

## Introduction

**Problem:** How to incorporate the spatial properties of the mmWave outdoor positioning problem into a neural network model?

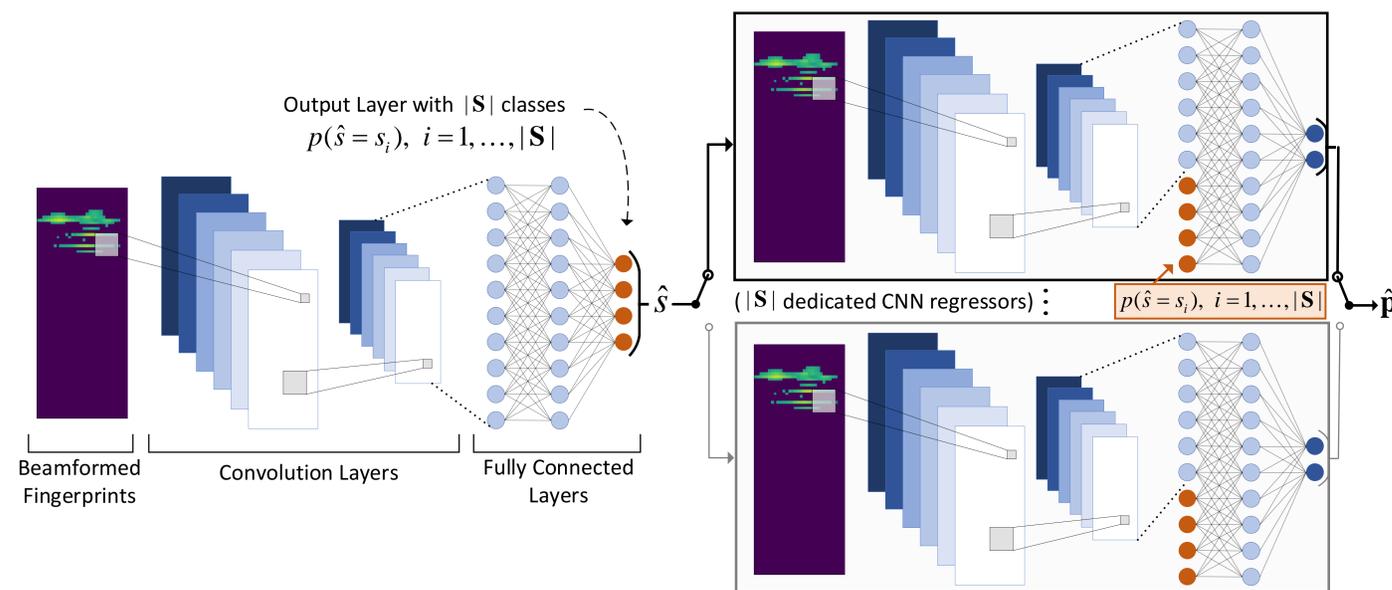
### Motivation

- In [1], we proposed a CNN-based localization system, based on **beamformed fingerprint** (BFF) inputs;
- The BFFs are obtained from a sequence of codebook-based **beamformed mmWave** transmissions;
- While the BFFs were designed with spatial properties in mind, the used model was a standard CNN.

### Proposed Approach

- As with other positioning methods, adjacent positions are expected to have similar input signals;
- Due to mmWaves, the BFFs will have some noticeable discontinuities throughout the considered area;
- We propose to use a **hierarchical model** to take advantage of these two distinct properties.

## Proposed System



- For each base station, the covered area can be seen as a set of sub-areas  $\mathbf{S}$  ( $\mathbf{S} = \{s_1, \dots, s_{|\mathbf{S}|}\}$ );
- The **first part** of the hierarchical model is a **classification model** that focuses in detecting the received BFF's sub-area  $\hat{s}$ , which is aided through the aforementioned **discontinuities**;
- The **second part** of the hierarchical model consists on a set of  **$|\mathbf{S}|$  regression models**, one per sub-area, where the final position estimate is given exclusively by the model associated with  $\hat{s}$ ;
- Each of the  **$|\mathbf{S}|$  regression models** is specialized in its sub-area, allowing the complete model to better distinguish **adjacent positions**;
- To allow the regression to partially recover from errors during classification, the **softmax** output of the classification model is also used as an **input of the regression models**.

## Bibliography and Acknowledgements

- [1] J. Gante *et al.*, "Beamformed Fingerprint Learning for Accurate Millimeter Wave Positioning", *IEEE 88th Vehicular Technology Conference (VTC Fall)*, 2018.

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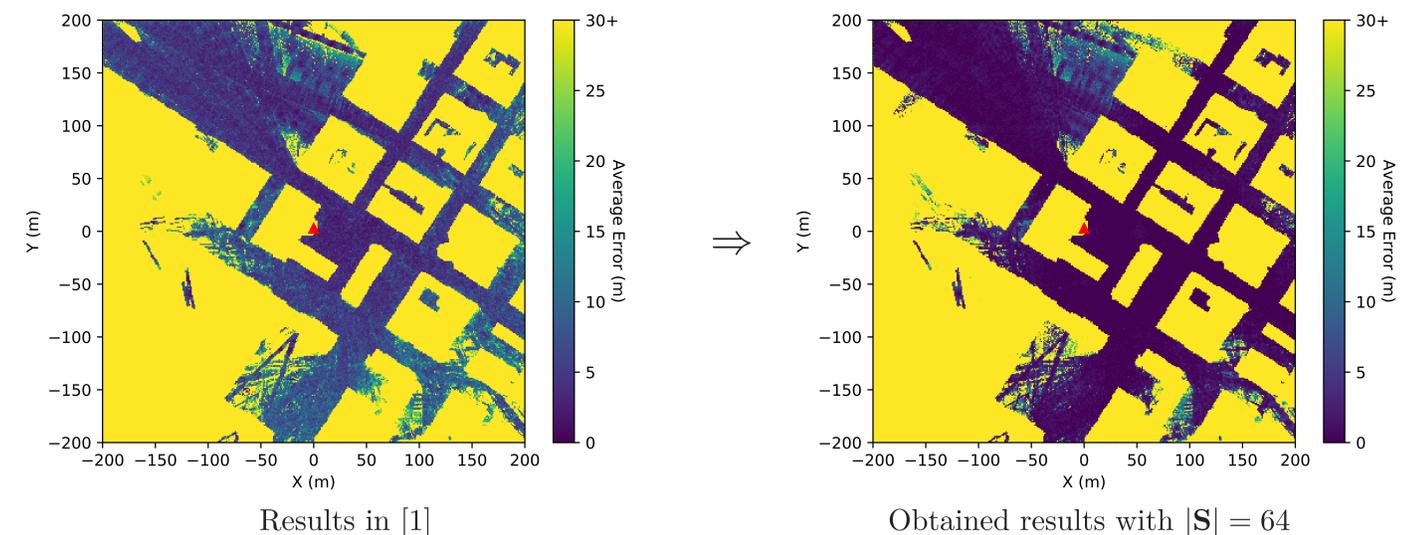
## Simulation Results

### Simulation Apparatus

Parameter Name	Value
Carrier Frequency	28 GHz
Transmit Power	45 dBm
Codebook Size	32 (155° arc, 5° between entries)
Receiver Grid Size	160801 (400 × 400 m, 1 m above the ground)
Convolutional Layers	1 layer (8 features with 3 × 3 filters, 2 × 1 max-pooling)
Hidden Layers	12 (256 neurons each)
Class. Output	Softmax with $ \mathbf{S} $ classes
Regression Output	2 Linear Neurons (2D position)
Added noise	$\sigma = [2, 10]$ dB (Log-Normal)
Assumed Rx. Gain	10 dBi
Detection Threshold	-100 dBm

- Propagation simulated through **ray-tracing** – the simulations matched experimental measurements at the NYU campus;
- BFFs obtained from the simulations, for 160801 positions;
- The  **$|\mathbf{S}|$  sub-areas** are created from **successive bis-sections** of both dimensions of the considered 2D area;
- The classification and the  **$|\mathbf{S}|$  regression models** share the same hyperparameters.

### Results



**Conclusions:** we obtained a 55% average error reduction when compared to our previous work. This sets a new state-of-the-art performance level for non-line-of-sight mmWave outdoor positioning, with an average error as low as 3.31 m.

