Analysis of RSSI-Based Localization for Room Level Deployment Accuracy

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Abstract

Beacon-based localization using Received Signal Strength Indicator (RSSI) is a common approach for indoor localization. However, signal variability remains a significant issue for precision localization accuracy, and existing methods involving extensive calibration and modeling to improve performance require significant deployment effort and specialization. Yet, for many applications, localization with room-level resolution is sufficient. This thesis explores configurations of a beacon-based system designed to capture receiver localization at the room level.

The accuracy of room level localization is assessed with regard to transmitter deployment schemes including generalized placement, quantity, and specific layout. Length of localization window is evaluated to ensure data quality and as proof of concept for real time operation. Six proximity localization algorithms are implemented and evaluated for their ability to accurately localize to the correct room of a floorplan.

Results indicate that configurations in which transmitters are placed in the center of room walls provide higher localization accuracy, and a minimum of 2 of RSSI beacon packets are necessary to process and stabilize optimal localization. However, analysis of algorithm performance, transmitter quantity, and layout reveals tradeoffs between accuracy, resources, and deployment effort. Configurations with 4 transmitters deployed per room coupled with a “Best of 5” voting algorithm delivered the highest accuracy of 0.9486 on average; however, maximal accuracy of algorithm performance only increases marginally as the quantity of beacons is increased, so true deployment optimum is dependent on equipment constraints and acceptable uncertainty for room-level localization accuracy.

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I. Introduction

Localization, the process of accurately evaluating position, is a critical component of many systems, particularly in the domain of remote sensing. Despite global widespread use of localization technology, fine grained indoor localization remains a significant challenge [1]. Commonly used large-scale systems, such as GPS, are unsuitable for this domain, as signal quality inside most structures is significantly degraded, thereby preventing accurate indoor localization [2]. Most localization schemes designed specifically for indoor use are highly susceptible to error and prone to inaccuracy unless substantiated with elaborate modeling and calibration techniques [1]. Despite many recent developments, the need to optimize a simple scheme for deployment and execution of indoor localization in an indoor context remains.

The most significant challenge related to indoor localization is that the majority of existing methodologies rely on precision positioning using Received Signal Strength Indicator (RSSI). RSSI is a metric of signal strength measured by a receiver antenna and is commonly translated into a quantifiable distance extrapolated from signal attenuation and a known intensity at the transmitter antenna. RSSI-based distance estimates are highest when the signal is emitted from a transmitter and attenuates predictably as the signal propagates through free space. However, RSSI is known to be susceptible to error from a wide variety of sources making it a highly erroneous metric in real-world conditions. First, RSSI signal is inherently a noisy quantity, so some degree of data processing is essential to extract meaningful information. Second, obstructions between transmitter and receiver – such as walls or human bodies – radically accelerate signal attenuation. Receiver orientation is also critical, since RSSI can be affected by the angle of the receiver antenna. Motion inherently increases the entropy of RSSI data since neither position nor orientation is constant. Finally, environmental ambient factors such as temperature, humidity, pressure, and RF interference are also known to impact RSSI variability and signal propagations. Each of these make RSSI a challenging quantity for use in reliable localization techniques [3]. Recent attempts to account for these factors typically require *a priori* knowledge of the deployment environment (e.g., floorplans, wall materials, environmental/ambient conditions, etc.) and/or significant installation effort (e.g., precise beacon placements, careful calibration measurements, data-driven model development, etc.) that may not be practical for some deployments.

However, for some applications, fine grained techniques for precision localization may be unnecessary. Instead, localization with room-level resolution may be sufficient and presents many advantages [14]. By adapting the frame of localization in this manner, there is the potential for reducing the *a priori* knowledge and installation effort required for accurate localization.

The goal of this thesis is to present an analysis of RSSI-based systems for room-level localization. Analysis will not be dependent on any *a priori* knowledge of floorplan or environmental/ambient conditions or any installation effort beyond simple transmitter placement. Variables relevant to the concept of indoor localization are presented within the context of an environmental sensing system and challenges associated with its deployment, including transmitter configuration, localization time window, and RSSI-based localization algorithms. Metrics are analyzed and optimized with the assumption of an equal weight to all data points and rooms to inform judgement regarding the deployment of similar localization schemes in the future.

A. Application

The Behavioral and Environmental Sensing and Intervention for Cancer (BESI-C) system was designed with the intention of using medical cyber-physical systems technology to help cancer patients and family caregivers manage symptoms of pain in an out-patient, in-home monitoring context [4]. The system consists of an array of environmental and wearable sensors designed to collect context data surrounding the perception of cancer pain.

Environmental sensors are mounted on the walls of each main room in the home of the dyad, and are designed to collect data on light level, temperature, humidity, barometric pressure, and ambient audio features. This data is uploaded to an Amazon Web Service (AWS) cloud server via a centralized base station and router for data storage and processing. This data will eventually be used in real time to detect environmental conditions likely to influence perception of cancer pain.

Both patient and caregiver in this study are given an Android based Fossil smartwatch equipped with a custom BESI-C Wear OS application. This app is designed to passively and continuously collect motion data with a 3-axis accelerometer and heart rate with a PPG sensor. The BESI-C app also provides an interface for the user to document pain episodes and daily qualitative context data. The user also has the ability to mark the timestamp when a pain episode occurs. This, in turn, prompts a brief survey in which the user is prompted with several questions relating to their pain perception. Additionally, timed surveys are issued once a day in the evening to collect further situational context data. All data collected on the smartwatch is uploaded directly to the AWS platform via Wi-Fi, where it is stored. This data will also eventually be used in real time to detect environmental conditions likely to influence perception of cancer pain.

A final key component of this system is the ability to accurately evaluate the positions of the respective patient and caregiver in their home environment. Accurate localization is critical in order to properly correlate patient and caregiver position to the appropriate environmental sensor nodes, and to study the effect of the dyadic relationship between the patient and caregiver, social interaction, and perceived impact they have on pain [5]. In BESI-C, localization is performed via a series of BLE transmitter beacons placed strategically throughout the floorplan in which the system is deployed. Proximity Beacons from Estimote are configured to transmit iBeacon packets to the aforementioned smartwatches which record the RSSI values (For future deployments of BESI-C, environmental sensors have been configured to transmit BLE iBeacon packets, eliminating the need for external Estimote Beacons). This data will be uploaded to the cloud platform, where the intent is to correlate position to the appropriate sensor metrics for cancer pain detection. Localization ground truth is collected via two questions on the smart watch surveys which prompt the user as follows:

Momentary Pain Survey: “What is your current location?”

Answer Choices: "Living Room", "Bedroom", "Kitchen", "Outside the home", "Other"

End-of-Day Survey: “Where did you spend most time?”

Answer Choices: "Living Room", "Bedroom", "Kitchen", "Outside the home", "Other"

Responses to these questions will be used in BESI-C to asses localization algorithm efficacy in a real-world uncontrolled environment. Initial analyses of localization algorithms, optimization, and tradeoffs involved with this process in a controlled environment are the topic of this thesis.

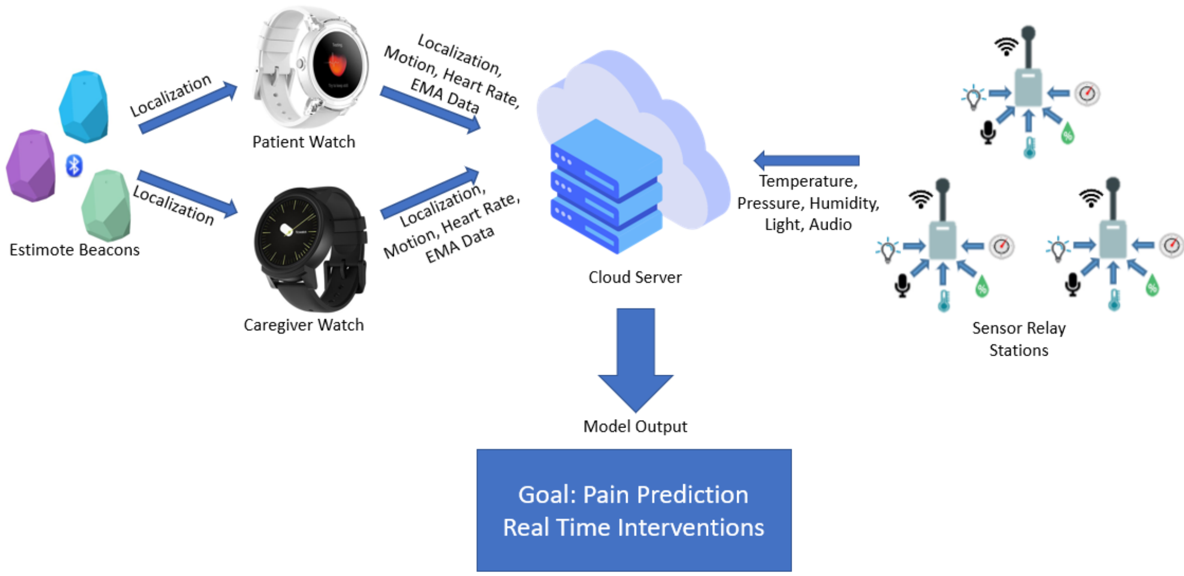

Figure 1. Overview of BESI-C system architecture showing localization data flow from Estimote Beacon transmitters to wearables and finally to the cloud where RSSI data will be processed and correlated to appropriate environmental sensor nodes.

B. Challenges

This thesis presents the development, deployment, analysis, and optimization of RSSI-based, room-level indoor localization, as presented in the context of an in-home health monitoring system. This requires a scalable system [8] that optimizes positioning accuracy using RSSI values from transmitter beacons. Specific challenges associated with these goals are outlined as follows:

1. **Accuracy Optimization** – Results of deployed localization scheme and correlation to data collected across other platforms in the system have the potential to provide real-world impact [4,5,8]. Therefore, it is vital that any localization scheme must be performed in a manner such that position can be reliably correlated to external sensor data.

2. **Generalizability** – Deployed localization algorithms must be suited to a diverse and unpredictable array of floorplans and environments. In addition, reliable ground truth collection and time constraints may inhibit the effective deployment of machine learning models [6,7]. It is therefore, the goal of this experiment to maximize the accuracy of offline algorithms for use in any indoor localization system.
3. **User Installation** – Long term system scalability makes user self-installation an essential feature. This requirement complicates the use of traditional localization techniques, many of which are already prone to error. Users cannot be expected to provide detailed cartesian floorplans for the purpose of coordinate localization. Further, it is an unrealistic expectation that users will take sufficient measurements, calibrations, and reliable ground truth necessary for the use of precision localization techniques [6,7]. This requires the implementation of simplified guidance with regard to transmitter positioning and a generalized localization schema functional with minimal *a priori* environmental knowledge.
4. **Minimization of Equipment Overhead** – The amount of equipment deployed presents challenges in several areas. In addition to further complicating installation, additional equipment is associated with increased cost and greater complexity resulting in deployments that are more prone to error [7]. Optimizing tradeoffs between, accuracy and overhead is key for deployment success.
5. **Real Time Performance** – Given the nature of the system application for predictive modeling and potential for real-world impact, it is vital that any implemented localization scheme show compatibility for performance and processing in real-time.

II. Background

A. Standard RSSI-Based Indoor Localization Techniques

The majority of existing techniques surrounding indoor localization rely on the use of RSSI for positioning. The use of this metric caries a host of challenges including inherent signal noise, environmental variability, and in-depth model calibration or training procedures. [3] This section overviews techniques used in effort to address the challenge of indoor RSSI localization.

Triangulation is a common geometric technique for indoor localization that involves RSSI propagation along with angle of arrival at the receiver. Trigonometric relationships are used to compute precision positioning. This procedure involves additional challenges regarding specialized equipment to measure angle of arrival and is also subject to the aforementioned RSSI variability. [10]

Trilateration is another standard practice for RSSI based indoor localization for precision positioning [10]. This technique requires at least 3 transmitters and 1 receiver for localization in 2-dimensions. In this process, RSSI measurements are correlated to a distance radius from their respective transmitters. In theory, the circles formed by these radii, centered on each transmitter, should intersect at a single point in the coordinate plane. This point of intersection is the output of the precision trilateration localization process.

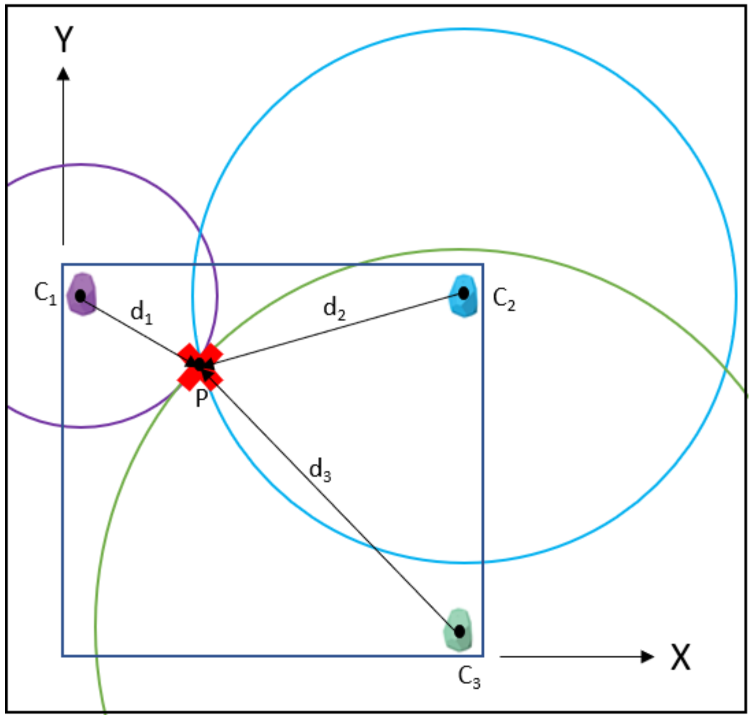

Figure 2. Shows example of standard trilateration in the XY-Plane. Three transmitters are indicated at the center of their respective circles by C_1, C_2, C_3 with d_1, d_2, d_3 indicating their corresponding radii. Intersection at point P indicates the point of localization.

However, there remain a number of problems with this approach. Traditionally, this approach utilizes the Log-Distance Path-Loss Model for RSSI calibration shown below [3]:

$$RSSI(d) = RSSI(d_0) - 10n \log\left(\frac{d}{d_0}\right)$$

In this relationship, *RSSI(d)* is the RSSI value at a radius *d* from the transmitter. By convention, $d_0 = 1$ meter with $RSSI(d_0)$ referring to the RSSI at a distance of 1 meter. By recording RSSI at known distances *d* and d_0, path loss index *n* can be computed [3]:

$$n = \frac{RSSI(d_0) - RSSI(d)}{10 \log\left(\frac{d}{d_0}\right)}$$

Path Loss is a scalar estimation of signal attenuation. Using this value, unknown distance *d* of a receiver can be computed as follows [3]:

$$d = 10^{\frac{RSSI(d_0)-RSSI(d)}{10\mathrm{n}}}$$

However, this model presents significant challenges, as RSSI is known to be a highly variable metric and is characterized by significant signal noise. Additionally, environmental factors such as temperature, humidity, and pressure as well as physical obstructions, motion, and signal interference all have an impact on recorded RSSI, making this quantity even more variable. Given the exponential and logarithmic relationships involved in this model, this presents a challenging scenario in which plotted trilateration circles may not yield the desired point of localization. A study of simple trilateration accuracy across a complex floorplan showed that variations in RSSI can fluctuate with a range of up to 10dB, which can result in greatly erroneous trilateration radii when coupled with the aforementioned logarithmic model [11].

In [3], a solution is proposed to address this problem in which Path Loss calibration is performed at a multitude of intermediate points rather than the standard 2 points. Distance was then computed for a point of known coordinates, and the error in calculated distance was used to set bounds for possible trilateration radii. This approach is not ideal for large scale system scalability as this rigorous calibration process must be repeated for every transmitter involved in the localization scheme. This presents a significant barrier when dealing with a large quantity of transmitters or localization across multiple rooms.

Several methodologies exist in which machine learning models used to reduce RSSI error in distance computation. In [12] and [13], the authors present solutions to localization in which the computed distance accuracy was increased by using a stepwise series of algorithms and online models to smooth

RSSI for accurate localization. However, methodologies such as these are designed to function online, and require periods of model training.

In addition, all of the aforementioned solutions to localization depend on prior knowledge and precision measurements of the deployment floorplan and transmitter placements. In each instance, localization is impossible without this *a priori* information.

B. Room Level Localization

In [14], it is proposed that some applications may not require the degree of precision sought after by many localization schemes. In this study, a series of directional door sensors were mounted in the doorways of rooms and used to track motion across room thresholds. These sensors operated using two channel infrared sensors to determine directionality of motion, and the localization of a human subject within a room. Motion across thresholds was validated using data collected on a 3-axis accelerometer, which is correlated to each threshold crossing event.

This approach introduces the notion of localization with room level granularity for indoor localization. While the use of infrared door sensors is not within the scope of this project and ultimately unsuitable for use in the given application, the notion of localization at the room level is applicable. Obstructions such as walls decrease recorded RSSI, so theoretically the strongest RSSI values recorded by a receiver would be from transmitters within the same room.

III. Methods

The goal of this project is to perform an analysis of RSSI-based room-level localization scenarios. This involves evaluating proximity localization algorithms for generalizable floorplans in an effort to optimize the performance accuracy and balance deployment tradeoffs. This section outlines the specific algorithms, variables, constraints, and setup involved with this process..

A. Variables

Variables evaluated in this project can be categorized generally in terms of Deployment Configuration, Data Collection, and Data Processing. Each was selected based on its perceived ability to address the specific localization challenges outlined in section IB. Variables are outlined as follows:

1. **Deployment Configuration - Transmitter Placement** – In an effort to establish an easy guideline for transmitter installation, two deployment scenarios were evaluated in which transmitters were placed in either the corners of a room or in the center of the walls in each room. Deriving a specific yet generalized approach to transmitter placement will aid in streamlining system deployment. This variable was be evaluated in terms of optimizing accuracy.
2. **Deployment Configuration - Transmitter Quantity** – The overall quantity of transmitters used can be a limiting factor with regard to deployment set up and equipment overhead. Thus, the optimal number of transmitters per room was evaluated with the intent of balancing tradeoffs between maximizing accuracy and minimizing transmitter quantity.
3. **Deployment Configuration – Specific Transmitter Layouts** – All possible layouts of transmitter configurations on each specific test floorplan were compiled and analyzed. This is done in an effort to garner knowledge regarding the impact of transmitter positioning choices on floorplan localization accuracy, and to identify any specific optimal deployment configurations.
4. **Data Collection – Localization Window** – RSSI is characterized by intense signal noise and is highly susceptible to error from external sources. To address this, the data collection was averaged with the intent of finding the minimum data collection period necessary to obtain a stable value and clear localization result.

5. **Data Processing - Localization Algorithms** – Six RSSI proximity algorithms were evaluated in terms of their accuracy and required equipment overhead to find the best algorithm in a variety of scenarios. Algorithms are given in Section IIIB.

B. Localization Algorithms Overview

Six distinct RSSI proximity localization algorithms were developed based on principles of reliability voting. Each algorithm was assessed to be compatible with localization to the room-level and requires no *a priori* floorplan knowledge for implementation or accuracy optimization. Algorithms are outlined as follows:

1. **Greatest RSSI (B1)** –This algorithm identifies the transmitter corresponding to the greatest RSSI received during the given localization time window. The output of this localization algorithm is the room in which that transmitter is located.
2. **Best of Three Vote (B3)** – Based on principles of reliability voting, this algorithm identifies the top three greatest RSSI values from the array of deployed transmitters within the designated time window and localizes to the room corresponding to the greatest number of RSSI values within the top three. In the event of a tie, this algorithm uses a fourth transmitter RSSI as a tentative tie breaker among the locations involved in the tie. In the event that a fourth RSSI adds no helpful information (e.g. entering an additional room into the tying scenario), this algorithm defaults to the location of the transmitter with the strongest RSSI involved in the tie.

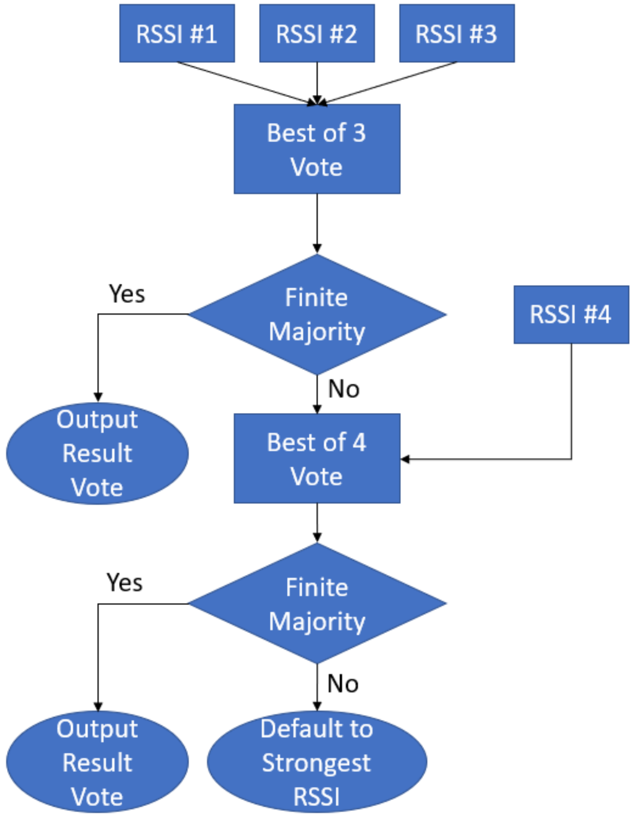

Figure 3. Algorithm flowchart illustrating the process behind the Best of 3 Vote (B3) algorithm. The Best of 5 Vote (B5) Algorithm functions similarly with additional RSSI inputs.

3. **Best of Five Vote (B5)** – Based on principles of reliability voting, this algorithm identifies the top five greatest RSSI values from the array of deployed transmitters within the designated time window and localizes to the room corresponding to the greatest number of RSSI values within the top five. In the event of a tie, this algorithm uses a sixth transmitter RSSI as a tentative tie breaker among the locations involved in the tie. In the event that a sixth RSSI adds no helpful information (e.g. entering an additional room into the tying scenario), this algorithm defaults to the location of the transmitter with the strongest RSSI involved in the tie.
4. **Overall Vote (OV)** – This algorithm takes in the results of the B1, B3, and B5 algorithms and votes among the outputs of the three for the localization result.

5. **First Confirmation (FC)** – This algorithm ranks and orders all RSSI values from the array of deployed transmitters and uses a hierarchical approach to the B3 algorithm. In order from greatest to smallest RSSI, the first location to receive two votes from different transmitters in the same room is the room of localization and the output of this algorithm. This scheme was developed as an alternative to the B3 approach that would eliminate the possibility of a tied vote.

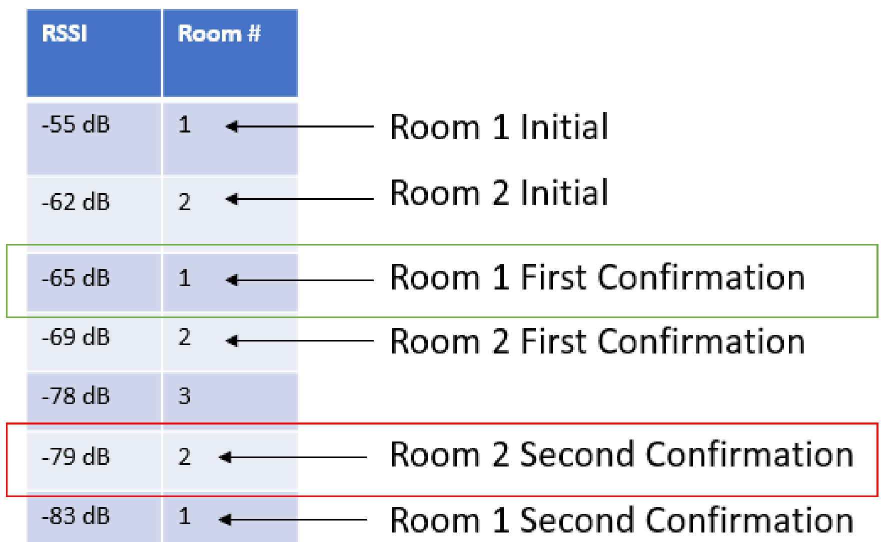

Figure 4. Example demonstrating the hierarchical processes and results of the First Confirmation (Green) and Second Confirmation (Red) algorithms.

6. **Second Confirmation (SC)** – This algorithm ranks and orders all RSSI values from the array of deployed transmitters and uses a hierarchical approach to the B5 algorithm. In order from greatest to smallest RSSI, the first location to receive three votes from different transmitters in the same room is the room of localization and the output of this algorithm. This scheme was developed as an alternative to the B5 approach that would eliminate the possibility of a tied vote.

An additional consideration in the evaluation of each localization algorithm is that each option requires a minimum number of transmitters per room to guarantee algorithm efficacy. Localization may still be possible with fewer transmitters than required to guarantee functionality; however, these scenarios are rare and highly case dependent (these cases are taken to be outside the scope of this thesis). Minimum transmitter requirements to guarantee algorithm functionality are outlined in the Table 1.

# Transmitters	B1	B3	B5	OV	FC	SC
1	YES	NO	NO	NO	NO	NO
2	YES	YES	NO	NO	YES	NO
3	YES	YES	YES	YES	YES	YES
4	YES	YES	YES	YES	YES	YES

Table 1. This table indicates the algorithms compatible with each number of transmitters to guarantee a finite result with "YES" (Green). Incompatible combinations are indicated with "NO" (Red). Note: For configurations with 2 transmitters per room, there is a possibility that algorithms B5 and OV will deliver an accurate localization result, but this cannot be guaranteed due to insufficient transmitter quantity and an algorithm exception is likely; these combinations are therefore indicated with "NO" (Yellow).

C. Constraints

The analysis in this project was designed to be an initial exploration into the optimization and tradeoffs associated with the deployment of an indoor localization system and was not intended to address all scenarios that may be encountered or analyzed in real-world deployments. This section outlines the major constraints, which although possibly of interest, fall outside the immediate scope of this analysis.

1. **Consistent Placement Guideline** – The generalized placement guideline (i.e. corner placement or center placement of transmitters) was a variable under evaluation in this project. However,

combinations of these two placement schemes were not considered in this analysis. For each test scenario, transmitters were set either all in the corner placement configuration or all in the center wall configuration. Configurations combining deployment of transmitters in both configurations falls outside the scope of this experiment.

2. **Consistent Number of Transmitters** – While the number of transmitters was a variable under consideration, all deployment tests and analyses were performed with respect to a consistent number of transmitters across each room in testing. Cases in which there were differing quantities of transmitters between rooms are not considered (e.g. no case was analyzed in which there were 2 transmitters in room A and 3 transmitters in room B). Keeping this quantity consistent in this manner gives equal weight to the evaluation of each localization algorithm and equal weight to each testing data point as various combinations of transmitters are iterated in data processing.
3. **No Precision Measurements** – The purpose of this project is to provide an accurate means of indoor localization without the need for any prior positioning measurements or calibrations. Therefore, no precision positioning or spatial measurements of any kind were taken as a part of this experiment.
4. **Stationary** – While motion is a fundamental factor in the deployment of any localization scheme, the act of motion itself drastically increases the entropy and error involved in the localization procedure by introducing a variety of additional variables including receiver orientation, additional obstructions, and ground truth uncertainty/transience. It is the intent of this study to establish a baseline evaluation for room level localization and, although future work should take motion entropy into account, it is not considered as a part of this study. Therefore, the test receiver was kept stationary for the duration of data collection at each test point.

5. **2-Dimensional** – Vertical distance between transmitter and receiver affects RSSI similarly to positioning in the horizontal plane. However, for this study the impact of vertical distance was assumed to be negligible compared to horizontal distance in the XY-Plane and compared to external sources of error. Therefore, all tests were performed with respect to 2-dimensional positioning only. Additionally, limited building access made testing across floorplans of multiple levels difficult. Therefore, deployments were performed on single story floorplans only, and all localization is assumed to take place in 2 dimensions in the XY-Plane.

D. Data Collection

Four unique single-story floorplans were used for data collection. Data was collected continuously for 5 minutes (for a total of 61 RSSI samples per transmitter) at each of 9 data points arranged in a 3x3 grid configuration per room in each floorplan. Points were positioned roughly in a uniform distribution with precise locations of test points unmeasured.

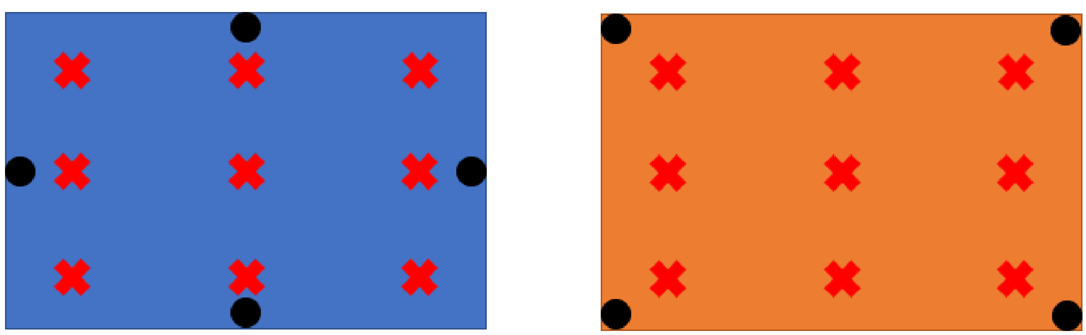

Figure 5. Displays the overhead view of the approximate test configuration for each room in the XY-plane. Black points represent transmitter positions and red X's represent test point positions. Left figure displays center wall transmitter deployment. Right figure displays corner transmitter deployment.

Four transmitters were deployed in each room across all floorplans and placed as high as feasibly and conveniently possible in the vertical direction using the aforementioned generalized position guidelines. This vertical positioning was in an effort to minimize potential obstructions between the transmitters and receiver which could result in lower RSSIs due to increased signal attenuation. Transmitters were configured to broadcast BLE iBeacon packets at a frequency of 3.33 Hz.

A Motorola G7 Play smartphone was deployed as the receiver and collected RSSI data using a custom developed Android app designed to scan for iBeacon packets emitted from BLE transmitters. Data was collected at a height of roughly 1 meter (precise height was not measured) and with the receiver stationary at each data point. Receiver was placed “screen-side up” for all data points and given a random rotational orientation about the vertical axis.

D. Data Pre-Processing

In evaluating deployment variables, it was necessary to evaluate all possible combinations of transmitters across each floorplan testbed. In all cases, 4 transmitters were deployed in each room during testing. In data pre-processing, localization accuracy was evaluated for all transmitter combinations by systematically iterating through all possible combinations of transmitters in each room of the floorplan. For each analyzed room in a floorplan, there are 4 iterations of 1 transmitter per room, 6 iterations of 2 transmitters per room, 4 iterations of 3 transmitters per room, and 1 iteration of 4 transmitters per room. Combinations were iterated for each room of the floorplan (keeping the number of transmitters consistent for each analysis) resulting in a total of $\sum_{k=1}^{4}\binom{n}{k}^{r}$ analyzed configurations for each tested floorplan, where *r* = the number of rooms and *n* = the number of transmitters per room.

In each case considered with less than 3 analyzed transmitters per room, the remaining additional transmitters were still active and functioning although neglected in analysis. Errant Bluetooth signals are known to affect the noise and value of observed RSSI for other transmitters under analysis. However, for purposes of this analysis, this impact was assumed to be negligible.

IV. Expectations

This section outlines hypothesized results for each evaluated quantity. These assertions are later compared to actual results for each variable in Section V.

A. Generalized Transmitter Placement

Prior to beginning testing, it was hypothesized that placement of transmitters in room corners would yield a greater room level localization accuracy. By placing transmitters in room corners at an approximately 45-degree angle, it was assumed that this deployment configuration would provide maximal coverage of each room and minimize potential obstructions yielding stronger RSSI values and greater localization accuracy. By contrast, center wall placement of transmitters was thought to be less a less accurate placement scheme due to the possibility of more prominent obstructions in the center of rooms and due to sub-optimal orientation of test points at the far extremities of each transmitter which may lead to smaller RSSI values and negatively impacting accuracy.

B. Localization Window

RSSI is known to be a noisy quantity, and averaging RSSI values over a collection window is an effective mechanism to smooth data. Therefore, it was predicted that averaging data over a greater number of collected RSSI samples would smooth the averaged RSSI to a relatively constant and stable value in the short run (assuming conditions of data collection remain the same), and consequently stabilizing the output of localization algorithms. Given the error associated with this signal, it was expected that data collection would be more prone to error for initial, smaller collection windows and that localization would become more accurate as window size increased with a greater numbers of samples.

C. Localization Algorithms

It was expected that utilizing more available transmitters to verify location would yield higher accuracy. As such, B5 and SC were predicted to be the most accurate localization algorithms. Due to semi-arbitrary tie breaking measures involved in B5, SC was predicted to marginally outperform the B5 algorithm. Since the B1 algorithm uses only a single transmitter, it was expected to be the least accurate algorithm. All remaining algorithms were expected to fall somewhere in between these extremities.

D. Transmitter Quantity

Redundancy is an important quality in the deployment of a reliable system. By deploying a maximal number of transmitters, there will be more available resources with which localization can be reliably verified. Deployment of a large number of transmitters per room would also reduce the impact of any single failure within the system. Therefore, it was expected that a greater quantity of transmitters in each room would result in a greater localization accuracy; likewise, a reduced quantity of transmitters in each room would result in a lower localization accuracy.

However, while maximal accuracy is desirable, it was also thought that after some quantity of transmitters only marginal increases in accuracy would be experienced. In this case, the highest accuracy might not be indicative of the true optimum deployment, and balancing accuracy standards with equipment overhead and availability would be necessary for deployment optimization.

E. Specific Transmitter Layouts

By iterating through all possible combinations of transmitters in each test, it was anticipated that certain configurations would undoubtedly outperform others and that some generalized optimizations in deployment would be observed. However, many analyzed transmitter combinations are simply counter intuitive and were similarly expected to perform less accurately. For example, it was expected that some iterations in which transmitters were effectively clustered adjacent to one another would perform less accurately since clustering would negatively impact voting efficacy and leave gaps in coverage in other positions throughout rooms. By the same intuition, configurations in which transmitters are more spaced out were predicted to perform more accurately due to lack of interference from other transmitters and greater room coverage.

V. Results and Analysis

To streamline data analysis with the goal of optimizing localization accuracy, analysis was performed in order of (1) Generalized Transmitter Placement, (2) Localization Time Window, (3) Localization Algorithms, (4) Transmitter Quantity, and (5) Specific Transmitter Layouts. This hierarchy allowed for the ability to find clear optimums for several variables of interest effectively eliminating the need to analyze them further and reducing the need to conduct redundant analyses for the remaining metrics.

A. Generalized Placement

Two deployment scenarios were considered as generalized deployment localization guidance: (1) Transmitter placement in corners of rooms and (2) Transmitter placement along center of room walls.

For each of the 4 floorplan tests, both the average RSSI over the full 5-minute data collection period (61 RSSI samples) and a single initial RSSI value were used to perform localization at each data point in effort to evaluate the bounds of all possible collection windows under analysis. Accuracies for each localization scheme were averaged across the 4 floorplans and these accuracies for the performance of each algorithm and number of transmitters for both cases are summarized in the Tables 2 & 3.

Figure 6. Displays an example deployment of all beacons positioned in the (1) Room Corners or (2) Center Walls.

Results for both averaged data collection and single point data collection show that Center placement of transmitters overwhelmingly provided greater accuracy than the corner placement configurations.

For the averaged data, the average overall accuracy for corner deployments was 0.8735 while for Center deployments it was 0.9048 for a difference in overall accuracy of 0.0313. In 14 out of 15 cases, center placement outperformed corner placement. The only case in which corner transmitter deployment exceeded the performance of the center deployment was in the B5 algorithm with 3 transmitters. This algorithm showed an accuracy of 0.9234 for the corner placement and 0.9126 for the center placement, with a difference of 0.0108. In the corner placement schemes, this instance was the second highest performing algorithm. The only case that performed more accurately was SC with 4 transmitters which had an accuracy of 0.9255 (although this accuracy was less than the corresponding center placement scenario which had an accuracy of 0.9426). Likewise, the maximum accuracy achieved by the center placement configurations was achieved by B5 with 4 transmitters which had an accuracy of 0.9486. In contrast, the minimum value for both arrangements was achieved by B1 with 1 transmitter which had an accuracy of 0.7772 for the corner placement and 0.8264 for the center placement.

Corner Placement- Averaged Data						
# Transmitters	**B1**	**B3**	**B5**	**OV**	**FC**	**SC**
4	0.8634	0.8634	0.9181	0.8634	0.8884	0.9255
3	0.8342	0.8772	0.9234	0.9121	0.8772	0.9190
2	0.8236	0.8546	-	-	0.8559	-
1	0.7772	-	-	-	-	-
Center Placement- Averaged Data						
# Transmitters	**B1**	**B3**	**B5**	**OV**	**FC**	**SC**
4	0.9046	0.9046	0.9486	0.9046	0.9046	0.9426
3	0.9001	0.9187	0.9126	0.9289	0.9289	0.9192
2	0.8922	0.8694	-	-	0.8711	-
1	0.8264	-	-	-	-	-

Table 2. This table summarizes the results of the corner placement and center placement testing configurations using data averaged over the entire 5-minute collection period for each test location. Values for each deployment scenario were averaged for tests across all 4 floorplans. Values were analyzed pairwise with each value in green outperforming the opposite configuration with the same algorithm in red.

For the data analyzed using only a single RSSI sample per transmitter, the average overall accuracy for corner deployments was 0.8598 while for center deployments it was 0.8914 for a difference in overall accuracy of 0.0316. There were 2 cases in which the corner placement outperformed the center placement with 13 of the 15 cases again indicating optimized accuracy with center transmitter positioning. The first case was in B3 with 2 transmitters which had a corner placement accuracy of 0.8189 and a center placement accuracy of 0.8037. The second case was FC with 2 transmitters which had a corner placement accuracy of 0.8260 and a center placement accuracy of 0.8078. Despite these corner placement schemes outperforming their center positioning analogs, these two scenarios were observed to be the two of the least accurate cases in all the corner positioning. B1 with 1 transmitter was again the minimum for both cases with accuracies of 0.7511 and 0.7907 for corner and center placement respectively. The maximum for both cases was SC with 4 transmitters with accuracies of 0.9083 and 0.9338 for corner and center placement respectively.

Corner Placement- Single Point Data						
# Transmitters	**B1**	**B3**	**B5**	**OV**	**FC**	**SC**
4	0.8745	0.8745	0.8718	0.8745	0.9041	0.9083
3	0.8440	0.8786	0.8677	0.9014	0.8769	0.8637
2	0.8211	0.8189	-	-	0.8260	-
1	0.7511	-	-	-	-	-
Center Placement- Single Point Data						
# Transmitters	**B1**	**B3**	**B5**	**OV**	**FC**	**SC**
4	0.9306	0.9306	0.9028	0.9306	0.9306	0.9338
3	0.9092	0.9028	0.8707	0.9187	0.9187	0.9040
2	0.8774	0.8037	-	-	0.8078	-
1	0.7907	-	-	-	-	-

Table 3. This table summarizes the results of the corner placement and center placement testing configurations using only one initial RSSI sample received from each transmitter over the entire 5-minute collection period for each test location. Values for each deployment scenario were averaged for tests across all 4 floorplans. Values were analyzed pairwise with each value in green outperforming the opposite configuration with the same algorithm in red.

Examining the cases in which each guideline performed more accurately revealed more insight on optimal positioning. In the few cases where corner positioning performed better, the average performance difference between corner and center positioning was 0.0108 for averaged data and 0.0167 for single point data. In the cases where center positioning performed better, the average performance difference from center to corner positioning was 0.0341 for averaged data and 0.0385 for single point data. This shows that the prospective gains from using center placement exceed those possible for using corner placement.

Therefore, it was concluded from this analysis that center placement of transmitters optimizes room-level localization accuracy over that of corner placement of transmitters for generalized localization deployments. The vast majority of scenarios showed optimal performance for the center placement configurations. Additionally, in the cases where corner placement performed better, performance gains did not surpass those observed in center placement scenarios.

This result subverts the expectation that corner placement would yield greater accuracy due to more due to increased coverage and fewer obstructions. There are several potential explanations for this phenomenon. By placing transmitters in the corners, BLE signal attenuation may have been inadvertently increased due to the surrounding walls of the more constricted environment. Also, corner positioning may have inadvertently resulted in a greater distance between transmitters and many test points as compared to center placement. Additionally, by placing transmitters in the corners, there were several instances in which transmitters were placed directly adjacent to one another (although perhaps with an obstruction such as a wall in between), which may have led to competing strong RSSI values recorded by the receiver and resulting in erroneous localization.

Given this information, the analysis moving forward will focus on localization for center placement configurations only.

B. Localization Window

In an effort to further simplify analysis, it is next necessary to analyze the period of data collection to determine the minimum period necessary for data stability and optimization. Data was collected using the iBeacon package in which the receiver scans for a data point at a frequency of 0.2 Hz (every 5 seconds). As such, 5s of data collection (inclusive of both endpoints) can be roughly correlated to 2 RSSI samples per transmitter.

Data collection periods ranging from a 1 instantaneous RSSI up to 5 minutes (61 RSSI samples) of averaged RSSI values were analyzed with respect to accuracy over windows of varying length. Preliminary results from Section IV.A. indicated that a single data point was much more erroneous than any of the averaged data windows. The standard deviation for each for each set of localization window accuracies was computed to evaluate the nature of the data variability over time. Additionally, these standard deviations were also computed a second time neglecting the initial single point data period to determine degree of variability induced by that point.

Floorplan	# Transmitters	Algorithm	STDev w/ SP	STDev w/o SP
1	4	B5	0.0422	0
2	3	SC	0.0395	0.0038
3	4	B1, B3, OV	0.0164	0.0157
4	3	SC	0.0172	0.0081

Table 4. This table summarizes the most variable localization accuracy with respect to period length for each floorplan. Standard deviation was computed with and without the single point localization window, highlighting the impact of that point on period accuracy variability.

Results indicated in every case that Standard Deviation dropped significantly when the single data point period was neglected. Examples of this phenomenon are summarized in Table 4 in which the most variable case for each tested floorplan was examined. In the most variable case, B5 with 4 transmitters, the standard deviation dropped from 0.0422 to nearly zero by excluding the single data point period. As expected, this highlights the impact that RSSI signal noise has on localization accuracy.

There were a total of 64 cases in which data period was analyzed. These cases include all combinations of algorithms and transmitter quantities on each individual floorplan. In 26.56% of cases, stability in the computed accuracy resulted in an accuracy less than that given by the a 1-sample localization window. In 65.63% of cases, stability in the computed accuracy resulted in an accuracy greater than that given by the 1-sample localization window. In the remaining 7.81% of cases, accuracy did not change substantially and stability was achieved from the onset. This demonstrates that accuracy is most likely to increase by averaging the data over an established period. The possibility remains that accuracy may decrease, but this elevated accuracy at onset was likely due to entropy in RSSI data and is therefore not a true representation of accurate indoor localization.

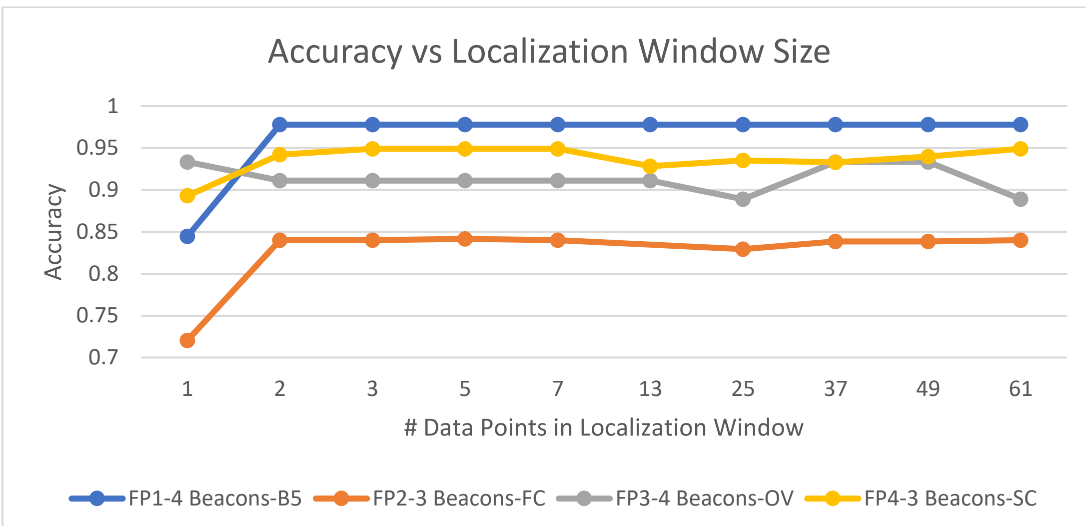

Figure 7. This figure plots the accuracies of the test scenarios displayed in Table 4 relative to the periods over which data was averaged. Figure illustrates how 2 RSSI samples stabilizes room level localization in the most erroneous cases.

Results indicated that stability in the RSSI Localization accuracy was achieved after a period of data collection with 2 samples per transmitter at minimum. The most variable case from each deployment was analyzed and plotted in Figure 7, and in each instance, results stabilized after 2 recorded samples. This period indicates that a minimum of roughly 5s of RSSI data collection is needed for optimization of the localization window for this application. It is unlikely that the average RSSI value itself stabilizes during this period, however, 2 averaged data points seems to provide enough smoothing to allow reliable functionality of the implemented proximity algorithms.

C. Localization Algorithms

Algorithms were evaluated based on accurate localization at the room-level. When comparing overall algorithm performance, the most accurate algorithm was B5 with an overall accuracy of 0.9306 averaged over the 4 tested floorplans. The least accurate algorithm was B1 with an overall accuracy of 0.8808 averaged over the 4 tested floorplans. Compiled overall accuracies are summarized in Table 5. While this analysis portrays a high-level view of overall algorithm performance, more substantive analysis considering performance relative to transmitter quantity revealed these results to be misrepresentative of algorithm performance in more specific scenarios.

Algorithm	Accuracy
B5 Avg	0.9306
SC Avg	0.9180
OV Avg	0.9168
FC Avg	0.9110
B3 Avg	0.8976
B1 Avg	0.8808

Table 5. This table displays the overall accuracies of each algorithm averaged across each floorplan testbed. Results are ranked in order of performance with B5 as the most accurate and B1 as the least accurate overall.

Figure 8 displays a breakdown of algorithm performance relative to transmitter quantity per room. This analysis demonstrated how the number of transmitters plays a significant role in the performance of any given algorithm. Given that smaller transmitter quantities limit the implementation of certain algorithms, it was revealed that the overall accuracies presented in Table 5 may be misrepresenting true overall performance due to unequal weighting of different algorithms. It was therefore necessary to appropriately weight each algorithm for a representative analysis.

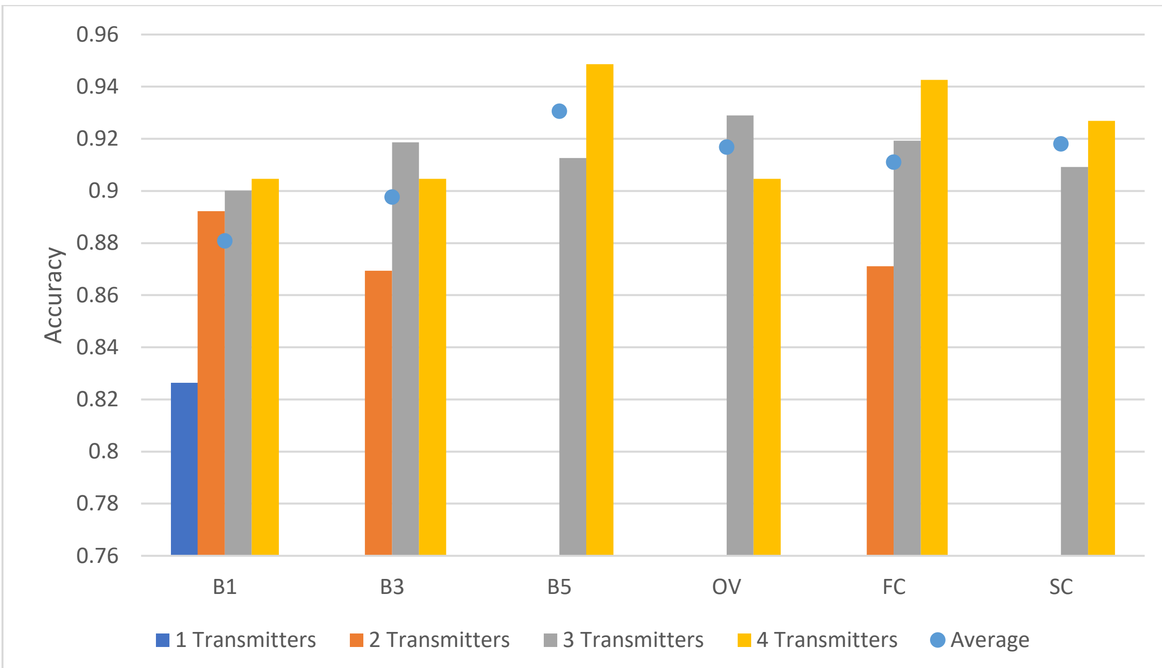

Figure 8. This figure shows a breakdown of the accuracies of each algorithm in terms of numbers of deployed transmitters.

Since fewer transmitters allow for fewer and less accurate localization algorithms, analysis of algorithm performance was effectively normalized by disregarding trials with less than 3 transmitters, giving equal weight to each algorithm since configurations with 3 transmitters and 4 transmitters each support all six algorithms.

Algorithm	Accuracy
FC Avg	0.9309
B5 Avg	0.9306
SC Avg	0.9180
OV Avg	0.9168
B3 Avg	0.9117
B1 Avg	0.9024

Table 6. This table displays the normalized accuracies of each algorithm averaged across each floorplan for configurations of 3 and 4 transmitters only. Results are presented in order of performance with FC as the most accurate and B1 as the least accurate overall.

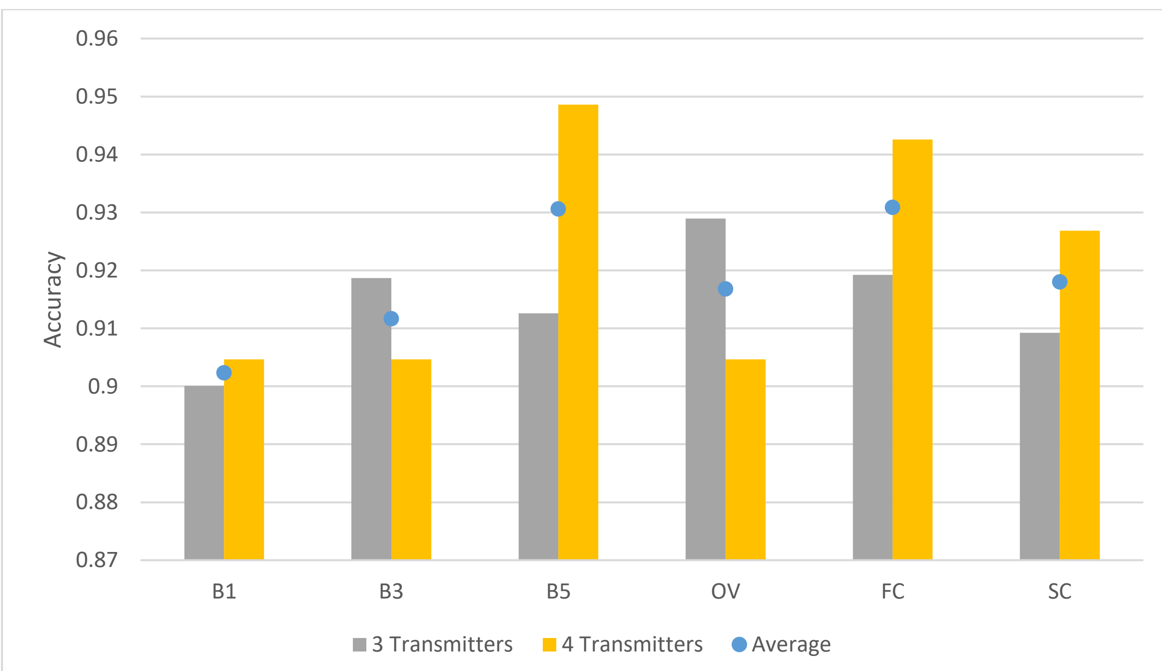

Figure 9. This figure shows a breakdown of the normalized accuracies of each algorithm for configurations of 3 transmitters and 4 transmitters.

Normalization revealed that FC was the best performing algorithm with a normalized accuracy of 0.9309. B1 remained the least accurate algorithm with an accuracy of 0.9024. Accuracies of B1, B3, and FC all increased after normalization (B5, SC, and OV remained the same since normalization did not impact those quantities).

Algorithms B3 and B5 are respectively analogous to algorithms FC and SC, which take a hierarchical approach to voting. A comparison between these two sets of analogs revealed the performance benefits of the different approaches.

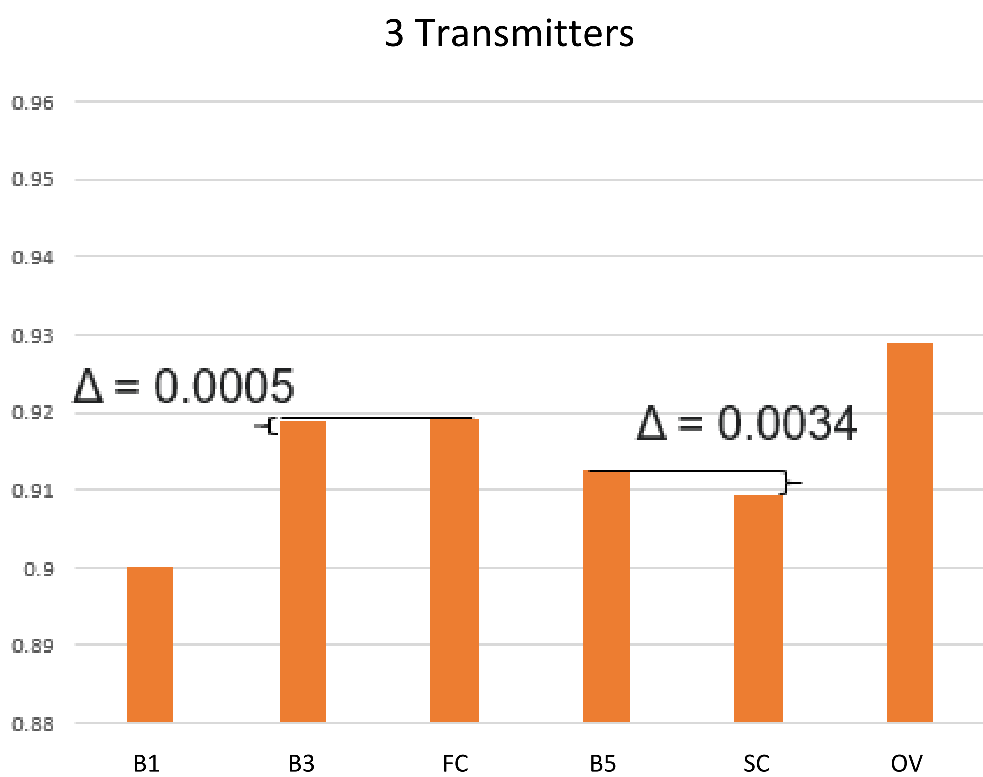

Figure 10. This table displays the normalized accuracies of each algorithm averaged across each floorplan for deployments of 3 and 4 transmitters only. Results are presented in order of performance with FC as the most accurate and B1 as the least accurate overall.

Considering the analogs B3 and FC, in cases of 3 transmitters and 4 transmitters per room only, FC performed better in each instance. In cases of 3 transmitters, FC performed only marginally better with a 0.0005 difference in accuracy from B3. However, in cases of 4 transmitters, the difference was much greater with FC outperforming B3 by a difference in accuracy of 0.0380. The increased performance for FC is due to improper tie breaking in B3; a situation that was eliminated in FC, making it the slightly more reliable algorithm. This result highlights the importance of eliminating potential ties in voting algorithms. In cases of 3 transmitters, ties were rare since the overall number of transmitters was limited and ties involved 3 different transmitters from 3 different rooms. But in the case of 4 transmitters, ties were more common since the overall number of transmitters increased the likelihood that a vote could involve 3 strong RSSIs from 3 different rooms.

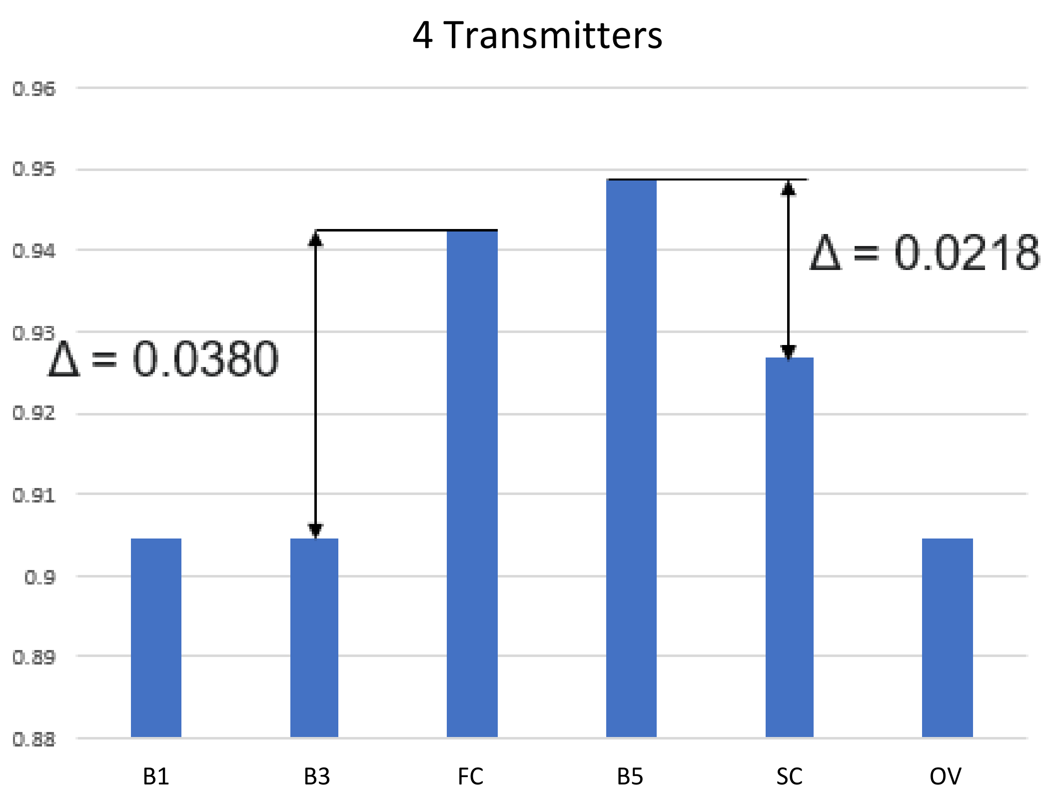

Figure 11. This table displays the normalized accuracies of each algorithm averaged across each floorplan for deployments of 3 and 4 transmitters only. Results are presented in order of performance with FC as the most accurate and B1 as the least accurate overall.

By contrast, with the analogs B5 and SC, the B5 algorithm performed more accurately in each case. In cases of 3 transmitters, B5 outperformed SC by a difference of 0.0034 in accuracy. In cases of 4 transmitters, the difference was greater again with B5 outperforming SC by a difference of 0.0218. The less accurate performance of SC in this instance could demonstrate diminishing returns for the hierarchical confirmation approach to voting.

D. Transmitter Quantity

As previously highlighted in Figure 8, it is clear that each the number of transmitters greatly affects the optimal choice of localization algorithm. In iterations with less than 2 transmitters, the B1 algorithm performed best with an accuracy of 0.8922 for 2 transmitters and 0.8264 for 1 transmitter, in which case B1 was the only suitable algorithm. For 3 transmitters, OV performed best with an accuracy of 0.9289. For 4 transmitters, B5 performed best with an accuracy of 0.9486, which was the maximum accuracy for all algorithms.

Generally, greater quantities of transmitters improved accuracy. The two most accurate scenarios both involved 4 transmitters. By contrast, the least optimal scenario was B1 with 1 transmitter. All deployment scenarios are summarized and ranked in Table 7.

Algorithm	Accuracy	Differential
4-B5	0.9486	0
4-FC	0.9426	-0.0060
3-OV	0.9289	-0.0197
4-SC	0.9269	-0.0218
3-FC	0.9192	-0.0294
3-B3	0.9187	-0.0299
3-5B	0.9126	-0.0360
3-SC	0.9092	-0.0394
4-B1	0.9046	-0.0440
4-B3	0.9046	-0.0440
4-OV	0.9046	-0.0440
3-B1	0.9001	-0.0485
2-B1	0.8922	-0.0564
2-FC	0.8711	-0.0775
2-3B	0.8694	-0.0792
1-B1	0.8264	-0.1222

Table 7. This table displays the normalized accuracies of each algorithm averaged across each floorplan for deployments of 3 and 4 transmitters only. Results are presented in order of performance with FC as the most accurate and B1 as the least accurate overall.

An important consideration in the assessment of transmitter quantity, is the degree to which accuracy improves by increasing the number of transmitters. The most accurate scenario with 3 transmitters, OV with an accuracy of 0.9289, was only 0.0197 less than the overall optimum. The results for deployments with less than 3 transmitters had a greater differential of more than 5% from the overall optimum.

While greater transmitter quantity did result in improved accuracy, weighing equipment overhead and cost of a given deployment against the marginal gains in accuracy is an important consideration. For large floorplans that inherently require additional transmitters, a marginal decrease in accuracy may be inconsequential compared to the overhead involved with the installation of many transmitters per room. Likewise, for smaller floorplans, the installation of additional transmitters may be an inconsequential overhead and maximizing the number of transmitters to provide the greatest possible accuracy may be ideal.

Finally, in the algorithms involving direct voting among transmitters, both in terms of quantity and hierarchy (i.e. neglecting the OV algorithm), each transmitter quantity was optimized by an algorithm requiring minimum *n-1* transmitters from a room for correct localization, where n is the total number of transmitters in each room. This trend does not hold for scenarios with 1 transmitter, as *n-1* yields 0 in these cases. However, the trend is observed in the remaining 3 instances. In cases of 2 deployed transmitters per room (*n=2*), localization is optimized by the B1 algorithm which requires 1 prevailing RSSI from the correct room (*n-1=1*). In cases of 3 deployed transmitters per room (*n=3*), localization is optimized by FC (and closely followed by B3) which requires a minimum of 2 prevailing RSSI values from the correct room (*n-1=2*). In cases of 4 deployed transmitters per room (*n=4*), localization is optimized by B5 which requires a minimum of 3 prevailing RSSI values from the correct room. This trend could help inform initial algorithm selection for a set quantity of transmitters, and demonstrates that algorithm reliance on too few or too many transmitters results in sub-optimal accuracy. Testing on additional floorplans may be necessary to confirm this trend.

E. Specific Transmitter Layouts

In completing each of the aforementioned analyses, 21804 distinct deployment configurations were compiled and analyzed (this quantity does not include scenarios with corner placed transmitters, which would double that quantity to a total of 43608 configurations). In keeping with the scope of this project in not using any advanced modeling for analysis, assertions regarding specific configurations of transmitters are somewhat limited.

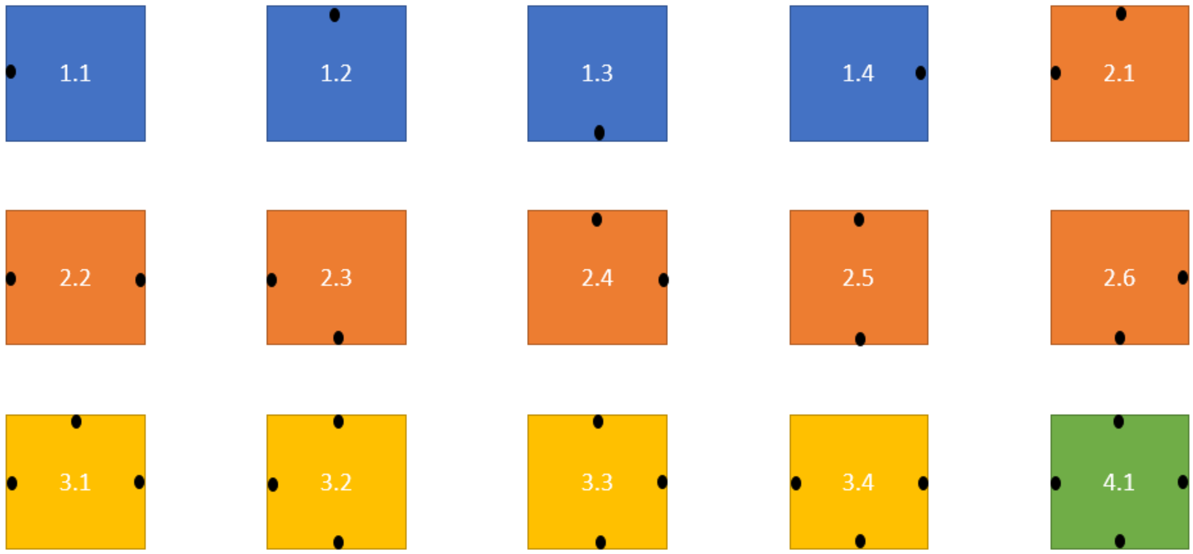

Figure 12. The figure above displays the 15 possible configurations of transmitters possible in each room. Beacon positions are indicated by black markers.

Accuracies were initially evaluated at the room level with the given room and configuration indicated by the ground truth label. Accuracies for each specific configuration (Figure 12) and each applicable algorithm were averaged individually with respect to the varying configurations of the all the other rooms. The range of average accuracies from this analysis is presented in Table 8.

Certain floorplans appear inherently more reliable than others when dealing with room-level proximity localization. As displayed in Table 8, Floorplan 1 maintained an accuracy of greater than 90% for all cases except B1 with 1 transmitter. For each other floorplan, there were several cases in which the range of accuracies for the set of configurations extended as low as 70%.

FP/ Alg	B1 (1) (c = 4)	B1 (2) (c = 6)	B1 (3) (c = 4)	B1 (4) (c = 1)	B3 (2) (c = 6)	B3 (3) (c = 4)	B3 (4) (c = 1)	FC (2) (c = 6)	FC (3) (c = 4)	FC (4) (c = 1)	B5 (3) (c = 4)	B5 (4) (c = 1)	SC (3) (c = 4)	SC (4) (c = 1)
1 (r = 5)	[0.8236, 0.9333]	[0.9185, 0.9556]	[0.9278, 0.9444]	0.9333	[0.9111, 0.9481]	[0.9556, 0.9778]	0.9333	[0.9111, 0.9481]	[0.9556, 0.9778]	0.9778	[0.9167, 0.9444]	0.9778	[0.9069, 0.9444]	0.9778
2 (r = 4)	[0.7431, 0.9421]	[0.8519, 0.9444]	[0.9028, 0.9583]	0.9444	[0.7652, 0.8426]	[0.8472, 0.8750]	0.9444	[0.7662, 0.8426]	[.8472, 0.8750]	0.8889	[0.8194, 0.8715]	0.8611	[0.8142, 0.8681]	0.8333
3 (r = 5)	[0.7576, 0.9194]	[0.8296, 0.8889]	[0.8736, 0.9167]	0.8889	[0.8858, 0.9546]	[0.8903, 0.9778]	0.8889	[0.8864, 0.9590]	[0.8944, 0.9778]	0.9778	[0.9014, 0.9778]	0.9556	[0.9014, 0.9736]	0.9333
4 (r = 3)	[0.7037, 0.8611]	[0.8920, 0.9119]	[0.7870, 0.8796]	0.8519	[0.7346, 0.9321]	[0.8704, 0.9444]	0.8519	[0.7346, 0.9398]	[0.8704, 0.9444]	0.9259	[0.9213, 0.9722]	1	[0.9352, 0.9722]	0.9630

Table 8. This table summarizes the results of indoor localization accuracy for all 21804 configurations analyzed. The range of averaged accuracies is presented for each possible configuration of transmitters in rooms (e.g. For configurations of 3 beacons, there are 4 possible transmitter iterations in each room. The range given summarizes the set of accuracies for each of those 4 iterations). Columns are grouped by localization algorithm with the number of available beacons noted in parentheses. Number of possible iterations per room is noted in each column by the variable *c*. Number of rooms in each floorplan is notes in each row by the variable *r*. Results

However, a challenge presented in evaluation is that the perspective of the floorplan effectively changes the results. For instance, given all possible configurations displayed in Figure 12, a 90-degree rotation transforms configuration 2.2 into configuration 2.5. Perspective is subjective, so it is therefore impossible to standardize this analysis without more advanced analytics. Results in Table 8, present a general overview of the likely average value for each configuration, but it is probable that reframing the perspective of each floorplan would alter the results. Therefore, the data in the table should be taken as general guidance only, and concrete results are inconclusive.

	Min. Accuracy	Max. Accuracy	Mean Accuracy	Med. Accuracy	Std. Dev.
1 Transmitter	0.7037	1	0.8489	0.8611	0.0624
2 Transmitters	0.6296	1	0.9091	0.9111	0.0453
3 Transmitters	0.5185	1	0.9301	0.9333	0.0433
4 Transmitters	0.8333	1	0.9220	0.9333	0.0485

Table 9. This table summarizes the statistics associated with all analyzed floorplan configurations in terms of transmitter quantity.

Summarized accuracies for explicit configurations at the floorplan level are presented in Table 9. Again, these results show that higher quantities of transmitters yield higher accuracies. These statistics also demonstrate the importance of careful consideration in the placement of transmitters, since in many iterations there were several scenarios in which the accuracy on an entire floorplan was 100%. However, with the improper selections of transmitter positioning, results were significantly diminished.

F. Discussion

Localization optimization involves balancing the tradeoffs associated with deployment variables and system requirements, and necessitates a situational awareness of the deployment environment. Priorities with regard to maximizing accuracy versus minimizing equipment and complexity must be assessed and evaluated prior to deployment. Optimal selection of localization algorithms and transmitter quantity are subject to specific deployment scenarios, and these variables are highly related and must be carefully considered together when conducting deployments. For smaller floorplans with fewer rooms, it would likely be beneficial to deploy 4 transmitters in each room and use the B5 voting algorithm since equipment overhead may not be a concern and this scheme will maximize accuracy. However, in a case with a slightly greater number of rooms, it may be ideal to reduce overhead and complexity by using only 3 transmitters per room and deploy in more rooms; the expected accuracy would only be marginally decreased. It is ideal to use at least 2 transmitters in each room, as this deployment scheme allows for some redundancy in the event of transmitter failure. However, in the most extreme cases, 1 functional transmitter may be sufficient; while the accuracy of B1 with 1 transmitter demonstrated the poorest performance, the cost of deploying additional equipment may outweigh the drop in accuracy. Minimum acceptable accuracy must be assessed prior to deployment and will help inform the minimum requirements for transmitter installation.

Analysis definitively revealed that placing transmitters on the center of room walls was an effective way to increase localization accuracy. This directly addresses challenges posed in section IB in that this should be a relatively simple guideline to follow; it requires no precision measurements; and is easily generalizable to nearly all floorplans (barring unusual room geometry).

Assessment of time windows for localization also revealed straight forward results, showing that a minimum of only 5 seconds of iBeacon data collection was required to optimize stability in localization accuracy. This latency has tremendous potential for implementation in real time.

Analyzing specific deployment configurations did provide additional insight into performance expectations surrounding localization algorithms and quantity. However, finite results of this nature are inconclusive as the floorplan perspective cannot be standardized. Ultimately, more advanced modeling may be required to garner any additional insights.

A final important factor in establishing an optimized deployment protocol is having some sort of redundancy in the system. In the event of a transmitter failure (possibly due to battery failure or accidental unplugging), localization can still be performed relatively accurately with fewer transmitters. The only exception to this would be in the case of a single transmitter per room.

VI. Conclusion

Despite significant work in the area of RSSI based indoor positioning, signal variability remains a significant barrier for many efforts to carry out localization. Even the most rigorous calibration or modeling efforts may prove insufficient for fine grained positioning accuracy and require significant deployment effort. However, for many applications this issue could be solved by performing localization at the room level. This thesis depicts the generalized challenges associated with the application scalability of an indoor localization system with room level precision and also describes the rigorous collection of proximity RSSI data across multiple floorplans with accuracy evaluated and analyzed at the room level. Specific variables addressing system challenges are addressed and evaluated in terms of their overall impact on expected localization accuracy.

In the context of an In-Home Health Monitoring system like BESI-C, key variables associated with deployment challenges are broken down in terms of generalized transmitter placement, localization time window, algorithm selection, transmitter quantity, and optimal configuration. Data was collected on single story floorplans with an array of test data points evenly distributed throughout each room. With the collected data, each variable was assessed and analyzed in terms of the impact on localization accuracy at the room level. Transmitter configurations were iterated in analysis to incorporate all possible deployment scenarios into the performance analysis.

For ease of self-installation associated with system scalability, it is important to have a generalized positioning guideline to streamline the deployment process. It was found that placing transmitters roughly in the center of room walls provided greater accuracy and generally stronger RSSI values from transmitters in the correct room of localization. This simple choice in the placement of transmitters was shown to have a significant impact on the ability to accurately perform localization.

BESI-C was designed with the intent to be used in real time to detect pain associated with cancer, and requires that any localization scheme have a speed sufficient to support real time data processing and correlation. This necessitates minimizing the window of localization data collection. It was found that 2 RSSI data samples afforded enough stability to average RSSI for meaningful implementation of localization algorithms.

Implementing indoor localization based upon room-level accuracy allows for the implementation of simple proximity algorithms rather than precision positioning. Proper implementation of algorithms is directly related to the number of transmitters deployed on several fronts. Each algorithm has a minimum number of transmitters required for implementation, and each algorithm performs most accurately with a different quantity of transmitters. Thus, appropriate algorithm selection remains highly situational and requires evaluation of minimum accuracy threshold and equipment constraints. However, generally algorithms with a reliance on greater quantities of transmitters and some form of redundancy tend to perform better.

Transmitter quantity can be a limiting factor in terms of system complexity and equipment overhead, so careful consideration must be given to selecting a sufficient number of transmitters for optimal localization. As expected, greater numbers of transmitters yielded greater room level accuracy, but only marginally. Therefore, deployment circumstances must again be weighed to determine if the cost of deploying additional transmitters is worth the marginal gains in accuracy.

Careful situational consideration must be given to the specific configurations of transmitters on any given floorplan. It remains the hypothesis of this thesis that transmitters more widely spread apart at both the room and floorplan level produce more optimal localization accuracy due to a lack of interfering RSSIs from adjacent, erroneous rooms. Given the scope of this analysis, precise results evaluating this parameter remain inconclusive. However, with careful placement choice and algorithm selection, in many cases it was observed that 100% room level localization accuracy can be achieved.

Overall, results of this project show tremendous potential for RSSI based room level localization as a viable alternative to current standards. In a majority of cases, optimal deployment requires a situational analysis and evaluation for appropriate implementation. It is the hope that information provided by this thesis will help to inform future decision making surrounding the deployment of indoor localization schemes.

A. Future Work

The domain of indoor localization remains an area of active research, and additional work remains to continue to establish room level localization as a viable alternative to traditional methods. Much of this work involves the implementation of Real-World testing and verification of accuracy in an uncontrolled environment. Additionally, while outside the scope of this thesis, Machine Learning has the potential to aid in bolstering accuracy even more than the schemes presented in this thesis alone.

The analysis presented in this thesis was streamlined by excluding circumstances inherent to real-world deployment, and next phases in this analysis involve conducting extended uncontrolled tests in a real-world environment. In this case, motion would become a significant source of entropy which may affect the results of localization in the real-world. Additionally, two-story floorplans and motion in 3-dimensions may become a relevant factor. There may be cases of rooms with unusual geometries or cases of large open concept floorplans which may affect installation setup. The information in this thesis can be used as a baseline for optimal deployment setup, but verification in a real-world setting is necessary to ensure efficacy.

Additionally, machine learning models may aid in increasing localization accuracy and increasing knowledge of optimal configuration. Models may provide a basis to accurately evaluate data points prone to error; although, ground truth and *a priori* knowledge may still remain a problem. Additionally, modeling of floorplan orientation to find optimal layout accuracies may help further inform installation guidelines for optimized accuracy.

B. BESI-C Deployments

Future deployments of BESI-C will incorporate many of the elements outlined in this thesis. By nature of these real-world deployments, there is a degree of uncertainty in even the most reliable proximity algorithms. To address this, each instance the user marks a cancer pain episode they are prompted with a question regarding their room location to collect ground truth. Redundancy would necessitate a minimum of 2 transmitters placed per room in these real-world deployments, but any greater quantity would only serve to increase accuracy. Initial deployments of the system will be centered around data collection only, but future developments will necessitate real time sensor processing and localization for predictive modeling.

References

[1] Qian Dong, W. Dargie, "Evaluation of the reliability of RSSI for indoor localization," *2012 International Conference on Wireless Communications in Underground and Confined Areas*, Clermont Ferrand, 2012, pp. 1-6, doi: 10.1109/ICWCUCA.2012.6402492.

[2] P. Puricer, P. Kovar, "Technical Limitations of GNSS Receivers in Indoor Positioning," *2007 17th International Conference Radioelektronika*, Brno, 2007, pp. 1-5, doi: 10.1109/RADIOELEK.2007.371487.

[3] A. Thaljaoui, T. Val, N. Nasri, D. Brulin, "BLE localization using RSSI measurements and iRingLA," *2015 IEEE International Conference on Industrial Technology (ICIT)*, Seville, 2015, pp. 2178-2183, doi: 10.1109/ICIT.2015.7125418.

[4] LeBaron V, Hayes J, Gordon K, Alam R, Homdee N, Martinez Y, Ogunjirin E, Thomas T, Jones R, Blackhall L, Lach J, "Leveraging Smart Health Technology to Empower Patients and Family Caregivers in Managing Cancer Pain: Protocol for a Feasibility Study," *JMIR Res Protoc 2019*, 8(12):e16178.

[5] LeBaron V, Bennett R, Alam R, Blackhall L, Gordon K, Hayes J, Homdee N, Jones R, Martinez Y, Ogunjirin E, Thomas T, Lach J, "Understanding the Experience of Cancer Pain From the Perspective of Patients and Family Caregivers to Inform Design of an In-Home Smart Health System: Multimethod Approach," *JMIR Form Res 2020*, 4(8):e20836.

[6] R. Alam, *et al*., "BESI: Reliable and Heterogeneous Sensing and Intervention for In-home Health Applications," *2017 IEEE/ACM International Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE)*, Philadelphia, PA, 2017, pp. 147-156, doi: 10.1109/CHASE.2017.73.

[7] Hnat T, Srinivasan V, Lu J, Sookoor T, Dawson R, Stankovic J, Whitehouse K, "The Hitchhiker's guide to successful residential sensing deployments," *SenSys '11: Proceedings of the 9th ACM Conference on Embedded Networked Sensor Systems*, 2–4 Nov 2011, pp. 232-245, doi: 10.1145/2070942.2070966.

[8] LeBaron V, Hayes J, Gordon K, Alam R, Homdee N, Martinez Y, Ogunjirin E, Thomas T, Jones R, Blackhall L, Lach J, "Exploring the Feasibility and Acceptability of the 'Behavioral and Environmental Sensing and Intervention for Cancer' to Improve Pain Management: Protocol for a Descriptive Pilot Study," *JMIR Res Protoc 2019*, 8(12):e16178.

[9] A. De Blas, D. López-de-Ipiña, "Improving trilateration for indoors localization using BLE beacons," *2017 2nd International Multidisciplinary Conference on Computer and Energy Science (SpliTech)*, 2017, pp. 1-6.

[10] S. Sadowski, P. Spachos, "RSSI-Based Indoor Localization With the Internet of Things," *IEEE Access*, vol. 6, pp. 30149-30161, 2018, doi: 10.1109/ACCESS.2018.2843325.

[11] M. Kaczmarek, J. Ruminski, A. Bujnowski, "Accuracy analysis of the RSSI BLE SensorTag signal for indoor localization purposes," *2016 Federated Conference on Computer Science and Information Systems (FedCSIS)*, Gdansk, 2016, pp. 1413-1416.

[12] Simon Yiu, Marzieh Dashti, Holger Claussen, Fernando Perez-Cruz, "Wireless RSSI fingerprinting localization," *Signal Processing*, Volume 131, 2017, pp. 235-244, ISSN 0165-1684, https://doi.org/10.1016/j.sigpro.2016.07.005.

[13] Z. Jianyong, L. Haiyong, C. Zili, L. Zhaohui, "RSSI based Bluetooth low energy indoor positioning," *2014 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Busan, 2014, pp. 526-533, doi: 10.1109/IPIN.2014.7275525.

[14] Nutta Homdee, Ridwan Alam, Sean Wolfe, John Lach, "Mind the gaps: Edge-based monitoring for continuous room-level location tracking," *Smart Health*, Volumes 9–10, 2018, Pages 297-306, ISSN 2352-6483, https://doi.org/10.1016/j.smhl.2018.07.020.

[15] C. Zhang, M. Kuhn, B. Merkl, A. E. Fathy, M. Mahfouz, "Accurate UWB indoor localization system utilizing time difference of arrival approach," *2006 IEEE Radio and Wireless Symposium*, San Diego, CA, 2006, pp. 515-518, doi: 10.1109/RWS.2006.1615207.

[16] Guang-yao Jin, Xiao-yi Lu, Myong-Soon Park, "An indoor localization mechanism using active RFID tag," *IEEE International Conference on Sensor Networks, Ubiquitous, and Trustworthy Computing (SUTC'06)*, Taichung, 2006, doi: 10.1109/SUTC.2006.1636157.

[17] W. Xue, W. Qiu, X. Hua and K. Yu, "Improved Wi-Fi RSSI Measurement for Indoor Localization," in *IEEE Sensors Journal*, vol. 17, no. 7, pp. 2224-2230, 1 April1, 2017, doi: 10.1109/JSEN.2017.2660522.

[18] C. Luo, H. Hong and M. C. Chan, "PiLoc: A self-calibrating participatory indoor localization system," *IPSN-14 Proceedings of the 13th International Symposium on Information Processing in Sensor Networks*, Berlin, 2014, pp. 143-153, doi: 10.1109/IPSN.2014.6846748.

[19] M. Abbas, M. Elhamshary, H. Rizk, M. Torki and M. Youssef, "WiDeep: WiFi-based Accurate and Robust Indoor Localization System using Deep Learning," *2019 IEEE International Conference on Pervasive Computing and Communications (PerCom*, Kyoto, Japan, 2019, pp. 1-10, doi: 10.1109/PERCOM.2019.8767421.

[20] J. Neburka *et al*., "Study of the performance of RSSI based Bluetooth Smart indoor positioning," *2016 26th International Conference Radioelektronika (RADIOELEKTRONIKA)*, Kosice, 2016, pp. 121-125, doi: 10.1109/RADIOELEK.2016.7477344.

[21] T. I. Chowdhury *et al*., "A multi-step approach for RSSi-based distance estimation using smartphones," *2015 International Conference on Networking Systems and Security (NSysS)*, Dhaka, 2015, pp. 1-5, doi: 10.1109/NSysS.2015.7042942.

[22] https://estimote.com/