment function \( F(x) \), we assume that one can predict the true wireless channel between any \( x^i \) to \( x^r \). Additionally, we assume that the channel is described by a standard multi-path ray model \[15\] with parameters:

\[
\theta := \{(a_\ell, \gamma_\ell), \ell = 1, \ldots, L\}
\]

(1)

where \( L \) is the number of paths, for each \( \ell \), \( a_\ell \) is the complex path gain, and \( \gamma_\ell \subset \mathbb{R}^d \) is the route of the path in space. We will assume that each route, \( \gamma_\ell \), consists of one or more line segments starting at the TX location, \( x^i \), and ending at the RX location, \( x^r \). A path is line-of-sight (LOS) if it consists of a single segment, that is, the path goes directly from the TX to the RX. Otherwise, it is a non-LOS (NLOS) path. From the path route, one can obtain the angles of departure, angles of arrival, and delay, from which the wideband MIMO channel response for arbitrary arrays can be computed \[15\].

To model that fact that an environment is partially observed, we assume there is a known set \( A \subset \mathbb{R}^d \), on which the environment has been observed. We call \( A \) the observed area. We also assume that we have (a possibly approximate) reconstruction of the environment in \( A \) through some function, \( \hat{F}(x) \) for \( x \in A \).

B. Link State and Omni-Directional Path Gain

The general problem is to estimate some function of the path parameters \( \theta \), from the partially observed environment. We will denote this function by:

\[
z = G(\theta),
\]

(2)

and we call \( z \), a channel statistic. We model the problem probabilistically and treat \( z \) as a random variable with the goal of estimating a conditional probability distribution:

\[
p(z|A, \hat{F}).
\]

(3)

which represents the conditional distribution of the channel statistic \( z \), given the observed area, \( A \), and the estimated environment \( \hat{F}(x) \). The randomness arises from the environment in the unobserved area and noise or errors in the observed area.

Although our methodology is general, in this work, we focus on estimating the channel statistic:

\[
z = (s, g_{\text{omni}}),
\]

(4)

where \( s \) is the link state and \( g_{\text{omni}} \) is the omni-directional path gain. For any channel between a TX and RX pair, we define its link state similar to \[16\]. Therefore, we will denote the link state by \( s \in \{\text{LOS, NLOS, Outage}\} \). Also, given a set of path parameters \( \theta \), we define the (clipped) omni-directional path gain as:

\[
g_{\text{omni}} := \max \left\{ 10 \log_{10} \left( \sum_{\ell=1}^L |a_\ell|^2 \right), g_{\text{min}} \right\},
\]

(5)

which represents the average wideband path gain in dB seen when isotropic antennas are placed at the TX and RX. To avoid singularities when the path gain is very low or when there are no paths, we clip the path gain at a minimum value \( g_{\text{min}} \). For the remainder of the paper we will use \( g_{\text{min}} = -150 \text{ dB} \). Path gain values below this level have little value for communication. We will use the convention that when a link is outage, that is, there are no paths, the omni-directional path gain will also be set to \( g_{\text{min}} \).

III. PROPOSED ALGORITHM

A. Overview

If the environment were completely known (that is, we knew \( F(x) \) for all \( x \)), in principle, one can find exactly the channel parameters \( \theta \), in \( \{\} \) between any given TX and RX locations by ray tracing or any other form of EM solver. Then, given the channel parameters, \( \theta \), theoretically one could exactly determine any statistic, \( z = G(\theta) \).

However, in the case of partial information on the environment, estimation of the distribution of the statistic, \( z \), is, in general, difficult. Suppose that we have an observed area \( A \) and an estimate of the environment, \( \hat{F}(x) \) for \( x \in A \), and we wish to compute the probability distribution \( p(z|A, \hat{F}) \). In principle, one would need a probabilistic model, \( p(F|A, \hat{F}) \), describing the distribution of the true environment from the partially observed environment. From such a distribution, one
could theoretically sample $F$ and compute the true channel parameters $\theta$ from the environment, and the channel statistic $z = G(\theta)$ from the channel parameters. However, obtaining a probabilistic model, $p(F|A, \hat{F})$, is equivalent to rebuilding the true environment of the complete environment, $F$, from the partial environment. Learning such a model would require tremendous amounts of training data. Moreover, computing the channel parameters for each potential true environment would be computationally infeasible.

For the link state and omni-directional path gain, $z = (s, g_{omni})$, we thus propose a simple heuristic algorithm. We first run an approximate ray tracing on the observed component of the environment, treating the unobserved area as free space. Then, we extract the key features of the estimated channel parameters from this partial map. Using these features we train simple machine learning predictors for the channel statistics. We now describe each of these steps.

B. Partial Map Path Prediction

For the first phase, we extend $\hat{F}(x)$ to all of $\mathbb{R}^d$ by simply assuming that $F(x)$ corresponds to free space for all $x \notin A$. Then, given the TX and RX locations, $x^1$ and $x^2$, we run ray tracing, or any other EM simulation, on this partial environment filled with free space to obtain an initial set of path estimates. This simulation will obtain a set of path parameters:

$$\theta_{FS} := \left\{ (\hat{\alpha}_\ell, \hat{\gamma}_\ell), \ell = 1, \ldots, \hat{L} \right\}$$

where $\hat{L}$ is the number of paths in the free space-filled environment, and, for each $\ell$, $\hat{\alpha}_\ell$ is the complex path gain and $\hat{\gamma}_\ell \in \mathbb{R}^d$ is the path route in the space. We call $\theta_{FS}$ the partial map path estimates.

C. Feature Extraction

Our goal is to estimate the conditional probability $P(s, g_{omni}|A, \hat{F})$ of the link state $s$ and omni-directional path gain $g_{omni}$ from the observed partial environment and $\theta_{FS}$. To simplify the prediction, we make the approximation that:

$$P(s, g_{omni}|A, \hat{F}) \approx P(s, g_{omni}|\phi),$$

where $\phi$ is a set of features extracted from the observed area $A$ and the estimated environment $\hat{F}(x)$ on the observed area, $x \in A$. In this work, we will explore a simple set of features:

$$\phi = (\hat{s}, d_{unobs}, d, \hat{g}_{omni})$$

where $\hat{s}$ and $\hat{g}_{omni}$ represent the estimated link state and omni-directional path gain in the partial environment respectively, $d$ is the distance between TX and RX, and $d_{unobs}$ is the total unobserved distance along the LOS between TX and RX.

Although the features are simple, they are sufficient to provide good models for two extreme cases: when the environment is completely unobserved and when the environment is fully observed. In the first case, we would expect to use a fully statistical model such as the 3GPP models in [14]. In these models, the LOS probability and the omni-directional

### Table I

| Estimated link state $s$ | Partial link state $\hat{s}$ | Input features | Hidden layers | Hidden units |
|---------------------------|-------------------------------|----------------|---------------|--------------|
| LOS                       | LOS                           | $d, d_{unobs}, \hat{g}_{omni}$ | 2             | 20           |
| LOS                       | NLOS, Out                     | $d$            | 2             | 10           |
| NLOS                      | NLOS, Out                     | $d, d_{unobs}, \hat{g}_{omni}$ | 2             | 20           |
| NLOS                      | LOS                           | $d$            | 2             | 10           |
| Out                       | Any                           | None           | None          | None         |

path gain are both simply functions of the TX-RX distance $d$. In the other case, when the environment is fully observed, we know that:

$$g_{omni} = (\hat{s}, \hat{g}_{omni})$$

Hence, the features (8) are also sufficient to provide accurate predictions when the environment is fully observed. Finally, the characteristic $d_{unobs}$ can be seen as a variable that represents the degree to which the relevant component of the environment is observed. A sufficiently rich predictor based on the above features can then interpolate between the fully observed and fully unobserved cases.

Now, we write the conditional distribution of $(s, g_{omni})$ given the features $\phi$ as:

$$P(s, g_{omni}|\phi) = P(s|\phi)P(g_{omni}|s, \phi)$$

We call the model that estimates the conditional probability $P(s|\phi)$ the link state classifier and the model that estimates the conditional distribution $P(g_{omni}|s, \phi)$ the omni-directional path gain predictor. Both are described in the following subsections.

D. Link State Classifier

As described above, the link state classifier predicts the conditional probability:

$$P(s|\phi)$$

For this model, we obtained the best performance when considering only a subset of the features of (8), namely: LOS distance $d$, unobserved LOS distance $d_{unobs}$, and free space-filled link state $\hat{s}$. Regarding the structure of the model, for each value of $\hat{s}$, we build a simple logistic classifier based on the two features $d_{unobs}$ and $d$. In this way, we can simply predict its mean and logarithmic variance:

$$\mathbb{E}(g_{omni}|s, \phi), \log \text{var}(g_{omni}|s, \phi).$$
Fig. 2. We constructed partial maps by exporting the explored regions of an indoor environment from the Active Neural SLAM procedure. We then fed this map into a ray tracing tool.

When the estimated link state is outage ($s = \text{Outage}$), by convention described above, the path gain is set to the minimum value $g_{\text{min}}$. For each of the other four cases as reported in Table I, we train a simple neural network depending on the estimated link state $s$ and partial link state $\hat{s}$. When the partial link state matches the estimated link state, we use the partial map features such as $d_{\text{unobs}}$ and $\hat{g}_{\text{omni}}$. However, when they do not match, we simply use $d$, ignoring any non-reliable partial map information.

IV. RESULTS

A. Dataset and Training

The methods are validated on a realistic simulation of robot navigation and visual SLAM map construction, used in prior work [17]. We used the Gibson indoor dataset which contains a collection of accurate 3D maps along with camera data [10]. We used 8 of the environments for training and 4 for testing. Within each training environment, we selected 400 random TX-RX location pairs, and within each test environment, we performed ray tracing simulations using Remcom Wireless InSite [11] at 28 GHz to obtain ground truth values for the channels in each TX-RX link. Then, similar to [17], we use the Active Neural SLAM algorithm [9] to simulate robot indoor exploration on the AI Habitat platform from visual information [18]. The robot explores the environment and gradually builds a simplified 3D map. As shown in Fig. 2, we constructed partial maps by exporting the explored region of an environment from the Active Neural SLAM procedure. We extracted partial maps from four stages: 50, 100, 150, and 200 steps, where 200 steps generally correspond to approximately 60% of the total indoor area. The higher the step count, the closer we get to observing a complete map. The partial maps along with the TX and RX locations served as input to the channel prediction algorithms that were trained to estimate the channel. Links were created where the TX and RX were both inside and outside the observed area, and in LOS, NLOS, and outage conditions.

B. Example Prediction

To illustrate the trained propagation predictor, we first consider an example of test environment shown in Fig. 3. This area is one of the maps in the Gibson dataset that was not used during training and is therefore representative of the predictor’s ability to generalize to completely new environments. In this case, the Neural SLAM ran over 150 steps, which led to an observation of 51% of the interior space.

We ran ray tracing on the full one-layer simplified Shelbiana environment from the TX location in Fig. 3 to 6840 RX locations that are deployed in a grid with 15 cm spacing.

The left panel of Fig. 4a shows the true link state (LOS, NLOS, or outage) at each RX location. The middle panel shows the predicted link state of the trained model when there is no partial information. Since the model outputs a probability, the color shown is the sum of the colors for the three link states, weighted by their probabilities. With no information in the environment, the predicted link state is only a function of the distance from the TX, since there is no environmental information to use.

The right panel of Fig. 4a shows the predicted link state with the partial information. We see that the link state is well predicted in the observed area, as expected. As the RX locations move out of the observed area, uncertainty increases and the prediction becomes less accurate.
networks, as proposed in [19].

Similarly, Fig. 5 depicts the true and predicted omni-directional path gain. A similar pattern can be observed with the link state comparing the true omni-directional path gain with the predictions with and without partial information.

C. Average Test Performance

To quantify the average performance, Fig. 5 shows the accuracy of link state estimation and the root mean square error of the omni-directional path gain as a function of the number of steps the robot has explored in the environment. The two metrics are plotted as the average performance on both the 8 training maps and 4 test maps. The difference in performance between the training and test data is due to the considerable variations between different interior spaces.

When step \( s = 0 \), the environment is completely unexplored and the link state and the path gain must be estimated from the TX-RX distance only. This type of model is similar to the case of fully statistical 3GPP models [14] that do not account for the 3D geometry of the environment. In this case, we obtain a test RMSE of the path gain of approximately 18 dB and test link state accuracy of only approximately 65%. As the robot explores the environment (steps = 200), the test RMSE for the path gain reduces to approximately 11 dB whereas the link state accuracy peaks at approximately 90%.

V. Conclusions

We have formulated a novel problem of estimating RF propagation in partially observed environments. Solutions to this problem may be valuable in scenarios where mobile agents have access to camera data that can assist RF communication and sensing, but the environment is not fully observed. We proposed a simple solution that improves channel prediction and allows us to assess the degree of uncertainty to guide further exploration. Future work will investigate more sophisticated models. For example, the explored area can be converted into image tensors so that radio propagation can be predicted as an image regression problem using deep convolutional neural networks, as proposed in [19].

Fig. 5. Blue: Accuracy of the link state prediction. Orange: Root mean squared error (RMSE) of the path gain. Both metrics are plotted as a function of the number of exploration steps in the environment.

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