Poster: MilliCloud: Beyond Vision PCD Generation using Millimeter-Wave

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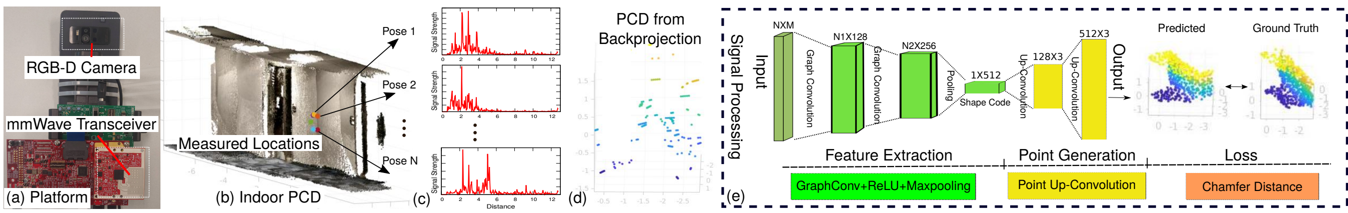

Figure 1: (a) *MilliCloud* system integrates a mmWave transceiver and an ASUS ZenFone AR smartphone; (b) Example of indoor PCD and measured locations; (c) Reflected mmWave signals; (d) PCD generated by traditional Backprojection algorithm is sparse; (e) *MilliCloud* network architecture to generate dense and high-quality PCD.

ABSTRACT

Existing 3D Point Cloud Data (PCD) generation systems based on RGB-D and LiDAR sensors require robust lighting and unobstructed field of views of target scenes. So, they cannot work properly under challenging environmental conditions. Recently, millimeter-wave (mmWave) based imaging systems have raised a huge interest due to their ability to see-through obstacles and work in dark environments. But the resolution and quality of the PCDs from traditional imaging algorithms are very poor. This work proposes and preliminary validates *MilliCloud*, a deep-learning based system for generating high-quality indoor PCDs using handheld mmWave devices.

CCS CONCEPTS

• **Computing methodologies** → **3D imaging**; • **Human-centered computing** → **Ubiquitous and mobile computing systems and tools**.

KEYWORDS

Millimeter-Wave, Graph Neural Networks, Point Cloud Data

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PCD GENERATION CHALLENGES

The rapid development of Robot, Autonomous Car, and AR applications has increased the demand for robust 3D visions of surrounding environments. Point Cloud Data is an efficient data structure for representing a 3D environment, and traditionally, RGB and Depth (RGB-D) cameras or LiDARs are used to generate PCDs. RGB-D cameras can produce high-quality PCDs and are widely used due to their low-cost and ubiquity; but they rely heavily on good ambient lighting and unobstructed views. LiDARs are robust to lighting conditions; but they are expensive, and their generated PCDs are sparse, leading to poor performance in vision applications.

With the accelerated deployment of 5G networks, mmWave devices will be ubiquitous soon, enabling many "*beyond vision*" applications [1]. Unlike optical sensors, mmWave can easily work under poor or zero visibility. However, the generated PCD is still very sparse and mostly contains ambiguous shapes of objects. In this work, *we propose MilliCloud, a low-cost solution to generate high-quality PCDs from mmWave devices*. *MilliCloud*'s key idea is intuitive: Since mmWave transceiver can accurately measure the range and angle of different objects from one viewpoint, we can identify the general structure of an environment by measuring and combining the reflections from multiple viewpoints. But combining the reflections using traditional imaging algorithms can only produce sparse PCDs (see Figure 1[d]). This is because the measured points are discrete in space, and traditional algorithm reconstructs each point independently, failing to exploit the geometric relationship among them. To this end, *MilliCloud* proposes a deep learning model that automatically learns the complex mapping between mmWave reflections and 3D space from several example data samples.

MILLICLOUD SYSTEM DESIGN

First, we use a co-located RGB-D device and a mmWave transceiver to briefly survey an environment: This generates a ground truth 3D PCD and mmWave reflections from different device poses. *Then*, the PCDs and corresponding reflections from different environments are used to train a deep learning model, creating a mapping between the geometrical structures to their mmWave reflections. *Finally*, at run-time, we use only the mmWave reflections and trained model to generate a dense, high-quality PCD without using the ground truth.

However, the number of data collection points across environments can vary, and the device poses may be distributed in 3D space randomly. So, traditional convolutions (such as, CNN) cannot be applied to the dataset as they require inputs of fixed sizes and voxels. Thus, we propose to use a Graph Neural Network (GNN), which works with variable input sizes. Figure 1(e) shows the network architecture. *MilliCloud first* uses the GNN (derived from existing PointNet++) with poses and reflected signals as input to generate a *shape-code* representing an abstract environmental structure. *Next*, it uses two up-convolution networks to convert the *shape-code* to 3D PCD. *Finally*, to train the network, it uses a gradient descent algorithm to update the convolution weights, and uses the Chamfer Distance (ChD) [2] as the loss function between predicted and ground truth PCDs.

Since existing 5G smartphones do not provide raw mmWave reflections, we design a handheld device integrating an ASUS ZenFone AR smartphone and a 60 GHz mmWave transceiver for data collection. Figure 1(a–c) show the platform and data sample. We collect datasets across 35 environments and used 28 environments to train *MilliCloud*. The results across 7 test environments show that *MilliCloud* achieves an average ChD of 0.309 m^2, and the generated PCDs are visually similar to the ground truth (see Figure 1[e]). In contrast, the traditional imaging algorithm achieves an average ChD of 0.608 m^2 only, and the generated PCDs are sparse and distorted (see Figure 1[d]). In the future, we will train and evaluate *MilliCloud* under various environmental conditions and explore different network structures and settings to improve the PCD quality further.

ACKNOWLEDGEMENT

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