mmWaveNet: Indoor Point Cloud Generation from Millimeter-Wave Devices

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Objective, Motivation, and Challenges

Objective

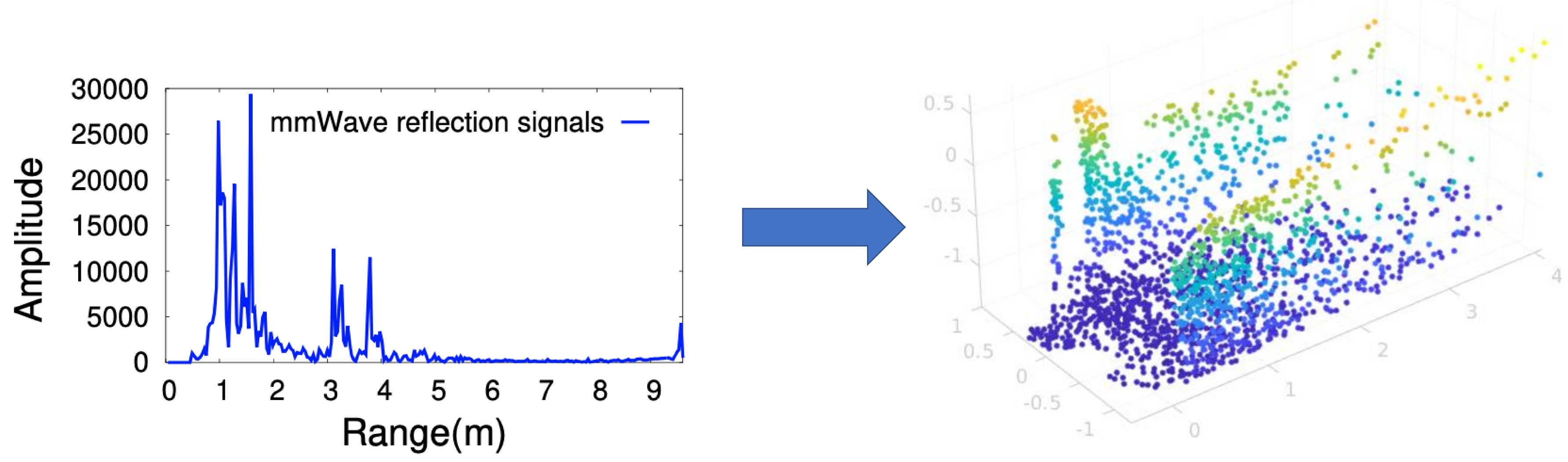
- Using millimeter-wave (mmWave) device to construct dense Point Cloud Data (PCD), which could be used for robot navigation during low-light

Motivation

- mmWave reflection signals can capture 3D information of the surrounding objects by measuring direction and time of signal arrival
- Processing raw mmWave reflection signals leads to a serious loss of information, which limits the performance of previous works

Challenges

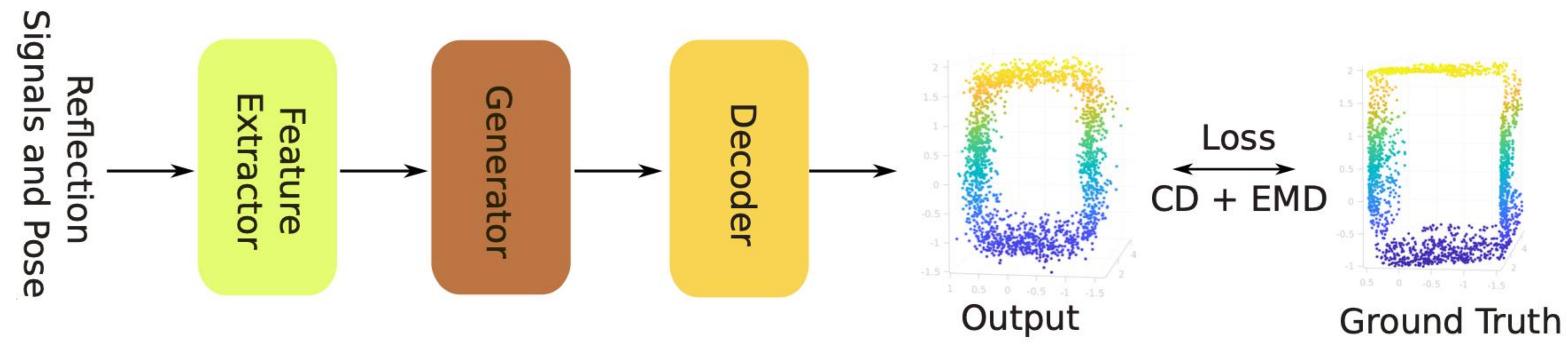
- **Noise.** mmWave signal is sensitive with various reflectors
- **Sparsity.** Due to the limitations of specular and weak signal reflectivity, only small parts of transmitted signals can be correctly reflected to receivers



Constructing Denser Point Cloud Data

Deep learning model for constructing denser Point Cloud Data

- **Feature Extractor** for extracting features from reflection signals and pose
- **Generator** for producing sparse PCD seed
- **Decoder** for expanding seed into complete PCD



Model loss

- **Chamfer Distance (CD)**: quantitative difference

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

- **Earth Mover's Distance (EMD)** : global distribution difference

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

mmWaveNet Architecture

Feature Extractor

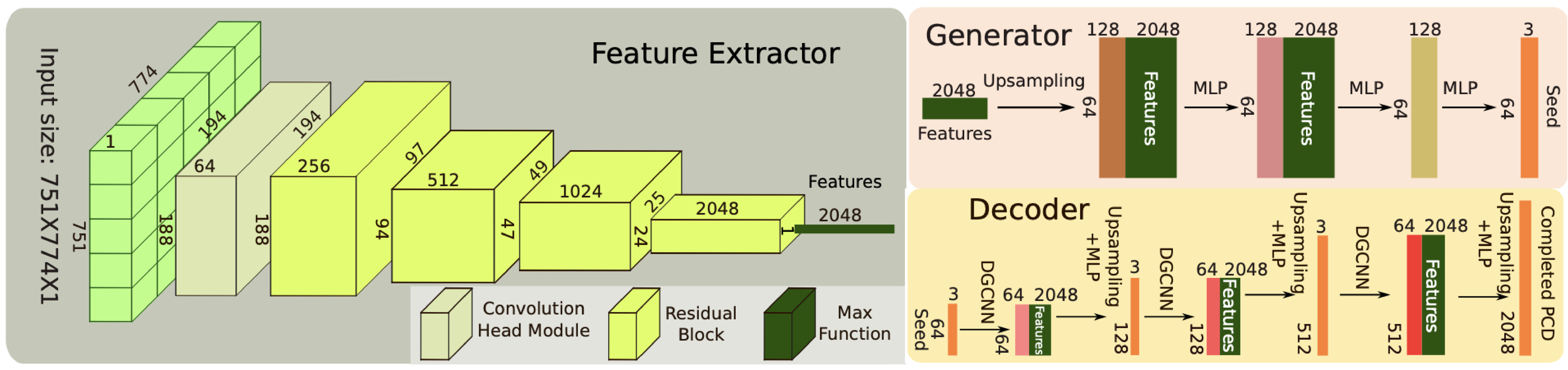
- It employs convolution filter to extract local features and continuously reduce the height and width of inputs to make convolution filters "see" larger region
- To keep detailed features, we leverage the residual blocks to concatenate features from all blocks together

Generator

- Transposed Convolution is applied to upsample features into initial PCD seed and combines seed with folding features
- Multi-Layer Perceptron (MLP) uses the combination of initial PCD seed and folding features to generate sparse PCD seed

Decoder

- DGCNN extracts local PCD shape from seed
- Upsampling layers reconstruct object shape by embedding regional features with duplicated features



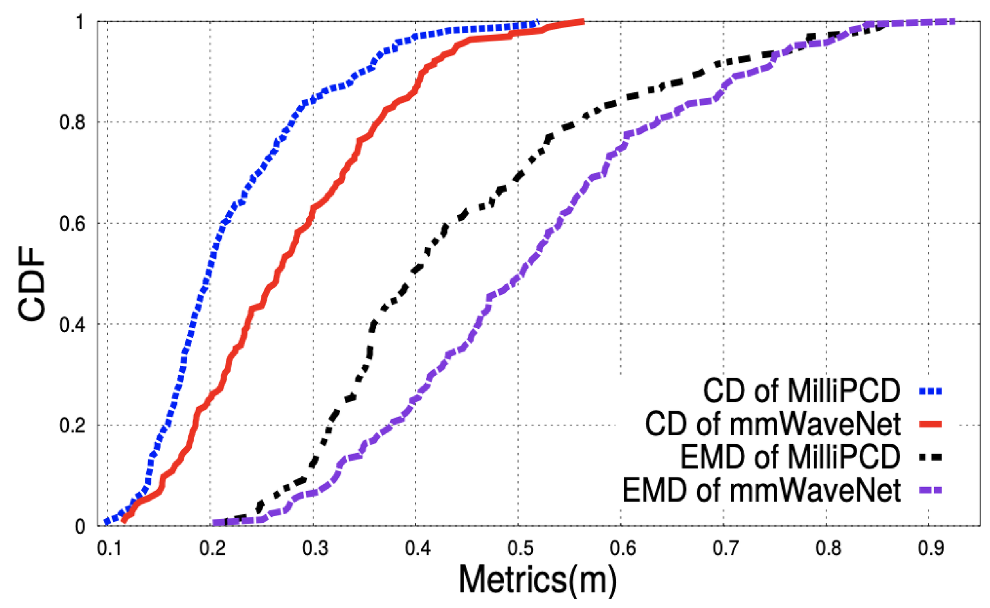
Results and Conclusion

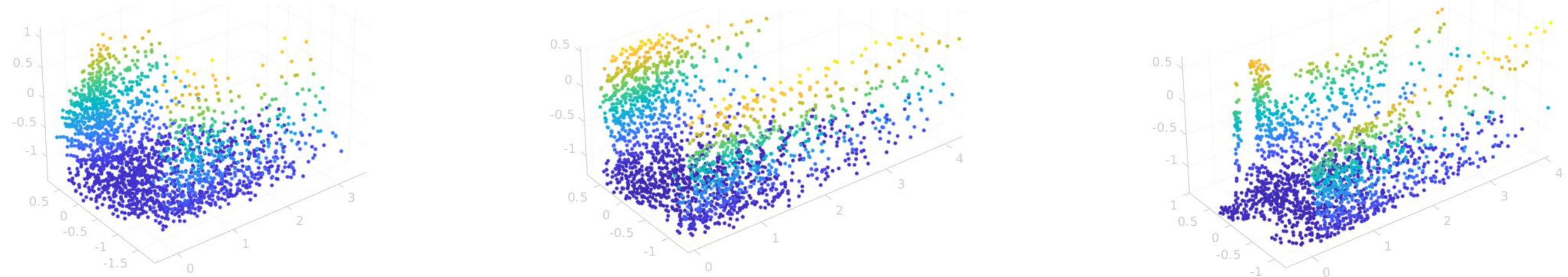
Dataset

- 1,274 indoor PCD samples
- 13 different indoor environments

Results

- **0.198** m on CD (median) improves 22.7% compared to MilliPCD
- **0.344** m on CD (90th percentile) improves 30.6% compared to MilliPCD





State-of-the-Art | *mmWaveNet* | Ground Truth

Conclusion and Future Work

- *mmWaveNet* directly utilizes mmWave reflection signal for PCD reconstruction, which performs better than MilliPCD in indoor environments
- We are planning to extend *mmWaveNet* to outdoor environment, which includes more complicated objects, terrain, and weather