# Poster Abstract: mmWaveNet: Indoor Point Cloud Generation from Millimeter-Wave Devices

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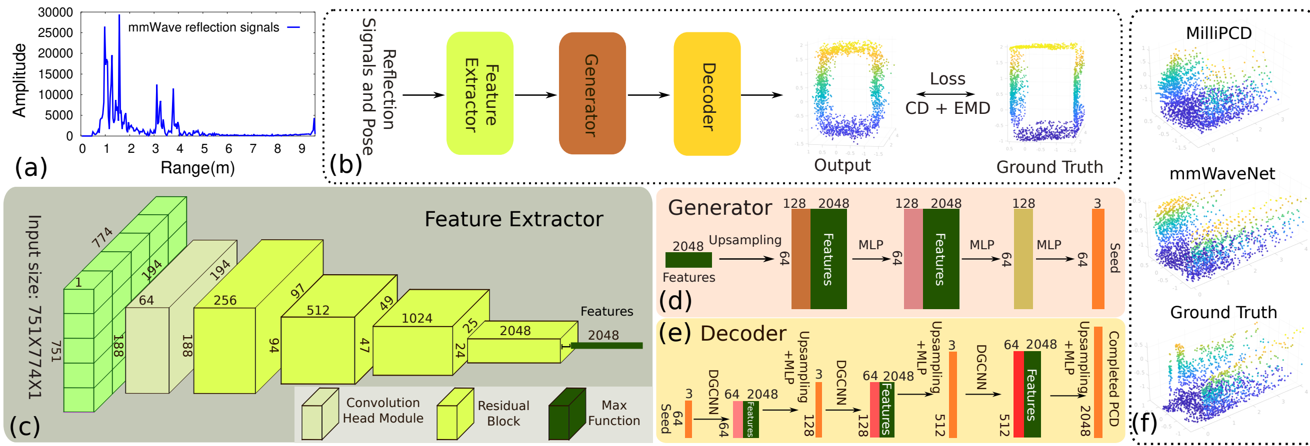


**Figure 1:** ***(a) Example of mmWave reflection signal; (b)* mmWaveNet *architecture overview; (c) Architecture of Feature Extractor; (d) Generator architecture; (e) Decoder architecture; (f) Output of MilliPCD and* mmWaveNet *comparing with ground truth PCD.***

## ABSTRACT

Millimeter wave (mmWave) 3D imaging has been applied for point cloud data (PCD) generation due to its valuable attributes, such as working under low light, compact size, and low-cost. However, past works have focused on transforming millimeter wave reflection signals into other data structures, like polar images and coarse PCDs before applying neural network to produce dense PCDs. Those algorithms will filter some useful features. To address this issue, our paper proposes an innovative prototype: *mmWaveNet*, a deep learning model that directly uses reflection signals as input and generates high-quality PCDs. We have experimentally evaluated *mmWaveNet* in a large indoor environment.

## CCS CONCEPTS

• **Computing methodologies → Vision for robotics**.

## KEYWORDS

Millimeter Wave; Point Cloud Data; Deep Learning

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## 1 INTRODUCTION

In recent years, robotics have found widespread application across various fields, *e.g.*, in factories and warehouses, numerous mobile robots are deployed to facilitate automatic production lines, relieving workers of repetitive tasks [1]. To navigate and operate, these robots rely on their sensors to produce a 3D map of an environment. A popular data structure to represent a 3D environment is the Point Cloud Data (PCD), which stores the 3D coordinates of the different points. Compared with other data structures like Meshes and Voxels, PCD provides high-resolution with a low memory footprint. And, millimeter-wave (mmWave) wireless signals from 5G-and-beyond smart devices can produce a PCD, which work under low or no light conditions in contrast to RGBD sensors and have lower cost compared to the LiDARs. MmWave devices rely on reflection signals from the environment and combine the signals from multiple antennas to construct the environmental structure. But the resolution of the PCD generated from the mmWave devices can be low due to specular and weak signal reflectivity [2].

Recently, some researchers have used deep learning models on mmWave signals to improve the quality of generated PCD [3, 4], by learning the relationships between environmental structures generated by RGBD/LiDAR and mmWave devices. For example, MilliPCD [3] proposes a two stages framework to produce complete PCD, where in the first stage, it uses Time Domain Backprojection algorithm on reflection signals to produce local PCD and then constructs rotation vectors from pose information to translate multiple local PCD into a global PCD. In the second stage, a deep learning model is applied to extract features and construct a dense PCD. RadarHD [4] applies a very low threshold on the heatmap generated by the mmWave signals for preserving strong reflectors' information, and it arranges these thresholded points into polar image, which consists of range along rows and azimuth along columns. However, processing raw reflection signals before feeding them into deep learning model, can lead to a serious loss of information, which limits the performance of these methods.

To overcome these drawbacks, we propose *mmWaveNet*, which directly uses mmWave reflection signals in a deep learning model to improve the quality of the generated PCD. The model directly extracts features from the reflection signals without any pre-processing to preserve a better environmental structure. To this end, we use residual Convolution Neural Network module to extract detailed local and global features from raw reflection signals and pose information. Then, a generator constructs a sparse PCD seed, followed by a decoder to expand the seed to generate a complete PCD. Figure 1 shows the input, network, and output from our model.

## 2 SYSTEM DESIGN

Figure 1(b) shows the overview of *mmWaveNet* architecture. It consists of three modules: A *Feature Extractor* for extracting features from reflection signals and pose; a *Generator* for producing sparse PCD seed, and a *Decoder* for expanding seed into complete PCD.

**Feature Extractor**: Previous works [3, 4] translate mmWave reflection signals into other regular data for deep learning model, such as polar image and coarse point cloud. However, such transformation filters weak reflection signals, which might eliminate valuable information from non-metallic objects. *mmWaveNet*, on the other hand, directly extracts features from the reflections and generates complete high-quality PCD, which can capture detailed features from all objects. Figure 1(c) shows the *Feature Extractor* architecture. The basic idea is employing convolution filter to extract local features and continuously reducing the height and width of inputs to make convolution filters "see" larger region. To keep detailed features, we leverage the residual blocks to concatenate features from all blocks together, so the final features contain both global features and detailed local features.

**Generator and Decoder**: To generate high-quality PCD from features, our *Generator* (Figure 1[d]) uses Transposed Convolution to upsample features into initial PCD seed, and combines seed with folding features. Then, a Multi-Layer Perceptron (MLP) composed by 1D convolution filter uses the combination of initial PCD seed and folding features to generate sparse PCD seed. Upsampling seed to a dense PCD is difficult due to the limited structure information in seed. Thereby, a *Decoder* (Figure 1[e]) applies DGCNN [5] to extract local PCD shape from seed. The upsampling layer can correctly reconstruct object shape by embedding regional features with duplicated detailed features. By repeating the DGCNN and upsampling process, we finally achieve dense, high-quality PCD.

**Loss Function**: Deep learning model requires loss function to backpropagate and update network parameters. *mmWaveNet* combines Chamfer Distance (CD) and Earth Mover's Distance (EMD) to optimize model weights. CD is a nearest-neighbour-based method and focuses on quantitative difference, while EMD mainly measures the global distribution difference. They are defined as:

$$L_{CD}(S_1, S_2) = \frac{1}{N_1}\sum_{x\in S_1}\min_{y\in S_2}||x-y||_2^2 + \frac{1}{N_2}\sum_{y\in S_2}\min_{x\in S_1}||x-y||_2^2 \quad (1)$$

$$L_{EMD}(S_1, S_2) = \frac{1}{N_1}\min_{\phi:S_1\to S_2}\sum_{x\in S_1}||x-\phi(x)||_2 \quad (2)$$

where $S_1$ and $S_2$ are the point sets, $N_1$ and $N_2$ are the number of points in them, and $\phi : S_1 \to S2$ is a Bijection function to exactly map points of $S_1$ to points of $S_2$. Combining CD and EMD, the final loss function for *mmWaveNet* is defined as: $Loss = L_{CD} + L_{EMD}$.

## 3 PRELIMINARY RESULTS

We test our model on indoor datasets from [3], consisting of 1,274 indoor PCD from 13 different environments. We use 1,109 PCD samples for training and 165 PCD samples for testing. Figure 1(f) shows an example of generated PCD of MilliPCD and *mmWaveNet*. MilliPCD filters out weak reflections on intensity map and loses object structure features in detail, especially in the far distance. But *mmWaveNet* can correctly predict the shape of the wall and produce PCD similar to the ground truth. Figure 2 further shows the CDF and quantitative performance of *mmWaveNet*, where *mmWaveNet* achieves better performance than a state-of-the-art method. *mmWaveNet* achieves 0.198 m on CD (median) and 0.344 m on CD ($90^{th}$ percentile), which improves 22.7% and 30.6% compared to MilliPCD.

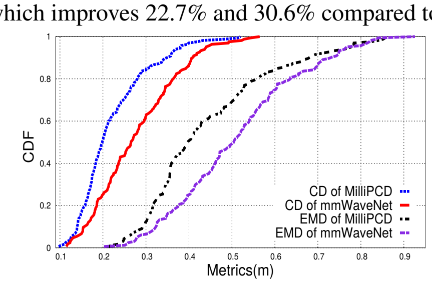


**Figure 2:** ***CDF for quantitative performance***

## 4 CONCLUSION AND FUTURE WORK

This work proposes *mmWaveNet*, an advanced deep learning model which directly utilizes mmWave reflection signal for mmWave PCD reconstruction. Without mmWave signals processing algorithm, *mmWaveNet* can generate high-quality PCD and performs better than MilliPCD in indoor environments. While the indoor dataset has limited variety, the outdoor environment includes more complicated objects, terrain, and weather. In the future, we plan to extend *mmWaveNet* to reconstruct PCD for different outdoor environments.

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