Effects of Obstructions on BLE Proximity Detection

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***Abstract*—Using PiPact's provided Raspberry Pis with BLE capability, I attempted to develop a proximity detection algorithm while also attempting to quantify and weight the effects of different kinds of obstructions on the algorithm's effectiveness and accuracy.**

Keywords—Obstructions, Proximity Detection, BLE

I. Introduction

A. Project Description

This project attempted to address the effects of different kinds of obstructions on proximity detection methods based in Bluetooth low energy (BLE) discovery. In doing so, it aimed to discover whether such information was relevant enough to make an active effort to measure and whether it would even be possible to accurately account for measured and described obstructions

B. Background Information

Raspberry Pis have built-in BLE modules that enable them to send out 'discovery' signals and detect other devices with such BLE modules. This is the basis of most BLE detection algorithms as the discovery signals also include an RSSI or Received Signal Strength Indicator value, which is affected by a variety of variables and generally has an inversely proportional relationship to distance.

II. Hypothesis/Hypotheses

This project aimed to investigate how different obstructions (varying in material, size, and distance) between two BLE modules would affect the transmission signal. It aimed to develop an algorithm to accurately predict distance between the BLE modules based on information about the obstructions and collected RSSI readings.

III. Experiments and Data Collections

First, baseline data (with no obstructions at all) was collected with one Raspberry Pi placed at a marker and the other Raspberry Pi was continuously moved a measured distance at an interval of 0.25m (up to 3 meters) as data was collected. Both Raspberry Pis were oriented in the same direction to control for internal interferences. After baseline data was collected, a number of different objects, including posterboards, tissue boxes, 1-gallon plastic water jugs, reflective-coated bubble wrap, and a metal power supply, were placed in between the Pis and moved. More specifically, the Pis were placed 1 meter apart and the obstruction was moved in increments of 0.25m and then the Pis were placed 2m apart and the same procedure was repeated.

A. Plan and Execution

It would have undoubtedly also been interesting to also measure other more readily quantified and measured variables, such as humidity or pressure, but unfortunately I did not have access to modules or sensors that would readily and accurately be able to measure these things. Instead, I opted to collect all of my data over the course of several subsequent days (where the publicly published humidity seemed to stay relatively constant) and in a climate-controlled room.

Material types were "one-hot encoded." That is, to say they were given binary values for each different obstruction.

In addition, to account for random fluctuations and noise, between 6-10 RSSI readings were taken at each distance with each obstruction.

B. Data Relevance

The data collected, while not nearly as specific or quantified as might have been ideal for accurate predictions, was still collected and curated in a relatively careful and methodical fashion. With each type of obstruction, I aimed to account for different types of materials as well as the size and shape of each obstruction.

C. Examples

SCAN	ADDRESS	TIMESTAM	UUID	MAJOR	MINOR	TX POWER	RSSI	Distance	Object Dist	Posterboar	Tis
0	DC:A6:32:3	49:49.1	9a337500-	1	1	1	-38	1	0.5	1	
1	DC:A6:32:3	49:50.0	9a337500-	1	1	1	-41	1	0.5	1	
2	DC:A6:32:3	49:51.2	9a337500-	1	1	1	-41	1	0.5	1	
3	DC:A6:32:3	49:52.1	9a337500-	1	1	1	-41	1	0.5	1	
4	DC:A6:32:3	49:53.1	9a337500-	1	1	1	-41	1	0.5	1	
5	DC:A6:32:3	49:54.1	9a337500-	1	1	1	-39	1	0.5	1	
6	DC:A6:32:3	49:55.3	9a337500-	1	1	1	-35	1	0.5	1	
7	DC:A6:32:3	49:56.3	9a337500-	1	1	1	-36	1	0.5	1	
8	DC:A6:32:3	49:57.4	9a337500-	1	1	1	-41	1	0.5	1	
0	DC:A6:32:3	50:29.5	b1ffdfd4-cf	1	1	1	-42	1	0.25	1	
1	DC:A6:32:3	50:30.0	b1ffdfd4-cf	1	1	1	-42	1	0.25	1	

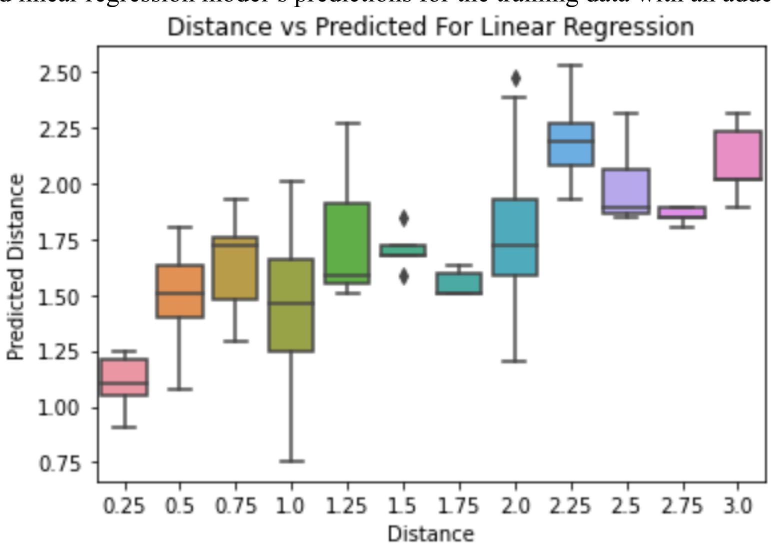
IV. Analysis and Algorithms

A. Description

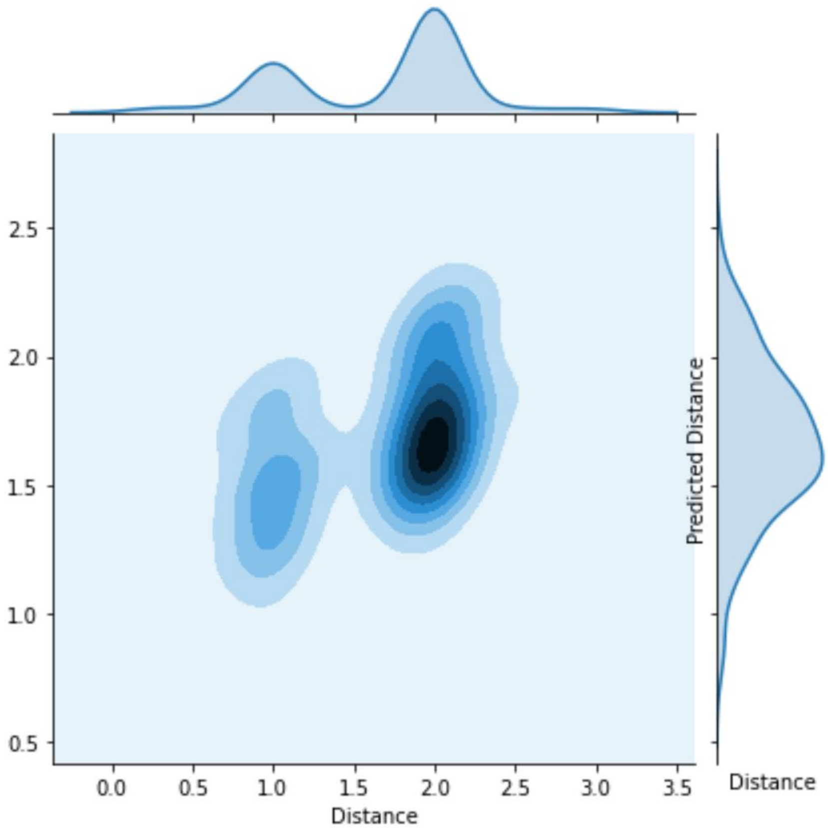
Object Distance was multiplied by each object type to get new columns containing the distance of each object. The column for the power supply*distance was dropped to eliminate linearly dependent columns. The data was then split at random using sklearn's train_test_split module with 25% of the data as test data (resulting in 435 training samples and 146 test samples). I then implemented a linear regression model, cross-validated it, and then also implemented a BFGS model with scipy's optimize.minize.

B. Results and Examples

This is a boxplot of the fitted linear regression model's predictions for the training data with an added intercept.

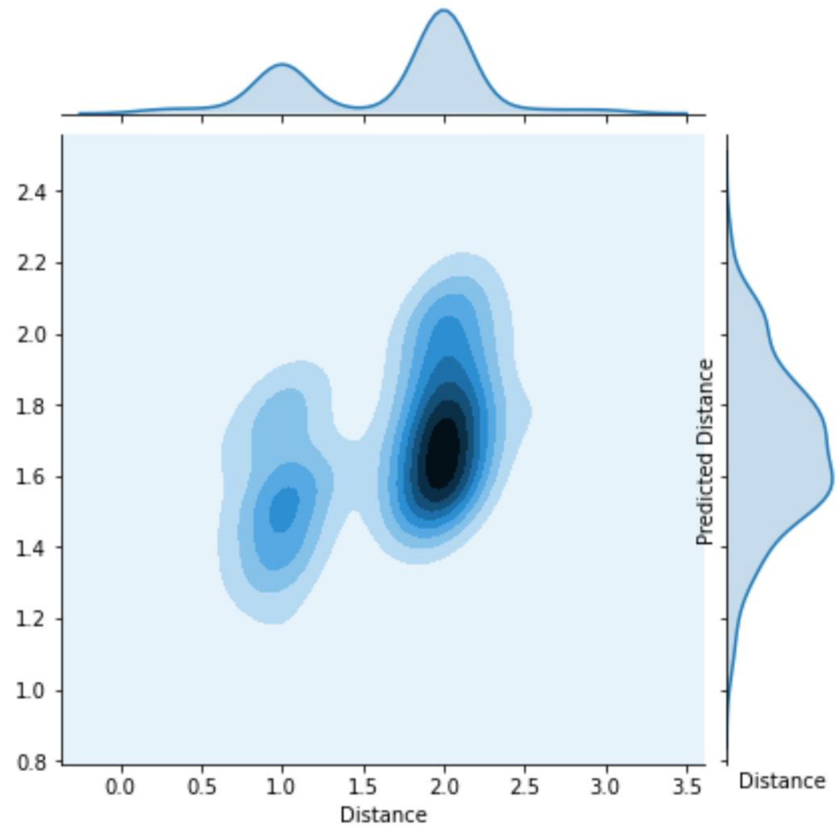


This is a KDE plot of the same data with a jointplot to further illustrate the inaccuracies of the algorithm.



Overall, the linear regression model had a training RMSE (Root Mean Squared Error) of 0.469 and a test RMSE of 0.489.
Due to the small sample size and overall variance of the data, cross-validating actually increased the training RMSE to 0.474.

Subsequently I used scipy's optimize.minimize module in conjunction with a RMSE loss model to fit a BFGS model to my data. This is the KDE/jointplot produced by these predictions.



Perhaps unsurprisingly, this model fared even worse (as might also be clear from the jointplots), with a training RMSE of 0.478 and test RMSE of 0.497.

V. Conclusions

A. *Hypothesis Evaluation*

The hypothesis the project aimed to investigate, whether or not certain material observations and distance combined with RSSI readings would enable an algorithm to accurately predict distance between two BLE modules, was ultimately proven false. That is to say that it was not possible to develop a sufficiently accurate algorithm with these limited and somewhat-simplistic material description methods.

B. *Noteworthy Conclusions*

The presence of these obstructions creates enough ambiguity, even with some types of information about the type of obstruction, to create significant inaccuracy (up to half a meter as was demonstrated in the results) and thus make collecting this sort of information functionally useless. Obstruction data would most likely only be useful in very specific situations with clearly defined and quantified information about the nature of the obstructions. Otherwise, it seems that in general, obstructions will remain a significant source of error in BLE proximity detection.

C. *General Lessons Learned*

It is generally clear from this project that attempting to collect general observational data about potential obstructions, even with relatively specific information about their location relative to the BLE modules, would not be an effective way of using resources to advance BLE proximity detection.

VI. Next Steps

As mentioned before, it could be a worthwhile pursuit to investigate specific applications of BLE proximity detection algorithms in areas with clearly defined and describable obstructions. But beyond those applications, efforts should be focused more definitively on easily measurable and quantifiable metrics like humidity and temperature and finetuning measurements/algorithms in those areas.