Demo : Synthetic Data for Data-Driven Wireless

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ABSTRACT

The fundamental bottleneck in adapting data-driven wireless solutions to real world is the lack of tools for augmenting good quality data which is environment-specific. Indeed, much of the data required for popular data-driven wireless communication and sensing systems requires domain expertise beyond the reach of an average consumer. This demo presents a radical new vision for generating synthetic data in consumer-specific environments by leveraging the power of modern compute.

This demo presents a vision for consumer-facing wireless tools that can augment synthetic data for development and adaptation of data-driven wireless systems. Our solution leverages existing ray-tracing based wireless simulators in a new way to map and visualize the coverage in three key use-cases for this technology. Further, we motivate the need for development of such tools for generating synthetic data is vital towards a broader vision of foundational wireless models for data-driven wireless communication and sensing systems.

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1 INTRODUCTION

Wireless communication is integrated deeply in our everyday life with devices becoming increasingly mobile. The sheer diversity of wireless technologies we use range from local (e.g. home WiFi, NFC payments, and RFID cards) to long distance (e.g. cellular, mmWave FR2 5G, satellite SOS). This deep penetration and usage of wireless technologies by average consumers makes them ideal for data-driven optimizations in consumer-specific scenarios. While there have been significant advances in developing data-driven wireless communication (e.g. beamforming [14, 18], decoding [12], channel estimation [13]) and sensing (e.g. location tracking [7, 15], radar imaging [8]) systems, these benefits have remained out of reach for the average consumer. The primary bottleneck in adoption of these solutions in real-world deployments is their generalizability. The heterogeneous nature of devices deployed as well as the varying impact of the different physical environments on wireless propagation makes it almost impossible to develop a one-shot data-driven wireless solution.

This paper and accompanying demonstration presents the first steps towards augmenting synthetic data in unknown environments by developing accessible visualizations in XR. The demo presents a general purpose pipeline for generating synthetic data in unknown environments by combining existing solutions for capturing environment, performing ray tracing and generating technology specific metrics. Our broader vision for the developed tool is to highlight this important problem of augmenting synthetic data for wireless solutions and present a pipeline for researchers and industry-alike to bring further transparency to services provided and new technologies developed and deployed. Further, we envision such consumer-facing applications to be source of invaluable diverse wireless data necessary to develop future wireless foundational models.

2 RELATED WORK

There has been some work on developing visualization tools for wireless technologies by either listening to wireless signals [6, 9] or using active tags in the environment to visualize signals [17]. Further, there has been much work on developing ray-tracing models [3, 4] that can model wireless propagation given a rough structure of the environment. There is also a significant work happening in further improving such models by modeling various effects [10, 11, 19]. Further, a significant number of data-driven wireless communication (e.g. beamforming [14, 18], decoding [12], channel estimation [13]) and sensing (e.g. location tracking [7, 15], radar imaging [8]) systems have been developed. Unfortunately, much of the above work requires domain expertise or requires understanding of wireless technologies to visualize

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and generate synthetic data in an unknown environment. In contrast, our work allows users to create their customized indoor environment and visualize WiFi propagation in 3D with very high resolution. We leverage existing on-phone LIDARs for capturing indoor environment and free public environment models available in Open Street Maps[5] for outdoor environments. We then leverage Sionna-based ray-tracing for generating synthetic data in the chosen environment for a given technology. We further demonstrate the value of generated data for three real-world applications. Finally, our tool allows users to visualize the 3D signal power via XR which makes it easier to explore.

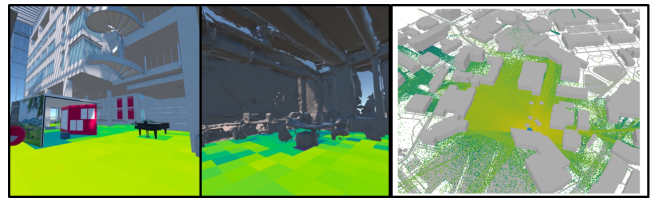

Figure 1: Our demo will augment synthetic wireless data for demonstrating three applications in XR : (1) Indoor Coverage (2) WiFi Deployment Usecase (3) Cell Tower Deployment

3 XR VISUALIZATION DEMONSTRATION

We will present 3 practical real-world scenarios that have the potential to significantly improve consumer awareness of popular wireless technologies in the real world: (1) coverage of indoor WiFi produced by router placed at various locations; (2) impact of building materials on wireless coverage; and (3) visualizing outdoor coverage across cell towers on a real world campus.

We make our visualizations intuitive to consumers focusing on throughput at a given location by colors. Specifically, we will visualize relative signal strength at different locations through color differences – a brighter color indicates a better throughput, and vice versa. Therefore, color like green and yellow signifies a location with good signal coverage, while a location colored by blue and purple will have worse coverage for a wireless technology operating at a given frequency communicating with a known ground station.

3.1 Demo 1 – Large-scale Indoor Propagation

In the first scenario, we take an accurate 3D model provided to us for a building from a detailed CAD files generated during construction of the building. In this well-designed scenario, we generate the signal propagation throughout the building for a given WiFi base station. Specifically, we demonstrate the variation of signal power in the XR tool which could assist the deployment of WiFi base station mesh. We leverage the information about the materials of objects such as walls, pipes and other reflectors in the environment to simulate the wireless environment more accurately. We further demonstrate how this generated synthetic data can be leveraged to develop and adapt data-driven algorithms to the environment.

3.2 Demo 2 – Indoor WiFi Coverage

The second demo scenario visualizes indoor WiFi coverage in a lab setting. An end consumer typically deploys their WiFi base station in their home in the location closest to the wire (copper/optical fiber) coming out of the wall. The primary reason behind this colloquial choice being the lack of accessible tools to ascertain a good location for maximum coverage inside their home. This necessitates deployment of additional relays or range extenders to provide WiFi coverage to the whole house. Further, many next-gen home WiFi solutions leverage 5G backhaul to provide reliable coverage indoors enabling free-form deployment of WiFi ground station.

We present one such proof-of-concept deployment in a lab setting with multiple obstacles. First, we leverage off-the-shelf iOS applications [1, 2] to capture the laboratory environment using an commodity iPhone 15 Pro Max. As one can imagine, the generated data from such low-quality LIDAR is much worse than the one seen in Demo Scenario 1. Second, we leverage the Sionna ray-tracing model [4] for generating synthetic data in the lab environment. We also demonstrate the coverage generated from this low-res environment model remain reasonably close to the true values.

In the demo, we show how various options of WiFi deployment in a lab setting indoors can affect the wireless coverage across the locations in the lab at various different heights. Further, the lab has multiple standing desks which means that the WiFi deployment will have to be cognizant of the 3D topology of the environment. We thus can leverage this visualized data to identify poor coverage at some students' desks at optimize the location of WiFi base station to maximize it.

3.3 Demo 3 – Outdoor Cellular Deployment

The third component of our demonstration represents an outdoor scenario where our goal is generate synthetic data for wireless coverage provided by cell-towers in an outdoor environment and provide cellular providers to optimize deployment of next-generation cellular deployments to maximize their quality-of-service (QoS) metrics for consumers. We first extract a rough estimate of outdoor environment by extracting the building models of a campus from publicly available open-source OpenStreetMaps Buildings [16] dataset. We then manually label the building materials for improved estimation of wireless propagation in the environment. Finally, we leverage the Sionna [4] ray-tracing engine to generate synthetic wireless coverage in the environment.

One expensive operational expense of deploying a cellular base station is identifying good locations that maximize coverage across locations. However, in complex urban and semi-urban environments, the conventional cellular deployment coverage models lack depth of information regarding the quality of service provided and primarily focus on reducing inter-cellular interference for spectrum license compliance. This demo will enable modeling of such complex environments in real-time allowing telecommunication companies to identify ideal deployment locations in advance. Our demo shows how a network deployment engineer can visualize the coverage provided across locations based on a given cell tower location. This ability to generate synthetic data in unknown environments at low-cost has the potential to significantly reduce the operational expense of cell tower deployment and yet maximize consumer satisfaction.

4 NEXT STEPS AND FUTURE VISION

There are several reasons why there exists no unified platform for generating synthetic data that performs environment capture, ray-tracing and wireless metric generation: (1) Each of the above components have been developed for different use-cases that are quite distinct (3D capturing for robotics, ray tracing for CGI lighting in movies and games, metric estimation in wireless domain) and requires significant engineering effort to plug together; (2) The pipeline is not co-designed to maximize the quality of synthetic data generated; (3) The accuracy of the generated synthetic wireless data is highly fickle due to heavy configuration requirements and requires domain expertise. We encourage researchers in the field to continue exploring new opportunities in this important domain.

We strongly believe that development of such platforms is inevitable in the unrelenting pursuit for wireless foundation models. The idea of developing a wireless foundation model is to revolutionize the prototyping of radio software and hardware and benchmarking it in multiple real-world scenarios to evaluate its effectiveness. Developing such unified foundation models in image processing, natural language processing and acoustics required synthesis of massive amount of data from both real-world and generative sources. The procurement of similar level of both real-world and synthetic data in diverse complex environments requires readily available tools to collect and real world applications to incentivize. We believe tools like ours present a unique application driven vision to fill that exact gap in the wireless ecosystem.

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