Leveraging on Deep Learning to Predict the Optimal Beam Index, Using Wireless Sensing Localization

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Abstract

This is an evolving project that explores the applications of machine learning in the area of wireless communication systems. Employing the traditional beam training methods for mmWave and Sub-6Ghz channels, usually results in unsatisfactory latency in wireless communication networks. This project turns to utilize the concepts of Deep learning to build a Multilayer neural network, which has the capability to predict a beam direction of a mmWave signal at a success probability of 65, at low latency.

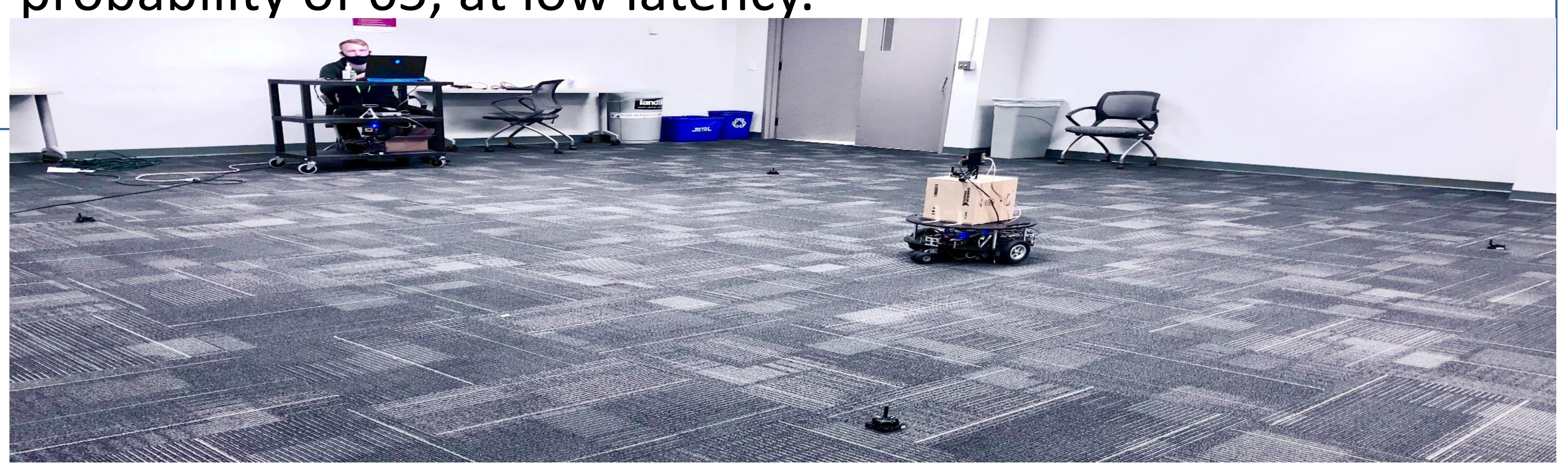

Figure 1: Picture of the Setup Prototype.

Introduction

The communication channels of very high frequency signals such as mmWave and Sub-6GHz are usually characterized by large channel variables and sparsity, due their susceptibility to environmental conditions. These characteristics results in considerably larger training overhead, in identifying the optimal beam direction in large antenna array[1].

In this project, a dataset is collected from a prototype of mmWave system, and machine learning tools are leveraged to predict the beam direction from the receiver with no overhead, given the position of the transmitter from a wireless localization sensors. The result from the performance of the model shows that with larger amount of dataset, the existing exhaustive search from codebook for optimal beam vector can be replace by neural network models for low overhead and latency.

Methods

Step 1: First Setup a prototype of mmWave transmitter and receiver, using a USRP Kit and horn antennas.

Step 2: The transmitter is made mobile by placing it on a robot, and the robot is being controlled with the aid a raspberry Pi microcontroller.

Step 3: Setup the localization system by calibrating and connecting the wireless sensors with the Dashboard software from Marvelmind.

Step 4: Wrote a python code to establish a socket connection between the server processor on the raspberry Pi and the client laptops.

Step 5: Data Collection from the mmWave system and the Localization sensor system.

Step 6: Generation of Dataset by preprocess the data from the setup to obtain the beam index and position of transmitter for each pilot signal propagation.

Step 7: The concept of Multilayer neural network is employed to build a model with an input, two hidden layers and an output, using Pytorch API.

Results

- A python code is written to extract the beam direction for each transmission, by Considering the beam with higher power.
- The text files with the Position of the transmitter for each transmission are opened and read to .csv file with the beam direction.

Model Parameters	Values
Input Size	3 (x, y, z)
Number of Hidden Layer	3 (Each with either 128 or 64 nodes)
Adam Optimizer	Lr = 0.01
No of Epochs	500

Figure 3: Hyperparameters for the Model

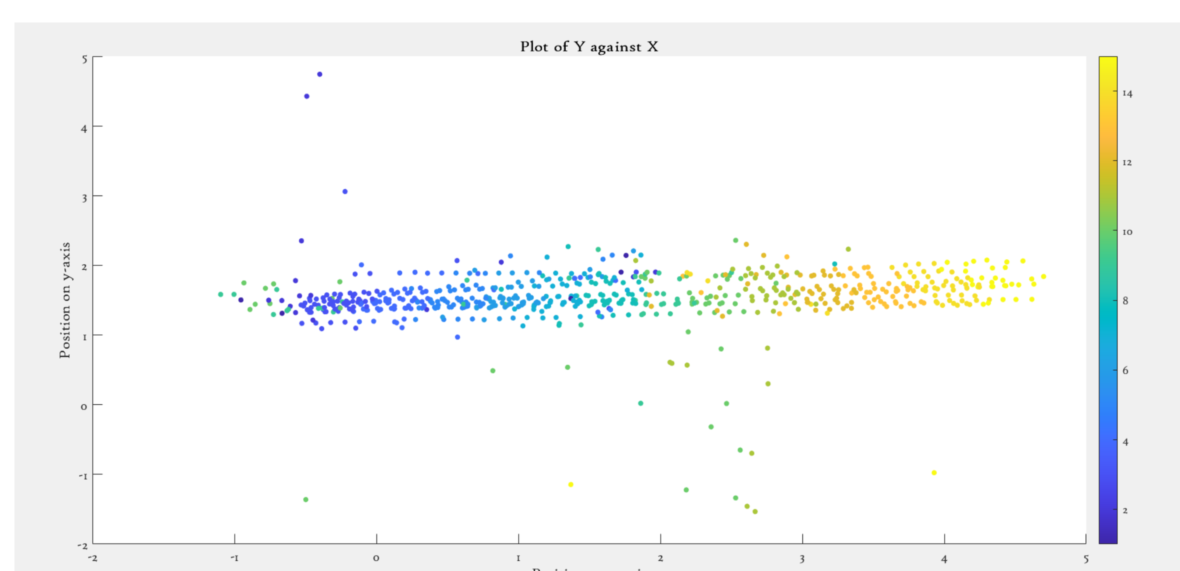

Figure 2: Preprocessed Data

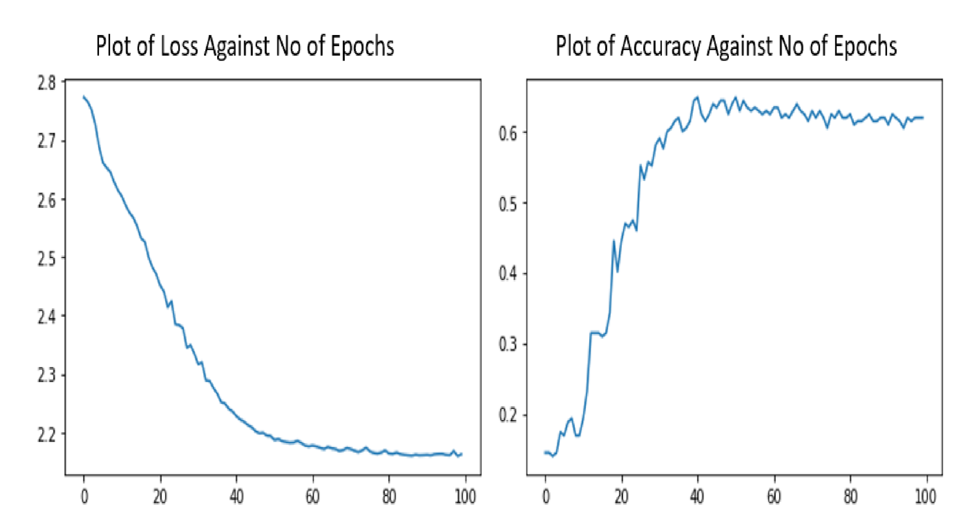

Figure 4: Evaluation of Loss and Accuracy

Findings And Next Steps

- I have realized that positional beamforming can be achieved with the aid of wireless sensors from the Marvelmind.
- The accuracy of any machine learning relies greatly on the size of the dataset.
- Standardizing the dataset before modelling, ensure the generalizing of models. Standardization was employed in the dataset preprocessing to reduce overfitting.
- In next step, the Raspberry Pi on the robot will be replace by Nvidia Jetson Kit, to ensure that model training and evaluation can be performed on the setup directly.
- I will need to collect more dataset to increase that accuracy of the model to more than 90%.

Conclusions

The Simple Multilayer Neural Network proposed can replace the tradition beam prediction schemes, if more dataset is collected for its training. The model will achieve low latency and no overhead in its prediction process.

This research affirms machine learning as a potential tool for improving the various layers of communication in wireless network..

References

[1] A. Alkhateeb, S. Alex, P. Varkey, Y. Li, Q. Qu and D. Tujkovic, "Deep Learning Coordinated Beamforming for Highly-Mobile Millimeter Wave Systems," in IEEE Access, vol. 6, pp. 37328-37348, 2018, doi:10.1109/ACCESS.2018.2850226.

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Acknowledgements

Special thanks to Prof. Alkhateeb for supporting me and allowing me to work in his lab. Also, I am grateful to Andrew, Gouranga, and Mohammed for helping with the data collection and neural network modelling.

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