The Effect of Obstructions on Received Signal Strength

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***Abstract*—This report details the collection and analysis of data points consisting of RSSI signal value and distance between two Raspberry Pis, where one Raspberry Pi broadcasts a low energy Bluetooth signal. At the same time, another Raspberry Pi receives the signal and logs its strength. The data analysis involves regressing an exponential function to map distance to RSSI signal strength that turns out to have an average of 71% accuracy in predicting distance. (*Abstract*)**

***Keywords—BLE, detection, obstruction** (key words)*

I. Introduction (*Heading 1*)

A. *Project Description (Heading 2)*

This project explores the effect of obstructions on the Bluetooth Received Signal Strength Indicator (RSSI) signal strength to distance relationship to better determine the viability of Private Automatic Contact Tracing (PACT). These effects were studied through the comparison of data gathered from an announcer Raspberry Pi and a detector Raspberry Pi without an obstruction between them and data gathered from two Raspberry Pis with an obstruction between them. (Body Text)

B. *Background Information*

The contact tracing system to which this project is related to relies on Bluetooth Low Energy (BLE) technology. BLE is a short range, low energy form of wireless communication [1]. Through advertising and communications protocols, BLE-enabled devices are able to communicate with other devices in range. By storing unique device ids and the RSSI signal strengths from every connection, it is possible to log the devices (as proxy to people) that came within a certain range of the detector.

This project relies on the assumption that real-world conditions are similar to those while testing e.g. humidity stays constant or connected devices are similar in all relevant categories to Raspberry Pis. Though this is not the case, these assumptions allow this project to continue and possibly contribute useful information.

II. Hypothesis/Hypotheses

Creating a reasonably accurate (> 80%) detection algorithm based on a combination of exponential regression equations fitted to the distance – RSSI signal strength data in both obstructed and non-obstructed cases should be possible. If this is shown to be true, then the problem of obstruction interference becomes a non-issue and those involved in the PACT program should be studying other points of weakness in the system.

III. Experiments and Data Collections

TABLE I. EXPERIMENT OVERVIEW (TABLE HEAD)

Exp. Name (table col head)	**Hypothesis**	**Reason**	**Repetitions**
No Obstruction (table copy)	Effect of obstruction	Control	20
Obstruction	Effect of obstruction	Empiircal quantification of effect	20

A. *Plan and Execution*

The data collection process spanned multiple days, though the bulk of data was gathered in one. Both Raspberry Pis were placed on the floor of an indoor room with the power indicator sides facing each other. The distance was measured with a tape measure. Data collection sessions were 10 minutes each, with two sessions for each distance from 1-10 ft, incrementing by 1. The obstruction used in the obstruction experiment was a stack of six 2”x4” wood beams with the grain parallel to the ground. A limiting factor for the potential testing areas was the usage of ethernet rather than WiFi to communicate from a computer to the 2 Raspberry Pis. Otherwise, the experiment setup was relatively simple. Ideally, different obstruction material types and obstruction thicknesses would be tested, but there, unfortunately, was not enough time to test those parameters.

B. *Data Relevance*

The data points collected from the No Obstruction and Obstruction experiments enable exponential regression to create a function mapping distance to RSSI signal strength. This function can then be used as a detection algorithm and tested to see if its accuracy holds for obstructed and non-obstructed devices.

C. Examples

Below, *Fig. 1* is a scatter plot of the No Obstruction data points and *Fig. 2* is a scatter plot of the Obstruction data points.

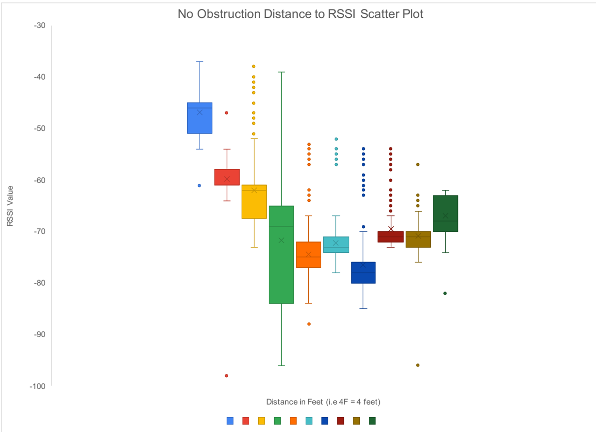

Fig. 1 – Scatter plot of No Obstruction data points

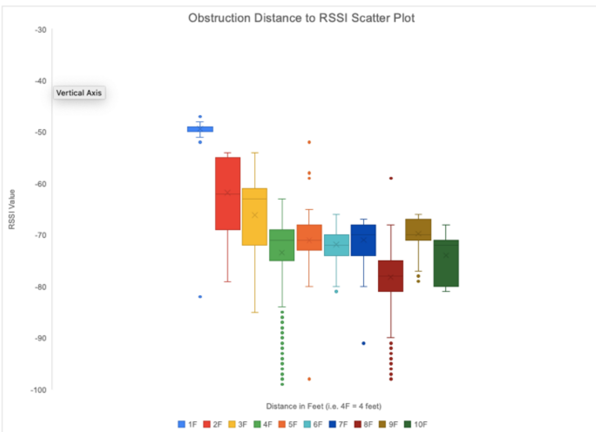

Fig. 2 – Scatter plot of Obstruction data points

IV. Analysis and Algorithms

A. Description

After consolidating the data from the Obstruction experiment and the No Obstruction dataset, a new table consisting of average RSSI values for each distance was created. By using exponential regression (chosen due to the inverse square law), best-fitting functions for both types of data were found, as can be seen in *Fig. 3* and *Fig. 4*. To combine the two functions in a meaningful way, a new function that outputted the average of the two functions was created. By running each datapoint through this new function and assigning it a "contagious" or "not contagious" designation, the accuracy of this function in determining a safe distance (6 feet or more apart) was quantified. The exponential regression was done through the Desmos Graphing Calculator, and all other calculations were done in an Excel spreadsheet.

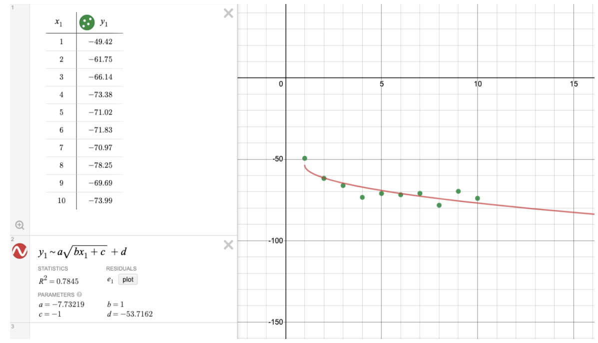

Fig. 3 – Exponential Regression of Obstruction Data

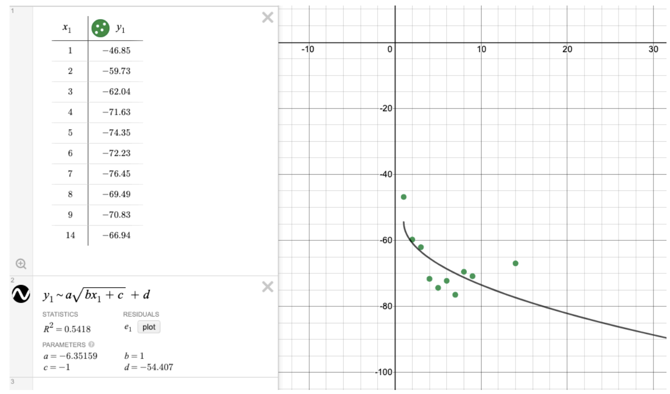

Fig. 4 – Exponential Regression of No Obstruction Data

B. Results and Examples

Due to the wide variety of RSSI signal values for each certain distance (standard deviations being as much as seven or higher), the regression did not provide tight-fitting functions. The correlation coefficient of the Obstruction Averages function was approximately 0.78, while the correlation coefficient of the No Obstruction Averages function was approximately 0.54. While there does exist some correlation, the data was too varied to show a strong correlation. This variation led to the function or "detection algorithm" to display a 72.58% accuracy for the No Obstruction dataset and a 70% accuracy for the Obstruction dataset.

V. Conclusions

A. Hypothesis Evaluation

Based on the data gathered from this project, it does not appear as though an exponential regression-based function can evaluate the distance from an RSSI signal strength with an accuracy of 80% or higher. The detection function performed at an accuracy 10% lower than wanted, showing that creating an exponential function to do so will be more complicated than initially expected, even without taking into account the numerous assumptions made during experimentation.

B. Noteworthy Conclusions

Although an exponential detection function performing with an accuracy of 80% or higher was not found based on the data gathered in this project, its existence is not necessarily ruled out. An evaluation of the data showed numerous outliers, suggesting that a more extensive data collection process would yield a more accurate exponential function-based detection algorithm. If this is not the case, however, then it may show that BLE signal strengths are too inconsistent to serve as a foundation for contact tracing without, perhaps, an algorithm factoring in other information such as neighboring devices or past RSSI signal strength data of each broadcasting device to determine the distance between the receiver and broadcaster device.

Additionally, on a severe deviation from the subject of further data collection efforts, this project has shown that obstructions do not necessarily impact BLE technology's viability for contact tracing. The detection function only differed by 2% accuracy-wise in the No Obstruction and Obstruction trials. Although this does not take into account other materials such as water, the data gathered in this project showed a minimal discrepancy in detection algorithm accuracy when placing obstructions between broadcasting devices.

VI. Next Steps

With more time, I would like to investigate different types of obstructions and the effects they have on RSSI signal strength as well as the collection of more data in general. If a simple, single-datapoint-based detection algorithm does not appear to be effective, I would like to investigate a continuous detection algorithm that provides real-time probabilities of a distance between two devices being contagious with past data as a type of predictive algorithm.

References

[1] Karr, S. (2020, April 2). *Intro to Bluetooth Low Energy*. Bluetooth® TechnologyWebsite.https://www.bluetooth.com/bluetooth-resources/intro-to-bluetooth-low-energy/ *(references)*