Towards Deep Learning Augmented Robust D-Band Millimeter-Wave Picocell Deployment

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ABSTRACT

D-band millimeter-wave, a key wireless technology for beyond 5G networks, promises extremely high data rate, ultra-low latency, and enables new Internet of Things applications. However, massive signal attenuation, complex response to building structures, and frequent non-availability of the Line-Of-Sight path make D-band picocell deployment challenging. To address this challenge, we propose a deep learning-based tool, that allows a network deployer to quickly scan the environment from a few random locations and predict Signal Reflection Profiles everywhere, which is essential to determine the optimal locations for picocell deployment.

1. INTRODUCTION

Millimeter-wave (mmWave) is the core technology to increase the capacity of existing wireless infrastructures [1], enabling new applications in transportation, education, telemedicine, and entertainment. Specifically, the recent availability of inexpensive hardware above 100 GHz [2] makes the time ripe for bringing D-band mmWave (110 GHz to 170 GHz) networks and applications to the masses. This will catalyze the vision of future network architecture, beyond existing 5G, where extremely high density of inexpensive, short-range base-stations, called "*picocells*," each with thousands of beam directions, can be deployed on indoor and outdoor structures and operate on hundreds of frequency bands. Moreover, the carrier frequency above 100 GHz allows wider contiguous channel bandwidth and makes the antenna size extremely small, facilitating higher data rate and lower latency, enabling secure communication channel, high-definition holographic gaming, wireless cognition, and hyper-spectral imaging [3].

Yet, mmWave communications are mostly limited to Line-Of-Sight (LOS) path and very few reflections in Non-LOS (NLOS) paths. While an open LOS can establish a strong link between the picocell and the user device, this path could often be obstructed by other users and environmental structures. So, the picocell needs to rely on NLOS paths mostly to communicate with the users. What's more, at mmWave frequency, especially at D-band, many structures do not provide strong enough reflections to establish a viable link, so the network could suffer from frequent outages [4]. While it may not always be feasible to transform the environment to help the picocells, such as adding or re-orienting strong reflectors, we can place the picocells smartly to improve their NLOS paths availability. Network deployers can achieve this goal using a full site survey by driving the mmWave transceiver (co-located transmitter and receiver) around an environment and measuring the Signal Reflection Profile (SRP) from every location (see Figure 1[d] for an example SRP), but the process is costly and time-consuming. They can also use propagation simulator tools based on Ray-tracing algorithm to save the time and cost for survey, but it's extremely challenging to mathematically model and validate NLOS signal reflectivity due to extremely short wavelength and lack of open-source datasets at high frequency, such as D-band mmWave.

In our recent work [5], we have designed and validated a low-cost, visual data and deep learning-based approach to predict the SRPs for indoor 24 GHz mmWave networks, which in turn, facilitates effective picocells deployment for better indoor connectivity. *The key idea is that visually similar-looking objects likely produce similar mmWave reflections; so, a learned model could predict predict the SRP from any viewpoint within the environment, even if the deployer has only measured the environment briefly*. This allows multi-fold reduction in survey time by transferring the learning from one environment to another. In this work, we extend our past work [5] towards facilitating D-band mmWave deployment. Specifically, we target 122 GHz D-band because of its off-the-shelf hardware availability [2]. *Our goal is to first re-design, implement, and validate the deep learning model used for 24 GHz towards 122 GHz and then find potential avenues for improvements*. To this end, we design a custom data collection hardware by integrating an ASUS Zenfone AR smartphone with the 122 GHz mmWave transceiver [2, 6] to collect the mmWave SRPs, visual Point Cloud Data (PCD), and poses of the device. Evaluation on 4 diverse environments show a correlation between visual PCD and SRPs, and with a deep learning approach, we are able to predict 122 GHz SRP with a median error of 3 dB across 8,000 test samples. While the preliminary results are encouraging, the worst-case prediction error could be more than 10 dB, leading to sub-optimal or incorrect deployment. So, in the future, we will explore multiple avenues for improvement, such as reducing the SRP prediction error with semantic knowledge of the environment, finding the optimal number and correct location of the picocells, combining lower-frequency picocell with D-band picocell, and investigating the use of re-configurable intelligent surfaces to enhance the SRPs [4].

2. SYSTEM DESIGN

To facilitate the network deployer in finding the optimal D-band picocell locations, we first estimate the mmWave SRP map of an environment. Instead of using an extensive survey or propagation simulator, we leverage the visual map of an environment and analyze its features to build a relationship with a few SRP from a brief scan in the environment. To this end, we train a Deep Convolutional Neural Network (DCNN) to extract the features automatically and learn its association with the measured SRPs. Then, we use the trained DCNN to predict SRPs for the rest of the locations in the

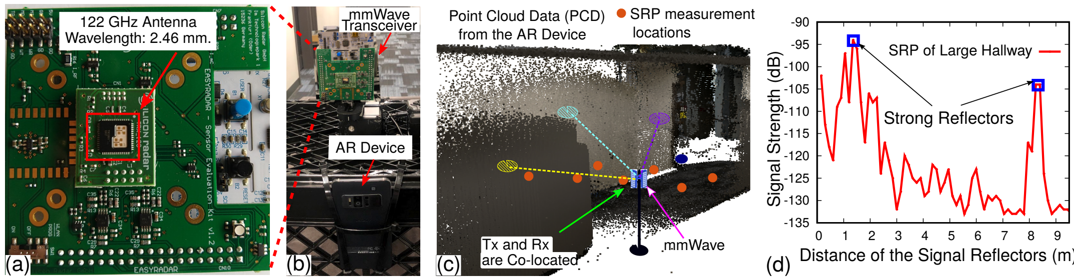

Figure 1: (a–b) 122 GHz mmWave transceiver and AR device setup. (c) An example PCD with strong reflectors and mmWave transceiver. (d) SRP at a pose (blue circle of Figure 1[c]).

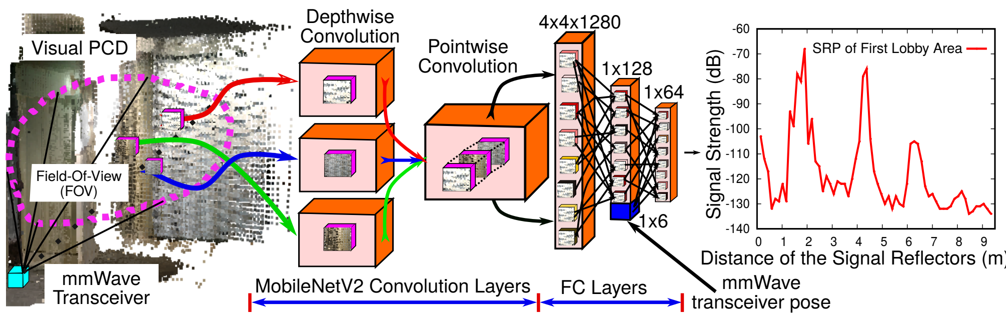

Figure 2: Deep Convolutional Neural Network (DCNN) architecture to learn association between visual PCD and SRPs.

environment. Next, we explain system design in detail.

Visual PCD to SRP Correlation: We first study the feasibility of SRP prediction from the visual data by estimating their correlation. Due to the lack of existing devices that can provide D-band SRP and measure the visual PCD simultaneously, we built a custom data collection set up by integrating an ASUS ZenFone AR smartphone and a 122 GHz mmWave transceiver and calibrate/sanitize the datasets following the method described in [5] (see Figure 1[a–b]). To estimate the correlation between the visual data and mmWave, we first project the PCD into several 2D depth images based on the device pose and Field-Of-View (FoV) [7]. We then calculate the Structural Similarity Index Measure (SSIM) [8] between the depth images for visual similarity and Mean Squared Error (MSE) between the measured SRPs for signal similarity from a pair of poses. SSIM closer to 1 indicates higher visual similarity and MSE closer to 0 indicates higher signal similarity. We use measurements across 4 indoor environments to build 80,000 pairs of MSE and SSIM.

Figure 3 shows the correlation results, where each dot represents one pair of SSIM and MSE. Although some environments show relatively stronger correlation between visual data and mmWave SRP, we observe that the relationship is mostly non-linear and complex. This is expected because SRP depends on multiple factors that may not be able to describe by depth image alone. In our recent works [5], we have also observed such a complex, non-linear relationship in our previous work with 24 GHz mmWave picocells [5], but we were able to predict the SRPs to facilitate near-optimal picocell deployment using a DCNN model. We now evaluate the effectiveness of such a model for 122 GHz deployment.

SRP Prediction Model: We re-design and implement the DCNN model in [5] to learn the complex relationship between the visual PCD and 122 GHz SRPs. We use the depthwise and pointwise convolutions from MobileNetV2 [10] to extract the features from the depth images and then map them to the SRP (see Figure 2). Our system uses the MobileNetV2 to reduce computational cost and make it suitable for mobile deployment. We then pass the features extracted from the convolution layers into the fully connected dense layers that are customized specifically to predict the 122 GHz SRP at the output. The output layer is of size 1×64, which corresponds to the predicted SRP at a location. Note that, before the final output layer, we supply the pose of the mmWave transceiver (location and orientation) explicitly to increase DCNN's robustness since the measured SRP is also affected by the way the deployer holds or moves the device. To update the DCNN's network parameters, we use the MSE loss between the actual and predicted SRPs.

Preliminary Results: To evaluate the performance, we use 20,000 data samples from each environment and train the DCNN with 17,000 training data samples for up to 1,000 epochs. During training, we save the model that performs best on 1,000 validation data samples. Post-training, we use the best model and the remaining 2,000 test data samples to predict the SRPs. Finally, we calculate the Mean Absolute Error (MAE) between the predicted SRP and actual SRP. Figure 4 shows the SRP prediction error, where each bar and errorbar represent the median and 90^{th} percentile error, respectively. While the 90^{th} percentile error could be high, close to 10 dB in certain environments, the median errors are between 2.49 dB to 3.7 dB only. The median prediction error for 122 GHz is also slightly higher than 24 GHz in the same environment because 122 GHz is more sensitive to environmental structures, suffers from high attenuation, and has distinct reflective properties [3].

3. DISCUSSION AND FUTURE WORKS

Although the preliminary results for 122 GHz are encouraging, the SRP prediction error is larger than 24 GHz [5] and may not be tolerable for practical picocells deployment. But we believe there are multiple avenues to improve the SRP prediction, such as adding semantic labels of the objects explicitly in DCNN for better feature extraction, limiting the number of real SRP values that DCNN needs to predict by ignoring values close to noise floor to aid faster convergence [5], customizing and evaluating other learning algo-

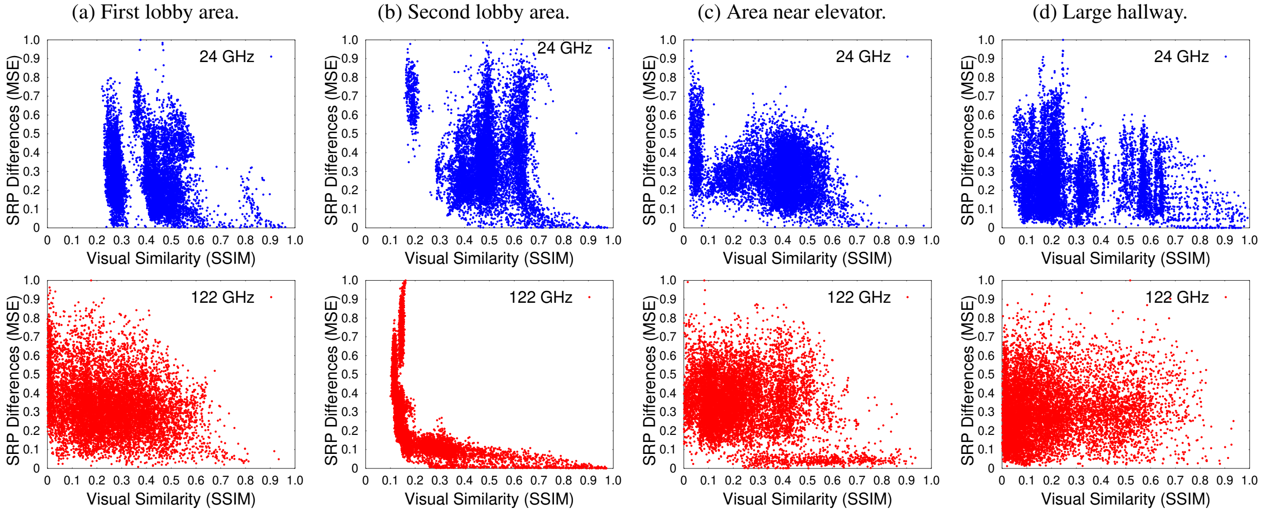

Figure 3: Relationships between the SRPs and visual data across four different environments (a–d) of the Storey Engineering and Innovation Center at the University of South Carolina [9] for two different mmWave frequency bands: 24 GHz (Blue) [5] and 122 GHz (Red).

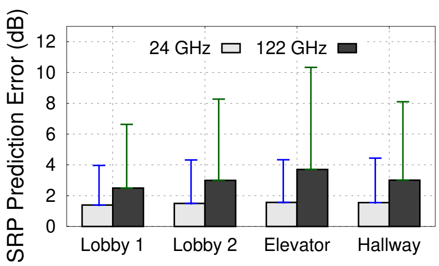

Figure 4: SRP prediction errors across four different environments. Bar is the median error and errorbar is the 90^{th} percentile error.

rithms, such as semi-supervised and reinforcement learning. Better SRP prediction will then allow us to not only achieve optimal picocell deployment but also enable multiple applications, such as indoor localization and VR/AR applications under poor visibility. The density of the picocells are expected to be much higher than existing Wi-Fi, LTE, or 5G [11], but the answer to the questions of "*how many*" and "*where to*" deploy those picocells is non-trivial.

In the future, it could also be feasible to deploy the lower-frequency mmWave picocells (like, 24 GHz) with higher-frequency D-band picocells (like, 122 GHz) for better connectivity. Based on the predicted SRPs at various frequency bands, we can quickly emulate different deployments by varying the number of picocells, operating frequency to find the expected network quality before the deployment. Furthermore, we can estimate the probability of link-outages, long-term throughput, and area spectral efficiency and decide the optimal deployment. But some environments may lack any strong reflectors that are essential for NLOS path; so, we may need to reconfigure the environment itself by installing Reconfigurable Intelligent Surfaces (RIS) [12] at judicious locations to enhance the SRPs. Our model predicted SRP within the current environment could give the location hints for such RIS deployment. In summary, we would like to focus on such "*what-if*" analysis on picocell's deployment in the future so that a network deployer can leverage multiple factors, such as changing the number of picocells, varying operating frequency, installing RIS at different locations, *etc.*, to improve the robustness and network quality of service.

4. CONCLUSION

In this work, we show that a deep learning based model can be trained with a few depth image and D-band mmWave SRP pairs from random locations in an environment, and the trained model can be used to accurately predict SRPs at unexplored locations. This is a first-of-a-kind approach to predict SRPs at D-band mmWave, and provides encouraging results for us to explore different D-band picocell deployment techniques in the future.

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