Spatial Prediction of Channel Signal Strength Map Using Deep Fully Convolutional Neural Network

Mert Torun, Hong Cai, and Yasamin Mostofi

Abstract—**In this paper, we propose a deep learning pipeline to predict the signal strength map of a wireless channel at unvisited locations over the space, based on very sparse channel samples. Our goal is to enable prediction in complex indoor environments where channels can experience drastic spatial variations. We show how to build a comprehensive large training dataset based only on simulated data that we generate through two complementary approaches: RF propagation simulation and probabilistic channel generation. By employing a fully convolutional neural network, we then develop a channel predictor that 1) does not require any environmental information (e.g., area map, transmitter location), 2) does not make any assumptions on the distribution or characteristics of the channel, and 3) can handle environments of different sizes. We conduct extensive evaluations on a large *real-world indoor* test set that consists of many different areas, as well as on a realistic ray-tracing test set consisting of 225 different environments. Our results show that our proposed approach can predict channel spatial details well, and further outperforms the state-of-the-art considerably in both accuracy and computation time.**

Index Terms*—*Spatial Prediction of Channel, Channel Signal Strength Map, Machine Learning, Deep Learning, Convolutional Neural Network

I. Introduction

Predicting the signal strength of a wireless channel at unvisited locations over the space (i.e., the signal strength map) is useful for many applications. In robotics, for instance, it is critical for unmanned vehicles to maintain connectivity in order to ensure a satisfactory task completion. Real-world wireless channels, however, do not provide reliable connectivity at every location. The channel signal strength varies spatially and depends on several factors, such as the locations and material properties of the objects in the space. Such complex spatial dynamics present a challenge for robots to stay connected as they traverse the environment. Thus, in order to properly plan its actions and maintain connectivity, it is key for a robot to predict the wireless channel strength at unvisited locations over the space. The robot can then plan its trajectory such that it can stay within the connected regions while carrying out its tasks. In case it has to traverse the disconnected areas, the robot can then predict for how long it will lose connection, or where to go to recover its connection.

Predicting the channel signal strength map at unvisited locations is also important for other non-robotic applications. For instance, if for a given transmitter location, we can predict the resulting channel signal strength over the workspace, we can then properly optimize the placement of the router in order to achieve the desired signal strength map, without the need to exhaustively measure the channel over the whole space.

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Motivated by the need for robotic channel prediction as well as other applications in the fixed wireless domain, there has been a considerable interest in predicting the channel signal strength map in recent years [1]–[3]. Formally speaking, given a few sparsely-collected measurements of a 2D wireless channel map, the objective is to predict the channel strength map at unvisited locations over the entire space. Fig. 1 shows a visualization of this problem. These sparse channel measurements could have been collected from previous operations, sparsely-deployed static sensors, and/or crowdsourcing.

In order to solve this problem, earlier work [1] adopts a disk model which assumes connectivity within a certain distance from the transmitter (Tx), with no connectivity outside. However, this over-simplified model can result in a poor performance in practice. As such, researchers have employed more realistic models to predict the signal strength map. For instance, in our past work [2], we have developed a Gaussian Processes (GP)-based approach for channel prediction, by using the three underlying dynamics of path loss, shadowing, and multipath fading. Such a GP-based approach has been utilized and extended by others, e.g., [3]–[6], and remains the state-of-the-art for spatial channel mapping [5]–[8]. However, it has a few drawbacks. First, it assumes stationary underlying channel parameters over the whole prediction space (e.g., fixed shadowing power/correlation coefficient, fixed path loss parameters, etc.) and as such it may not perform well (or needs to be extended) in more complex/larger areas where channel parameters change spatially. This is important as the robot, for instance, can group the sparse measurements with different underlying parameters together for channel mapping, which can result in an erroneous prediction. Furthermore, it is computationally expensive, and does not scale well with the area size since it involves matrix inversions (more on this in Sec. IV-F). Finally, the underlying Gaussian model assumption may not be valid in all environments, and the three dynamics of path loss, shadowing, and multipath fading may not suffice to model all the channel details.

More recently, researchers have started to utilize machine learning to predict various aspects of the wireless channel, such as temporal prediction [9], predicting Angle-of-Departure [10], and predicting the received Channel State Information from the Tx side [11]. See recent surveys on using deep learning for various aspects of wireless communications [12], [13] (not including spatial channel prediction, which is an emerging topic). More related to this paper are those work on the spatial prediction of the channel map. Along this line, [14]–[16] focus on predicting the path loss and not the entire channel, using machine learning. [17] uses machine learning to predict the received signal strength for an

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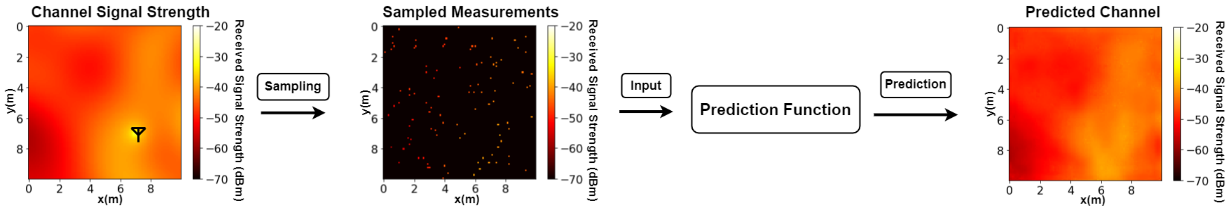

Fig. 1: Visual demonstration of the problem of interest – Given a few sparsely-collected measurements of a wireless channel, the objective is to design a prediction function that utilizes these sparse measurements and predict the channel strength at unseen locations over the space.

urban city-like outdoor wireless channel with a pixel resolution of 4 meters. However, this method is not tested with real data, is limited to outdoor urban environments that do not experience rapid fading channel variations, and requires the environment map as part of the input, which may not always be available. From a technical aspect, it further requires a fixed-size input (i.e., height and width), which can limit its practical applicability. Similarly, [18]–[22] also focus on outdoor urban channels. Among them, [18]–[21] are not tested with real data and [22] requires real measurements for training.

In this paper, we propose a general Deep Learning (DL)-based approach for the spatial prediction of the channel signal strength map, with an emphasis on capturing detailed rapid variations that are common in complex indoor settings. Our method does not require the map of the environment or the Tx location, does not assume a single Tx, and can be applied to the more challenging indoor environments. Furthermore, by utilizing a fully convolutional network, our proposed approach can be used for environments with various sizes. We conduct extensive evaluations on a real-world indoor wireless test set, as well as on a realistic simulated wireless test set generated by a commercial ray-tracing software. The results demonstrate that our approach can predict the channel spatial map with a high quality, and further outperforms the state-of-the-art, in terms of both accuracy and run time.

We next summarize the contributions of this paper.

1. We propose a DL-based pipeline for predicting the channel strength map at unvisited locations over the workspace, based on very sparse channel samples (i.e., problem of Fig. 1). **Our goal is to enable prediction in challenging complex indoor environments where channels can experience drastic spatial variations (in addition to outdoor environments that typically experience slower variations).** Moreover, we show how to develop a comprehensive training dataset, based solely on simulated data, which we generate through two comprehensive pipelines: RF propagation simulation in many different environments and probabilistic channel generation. This is important as relying on collecting real channel data for training purposes limits the generalizability of the trained network. Finally, our approach does not require the transmitter position or the environment map.

2. By modifying U-Net [23], we utilize a fully-convolutional network to handle inputs of different sizes and shapes, making our pipeline more widely applicable.

3. We conduct extensive evaluation on both a real-world indoor test set and a realistic ray-tracing test set, and show that our proposed approach can well predict channel spatial details, and further outperforms the state of the art in both accuracy and computation time. To the best of our knowledge, this is the first time that a DL-based approach is shown to provide accurate spatial channel prediction in real-world environments.

II. Spatial Prediction of Wireless Channel

In this section, we first describe the problem of predicting the wireless channel strength over the space, based on a small number of channel measurements previously collected in the same environment. We then present our proposed DL-based prediction approach, which utilizes a deep fully-convolutional network (DFCN) architecture that only takes the sparse channel measurements as input and provides the predicted wireless channel strength over the space as the output.

A. Problem Formulation

Consider a 2D wireless channel environment, $W \subset \mathbb{R}^2$. For each spatial location, $x \in W$, the corresponding wireless channel strength is y. Given a small number of channel measurements previously collected in W, our objective is to predict the wireless channel strength at the remaining unobserved locations, as illustrated in Fig. 1. We denote the set of prior measurements as $\Omega = \{(x_1^o, y_1^o), (x_2^o, y_2^o), ..., (x_M^o, y_M^o)\}$, where M is the total number of available measurements. Then, given the set of unvisited locations $X = \{x_1^u, x_2^u, ..., x_K^u\}$, we want to find a function, f_θ, to predict the channel strength $Y = \{y_1^u, y_2^u, ..., y_K^u\}$ at their respective locations in X: $\widehat{Y} = f_\theta(X \,|\, \Omega)$, where θ denotes the parameters of the prediction function, f. In the case of a GP-based approach (e.g., [2]), θ contains the estimated channel parameters such as path loss parameters, shadowing power/decorrelation distance, and multipath power. Due to space limitations, we skip the signal model and technical details of this approach. See [2] for more details. As for our DL-based method, θ denotes the trainable parameters of the neural network.

B. Prediction Using Deep Convolutional Neural Network

Given the complex spatial dynamics of the wireless channel, it is intractable to analytically derive the prediction function.

We then utilize a deep fully-convolutional neural network for the prediction function f_θ. Our approach does not impose any assumption on the distribution of the wireless channel and as such can be generalized to any environment. While it is typically expensive to train a deep neural network, running the network for inference/prediction is fast and simple during the operation phase, as we shall see.

Our proposed network (shown in Fig. 2) is a modified version of U-Net [23], which has been shown to be an effective architecture for 2D visual prediction tasks, such as segmentation [24] and depth estimation [25]. This architecture consists of an encoding stage, which progressively reduces the dimension of the input via convolution and pooling operations, and a decoding stage, which then increases the dimension via both transposed convolution and regular convolution. This allows the network to learn to distill the key information from the input and further be robust to noise during training. In early encoder-decoder neural networks, fully-connected layers are present between the encoding and decoding stages, which then require all the inputs to have the same size. In our architecture, on the other hand, we have no such layers which makes our model a fully-convolutional network that can handle variable-size inputs. This is important as we need to predict the channel in environments with different sizes.[1] Since our problem requires the prediction of continuous channel strength values, a regression output layer (i.e., a 1×1 convolution layer which generates a 2D output) is included at the end of the network. In order to provide higher-resolution features to the decoding stage and improve gradient flow during backpropagation, skip connections are used, which combine encoding-stage features with decoding-stage features via concatenation.

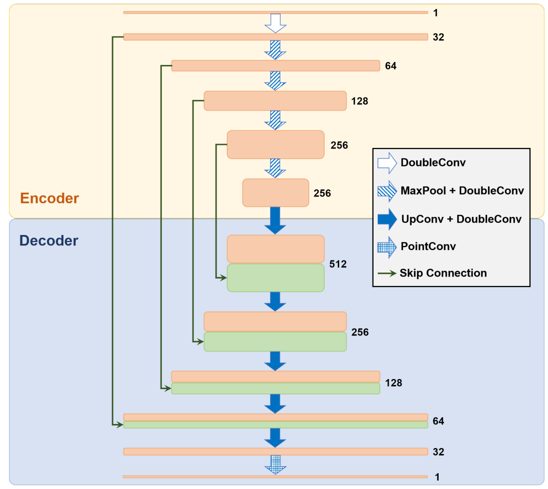

Fig. 2: Our deep fully-convolutional network architecture for spatial wireless channel prediction (modified from U-Net). Our network can handle inputs of different sizes due to not having fully-connected layers. Orange blocks indicate data (e.g., input, feature maps, and output), with the numbers indicating the sizes of the depth dimension. The arrows indicate different operations. DoubleConv consists of two 3×3 convolutional layers, each followed by a batch normalization layer and a ReLU activation. MaxPool is 2×2 max-pooling. UpConv is 2×2 transposed convolution. PointConv is 1×1 convolution. We use concatenation for the skip connection, where green blocks indicate copies of the corresponding features from the encoding part. See color PDF for better visibility.

III. Training and Test Data

We construct a large training set consisting of realistic simulated spatial wireless channel data. For evaluation, we construct two test sets. The first one contains realistic simulated wireless channels generated by a ray tracing software while the second one contains real-world wireless channel measurements collected from a complex indoor environment.

A. Training Data

A large dataset with sufficient variety is required to properly train a deep neural network. However, it is extremely costly to construct such a large training set by collecting real wireless channel measurements from a variety of environments. As such, we utilize realistic simulated wireless channel data for training. More specifically, we utilize two types of simulated data. Our first set of data is generated by using Wireless InSite [26]. Wireless InSite is a high-fidelity EM solver and RF propagation simulator. This software is commercially available from Remcom and is commonly used for both academic research and industrial applications. Given a floor plan with its associated objects, the Tx location, and the propagation parameters (e.g., number of reflections, diffractions), Wireless InSite simulates the resulting spatial wireless channel based on ray tracing. It also has a library of several different floor plans/objects and can further allow importing new ones.

We further generate additional realistic simulated training data by using a probabilistic channel simulator [27]. This simulator generates a channel whose statistics are dictated by a given set of underlying path loss, shadowing, and multipath parameters, and the associated GP model. More specifically, given the Tx location and a set of wireless channel parameters (path loss constant/exponent, shadowing power/correlation, multipath fading power), the simulator generates a correlated 2D Gaussian process whose statistics satisfy the prescribed channel parameters. These two types of simulated data complement each other in the following sense. The ray-tracing data provides channels based on the given floor plans, while the probabilistic channel simulator generates channels that can cover many different scenarios by randomly sampling the underlying parameters from a large range, thus adding more diversity to the training pool. Fig. 3 (a) shows a sample ray-tracing-based channel generated by Wireless InSite, for the floor plan of the left figure, while a sample simulated channel generated by the probabilistic simulator is shown in Fig. 3 (b). We next discuss these two sets in more details.

1) Training Data Based on Ray Tracing: Our ray tracing training set consists of 10,000 channels, based on 200 unique floor plans extracted from [28], with varying sizes and structures. For each floor plan, we randomly populate it with additional walls and daily objects (e.g., desks, chairs, which are acquired from a public database [29]), and randomly place the Tx in the environment. We generate 50 scenarios per floor plan (including 10 no-object cases to capture the empty indoor scenarios). Given these populated floor plans and the corresponding Tx locations, we then simulate the corresponding wireless channels using Wireless InSite.

[1] Although an input to the network should be in a rectangular shape in our current setup, we can handle a non-rectangular area by padding it to the closest rectangle. Given the channel prediction over this rectangle, we then simply take the prediction values over the region of interest and ignore the remaining values.

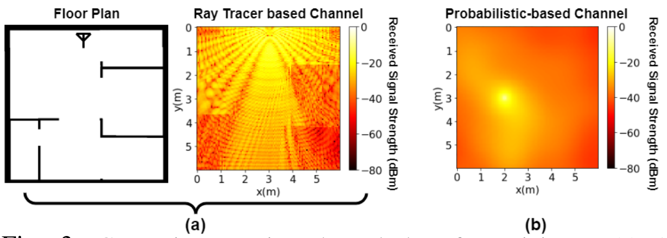

Fig. 3: Generating massive channel data for training – (a) A sample simulated wireless channel based on ray tracing in an indoor environment whose floor plan is shown in the leftmost figure. (b) A sample simulated wireless channel using a probabilistic simulator. A brighter (darker) color indicates higher (lower) channel strength in the Received Signal Strength (RSS) map.

2) Training Data Based on Probabilistic Channel Simulator: Given the path loss, shadowing, and multipath parameters, and the Tx location, this simulator generates a plausible spatial wireless channel whose joint Gaussian PDF satisfies the input channel parameters (see [27] for more details). We generate 10,000 such channels by randomizing the environment size, the Tx location, and the wireless channel parameters, including the path loss constant and exponent, the shadowing power and decorrelation distance, and the multipath fading power.

For all the simulated wireless channels, the signal strength is clamped to the range of $[-80, -5]$ dBm and the spatial resolution is set to 5 cm per pixel. During training, the inputs to the network are then the sparsely-sampled versions of these generated channels. More specifically, each generated channel is sparsely sampled with many different sampling rates ranging from 1% to 30% (and with several different random realizations for each rate), to provide the inputs for training, while the full channel provides the ground-truth data for training the network to predict the channel at unseen locations. For each generated channel, the sparsely-sampled channel values are normalized to $[0.5, 1]$, while values of the unseen locations that need to be predicted are set to 0.

B. Test Data

Our evaluation dataset consists of two parts: 1) a test set based on ray-tracing simulated data and 2) a real-world wireless channel test set.

1) Test Data Based on Ray Tracing: We use 9 unique floor plans for this test set, which are different from the floor plans used in training. We randomly place a Tx in each space and populate it with objects (25 random realizations per floor plan). In total, this test set consists of 225 channels.

2) Real-World Wireless Test Data: In order to evaluate our DL-based pipeline in real-world wireless environments, we utilize the real wireless channel measurements from [27].[2] These measurements are collected in a large, complex basement environment, with rooms of different sizes and several hallways, as shown in Fig. 4. See [27] for more details.

Sparsely-sampled test channels are scaled to $[0.5, 1]$ when fed to the trained network, as described in Sec. III-A1. The predicted channel outputs are then scaled back to their normal range for prediction error analysis. In addition to testing our

[2]This dataset is available from: http://dx.doi.org/10.21229/M9159S.

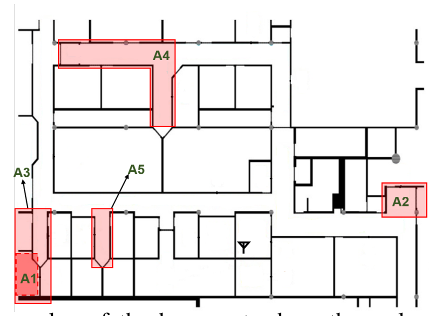

Fig. 4: Floor plan of the basement where the real-world wireless channels are measured [27]. We test our approach in several areas in this environment, as marked on the figure.

predictor on individual regions of the basement, such as a room or a hallway, we also evaluate it on larger areas, each of which consisting of multiple regions (e.g., over a few rooms or over a combination of hallways and rooms). Predicting an indoor channel in a large complex area with multiple regions is more challenging as the spatial dynamics becomes more complex and the underlying channel parameters become spatially varying. While existing approaches (e.g., [2]) can pool all the sparse samples of a large area to estimate the underlying channel parameters without knowing the floor plan and the objects within, this can result in erroneous parameter estimation. Our DL-based approach, on the other hand, is immune to such issues as we shall see.

IV. Performance Evaluation

In this section, we extensively evaluate our proposed deep learning pipeline for spatial wireless channel prediction. We evaluate our approach on both a realistic ray-tracing test set and a real-world wireless channel test set, as discussed earlier, and further compare it with the state-of-the-art.

A. Training Setup

We use Mean Squared Error (MSE) between the predicted and ground-truth channels as the loss function for training the network, which is a common choice for regression tasks. We use the Adam optimizer [30] with a learning rate of 10^{-5}. We train the network for 400 epochs with a batch size of 32.

B. Evaluation Metric

We use the Normalized Mean Squared Error (NMSE) to evaluate the prediction quality for a given sparsely-sampled channel input: $\frac{1}{N_i}\sum_{k=1}^{N_i}(f_\theta(x_k) - y_k)^2/y_k^2$, where N_i is the number of unmeasured spatial locations for the i^{th} channel, and the predicted and actual channel strength values are in dBm. For a given sampling percentage and a specific channel environment, we then sample the channel according to the given sampling percentage, and average the NMSE over 20 such randomly-sampled inputs to obtain an average NMSE.

C. Evaluation on a Ray-Tracing Test Set

Fig. 5 shows sample channel prediction performance in two different environments. Note that each environment is populated with random objects, which are not shown in the figure. The input measurement rates are 15% and 5% for the first and second rows, respectively. It can be seen that our proposed DL pipeline (last column) can accurately predict the

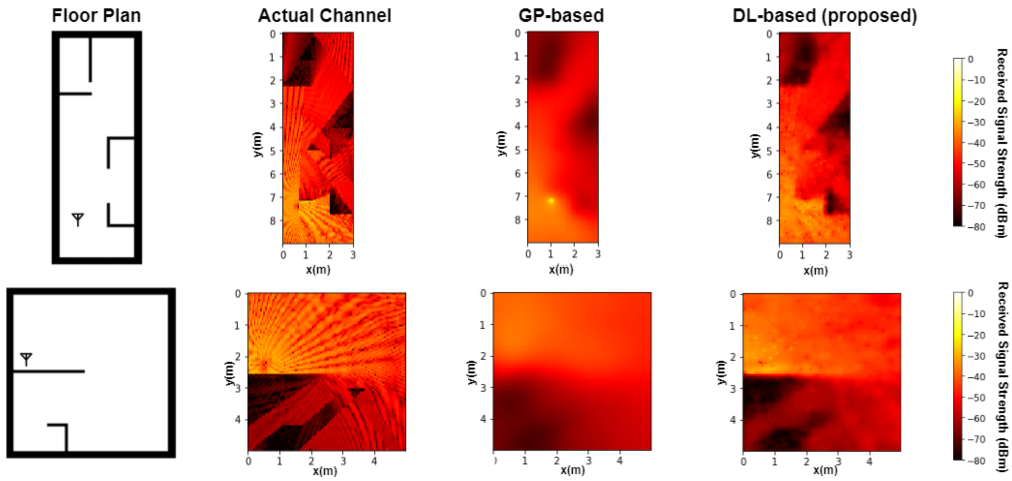

Fig. 5: Two sample results of channel prediction over large areas, on the ray-tracing test set. Each row shows the results for a different channel environment. The first column shows the floor plan and the Tx location, the second column shows the ground-truth ray-tracing-based channel, the third column shows the GP-based prediction, and the fourth column shows our proposed DL-based prediction. We note that each environment is populated with several random objects, which are not shown in the figure. See the color PDF for better visibility.

Sampling Rate	Avg. NMSE (in dB) for GP-Based [2]	Avg. NMSE (in dB) for DL-Based (proposed)
1%	-15.01	-17.52
5%	-16.91	-19.42
10%	-17.35	-20.19
15%	-17.99	-20.60
20%	-18.22	-20.72

TABLE I: Prediction accuracy on ray-tracing test set. Performance is averaged over 225 different channel environments and 20 different random sparse sampling realizations for each percentage.

details of the channel, when compared to the true channel shown in the second column. In particular, spatial channel variations due to the changes from one area to another are well captured. The third column also shows the performance of the state-of-the-art GP-based approach. As mentioned earlier, this approach uses a Gaussian Process to model the spatial variations of the channel, based on a model that captures path loss, shadowing, and multipath fading [2]. As can be seen, GP-based prediction mainly captures the path loss and slow spatial variations, and cannot capture the details to the same level. This is because mathematically modeling the small-scale rapid variations in an indoor environment is considerably challenging. Moreover, in larger complex spaces, such as those in Fig. 5, the underlying channel parameters change spatially, which makes it challenging for the GP-based approach.

Table I next shows the performance averaged over 225 different environments and for different sampling rates. It can be seen that for all the sampling rates, our proposed approach considerably outperforms the state-of-the-art GP. For instance, for 5% channel samples, the GP-based approach has an NMSE about twice as high as that of ours in the linear scale.

D. Evaluation on Real-World Wireless Data

We next test our approach on real channel data collected in the environment of Fig. 4. We select several individual and combined regions to test our approach, as marked in the figure.

Fig. 6 shows the prediction accuracy of our approach (average NMSE in dB scale) for these test regions. As can be seen, our approach can accurately predict the channels, even in large complex indoor areas consisting of multiple regions. For instance, A3 covers a large area of two rooms and a hallway while A4 covers two long hallways. Note that A3 includes A1. A3,5 then refers to prediction over a larger area consisting of both A3 and A5. The figure also shows the performance of the GP-based approach. It can be seen that our approach can increase the accuracy of channel prediction. For instance, for A1, given 10% prior channel measurements, our DL-based approach has a significantly lower prediction error of -25.68 dB, while the GP-based approach has an average NMSE of -19.91 dB. Overall, this evaluation demonstrates the efficacy of our method, showing that it can generalize to real-world environments, although the network has only seen simulated data during training.

E. Robustness to Sampling Locations

In this part, we study how robust our approach is to the exact sparse sampling locations. In general, we find the DL-based approach not sensitive to the exact locations of the prior samples. Fig. 7, for instance, shows the average NMSE for Area 2 of Fig. 4, with the standard deviation marked. It can be seen that the DL-based performance concentrates around the mean (right sub-figure), while the GP-based approach can be more sensitive to the sampling locations, with higher variations around the mean (left sub-figure). This is due to the fact that the GP-based approach performs better when the prior samples are more uniformly distributed over the space whereas more spatially-clustered samples can result in performance degradation. Our proposed DL-based approach, on the other hand, is more robust to the exact sample locations.

F. Computation Efficiency

While training a DNN is computationally expensive, running it at inference time is fast. Fig. 8 shows the inference run time of our approach as a function of the % of available measurements, on an Intel i7-9700K CPU. We see that our approach is scalable as its computation time is not affected by the number of available measurements, whereas the run time

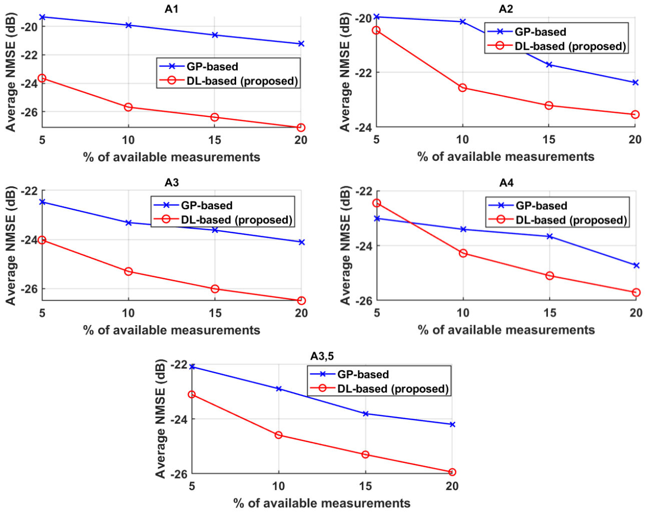

Fig. 6: Performance in real indoor channel environments – Prediction error for sample areas of the basement of Fig. 4.

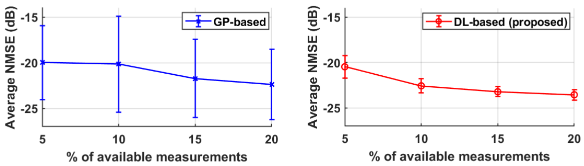

Fig. 7: Robustness to sampling locations – Vertical lines indicate the standard deviation (w.r.t. the randomness of the sampled locations) of the respective prediction errors for a sample environment (A2).

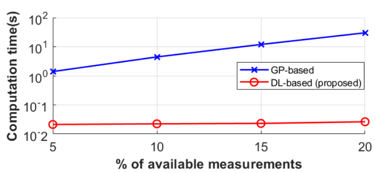

Fig. 8: Average prediction computation times (on CPU).

of the GP approach significantly increases with more samples, since it involves matrix inversion.

V. Conclusion

In this paper we proposed a machine learning pipeline to predict the channel signal strength map over a region of interest. Our approach does not require any environmental information, e.g., area map, transmitter location, and can handle environments with different sizes. It is furthermore applicable to both outdoor and indoor settings as it can capture complex spatial channel variations. Finally, it is trained on comprehensive simulated data, and tested in real environments as well as with a realistic large ray-tracing test set. Our results show that our pipeline can predict the channel spatial variations well in highly-varying indoor settings. It furthermore outperforms the state-of-the-art in both computation time and performance, and is also not sensitive to sampling locations.

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