Poster: VisualMM: Visual Data & Learning Aided 5G Picocell Placement

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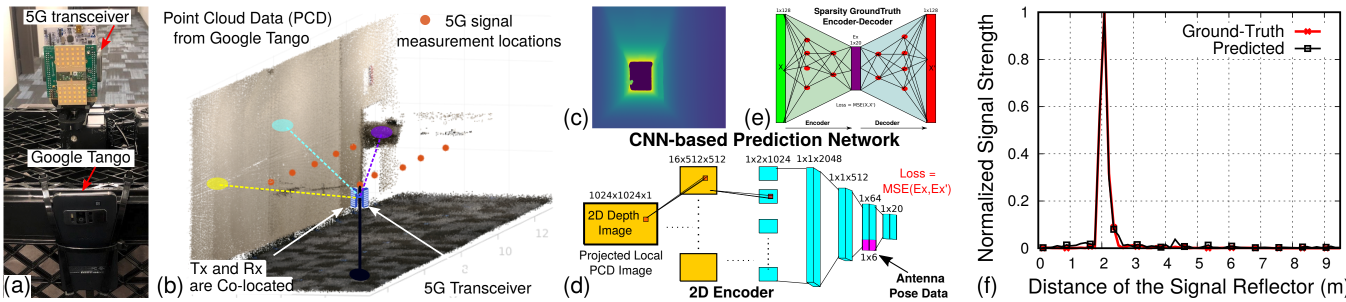

Figure 1: (a) Measurement setup with a 5G transceiver and a Google Tango phone; (b) Visual Point Cloud Data (PCD); (c) 2D depth projected from one viewpoint inside the PCD; (d) CNN-based prediction framework that learns the correlation between visual features to mmWave signal strength; (e) Sparsity encoder-decoder to learn the strongest reflectors in the environment; and (f) An example of signal strength predicted in the environment in comparison to the ground-truth.

CCS CONCEPTS

• **Networks** → **Network management**; • **Computing methodologies** → **Neural networks**.

KEYWORDS

Millimeter-Wave, Picocells, Convolutional Neural Network, Transfer Learning

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PICOCELL DEPLOYMENT CHALLENGES

Millimeter-wave (mmWave), the core technology of 5G, offers substantially higher data-rates than traditional wireless, but the communications are limited to Line-Of-Sight (LOS) and very few reflection paths. So, the network relies on short-range base-stations called "*picocells*." Since the paths are prone to obstructions and specular reflections, networks require careful picocell placement. Furthermore, picocells must be densely deployed to compensate for their short-range, and often demand unintuitive placement locations to maximize their effectiveness. Because of the placement density and accuracy requirements, thorough site surveys are often time consuming and expensive. In summary, we have two related challenges: (1) Effective utilization of 5G networks could be hampered without sufficiently judicious picocell deployments; and (2) Small changes in an environment after deployment could necessitate re-arranging the picocells, requiring repeat site surveys, and thus, increasing network maintenance costs.

We propose *VisualMM*, a tool to enable 5G deployers to quickly and efficiently complete site-surveys without sacrificing the accuracy and effectiveness of thorough placement surveys. Our approach is intuitive: *VisualMM* identifies deployment locations that maximize a set of picocells' likelihood of having reflection paths. Thus, the network could be more effective in a dynamic environment, by virtue of not being dependent on only the LOS path. The key idea is to first model the mmWave reflection profile of an environment, considering dominant reflectors, and then use this model to find locations that maximize the usability of the reflectors.

VISUALMM DESIGN

First, a deployer uses an AR device, like Google Tango (Fig. 1[a]), to quickly create a visual map by walking around (Fig. 1[b]); *Second*, as the deployer is walking around, a co-located 5G transceiver continuously measures the reflections from various objects by steering the mmWave beam rapidly. *Finally*, *VisualMM* leverages the visual data and corresponding reflections to create a mapping between objects to their mmWave reflections. Intuitively, similar looking objects likely produce similar reflections; thus, the learned model can potentially predict the signal reflection patterns from any other viewpoint, even if the deployer has not measured them. *VisualMM* then uses this prediction to estimate the locations that have the maximum likelihood of finding reflection paths.

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To learn the mapping, we propose to use a Convolutional Neural Network (CNN) that maps depth and color to the reflections through supervised learning [1]. From the 3D visual data, we project a 2D depth image from a viewpoint where the reflections were collected, and then feed the reflection as the training ground-truth to the CNN. The prediction network extracts the features with multiple convolutions followed by batch-normalization and leaky ReLU layer [1]. We further amend the network by incorporating the antenna pose information since reflection is also affected by the way the deployer holds the device, and the device steers its beam.

Furthermore, mmWave reflections are mostly sparse, *i.e.*, many objects in the environment do not reflect back signals. So, instead of predicting the reflections from every point, *VisualMM* only predicts the strongest ones. We apply a sparsity encoder-decoder to extract such sparse patterns in the reflected signal (Fig. 1[e]); the encoder converts the original reflections (mostly sparse) to only 10 reflection points, and the decoder predicts the signal strength. Fig. 1(f) shows an example signal strength prediction result, which closely matches to the ground-truth. In the future, we will evaluate *VisualMM* in multiple indoor and outdoor environments, with different lighting conditions, its deployment effectiveness, and its ability to transfer learning between environments.

ACKNOWLEDGEMENT

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REFERENCES

[1] Thomas Wiatowski and Helmut Bölcskei. 2018. A Mathematical Theory of Deep Convolutional Neural Networks for Feature Extraction. *IEEE Transactions on Information Theory* 64, 3 (2018).