Outdoor Millimeter-Wave Picocell Placement using Drone-based Surveying and Machine Learning

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Proliferation of 5G

• 5G use has rapidly increased in recent years and is expected to support massive numbers of smart devices worldwide

• 5G is used for mobile communications, virtual/augmented reality, Internet of Things, autonomous vehicles, etc

• 5G uses millimeter-wave (mmWave) as its major wireless technology and short-range base stations called picocells to provide high data rates
Challenges with Picocell Placement

• Line-of-Sight (LoS) paths to picocells are easily obstructed and thus often rely on Non-Line-of-Sight (NLoS) paths

• Finding NLoS paths in outdoor environments can be difficult when many objects do not reflect strongly

• Deployers must find strong NLoS paths for picocells to use when LoS paths are blocked
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Existing Approaches

• Existing approaches mostly rely on site surveys or propagation models to estimate the mmWave Signal Reflection Profile (SRP) in the environment.

• They then use the SRPs to place picocells in a way that achieves high signal strength through NLoS paths.

• Site surveys are expensive and time-consuming in large outdoor environments, and propagation models are often unable to represent them at high frequencies.

• Past works that aim to reduce survey time are limited to small-scale indoor environments, and do not address issues present in large outdoor environments.

“ExterNetworks charges $4,200 for outdoor wireless site surveys up to 100,000 sq.ft.”

Source: ExterNetworks  
Source: Remcom
Our Approach: Theia

- Theia aims for easier outdoor surveying and enables deployers to identify near-optimal picocell locations.
- Theia leverages visual information to model the complex relationship between visual data and the mmWave SRPs.
- Theia utilizes advancements in deep learning and builds a customized deep convolutional neural network.
- This enables Theia to predict SRPs from unseen viewpoints and use them to place picocells that maximize available NLoS paths.
Signal Reflection Profiles

- Using a mmWave transceiver, we send signals at increasing frequency into the environment.
- The signal bounces off reflecting points in the environment and returns to the receiver.
- With the time of flight of the signal and a Fast Fourier Transform (FFT) we get the reflectors’ distance.
- With 3 transmit and 4 receive antennas, we get SRPs from 12 virtual channels at slightly different poses.
System Overview

- Theia enables deployers to achieve optimal picocell placement with easy SRP prediction

- The drone platform collects depth images, pose data, and SRPs from the outdoor environment

- The depth and pose data is synchronized with SRPs then fed into a Deep Convolutional Neural Network

- The DCNN predicts SRPs at different environmental locations, which are used for picocell placement
Visual to SRP Relationship

- Test Hypothesis: *Similar looking objects produce similar mmWave reflection profiles*

- Compute SSIM between depth images and MSE between corresponding mmWave reflections

- A complex, nonlinear trend cannot be captured by a simple regression-type model

- Differences between environments would make a single model nongeneralizable
SRP Prediction using DCNN

- Measured SRPs act as low-resolution images, predicted SRPs act as high-resolution images, and positions as labels.

- Our problem is in the same vein as the super-resolution problem.

- Depth images and antenna pose are fed as input with SRPs at the same pose used as ground truth.

- MSE between predicted and ground truth SRPs are used as the loss function.
Preprocessing: Data Synchronization

- The different systems start at different times and have different sampling rates, but hardware-level synchronization is not available for our platform, so we implement software-level synchronization.

- By recording starting timestamps for each system, we can use the time offset to align the data.

- Using interpolation and decimation to match rates, using an overlapping time window for the SRPs.
Preprocessing: Constructing DCNN Input

• The transceiver’s signal emission (beam) pattern means not all depth information contributes equally

• We first get the Inverse Depth Image (IDI) to prioritize closer objects

• Using the normalized transmit and receive power for different angles, we get a 2D beam pattern matrix

• We adjust the 2D matrix to match the depth sensor’s Field of View (FoV), then mask the IDI with this

• We supply the Masked Inverse Depth Image (MIDI) and transceiver pose as input for the DCNN
DCNN Model

• We evaluated multiple models as convolution layers, deciding on MobileNetV3_Large as it produced the highest performance with the lowest memory and computational constraints.

• We concatenate the MIDI for input into MobileNetV3_Large for feature extraction, trimming the model after its convolution layers, then feed the output to customized FC layers for regression.

• We include the transceiver pose directly into the FC layer to increase the network's generalizability.
Picocell Deployment

• Since SRPs provide information about strong reflectors, we can place picocells to best utilize the NLoS paths the reflectors provide

• The placement algorithm uses a Ray-tracing approach to simulate a separate transmitter and receiver and includes realistic reflections from predicted SRPs

• We use three placement strategies:
  • “Average” aims to provide higher mean throughput to all clients in the environment
  • “Variance” aims to achieve similar signal strengths across the environment
  • “Link-outage” aims to ensure a certain level of signal strength across the environment

Regmi, et al., 2022
Real-world Data Collection

• Hardware Setup:
  • DJI Matrice 100 Drone for flight
  • DJI Guidance System for depth and IMU
  • TI IWR1443BOOST 76-81GHz mmWave transceiver and DCA1000EVM capture card for SRP collection

• We use a 2 meter tethered connection between drone and laptop for safety and data integrity

• Zigzag paths are used with each 10-minute data collection consisting of multiple passes

• Different paths are used to compare path variability
Real-world Data Collection

- Datasets are collected across 6 environments in 3 different outdoor spaces over a period of 4 months
  - Environments A.# are all located in outdoor space A

- We have collected and processed over 44 GB of data with about 144,000 data samples

<table>
<thead>
<tr>
<th>Environment</th>
<th>Drone Path</th>
<th>Base Yaw Angle</th>
<th>Purpose</th>
<th>Elements of Environment</th>
</tr>
</thead>
<tbody>
<tr>
<td>A.1</td>
<td>P1</td>
<td>0°</td>
<td>Courtyard and Patio</td>
<td>Trees, patio tables, patio seating, stairs, handrails</td>
</tr>
<tr>
<td>A.2</td>
<td>P1</td>
<td>90° CW</td>
<td>Courtyard</td>
<td>Trees, benches, glass windows</td>
</tr>
<tr>
<td>A.3</td>
<td>P2</td>
<td>45° CCW</td>
<td>Courtyard and Patio</td>
<td>Trees, patio tables, patio seating, stairs, glass windows and doors</td>
</tr>
<tr>
<td>A.4</td>
<td>P3</td>
<td>0°</td>
<td>Courtyard and Patio</td>
<td>Trees, patio tables, patio seating, glass windows and doors</td>
</tr>
<tr>
<td>B.1</td>
<td>P3</td>
<td>0°</td>
<td>Sports Field</td>
<td>Trees, bushes, benches, fences, glass windows and doors</td>
</tr>
<tr>
<td>C.1</td>
<td>P1</td>
<td>180° CW</td>
<td>Sports Field Lounging Area</td>
<td>Trees, bushes, picnic table, fences</td>
</tr>
</tbody>
</table>
Network Training

- Theia’s SRP prediction model is trained with the following parameters:
  - **Training time**: 1000 epochs, halted after 20 epochs of learning stagnation
  - **Optimizer**: NAdam with learning rate of 0.005
  - **Loss Function**: Mean Squared Error (MSE)

- The models are designed and implemented using Python and Pytorch on a server to reduce training time to ~1 hour for each model
  - AMD EPYC CPU @ 2.8GHz
  - 264 GB RAM
  - Nvidia RTX A6000 GPU
DCNN Model Performance

- Trained on datasets from outdoor space A only using 1 virtual channel
- Samples chosen at random with 90:10 train-test ratio (2145 test samples)
- Median error: **3.7 dB**
- 90\textsuperscript{th} percentile error: **9.3 dB**
- 90\textsuperscript{th} \%ile error has little effect on picocell placement.
Multi-Channel Surveying

- Trained on datasets using different numbers of virtual channels
- The number of virtual channels has little effect on the median and 90\textsuperscript{th} percentile error
- *Deployers can use any number of virtual channels*
Drone Path Variability

- Trained on datasets using low, medium, and high path variability (Drone paths P1, P2, and P3)

- Errors are within 0.2 dB for both metrics for all path types

- Deployers likely won’t need to worry about path variability
Survey Time Requirement for Fine-Tuning

- The model is initially trained on datasets from environment A.1
- Then the model is trained on samples from A.2 based on survey time, then tested with A.2 samples
- With no fine-tuning, the median and 90\textsuperscript{th} percentile errors are 6.3 dB and 13.4 dB respectively
- Just 1 minute of fine-tuning reduces errors to 4.2 dB and 10.4 dB, and 5 minutes performs like the base model
- *Deployers will save time collecting new samples*
Generalizability to New, Similar-Looking Environments

- The model is trained on datasets for each outdoor space.

- Despite environmental differences, the model is able to learn with all errors within ~0.1 dB of each other.

- *Theia performs well in new, similar looking environments*
Picocell Deployment Performance

• We build a Ray-tracing method with separate transmit and receive antennas using measured SRPs, using Theia’s prediction error to enable realistic placement errors

• We also simulate 3 other placements:
  • Random chooses random placements in the environment
  • Common-Sense places picocells at corner locations
  • Optimal is placed assuming zero SRP error

• Theia performs close to Optimal when placing picocells in outdoor environments
Picocell Deployment Performance

- We look at the performance of the “average”, “variance”, and “link-outage” strategies for in outdoor space A.

- All methods have median average signal strength within 5 dB, and Theia is able to limit SRP variation to 0.8 dB and reduce the area without links by ~2.76x compared to Random and Common-Sense.

- This shows the importance of accurate SRP prediction for deploying picocells in outdoor areas.
Conclusion

- Theia enables accurate mmWave SRP prediction in multiple large-scale outdoor environments
- Theia can fine-tune to new environments with as little as 5 minutes of survey data
- Theia’s SRP prediction accurately estimates picocell placements to enable reliable outdoor mmWave networks

Thank you for your time!

Check out our paper for more results:

If you have questions: Email to mcdoweli@email.sc.edu

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