Optimization of BLE Beacon Density for RSSI-based Indoor Localization

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***Abstract*—Location Based Services (LBS) and Proximity Based Services (PBS) can play an important role in our daily life by simplifying tasks. Functions such as turning on and off lights can occur automatically or locking and unlocking doors can be done using LBS. By knowing the location of a user, appliances can be automated to function once the user is near them. Through the use of indoor localization, a user's position can be calculated. When designing an indoor localization system the density of transmitters plays an important role in maximizing the accuracy obtained. Increasing the number of references can improve the accuracy by providing additional information that the system can use in calculating a location. However, placing too many transmitters in the area can create interference in signals and negatively impact the localization results, while not having enough transmitters will hinder localization as not enough information is available. In this paper, we examine the optimal number of Bluetooth Low Energy (BLE) beacons to be used for indoor localization to optimize localization accuracy. Two algorithms were compared: trilateration and nonlinear least squares applying two types of filtering: moving average, and Kalman. Nine different types of systems were developed and compared in terms of accuracy and precision. According to experimental results placing six beacons in an environment will produce the optimal results. Using a nonlinear least squares algorithm with the three closest references with a moving average filter produced the lowest error of 1.149 meters with a standard deviation of 0.698 meters.**

***Keywords*— Indoor Localization; Bluetooth Low Energy; iBeacon; Nonlinear Least Squares; Trilateration; Filtering.**

I. INTRODUCTION

Through the development of the Internet of Things (IoT), new applications in Location Based Services (LBS) and Proximity Based Services (PBS) have been created. LBS use the user's location to provide enhanced automation for appliances and devices to improve an individual's quality of service [1]. PBS focuses on using a user's proximity to a device to locate where and what they are nearby in an area. One commonly used LBS application is the Global Positioning System (GPS) [2]. When outdoors GPS can provide accuracy up to 5 meters. Once indoors, however, there is less room for error and other methods need to be applied to produce a more accurate localization system.

Indoor localization presents a much larger challenge compared to outdoor localization due to the increased number of obstacles and multipath effects [3]. When performing localization indoors, wireless technologies such as WiFi, Bluetooth Low Energy (BLE), Zigbee, Long Range (LoRa), Radio Frequency Identification (RFID), and Ultra-Wide Band (UWB) are most commonly used [4]–[6]. In order to use the wireless technologies for localization, the strength of the signals from transmitters at reference points in the area can be used. The strength of a signal at a point is known as the Received Signal Strength Indicator (RSSI). Through the use of the RSSI value and knowledge of the environment, the distance between two devices can be determined. However, RSSI is easily affected by other signals, interference, obstacles, and reflections. To improve RSSI signals methods such as filtering are often used. In addition, there are algorithms that can be used for performing localization. One popular device commonly used in PBS and are now being employed for localization are BLE beacons [7]. Beacons are small battery-powered devices that continuously broadcast BLE signals to all devices that are listening. By applying the iBeacon structure to beacons, their signals are able to be easily identified along with the RSSI values.

In this paper, through experimentation, we determine the optimal density of iBeacons that can be placed in an environment to improve localization accuracy. For our analysis, a comparison is presented between two localization techniques; trilateration, and nonlinear least squares where the number of transmitters is incremented from three up to eight. To improve the performance of the system two types of filters are applied and compared; moving average, and Kalman. Experimental results determined that placing six reference devices in an environment and using nonlinear least squares processing with the three closest devices with a moving average filter produces the best results. The main contributions of this work are as follows:

- Although intended for proximity-based services, iBeacons were successfully used for accurately locating in indoor environments.
- Implementing moving average filtering and Kalman filtering improved localization accuracy by 24.49% and 27.05% respectively compared to trilateration with no filtering.
- Applying nonlinear least squares using the three closest references and all the references improved the localization accuracy by 51.53% and 40.45% respectively compared to trilateration with a moving average filter.

The rest of this paper is organized as follows: the related work is reviewed in Section II, followed by the system framework in Section III. The experimental setup is discussed in Section IV, along with the results and discussions in Section V. Section VI concludes this work.

II. RELATED WORK

Indoor localization can be much more challenging compared to outdoor systems, due to the challenges faced when performing. One of the most common methods has been WiFi-based systems using WiFi access points due to their presence and availability [8]–[12]. However, in recent years a larger interest has been placed on using BLE beacons for PBS, proximity detection, and indoor localization due to their small scale devices, portability, and ease of installation [13]–[17].

In [18], an indoor localization system was developed using iBeacons. Experiments were conducted to determine the number of beacons that would provide the most accurate 2D localization results. A nonlinear least squares technique was used to calculate the estimated receiver location. In addition, Particle and Particle-Kalman filters were applied to the RSSI values to reduce the error. Results determined that the lowest error occurred when seven iBeacons were placed in an environment. Results also showed that using a Particle-Kalman filter had better accuracy compared to when Kalman filters were used. In [19], the density of beacons that can be placed within an area was determined. Using iBeacons, an adaptive scanning mechanism fusion with a spontaneous differential evolution (AS+sDE) was used to determine the density that beacons could be deployed in. It was determined that using AS+sDE was able to successfully allow for beacon signals to be scanned more often and have signals processed in parallel. A 90% increase in accuracy could be achieved compared to regular scanning systems. It was calculated that using a system with a density of less than five beacons per square meter allowed for the best accuracy to be achieved before noise and interference reduced the localization accuracy.

In this paper, we determine the optimal density of BLE beacons required in an environment to improve localization accuracy. For our experiments Gimbal Series 10 beacons were used which function using the iBeacon protocol and are easily configurable. Different types of localization techniques and filtering methods were used comparing the accuracy and precision obtained with each of the different systems.

III. System Framework

A. Localization Techniques

Localization techniques play an important role in accuracy, precision, and speed of the system. Often the technique that produces the most accurate estimation takes the longest time to compute a location. In addition, different techniques can be used under different circumstances such as multiple reference points or Line-of-Sight (LoS) and Non-Line-of-Sight (NLoS) conditions. Two popular techniques used for localization are trilateration and nonlinear least squares.

1) Trilateration: Trilateration is known as one of the most commonly used techniques for indoor localization purposes [20]. Due to its ease of use and simple implementation trilateration can be applied using a variety of techniques such as the Received Signal Strength Indicator (RSSI), Time of Arrival (ToA), or Time Difference of Arrival (TDoA).

In order to calculate a 2D position using trilateration three reference nodes and the receiver are required. To determine the distances between the reference nodes to the receiver the path-loss model is used along with the RSSI values of the wireless signals [21] . When calculating using trilateration a similar process as in [4] was followed. While trilateration can be accurate if ideal input is used, once more than three nodes are used, a decision needs to be made in selecting the proper references for the calculation.

For our purposes, when more than three reference nodes are available, then the three nodes with the highest RSSI values, indicating that they are the closest to the receiver, are selected for the calculation. Once the three closest reference points are determined, the coordinate system is then altered around the closest reference. This allowed for the receiver to be located in reference to those three nodes.

2) Nonlinear Least Squares: Nonlinear least squares is an optimization technique that can be used to solve a nonlinear problem where the number of observations is greater than the number of unknown parameters. When there are three or more reference points, nonlinear least squares can be used to solve for the receiver's location as follows:

$$r_i^2 = (x - p_i)^2 + (y - q_i)^2 \tag{1}$$

where r_i is the distance between the reference points at location i and the receiver, found using the RSSI and path-loss model, (x, y) is the position of the receiver, and (p_i, q_i) is the location of reference *i*. Using Eq. (1), when there are i reference points, there would be i equations that could be used to calculate a position.

Nonlinear least squares determine a position by calculating different sets of coordinates using the information available and then summing the squared error between this point to the reference points. The localization error formula is as follows:

$$Error = \frac{\sum_{i=1}^{n} \sqrt{(x_i - x_{est})^2 + (y_i - y_{est})^2}}{n} \tag{2}$$

where n is the number of reference points, i is the current reference point, (x_i, y_i) is the location of the reference point, and (x_{est}, y_{est}) is the estimated position. The goal of nonlinear least squares is to find the sum of squared distances that is as small as possible or within a threshold.

B. Filtering Algorithms

In indoor localization systems, RSSI is one of the most commonly used characteristics due to its simplicity and ease [22]. However, while RSSI is easy-to-use, it can often be inaccurate due to wireless signals being easily affected by NLoS and multipath effects [23]. This can lead to RSSI values fluctuating greatly over a period of time. One of the most common ways of reducing the error that can occur with RSSI values is through filtering. Some of the most popular filters used in RSSI are the moving average, and Kalman [24].

1) Moving Average: The moving average filter is one of the simplest filters that can be implemented using RSSI measurements. Moving average filters work by gathering *n* RSSI samples and averaging the values to create a new value, which is often a better representation of the actual RSSI between the communicating devices. The process followed was similar to that in [25] with the formula as follows:

$$\overline{RSSI} = \frac{1}{n}\sum_{i=0}^{n} RSSI_i \tag{3}$$

2) Kalman: The Kalman filter is one of the most used filters for RSSI processing. A Kalman filter works using two stages: prediction and update. In the prediction stage, the Kalman filter gets a value, compares it to the previous value obtained, and estimates a new value and the error between the values. During the update stage, all the variables are then updated for the next calculation. The Kalman filter algorithm followed was similar to that in [18]. The Kalman filter formulas used for smoothing the RSSI are as follows:

Prediction:
Predict the current state:

$$x_k = A * x_{k-1} \tag{4}$$

Predict the error covariance:

$$P_k = A * P_{k-1} * A^T + Q \tag{5}$$

Update:
Calculate the Kalman gain:

$$K = P_k * H^T * (H * P_k * H^T + R)^{-1} \tag{6}$$

Calculate the new state:

$$x_k = x_{k-1} + K * (Z_k - H^T * x_{k-1}) \tag{7}$$

Calculate the new error covariance:

$$P_k = P_{k-1} - (K_k * H * P_k) \tag{8}$$

where:
Z_k: Measurement vector for current time.
x_k: Estimate of the current state.
P_k: Estimate of average error for the current state.
A: State transition matrix.
K: Kalman gain.
H: Observation matrix.
Q: Estimated process error covariance.
R: Estimated measurement error covariance.

IV. Experimental Setup

In order to evaluate the performance of the proposed techniques for indoor localization, an environment was selected that would allow for a large number of reference points to be placed throughout the area. For performing the experiment a 10.8 m x 7.3 m research lab was selected due to its large size that allowed for a set of references to be arranged in the area. In addition, the lab contained computers and wireless devices using WiFi and BLE that could cause interference in the signals. This made the area a very noisy environment for testing and would allow for filtering to better affect the results.

When setting up the references around the testing environment, it was determined that keeping LoS between the transmitters and the receiver was necessary in order for accurate testing to occur. Keeping LoS forced the experiment

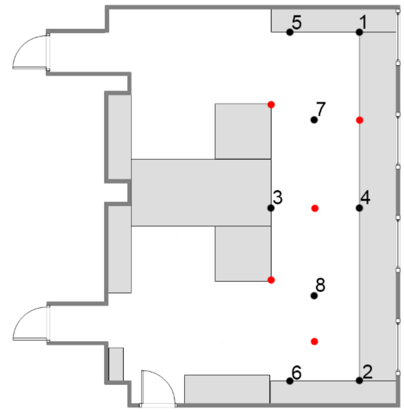


Fig. 1: Floor plan of experiment with eight reference points (black) and five test points (red).

to take place in a smaller area in the environment. Based on the related work, it was determined that eight reference points would be the limit for the number of transmitting devices. Based on the eight transmitters placed around the area, five testing points were then selected to gather RSSI data. The floor plan of the experimental layout can be seen in Fig. 1. The experiments were conducted by scaling the number of transmitters from three to eight one at a time gathering the experimental data from all of the test points each time a transmitter was added.

For the tests, Gimbal Series 10 beacons were used as the transmitting devices. The beacons were configured to use the iBeacon protocol developed by Apple. The iBeacon packet configuration uses the Universally Unique Identifier (UUID), Major value, and Minor value to separate individual beacons. For the experiments, beacons were configured with the same UUID and Major values, with unique Minor values. In addition, all of the beacons were set to broadcast using the same transmission interval and power. For the transmission interval 500 ms was chosen to allow for the receiver to obtain a large amount of data in a short time, but not enough to overload the system once eight beacons are transmitting at once. The power consumption of the beacons was set to -10 dBm. This was to reduce the power consumption of the devices and improve the lifetime of the device using a single battery charge.

In order to produce results that would better relate to an indoor localization system, all reference and testing points were placed on tables throughout the whole experiment. This allowed for the system to function as a real localization application since receivers would be carried in a pocket or a bag, while the transmitters would be placed above the obstacles on the ground. When gathering data at each of the testing points, the receiver was left stationary for approximately five minutes to gather RSSI data from the transmitters. The data was then stored and saved for analysis and filtering offline. When filtering, all the RSSI data gathered from a device was used. When using raw RSSI measurements in the calculations the average value was used.

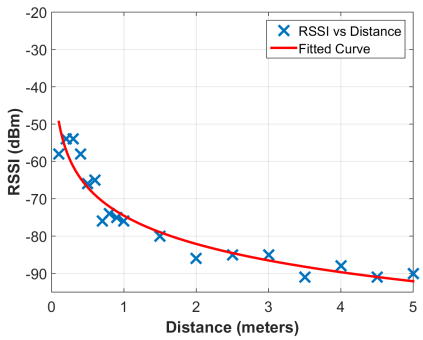


Fig. 2: Path-loss model created for BLE beacons.

Parameter	Value
n	2.511
C	-75.54
R^2	0.9697

TABLE I: Path-loss parameters for BLE in the experiment environment.

To convert the RSSI values to distances, the path-loss model was used. To create the model the RSSI was found over a range of distances in the environment. This was done by placing one transmitter at a stationary spot and moving the receiver farther away while gathering the RSSI values at required distances. The RSSI was gathered at eighteen points, nine between 0 and 1 meter, every 0.1 meters, and nine between 1 and 5 meters, every 0.5 meters. The environment used for these experiments was the same as the one used during previous experiments performed in [4]. The path-loss model created can be seen in Fig. 2 and the parameters determined for BLE in the experimental environment can be seen in Table I.

To determine the error between the calculated (x_{cal}, y_{cal}) and actual position (x_{est}, y_{est}) of the receiver the mean squared error was used as follows:

$$Error = \sqrt{(x_{est} - x_{act})^2 + (y_{est} - y_{act})^2} \tag{9}$$

V. Results and Discussion

A. Results

In total, 30 tests were conducted throughout all the experiments. In each of the tests, the locations of the references and the testing points were recorded. Three types of filter methods were used: raw, moving average, and Kalman. For each of the filtering methods, three types of localization techniques can be seen comparing: trilateration using the three closest references (Trilateration), nonlinear least squares using the three closest references (NLLS3), and nonlinear least squares using all the available references (NLLS). For the trilateration results, note that some of the results are excluded from the graphs. When the three closest nodes were selected and the coordinate system created, the nodes would appear in a line and a location could not be calculated. An overall summary of the best results for each of the filtering methods and localization techniques can be seen in Table II.

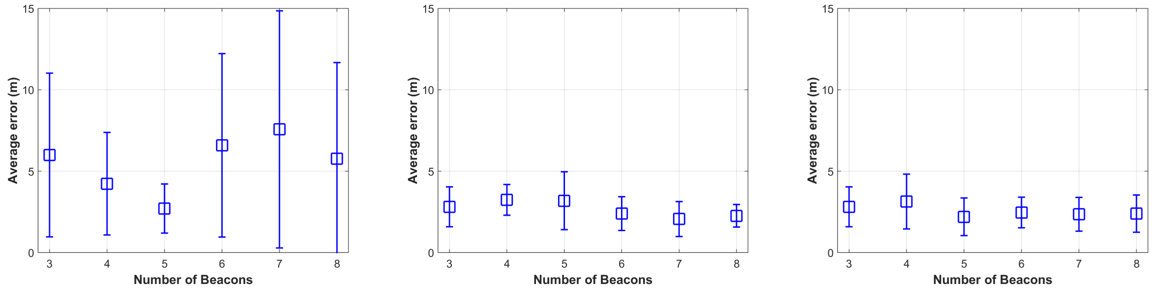
Filtering Method	Localization Technique	Error (m)	Standard Deviation (m)	Number of Beacons
Raw	Trilateration	2.704	1.508	5
	NLLS3	2.058	1.073	7
	NLLS	2.198	1.155	5
Moving Average	Trilateration	2.628	1.308	7
	NLLS3	1.149	0.698	6
	NLLS	2.305	1.280	7
Kalman	Trilateration	2.415	1.443	4
	NLLS3	1.151	0.703	6
	NLLS	2.308	1.312	7

TABLE II: Summary of best errors obtained with the number of beacons used.

Figure 3 displays the average 2D localization error and standard deviation for the different number of beacons when using raw RSSI values. Figure 3a uses trilateration processing. It can be clearly seen that as the number of beacons is increased from three to five, the accuracy and precision increases. At five beacons the average error was 2.704 meters. Once past five beacons, the accuracy and precision greatly decreased. Figure 3b uses NLLS3 processing. When compared to trilateration, accuracy has greatly improved. Using NLLS3 processing, the accuracy changes slightly as the number of beacons is increased. Reaching the minimum error of 2.058 meters using seven beacons. The results using NLLS processing can be seen in Fig. 3c. Using NLLS processing produced results similar to those with NLLS3 processing. The best result was 2.198 meters when using five beacons. It can be seen that as the number of beacons increased the error jumped slightly at six beacons.

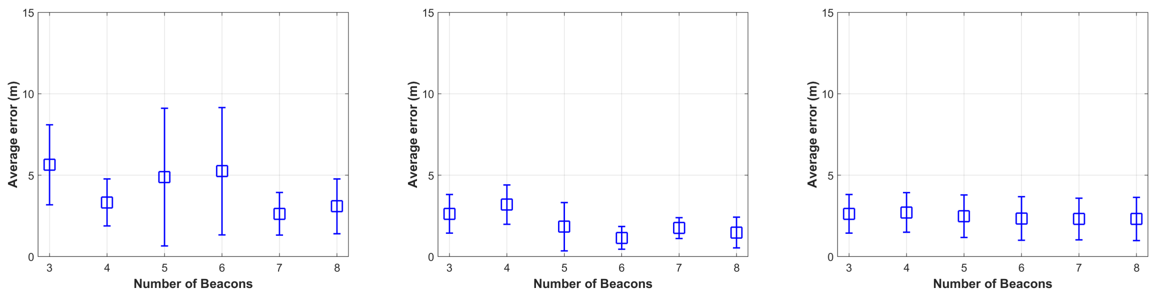
Figure 4 displays the average 2D localization error and standard deviation for a different number of beacons when using RSSI values with a moving average filter. Results using trilateration processing can be seen in Fig. 4a. Based on the results, when seven beacons are deployed in an environment the best error of 2.628 meters was achieved. When NLLS3 processing was used, seen in Fig. 3b, a large increase in accuracy could be found. With NLLS3 the optimal number of beacons found was six producing an error of 1.149 meters. Using NLLS process, as seen in Fig. 4c, the number of beacons did not greatly affect the accuracy of the system. The best average result produced was 2.305 meters when seven beacons were deployed.

By applying a Kalman filter to the RSSI values a slight change in the results can be seen compared to when a moving average filter was used. The results when using a Kalman filter can be seen in Fig. 5. Overall, the results appear similar to those in Fig. 4. When trilateration processing was used, seen in Fig. 5a, the optimal average error obtained was 2.415 meters using four beacons. Seen in Fig. 5b are the results when NLLS3 processing was applied. Optimal results were determined when 6 beacons were used, averaging to an error of 1.151 meters. Similar to when a moving average filter was used, the Kalman filter results in Fig. 5 saw very little changes as the number of beacons increased. The best average result was 2.308 meters using seven beacons.



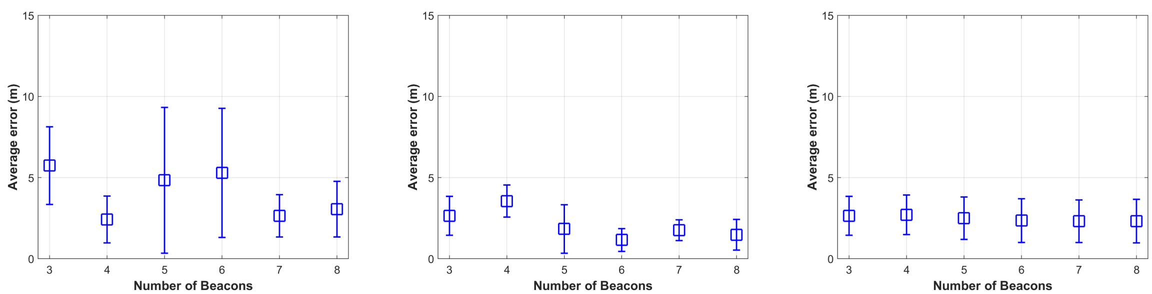
(a) Trilateration. (b) NLLS3. (c) NLLS.

Fig. 3: Average localization error with no filtering for different types of localization techniques.



(a) Trilateration. (b) NLLS3. (c) NLLS.

Fig. 4: Average localization error with moving average filtering for different types of localization techniques.



(a) Trilateration. (b) NLLS3. (c) NLLS.

Fig. 5: Average localization error with Kalman filtering for different types of localization techniques.

B. Discussion

The experimental results revealed useful insights in terms of the most accurate localization technique and filtering method. In terms of the optimal number of beacons for most methods, having seven transmitters in an environment produces good results. However, overall the best average error that was achieved was 1.149 meters using six beacons.

In terms of filtering methods, it can be seen that filtering RSSI values can provide an increase in system accuracy. Based on the filters used in these experiments, both moving average and Kalman provide similar increases in performance. While Kalman filters provided a slightly higher average accuracy, moving average filters were able to provide higher average precision.

Applying different types of localization techniques some interesting results were produced. Trilateration is a highly used technique due to its simplicity and ease using only three transmitters. One issue with using trilateration were the errors that occurred when using more than three transmitters and the three that were selected appear in a line. This forced the system to fail and produce large errors that were not possible. It was determined that trilateration performs best when only three transmitters are located in an area. If more than three transmitters are stationed in an area, trilateration could be used however, the transmitters would need to be arranged in a manner which if three were selected they would not form a straight line.

Through the application of nonlinear least squares processing for localization, a large increase in accuracy and precision could be achieved. One difference between nonlinear least squares and trilateration was that no issues were found if the three closest devices appeared in a line. Nonlinear linear least squares were still able to calculate a location that was reasonable to the environment. Using NLLS3 processing the best results overall were produced. Estimated locations were within a maximum error of 2.058 meters error and a standard deviation of 1.073 meters. When both filters were applied to the data it was determined that using six beacons produced the best results. Based on the layout of the room and placement of the six beacons, it is ideal that the transmitters are placed around the edges of the room for the best results.

When nonlinear least squares processing was done using all of the beacons data, results were very constant no matter the number of beacons used. As the number of beacons increased the accuracy and precision did not improve. Throughout all of the tests, the average error was found to be between 2.3-2.7 meters and the standard deviation between 1.1 - 1.3 meters with both filtering methods. Based on the individual results for each of the receiver positions it was determined that NLLS processing produces the best results when the receiver is in the centre of all the transmitters. While this is not ideal, it makes sense based on the sum of squared distances seen in Eq. (2). The formula is attempting to determine the optimal position that produces the lowest error between all of the transmitters, hence, why it produces an estimated location that is near the centre. In order to prevent this, the NLLS algorithm would need to be altered to not use all of the data received from the reference devices.

VI. Conclusion

In this paper, we compared different types of localization systems to determine the optimal number of reference devices to place in an area to improve localization accuracy. The three types of localization techniques used were: trilateration using the three closest references, nonlinear least squares using the three closest references, and nonlinear least squares using all the references. Filtering methods such as moving average, and Kalman were applied to the RSSI data to determine how the output was affected. Through experimentation, it was determined that the optimal number of references to place in an environment is six. The references were to be placed around the edges of the room in order for the system to produce the best results. The optimal localization technique was nonlinear least squares using the three closest references when filtering was applied to the RSSI data. Both moving average and Kalman produced similar results, with Kalman having better accuracy and moving average producing a higher precision.

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