Testing the feasibility of using Bluetooth Low Energy Beacons for COVID-19 Proximity detection

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***Abstract*—The purpose of this study is to examine the feasibility of using Bluetooth Low Energy (BLE) beacons as a method of enabling proximity-detection for COVID-19. Preliminary analysis and research BLE signal metrics found RSSI to be the best indicator of proximity between advertising and scanning devices in different environments (i.e. indoors and outdoors). As such, this study seeks to determine the feasibility BLE beacons for proximity-detection through controlled experiments with two single-board computer Raspberry Pi 4 Model B devices. The experiments provide for an empirical quantification of the effect of different environments and configurations of devices (e.g. orientation, BLE signal transmit power) on the received signal strength (RSSI) logged by a scanning device. With that, the experimentation and data analysis conducted in the study is complemented with a basic detection algorithm to better explore feasibility of using BLE for proximity detection. The performance of BLE proximity detection algorithm developed from data analysis of RSSI values under variable conditions was quantified via calculation of maximum error. The study found this maximum percent error to be 7.3% when determining the time that devices were within 2m indoors. The percent error falls within acceptable margins and thus, the study upholds the feasibility of BLE beacons for COVID-19. The study addresses with several noteworthy comments and discusses several aspects of BLE phenomena that require future investigation prior to wide-spread implementation of systems based upon BLE Beacons.**

Keywords—Bluetooth Low Energy, Obstructions, RSSI, Distance, COVID-19, PACT, Contact-Tracing, Raspberry Pi 4 Model B, Proximity-Detection.

I. Introduction

A. Project Description

The project detailed in this report is directly relevant to the piPACT's goal of "exploring the technology of Bluetooth and its application toward proximity detection for COVID-19" [11][9]. The project sought to test the effect of unique external factors on the received signal strength indicator (RSSI) of a Raspberry Pi 4 Model B scanning for Bluetooth transmissions. The insight gained from RSSI measurements in different conditions enabled the development of a basic detection algorithm that is able to determine whether devices were in close proximity (>2 meters) and if so, for how long. The analysis of data collected paired with a basic detection algorithm will help to showcase the feasibility and application of Bluetooth toward proximity detection for COVID-19.

B. Background Information

Contact-Tracing

Contact tracing is an epidemiological technique that is used by health departments to prevent or slow the spread of an infectious disease. The technique involves identifying the individuals who have come into contact (the close contacts) with an infected individual (the case) and thus may have been exposed [4]. Manual contact-tracing methods typically involve the infected individual speaking to a health official or filling out an online form to identify everyone whom they have had contact with over the time they have had the infectious disease. Following the interview/form, the health department will notify contacts of their potential exposure and recommend varying courses of actions, to include self-quarantine, testing, and symptom watch [4].

Manual contact-tracing methods have been traditionally used for slow-spreading diseases: Tuberculosis (TB), Smallpox, sexually transmitted diseases (STDs); TB has 2.9 cases per 100k people [5]. However, manual methods of contact-tracing become insufficient when dealing with highly-infectious diseases such as COVID-19 which has over 900 cases per 100k people [6]. The large volumes of cases for COVID-19 make manual contact-tracing infeasible for the following reasons:

- Heavy reliance on the memory of the index case to determine details of close contacts
- High risk of data error and thus unreliability of data analytics
- labor intensive and time consuming due to scaling issues
- The need to know identification information for individuals in contact with the infected individual [12]

The pitfalls of manual contact-tracing highlight the need for a more robust, automatic form of contact-tracing [9].

PACT Mission and Goals

The PACT project is a collaboration led by "MIT Computer Science and Artificial Intelligence Laboratory (CSAIL), MIT Internet Policy Research Initiative, Massachusetts General Hospital Center for Global Health and MIT Lincoln Laboratory. It includes close collaborators from Boston University, Brown University, Carnegie Mellon University, the MIT Media Lab, the Weizmann Institute and a number of public and private research and development centers” [8]. PACT’s mission is to enable enhance contact tracing for pandemic response through the use of a decentralized, privacy-preserving protocol. The protocol involves the use of Bluetooth Low Energy signaling in personal smartphones for automated disease exposure notification [8].

The PACT project has been divided into three distinct layers of effort: (1) Proximity Measurement, (2) Private Cryptographic Protocol, (3A) Public Health Interference, and (3B) Individual Interference [8] .

piPACT Overview

The piPACT project was developed in coordination with MIT and the PACT to enable students to explore the different layers in the PACT protocol with particular regard to Proximity Measurement. The piPACT project focuses on the observation of Bluetooth phenomena and collection of data using two Raspberry Pi 4 model B devices mimicking smartphone to smartphone interactions using BLE. Through the use of low-cost hardware, piPACT students will be able to explore new methods of developing proximity detection for COVID-19.

Bluetooth and Bluetooth Low Energy

Bluetooth is a standardized protocol for sending and receiving data via 2.4 2.4GHz wireless link. This protocol is often used due to its low-power, low-cost, and inter device wireless transmission capabilities. Bluetooth is perfect for transmitting small amounts of data over short ranges (<100 m) [1]. A subset of Bluetooth is Bluetooth Low Energy (BLE) which was originally introduced in Bluetooth version 4.0. BLE is a smart, light-weight, low-power subset of classic Bluetooth [1].

The architecture of the PACT protocol and the need private automated contact tracing for COVID-19 require a form of wireless data exchange between devices carried by individuals. Due to power and safety constraints, the data exchange must be power efficient and robust [8]. The below table compares the specifications associated with wireless protocols. The low power consumption of Bluetooth Low Energy (BLE), albeit a significantly lower bit rate (data rate) than WiFi, make it the most advantageous for proximity detection software that will be running continuously on smartphones and devices with limited battery capacity. Consequently, the benefits of Bluetooth Low Energy (BLE) make it the most advantageous wireless protocol for PACT and proximity detection for COVID-19.

TABLE I. WIRELESS COMPARISON [1]

Name	**Bluetooth Classic**	**Bluetooth 4.0 Low Energy (BLE)**	**ZigBee**	**WiFi**
IEEE Standard	802.15.1	802.15.1	802.15.4	802.11 (a, b, g, n)
Frequency (GHz)	2.4	2.4	0.868, 0.915, 2.4	2.4 and 5
Maximum raw bit rate (Mbps)	1-3	1	0.250	11 (b), 54 (g), 600 (n)
Typical data throughput (Mbps)	0.7-2.1	0.27	0.2	7 (b), 25 (g), 150 (n)
Maximum (Outdoor) Range (Meters)	10 (class 2), 100 (class 1)	50	10-100	100-250
Relative Power Consumption	Medium	Very low	Very low	High
Example Battery Life	Days	Months to years	Months to years	Hours
Network Size	7	Undefined	64,000+	255

Bluetooth Low Energy Beacons and Chirps

Bluetooth Low Energy beacons are low-power radio transmitters and scanners. These transmitters send and receive small amounts of data over short distances at a regular interval of time, similar to a lighthouse and a boat. Many common electronic devices (e.g. smartphones, tablets, etc.) supporting Bluetooth 4.0 and above have support for BLE and are able to function as BLE beacons. Automated contact-tracing systems in development by MIT and PACT have found these BLE beacons to be especially useful in advertising (BLE Beacon advertiser) small Bluetooth signals carrying a random string of letters and numbers called a “chirp”. Nearby devices, serving as BLE beacon scanners, can then scan and record the unique chirps that they heard. If a person is diagnosed with COVID-19 then they can coordinate with health officials to upload the list of chirps that their phone has sent out over two weeks to a local database [9]. Devices will be downloading data uploaded to the database and checking for any matches between chirps uploaded to the database and those heard by the device [9]. If any matches are found, the individual will know how close and how long they were in contact with someone diagnosed with COVID-19. Following too close for too long (TCTL) alert regions, set by public health authorities, the system will alert the individual of being exposed to COVID-19 if they were closer than 2m for more than 10 minutes to the infected individual [12]. The method by which chirps are generated and transmitted will be cryptographically encoded to ensure that the system preserves privacy and does not reveal any personal information.

Raspberry Pi 4 Model B

The Raspberry Pi 4 Model B is the newest edition of the Raspberry Pi low-cost single-board computers. The device features a full-Linux operating system and is able to mimic typical desktop experience. For the purposes of piPACT the Pi is especially useful for testing and coding using low-cost equipment. Moreover, because both Pi’s have similar architecture and Bluetooth 5.0 capabilities, experiments conducted using one Pi as a BLE Beacon advertiser and another as a BLE Beacon Scanner will be more controlled. The two devices when in range will be able to transmit and receive data regarding device universally unique identifier (UUID), RSSI, TX Power, and time.

II. HYPOTHESIS/HYPOTHESES

Hypothesis 1

If two devices are in a controlled environment without any obstructions then the RSSI received by the scanner device will be decrease as the distance between the devices increases.

- The aforementioned hypothesis is crucial toward the understanding of how BLE signal strength (measured with RSSI) may vary as a function of the distance between two devices. Understanding this relationship is crucial toward developing an algorithm that can use collected RSSI values to determine the approximate distance between two devices. Successful approximation of distance between devices will facilitate a more robust proximity detection system for COVID-19.
- The hypothesis will require the collection of large amounts of RSSI measurements at a varying distances 0m to as far as 11m. It is crucial that the experiment be conducted in a control environment with no obstructions.

Hypothesis 2

If two devices are separated by an electrically-conductive medium then the RSSI will be weaker than if the two devices were separated by a non-electrically-conductive medium.

- This hypothesis is crucial to the understanding of BLE signal attenuation through different mediums. It is important to be aware of how these different materials affect the BLE signal in order to account for the error that a proximity detection may face when implemented in a variety of unique environments.
- Two devices being carried by individuals may be stored or carried in different areas. This may include pockets, backpacks, etc. The type of material surrounding the device as a result of the storage location may induce different BLE signal attenuation. This phenomenon is directly relevant to the development of a versatile, robust proximity detection software.
- The hypothesis will require a thorough investigation of what materials are considered electrically-conductive and will thus affect the BLE signal the most. It is also important to observe the differences between different materials that may or may not be electrically-conductive. Finally, to ensure that data collected can be more directly applied toward proximity detection, common mediums found indoors (e.g. drywall) must be tested.
- Moreover, the hypothesis will require the transmitting Raspberry Pi to be placed in a variety of different locations on a person (e.g. front pocket, back pocket, and backpack) to test its effect on RSSI measurements collected by scanner. Ultimately, the hypothesis will illuminate the effect of different obstruction mediums on RSSI.

Hypothesis 3

If TX power is increased then there will be an increase in the RSSI value.

- Many mediums typically thick drywalls can block and cause Bluetooth signals to attenuate. This may result in a device scanning for BLE signals from an advertiser device to not receive BLE signals or receive very weak BLE signals. This poses a large problem for accurate distance approximation between devices using BLE signals, which is a PACT goal. As such, the hypothesis seeks to test the effect of increasing the TX (Transmit Power) of the advertiser device to observe its effect on the RSSI value on the scanner device.
- The hypothesis will require the TX Power of the Raspberry Pi advertising the BLE signals to be adjusted. To control for external factors, the experiment will be conducted under controlled conditions with no obstructions and at a constant distance.

Hypothesis 4

If the TX power of the advertiser is increased then there is less observed variation in RSSI.

- RSSI measurements tend to vary due to attenuation through different medium, air moisture, obstructions, and multipath. Typically, the weaker the signal, the more it becomes drowned out by noise from other signals in the 2.4GHZ frequency band of BLE. The additional noise can cause high fluctuations in RSSI measurements and induce error in proximity detection algorithms. Consequently, the hypothesis seeks to test whether more stable RSSI measurements can be collected if TX power of the advertiser beacon were to be increased.
- The hypothesis will require the TX power of the advertiser to be adjusted to observe its effect on the standard deviation of RSSI data collected by the scanner. The experiment will be repeated with the devices at different distances.

Hypothesis 5

If two devices are outdoors then RSSI values will be higher than those observed indoors.

- Proximity detection software for COVID-19 will need to function in both outdoor and indoor environments. Due to the increased confinement and increased obstructions in an indoor environment, RSSI measurements will likely be different due to Bluetooth phenomena such as multipath. Understanding of the different interactions of BLE signals in both environments is crucial toward achieving the goals set by piPACT and PACT.
- Large amounts of RSSI data will need to be collected at varying distances. This procedure will be replicated several times both in an indoor environment and an outdoor environment.

Hypothesis 6

If the advertiser and scanner are in an orientation different than 0^o relative to the ground then the RSSI will be lower because of multipath.

- Proximity detection using BLE will require signals to be transmitted from a smartphone being carried by an individual. Two smartphones being carried by two individuals may be in a multitude of different orientations with their respective antennas being pointed at varying degrees. As such, the hypothesis seeks to test the effect of orientation on RSSI using the advertiser and scanner Pi.
- Changing the orientation will cause a drastic change in the antenna direction of the device. This greatly increases the chances that multipath will take place. Multipath is a phenomenon where RF signals tend to bounce off multiple surfaces, straying away from a straight-line path, during its propagation from the transmitter to the receiver. This random path taken by the RF signal can often cause the signal to travel great distances, constantly bouncing from surface to surface, before reaching the receiver. The increased distance will result in a weaker signal read by the receiver due to signal attenuation from air and other possible obstructions [1]. As a result, multipath is a large source of error for RSSI distance approximation algorithms.
- The hypothesis will require the collection of RSSI data with the Pis in different orientations relative to the horizontal. This will be repeated with the Pis at different distances.

Hypothesis 7

If the brightness of LED light is increased then there is a decrease in the RSSI value.

- LED light can emit electromagnetic radiation which may interfere with Bluetooth [7]. The implications of this effect can enable for greater understanding of Bluetooth phenomena under different conditions and interferences.
- The hypothesis will require the strength of LED light to be varied and recorded in order to observe its effect on RSSI.

III. Experiments and Data Collections

TABLE II. EXPERIMENT OVERVIEW

Exp. #	Hypothesis	Reason	Repetitions
1	Effect of distance on RSSI	Empircal quantification of effect	4
2	Effect of obstruction type on RSSI	Empircal quantification of effect	2
3	Effect of TX Power on RSSI	Empircal quantification of effect	1
4	Effect of TX Power on RSSI varience	Empircal quantification of effect	1
5	Effect of enviornment on RSSI	Empircal quantification of effect	1
6	Effect of orientation on RSSI	Empircal quantification of effect and observation of Bluetooth phenomena (e.g. Multipath)	3
7	Effect of LED Light on RSSI	Empircal quantification of effect and observation of LED signal interferance due to electromagnetic radiation	2

A. *Plan and Execution*

In most of the experiments conducted, multiple trials were conducted to decrease error in data. Most experiments except those specifically said to be conducted outdoors were conducted in a common indoor environment at low level of humidity (~55%) and controlled temperatures around 25ºC. All outdoor experiments were conducted on dry, sunny days where temperatures ranged 27 – 32 ºC.

Several constraints and limitations existed due to the nature of the project and the lack of sophisticated environments. The first major limitation was the presence of walls in close proximity for many of the indoor experiments; this greatly increases the chances that Bluetooth phenomena such as multipath will impact results. Due to space and indoor furniture constraints, a large open area indoors was a major limitation in getting more accurate results of RSSI values at larger distances (e.g. 12 m and further). For outdoor experiments, large extension cords were required to conduct experiments as portable battery packs were not available at the time. Thus, there were constraints on how far away the two Raspberry Pi devices could be placed outdoors. The final limitation on the level of control in experiments is external Bluetooth and WiFi 2.4 GHz interference. To control external interference, an anechoic chamber would be required. Below figures showcase indoor experimental setups, outdoor experimental setups, and screenshots of typical external interference present found using nRF Connect.

Figure I. OUTDOOR EXPERIMENT SETUP

Figures II, III, IV. Indoor Environment and Experiment setup

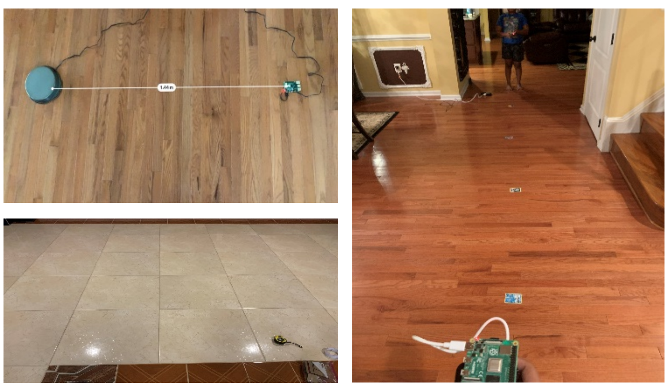
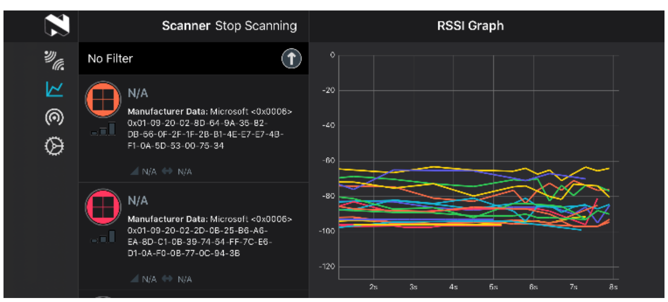


Figure V. External signal interference



B. Data Relevance

All of the hypotheses required the collection of RSSI values under different circumstances and environments. The data was collected through the use of python code and libraries that enabled for the setup of one Raspberry Pi as a BLE beacon advertiser and another as a BLE beacon scanner. As the BLE beacon advertiser began transmitting signals at regular intervals, the BLE beacon scanner began scanning and logging the details signals it received to include RSSI, UUID, TX Power, and time. The data was stored in a .csv file which could then be later analyzed. RSSI was found to be the best metric by which BLE signal interactions could be quantified. Consequently, statistics and graphs were developed using RSSI values. The statistics and graphs were analyzed to find trends in data and test the validity of hypotheses.

C. Examples

Figure VI. RSSI VS. Distance graph relevant to hypotheses 1 & 5

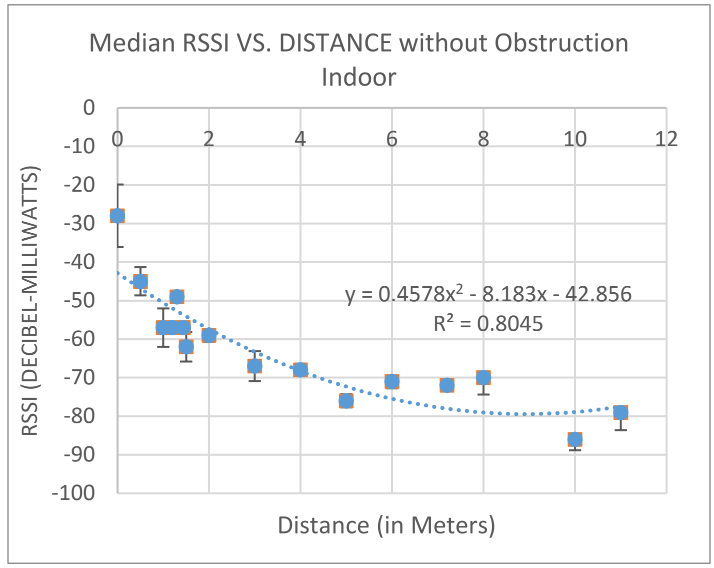


Figure VII. Histogram relevant to hypothesis 1 & 5

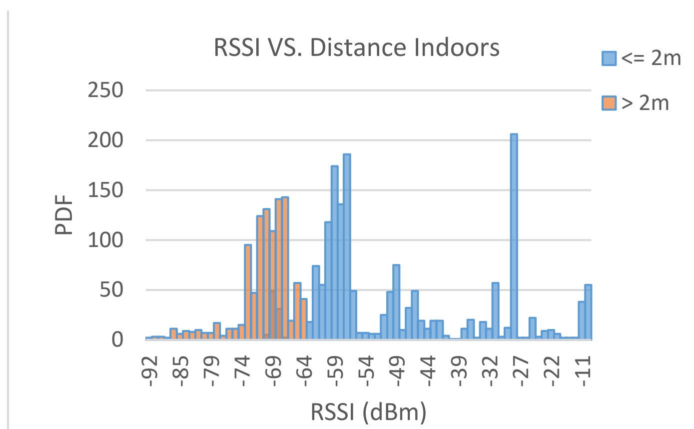


Figure VIII. Histogram relevant to hypothesis 5

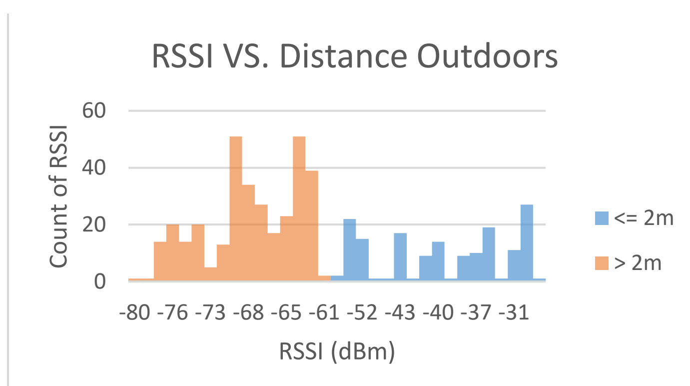


Figure IX. RSSI VS. Distance graph relevant to hypothesis 5

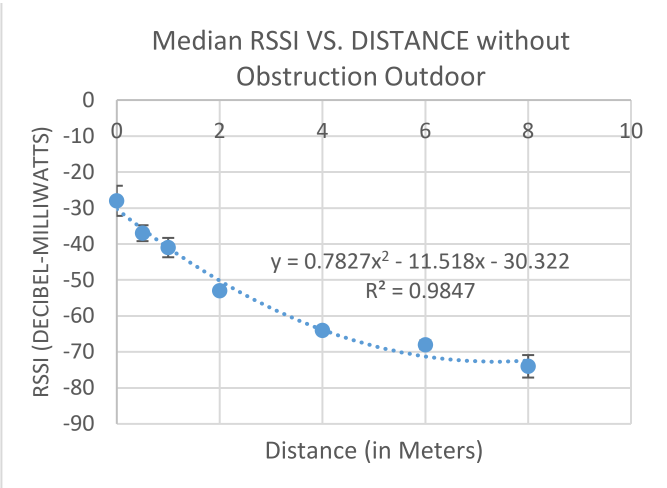


Figure X. RSSI VS. Obstruction type graph relevant to hypothesis 2

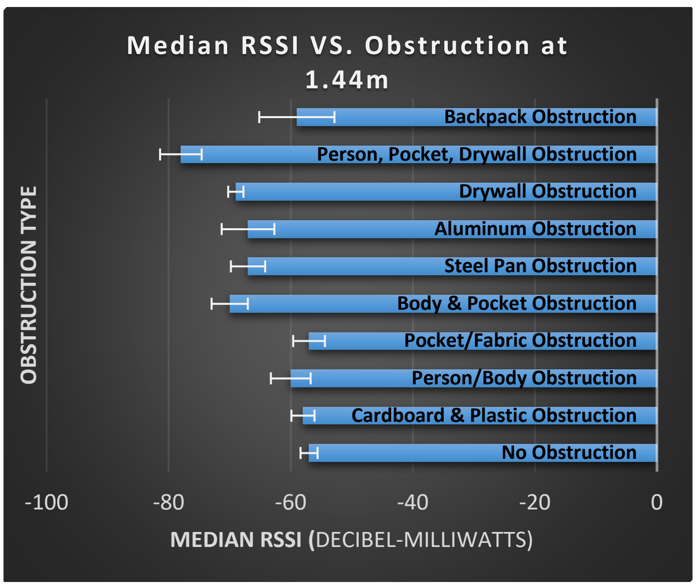


Figure XI. RSSI VS. TX Power level type graph relevant to hypothesis 3

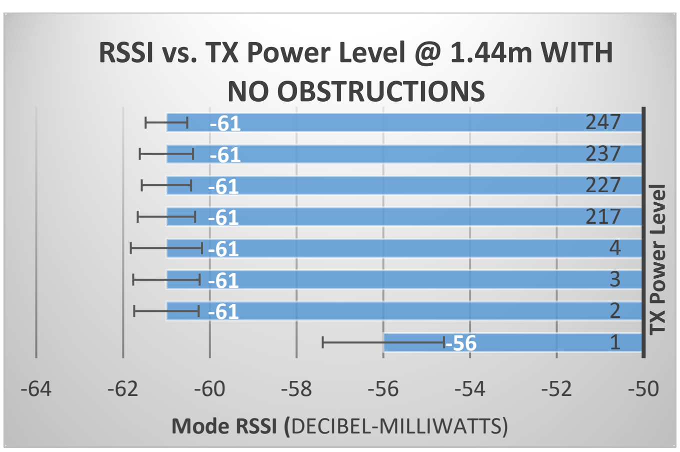


Figure XII. RSSI Variance VS. TX Power level type graph relevant to hypothesis 4

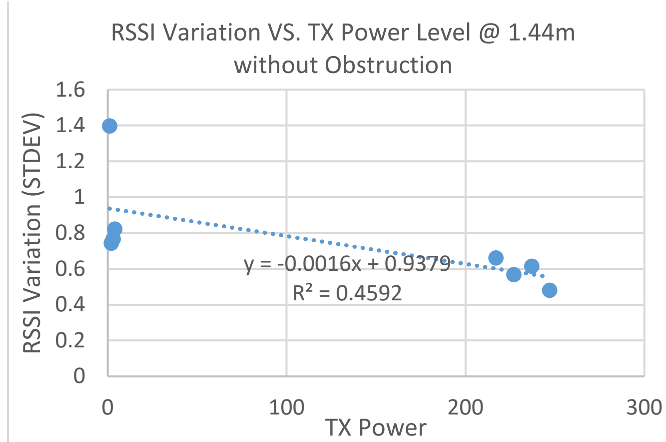


Figure XIII. Distance VS. RSSI at different orientations graph relevant to hypothesis 6

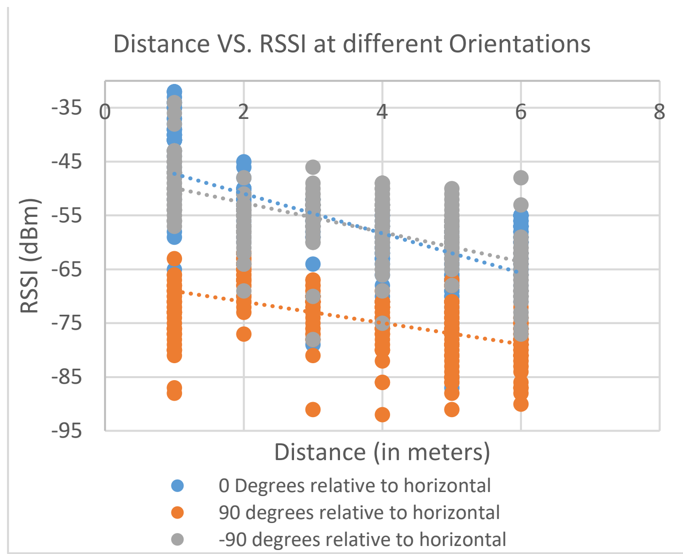
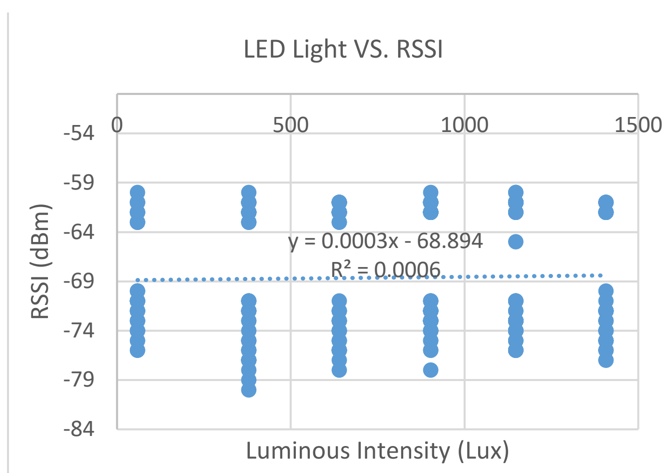


Figure XV. RSSI VS. LED Light level graph relevant for hypothesis 7



IV. Analysis and Algorithms

In this section, you should provide the following information.

A. Description

All hypotheses required the collection of RSSI data from the BLE Beacon Scanner Pi. The data, compiled in a .csv file, was imported to an excel spreadsheet. Data in the spreadsheet was then converted in relevant scatterplots, bar graphs, and histograms to analyze trends in data that may reveal the validity of hypotheses.

Scatterplot charts were used to display data relevant to hypotheses 1 ,4, 5, and 7. In the scatterplot each relevant datapoint is placed and a trendline is drawn. The R^2 and equation for the trendline is shown. The trendline seeks to model how the independent variable (IV) in the hypothesis affects the dependent variable (DV), RSSI, under controlled conditions. To determine the ability of the trendline to accurately model data, the R^2, the statistical coefficient of determination, is shown.

Bar graphs were used to compare median RSSI values collected under different conditions such as the type of obstruction medium between the scanner and advertiser Pis.

RSSI values across all experiments were collected and organized into two columns: those collected when devices were within 2m and those collected beyond 2m. The RSSI values compiled from the experiments were taken under many unique controlled conditions and thus account for a variety of obstacles and environments.

The detection algorithm used binary hypothesis test to determine when to declare TCTL (e.g. when beyond a certain threshold, declare TCTL). The RSSI threshold or critical-value for the binary hypothesis test was determined using generated histograms. The performance associated with using the single-point/critical-value threshold for the detection algorithm was measured using a Receiver Operating Curve (ROC). The ROC is a plot of true positive rate vs. false positive rate at different cutoffs. The closer the curve is to the to the top-left of the graph, the better the test will perform. The operating point closest to (0.0, 1.0) on the ROC curve was considered the optimal threshold value to use.

B. Results and Examples

Figure XVI. Receiver Operating Curve (ROC) of RSSI Binary Hypothesis testing for outside data

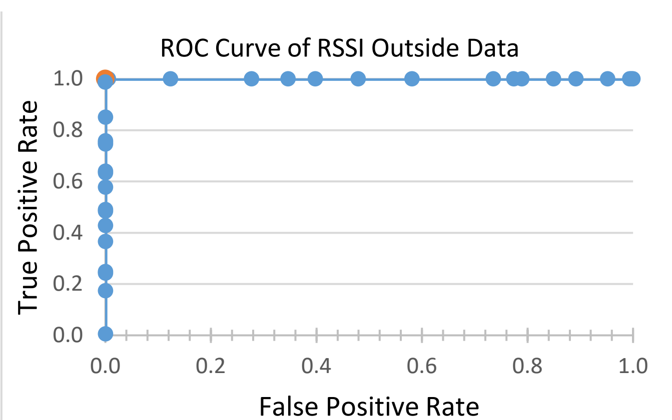
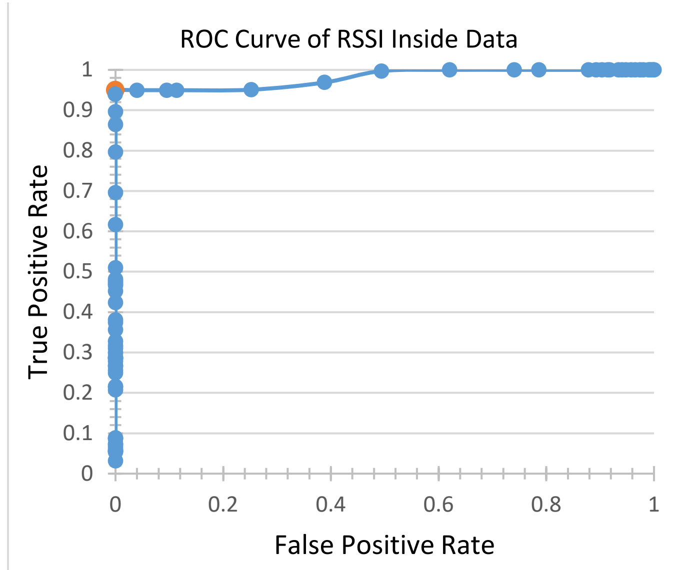


Figure XVII. Receiver Operating Curve (ROC) of RSSI Binary Hypothesis testing for Inside data



The two figures presented above detail the ROC curves used to measure the performance of binary hypothesis testing. The orange point is labeled in each curve is considered the optimal performance point. The RSSI threshold associated with this point is used in the detection algorithm. For the inside data the optimal point resulted in an RSSI threshold of -63 dBm and the outside data resulted in an RSSI threshold of -54 dBm. Consequently, the detection algorithm will need to be configured separately for detection indoors and outdoors due to significant differences between the two.

Manual testing of the binary-hypothesis detection algorithm revealed similar results to those presented in the ROC curve with the algorithm reaching a maximum percent error of 7.3% for indoor configurations and 0.1% for outdoor configurations.

V. Conclusions

In this section, you should address the following.

A. Hypothesis Evaluation

Hypothesis 1

If two devices are in a controlled environment without any obstructions then the RSSI received by the scanner device will decrease as the distance between the devices increases.

Data collected for this hypothesis were graphed in a scatterplot with RSSI on the y-axis and distance on the x-axis. A trendline was developed to empirically model the relationship between the two variables. The trendline is set to a second order polynomial and bears a resemblance to a leftward translated version of the function:

$$y = -\ln(x)$$

The trendline details a non-linear relationship where the RSSI decreases with increased distance. The scatterplot trendline has an R^2 of 0.80 and 0.98 for indoor and outdoor configurations of the experiment, respectively. This value suggests a strong magnitude of correlation between the two variables. Since the hypothesis was tested in an experimental fashion under controlled conditions, correlation between value of the trendline detail a strong second order polynomial relationship between the variables.

Based on these assessments, the hypothesis is found true.

Hypothesis 2

If two devices are separated by an electrically-conductive medium then the RSSI will be weaker than if the two devices were separated by a non-electrically-conductive medium.

Experiments conducted for this hypothesis were done under controlled conditions indoors at a constant distance of 1.44 meters between the BLE Beacon Advertiser Pi and the BLE Beacon Scanner Pi. Multiple RSSI readings were collected and imported into a spreadsheet. The RSSI readings underwent statistical analysis, of which the median was taken and plotted on a bar graph (refer to figure X under section IIIC.). The plot includes typical mediums found indoors and, in some circumstances, combines several mediums that typically block the BLE signal all at once. Of the mediums listed individually, the ones that caused resulted the weakest RSSI values were metallic mediums that are electrically-conductive. This means that electrically-conductive mediums caused the highest BLE signal attenuation. Based on this assessment, the hypothesis is found true.

Hypothesis 3

If TX power is increased then there will be an increase in the RSSI value.

Experiments conducted for this hypothesis were conducted in a controlled indoor environment without any direct obstructions. Moreover, the BLE Beacon advertiser Pi and Scanner Pi were kept at a constant 1.44m apart. The BLE beacon advertiser was configured to broadcast at a particular TX power. The BLE scanner would record the TX Power and the RSSI values associated with the advertisement signal. The RSSI readings underwent statistical analysis, of which the median was taken and plotted on a bar graph with the corresponding TX power (see figure XI under section IIIC.). It can be seen from the graph that there is a large decrease in RSSI from TX power 1 to TX power 2. From there, the median RSSI value stabilizes. As a result, the hypothesis is considered to be false and no definite relationship can be defined between TX power and RSSI.

Recent research and lectures given by piPACT staff have helped to illuminate a possible reason for this stabilization in RSSI: BLE signals account for higher transmit power and adjust RSSI to maintain consistency.

Hypothesis 4

If the TX power of the advertiser is increased then there is less observed variation in RSSI.

Experiments conducted for this hypothesis were conducted in a controlled indoor environment without any direct obstructions. Moreover, the BLE Beacon advertiser Pi and Scanner Pi were kept at a constant 1.44m apart. The BLE beacon advertiser was configured to broadcast at a particular TX power. The BLE scanner would record the TX Power and the RSSI values associated with the advertisement signal. The RSSI readings underwent statistical analysis, of which the standard deviation was taken and plotted on a scatterplot graph with the corresponding TX power (see figure XII under section IIIC.). It can be seen from the graph that there is an inversely proportional linear correlation between the TX power and RSSI variation (measured via standard deviation in RSSI values). However, the R^2 of the trendline is 0.46 signifying a weak correlation between the two variables. As a result, no definite relationship can be determined and the hypothesis is indeterminate.

Hypothesis 5

If two devices are outdoors then RSSI values will be higher than those observed indoors.

Experiments conducted for this hypothesis were conducted in controlled environments without any direct obstructions. Data collected for this hypothesis were graphed in two scatterplots with RSSI on the y-axis and distance on the x-axis. One of the scatterplots incorporated RSSI vs. Distance data taken indoors and the other incorporated RSSI vs. Distance data taken outdoors (see figures VI & IX under section IIIC.). Comparing the two scatterplots and their respective trendlines, it can be seen that the points and trendline in the scatterplot for indoor data appear to be translated downward with respect to the scatterplot and trendline for outdoor data. This signifies that on average, outdoor environments yield higher RSSI values at similar distances when compared to their indoor counterparts. Similar conclusions can be derived from generated histograms (see figures VII & VIII under section IIIC.). The histograms showcase the distribution of RSSI values at different distances. For distances shorter than 2m, it can be seen that RSSI values can dip as low as -72 for indoor environments while only -54 for outdoor environments. This signifies that the same distances between devices, RSSI values are lower for inside environments when compared to outside. Based on this assessment, the hypothesis is found to be true.

Hypothesis 6

If the advertiser and scanner are in an orientation different than 0º relative to the ground then the RSSI will be lower because of multipath.

Experiments conducted for this hypothesis were conducted in a controlled indoor environment without any direct obstructions. Data collected for this hypothesis were graphed in one multi-series scatterplot with RSSI on the y-axis and distance on the x-axis. The series represent RSSI vs. Distance data collected with the BLE beacon advertiser and BLE beacon scanner facing each other in three different orientations relative to horizontal. From the multi-series scatterplot (see figure XIII under section IIIC.), it can be seen that there is a significant distinction between values collected at a 90º orientation and those collected in the other two orientations. The 90º orientation series is shifted vertically downward signifying a consistently lower RSSI and a weaker signal strength. However, there is little to no distinct difference between the 0º and -90º orientations. This is likely due to external condition sand the probabilistic nature of multipath. Based on this assessment, the hypothesis is considered to be indeterminant as there is insufficient data to prove the validity of the hypothesis or its null counterpart.

Hypothesis 7

Experiments conducted for this hypothesis were done so in a controlled indoor environment without any direct obstructions between the two Raspberry Pi devices. Illuminance from an overhead LED lights and an additional LED desk lamp was measured in lumens per square meter (LUX). This measurement was done using an Arduino Uno and a photoresistor. Results from the experiment were plotted onto a scatterplot with RSSI on the y-axis and illuminance on the x-axis. The generated scatterplot and trendline (see figure XV) show little to no relationship between LED illuminance and RSSI. The R^2 value of 0.0006 further showcases the point that no accurate trendline can represent the relationship between the two variables. As a result, the hypothesis is found to be false. The likely reason for this is that external signal noise impacts the RSSI to a greater magnitude than any noise from LED. Moreover, it is likely that the Raspberry Pi doesn't even pick up any of the EM emissions from the LED lights due to extensive differences in the frequencies of the EM waves emitted by the LED lights (likely in the THz range) and those emitted by the BLE beacon advertiser (in the 2.4 GHz range).

B. *Noteworthy Conclusions*

Several noteworthy conclusions arose from the hypotheses tested and the experiments conducted. The first conclusion is that RSSI values differ greatly between indoor and outdoor environments. RSSI threshold/critical-values used in the proximity detection differed by -9 dBm. This presents a large challenge in developing a robust proximity detection algorithm that can function in both outdoor and indoor environments. This is the primary reason why the basic detection algorithm presented has two separate thresholds for indoor and outdoor proximity detection. The likely reason that indoor environments experience lower RSSI values and greater signal attenuation is due to RF signals bouncing off interior wall as a result of multipath.

A second noteworthy conclusion derived from experiments is the challenge that obstructions create for accurate proximity detection. The presence of multiple obstructions (e.g. a person, drywall, and a pocket) blocking the signal creates large ambiguity. That said, the ambiguity created is manageable if a binary-hypothesis system is implemented. The binary-hypothesis system and ROC curve generated in this report showcase a 94% true positive rate and a 0% false positive rate when accounting for all sorts of obstructions indoors. Moreover, manual tests of the proximity detection algorithm highlight a maximum percent error of 7.3% when determining the time that devices were within 2m indoors. While not ideal, the error is acceptable from an engineering standpoint. Ultimately, it is up to public health officials whether or not that level of error is acceptable.

A third noteworthy conclusion is that orienting devices downward causes significant decrease in RSSI. While the orientation vs. RSSI hypothesis was not proven nor disproven, the orientation of the two devices relative to each other is a large factor in determining the types of RSSI values that will be received.

C. *General Lessons Learned*

Overall, the data analysis conducted and testing of the developed detection algorithm showcase the feasibility of using BLE signals for proximity detection. While not perfect, the technique is be considered to be feasible and warrants further research and development.

VI. Next Steps

There are many steps required to transition the basic detection algorithm developed on the Raspberry Pi to a robust system that can be used in a smartphone. The biggest aspect of Bluetooth-based contact tracing that needs to be evaluated is the battery drain of a continuously running Bluetooth-detection algorithm that is transmitting and receiving chirps/signals. While BLE itself drains very little battery, other aspects of the algorithm such as downloading from a local database may strain the battery life of smartphones.

Secondly, orientation vs. RSSI is something that briefly evaluated in the report. Additional time would allow for the use of additional sensors like absolute orientation gyroscopes, accelerometers, magnetometers to determine roll, pitch, and yaw. This metrics would be useful in gaining a more in-depth view into how the orientation of two devices/smartphones will affect the BLE signal strength. It is important to note that some of these sensors are already built into modern smartphones and can be leveraged for future testing with smartphones.

A large obstacle in the generalizability of developed detection algorithms to all smartphones. Smartphones are very diverse in hardware and software specifications. The large disparity in specifications can cause large ambiguity in RSSI values, making them essentially arbitrary. The main reason for this is that different vendor's antennas and chipsets encode RSSI values differently than others [2]. Moreover, different smartphones use different specifications of Bluetooth (e.g. Bluetooth 3.0 which doesn't support BLE). Thus, a large, widespread effort is required to document the specifications of popular smartphones and optimize detection software for those devices before moving onto more specific cases. This research and documentation will require large amounts of data, time, and resources. This aforementioned obstacle was overcome in this report through the use of two identical Raspberry Pi Model 4 Model B devices equipped with the same hardware and the latest version of Bluetooth: Bluetooth 5.0.

Finally, there are many aspects of the basic detection algorithm that require additional time and resources to refine. Firstly, the detection algorithm warrants the use of an external database to upload and download chirps from the devices of infected individuals. Small-scale, free methods of doing so include Airtable, Microsoft Access, SQL, etc. Python integration is readily available for some of the aforementioned methods (Microsoft access can be integrated using the python pyodbc library). However, maintaining large scale databases for the scope of the PACT project will require subscription and extensive maintenance. The next core component of the detection algorithm is the cryptographic aspect. The basic detection algorithm developed includes no cryptographic protocols to preserve the privacy of metrics collects. Additional time and resources would enable to the exploration of these aspects.

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