“We Know Where You Are”: Indoor WiFi Localization Using Neural Networks

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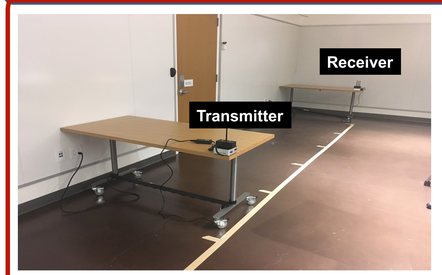
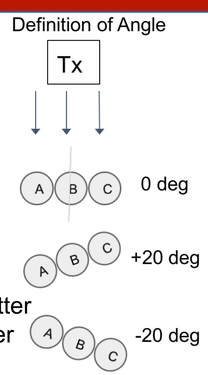
Abstract

The goal of this project is to predict the location of a Wi-Fi transmitter unit with respect to a Wi-Fi receiver unit. Using a transmitter with one antenna and a receiver with three evenly spaced antenna, channel state information (CSI) data with amplitude and phase information were collected. These data were fed into a neural network for training so that we could predict the distance and angle of arrival between transmitter and receiver. We hypothesized that there would be a relationship between amplitude data and distance, and one between phase difference data (phase difference between Antennas A and B, A and C, and B and C) and angle of arrival (AoA). However, we determined that only phase difference data is better at predicting both distance and angle of arrival.

Data and Features





Data Collection: We used Wi-Fi transmitter with a single antenna and a Wi-Fi receiver with three antennas spaced 2.6cm apart. The Wi-Fi transmitter transmits at 30 different subcarrier frequencies each spaced 312.5KHz apart centered at 5GHz.

Data:

Ground Truths	Values
Distance [m]	1,2,3,…,10 (10 total values)
AoA [deg]	-40,-30,…,30,40 (9 total values)

Data	Values
Features	90 (= 3 antennae *30 subcarriers) values of CSI Phase Data
Samples per AoA Distance pair	~1900
Total samples	171891

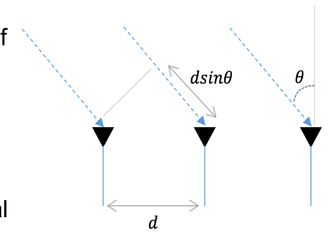
While our raw data was absolute phase data, we transformed this into phase difference data (phase difference between antennas, A and B, A and C, and B and C for each subcarrier frequency), linearized it, and used this new linearized phase difference as our features.

Model

For a line-of-sight angle of arrival θ, a signal travels an additional distance of $dsin(\theta)$ to the second antenna in the array compared to the first antenna. This results in a difference of $2\pi d\ sin(\theta)f/c$. However, for each signal, there is more than one propagation path resulting in an actual observed phase difference:

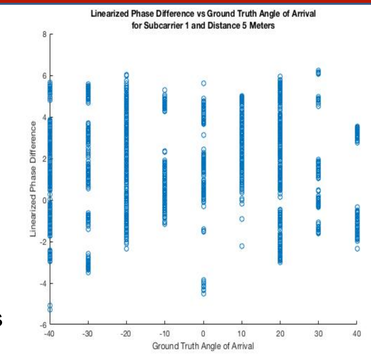
$$\angle\left(\sum_{i=1}^{N} r_i e^{j\varphi_i}\right) - \angle\left(\sum_{j=1}^{N} r_j e^{j\varphi_j}\right)$$

We hypothesized that a neural network could learn a pattern for the multipath terms, and thus, be able to draw a relationship between line-of-sight angle of arrival and phase difference.



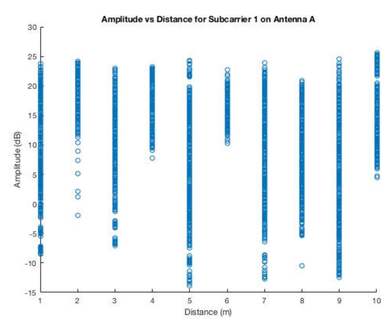
We cast the problem as a classification problem with 9 AoA classes.
We used MATLAB’s neural network tool with 30 hidden layers and the default configuration: using a sigmoidal activation function for each hidden layer and scaled conjugate gradient backpropagation as the weight/bias update procedure.

Similarly, we tried to establish a relationship between phase difference and distance. The different multipath components can sometimes destructively interfere. In this case, the receiver will not observe a signal component with that phase. Since the phase of each multipath component is a function of distance and room geometry, we hypothesized that each distance would have a characteristic set of “missing” phases that the neural network could learn.

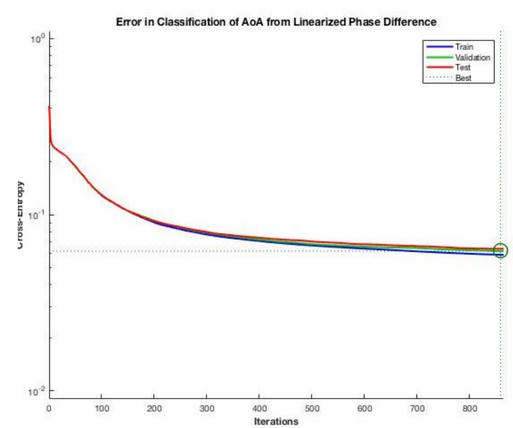


(phase pattern for one distance shown above). We ran a regression with same hidden layer configuration as used for the AoA case.

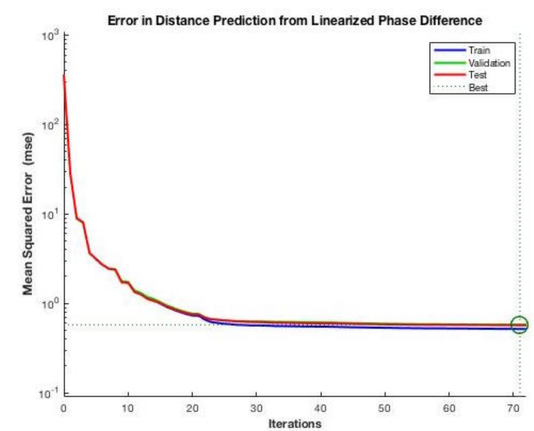
Results and Discussion



There was no observed dependence between the distance and amplitude of the received signal. However, through neural networks, we were able to observe a dependence between Phase Difference and Distance and Angle of Arrival.



Classification of AoA	Samples	Cross-Entropy
Training	125923	13.5%
Validation	26984	14.1%
Test	26984	14.3%



Distance from Regression	Samples	MSE
Training	125923	0.518m
Validation	26984	0.578m
Test	26984	0.570m

Discussion:
We did not find any correlation between amplitude and distance as we initially predicted; however, we found that phase difference data was sufficient to make both AoA and distance predictions. Intuitively, our neural network learns a phase difference "fingerprint" or specific pattern for each AoA and distance and makes predictions based on which "fingerprint" the new data point matches best. We were able to predict distance almost with 0.5 m and classify AoA with ~14% error. While both of these are less accurate than the MUSIC algorithm used in SpotFi, our method makes predictions much faster that MUSIC does. So while we have taken a small hit in accuracy, we obtained a large increase in speed. Furthermore, we expect accuracy to improve if the receive chain phase-shift is accounted for (see Future Work). The only caveat is that we do not know to what extent these results are can be generalized without further research.

Future Work

To improve our results in the future, we would try removing the phase shift introduced by the receiver circuitry from the data before feeding it into the neural network. This would most likely increase accuracy for both distance and angle of arrival prediction. We would also check if the accuracy of our predictions significantly change when we introduce or move objects around the room. Finally, if we could find a bigger or longer room, we would also try collecting data at larger distances to see if we can get significant results from amplitude data.

References

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[2] X. Wang, L. Gao, and S. Mao, “PhaseFi: Phase fingerprinting for indoor localization with a deep learning approach,” IEEE Internet of Things Journal, Dec, 2015.

[3] M. Kotaru, K. Joshi, D. Bharadia and S. Katti, “SpotFi: Decimeter Level Localization Using WiFi ,” SIGCOMM ’15, August 17 - 21, 2015.