Argus: Predictable Millimeter-Wave Picocells with Vision and Learning Augmentation

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ABSTRACT

We propose *Argus*, a system to enable millimeter-wave (mmWave) deployers to quickly complete site-surveys without sacrificing the accuracy and effectiveness of thorough network deployment surveys. *Argus* first models the mmWave reflection profile of an environment, considering dominant reflectors, and then uses this model to find locations that maximize the usability of the reflectors. The key component in *Argus* is an effective deep learning model that can map the visual data to the mmWave signal reflections of an environment and can accurately predict mmWave signal profile at any unobserved locations. It allows *Argus* to find the best picocell locations to provide maximum coverage and also lets users self-localize accurately anywhere in the environment. Furthermore, *Argus* allows mmWave picocells to predict device's orientation accurately and enables object tagging and retrieval for VR/AR applications.

We implement and validate *Argus* on two different buildings consisting of multiple different indoor environments. However, the generalization capability of *Argus* can easily update the model for unseen environments; so, *Argus* can be deployed to any indoor environment with little or no model fine-tuning.

CCS CONCEPTS

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

KEYWORDS

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

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1 BACKGROUND AND MOTIVATION

Millimeter-wave is the core technology for the new wireless LAN and cellular standards, such as IEEE 802.11ay [1] and 5G NR [2], and the key enabler for many high throughput and ultra-low latency wireless applications. Millimeter-wave (mmWave) networks offer a substantially higher data rate than the traditional wireless networks, but the communication is limited to Line-Of-Sight (LOS) path and very few reflections in Non-LOS (NLOS) paths [3, 4]. So, the network relies on light-weight, short-range, and densely deployed base-stations called "*picocells*," which use electronically steerable beams and communicate on very high frequency, on the order of tens of GHz, and wide bandwidth. Due to the short wavelength, each picocell can host multiple palm-sized antenna arrays that can create hundreds of beams to serve mobile users. With such capabilities, the picocells and mobile devices can also function as high-precision environment sensors.

But the short wavelength, high signal attenuation, and environmental obstructions of mmWave links often yield unavailability or misalignment of the paths, which makes the performance of the picocells unpredictable [5–7]. Picocells can electronically steer beams to track their paths and coordinate among neighboring picocells to enable robust connectivity. But the effectiveness of coordination and adaptation depends on whether the neighbors can support reliable connectivity since their links are also sensitive to the environmental structure [8–10]. While it is not always feasible to transform the environment to aid the picocells (*e.g.*, by adding more reflectors), a network deployer can place the picocells smartly to improve the NLOS paths availability and thereby improve the predictability of mmWave links. Full site surveys may achieve this goal by war-driving a mmWave transceiver and measuring the *Signal Reflection Profile* (SRP) from every *nook and cranny*, but they are costly and time-consuming [11, 12]. Ray propagation-based simulators may reduce the cost and time, but they are frequency-specific since the NLOS signal reflectivity is frequency-dependent. So, it is either costly or challenging to identify the mmWave SRP in a given environment.

2 VISION AND LEARNING MODEL

We propose Argus, which explores a low-cost, visual data and deep learning based approach to predict the SRPs in indoor mmWave picocell networks.[1] Prior approach based on channel sparsity and geometrical propagation aimed to predict the reflection profiles in 60 GHz networks [8, 9], but the design has been tested and validated only in a single indoor environment. However, the extreme density of mmWave picocells, ultra-wide bandwidth of links, lack of coherency in hardware, and under-explored models of mmWave channels across multiple environments limit the applicability of sparsity or traditional signal processing. On the other hand, visual data can extract higher resolution environmental information, and

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[1] *Argus* was the Roman god of surveillance and watch, and the great vision and wisdom of *Argus* is analogous to our proposed model with visual data and deep learning.

deep learning can reveal complex models to tackle hard optimization problems. At a high level, *Argus* builds a framework to identify the mmWave SRP in an environment enabling network deployers to quickly and efficiently complete site surveys without sacrificing the accuracy and effectiveness of a thorough deployment survey. Our approach is intuitive: *Argus* identifies deployment locations that maximize a set of picocells' likelihood of having reflection paths; so, the network could be more effective and predictable in a dynamic environment by virtue of not being dependent on only the LOS path. The key idea is to first identify reflectors' properties, *i.e.*, reflectivity, location, and orientation, to model the SRP of an environment, and then use it to find the locations that maximize the usability of the reflectors.

To identify the reflectors' properties, *Argus* combines a visual Point Cloud Data (PCD) and a few SRPs measured sparsely inside the environment to build a deep learning model. Intuitively, *visually similar objects likely produce similar reflections; so, the learned model could predict the signal reflection patterns from any other viewpoint within the environment, even if the deployer has not measured them.* But training the model with the entire PCD will unlikely work since it will learn the noise from random pixel colors and distances. Besides, there are only a few objects in the environment that contribute strongly to the mmWave SRP [9]. So, *Argus* extracts the objects from the PCD within a limited FoV and uses prior knowledge of object labels as training input. The trained model can then be transferred to other environments which have similar structures, such as walls, ceilings, beams, columns, floors, *etc.*, with little to no fine-tuning. Besides identifying effective deployment locations, *Argus* can also use the predicted SRPs to enable several applications: (a) Identifying user's location or aiding robot navigation based on the pre-characterized SRPs; (b) Classifying or tagging objects under low-light conditions in VR/AR; (c) Adapting picocell's data transmission rate for different users; and (d) Uncovering "*signal holes*" in the environment and facilitate mounting intelligent surfaces on the walls to improve the SRP distributions [13].

3 RESULTS AND CONTRIBUTIONS

We implement and evaluate *Argus* by building a custom platform for data collection. The setup uses an ASUS Zenfone AR smartphone [14] to collect the PCD and poses of the device and a co-located 24 GHz mmWave transceiver [15] to collect the SRPs. Since it is hard to trigger the mmWave transceiver and smartphone at the same time due to various software-level delays, *Argus* post-processes the SRP and visual data in software to achieve synchronization. Our experiments across 16 indoor environments in two buildings over a period of 5 months, with 11 GB of data (~1.1 million samples), show that by re-training *Argus* for individual environments, it can predict the SRP with a median error of 1.5 dB and 90^{th} percentile error of 4.2 dB only with a base learning model. But the base model, which only considers the distance of the reflecting objects from the transceiver, fails to generalize over other environments. When transferred and tested in untrained environments, the median error is close to 12 dB, and the 90^{th} percentile error could be up to 35 dB! Fortunately, by incorporating the prior knowledge of the environment during training, *Argus* is able to contain the error to only 6.2 dB on the median. Furthermore, by predicting only important points of SRP, *Argus* is able to identify the SRP with a median error of 4.5 dB for completely unseen environments. For picocell deployment, *Argus* is able to reduce the link outage probability in multiple environments by almost 1.55× compared to random and common-sense deployment strategies. For localization and orientation, *Argus*'s predication errors are less than 35 cm and 1.7°, respectively, on all axes for 90^{th} percentile of measurements in diverse environments. For object tagging, *Argus* can classify objects and retrieve them with more than 98% accuracy.

In summary, we have the following contributions: (1) We design a framework for visual data and deep learning augmented mmWave signal reflection profile prediction. It includes the semantic understanding of the environment to make the model robust and effective across multiple environments. *Argus* is the first system to enable such accurate prediction for practical mmWave picocells. (2) We design and evaluate methods for picocell deployment, device's location and orientation prediction, and object classification for VR/AR applications under poor visibility. Our results demonstrate that *Argus* generalizes well across diverse environments, and it enables reliable and versatile mmWave networks and applications.

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