Smartphone-Based Real-Time Indoor Positioning Using BLE Beacons

Robert Riesebos[1], Viktoriya Degeler[1,2], and Andrés Tello[1]

Abstract— **To deal with the degraded performance of Global Navigation Satellite Systems (GNSS) in indoor environments, Indoor Positioning Systems (IPS) have been developed. The rapid proliferation of smartphones has led to many IPSs that utilize positioning technologies that are readily available on modern smartphones; including Bluetooth Low Energy (BLE). Using radio signals such as BLE in indoor environments comes with a number of challenges that can limit the reliability of the signal. In dealing with these challenges, most existing BLE-based IPSs introduce undesired drawbacks such as an extensive and fragile calibration phase, strict hardware requirements, and increases in the system's complexity. In this paper, an IPS is developed and evaluated that requires minimal setup for indoor environments and has a sufficiently low complexity to be run locally on a modern smartphone. An extensive exploration of the IPS' parameters was performed. The best performing parameter combinations resulted in a median positioning error of 1.48 ± 0.283 meters, while using the log-distance path loss model for distance estimation and Weighted Centroid Localization with a weight exponent between 2.0 and 3.5 for position estimation.**

I. INTRODUCTION

The Global Positioning System (GPS) alongside other Global Navigation Satellite Systems (GNSS), such as the European Union's Galileo, are a straightforward approach to provide position estimates to users across the globe. But these systems are significantly limited in indoor scenarios, because the GNSS' signal is not strong enough to penetrate through solid building materials — degrading the indoor performance of these systems. Consequently, Indoor Positioning Systems (IPS) have been developed to fill the gap in the global coverage of satellite-based systems.

The rapid proliferation of smartphones with support for receiving and transmitting various radio frequency has led to accessible, low-cost solutions. Additionally, smartphones are directly linked to their users, making positioning of these smartphones synonymous to positioning the corresponding users. This, in turn, enables Internet of Things (IoT) integration and provides opportunities for market research, navigation aid and context-aware assistance. While there are many different technologies that are used for indoor positioning, only a handful are currently available on modern smartphones. Notable examples include Bluetooth Low Energy (BLE)[3] and Wi-Fi. This paper aims to take full advantage of the ubiquity of modern smartphones and their sensing capabilities. In particular, it focuses on using BLE beacons as reference points to determine the position of a positioning subject that is carrying a smartphone serving as a BLE receiver. The main challenge of using radio signals such as BLE for indoor positioning is dealing with various effects that compromise the radio signal, decreasing its reliability. Examples of such effects include complicated interference patterns, multipath propagation where the signal reaches the receiver through multiple different paths, and Non-Line-of-Sight (NLOS) conditions in which the signal strength is reduced due to obstacles between the transmitter (beacon) and receiver. In dealing with the challenges of using BLE, many existing solutions introduce undesired drawbacks such as requiring an extensive calibration phase (that is invalidated when the indoor layout changes), strict hardware requirements, and increases in the system's complexity [1]. When the system becomes too complex to be run locally on the smartphone, significant latency between receiving BLE signals and position estimation can be introduced. Additionally, offline positioning becomes infeasible.

The main objective of this paper was to create a BLE-based IPS that avoids these undesired drawbacks. As such an IPS was developed that requires minimal setup for indoor environments, has a sufficiently low complexity that positioning can be done in real-time — locally on the smartphone — and that uses inexpensive, readily-available BLE beacons.

In short, the main contributions of this paper are: (1) An Indoor Positioning System (IPS) with a median positioning error of about 1.5 meters, that runs locally on a smartphone and requires minimal setup; (2) An exhaustive exploration of the parameters involved in the different stages of the IPS by replaying recorded BLE beacon measurements.

The remainder of the paper is structured as follows. Section II contextualizes this paper, and examines recent related works that also utilize BLE as their primary positioning technology. Next, in Section III, the implementation of the proposed IPS is discussed. Section IV discusses the experiment environment, experiment parameters and how they can be efficiently explored. It also presents the ground truth for the experiments and introduces ground truth interpolation. The results of the experiments are presented and discussed in Section V. Finally, the paper is summarized in Section VI.

II. RELATED WORK

The work by Faragher and Harle [2], written in 2015, is one of the most influential works on BLE-based indoor positioning [1]. It provided the first experimental test of fine-grained BLE positioning using fingerprinting, and it was the first to show that the use of three advertising channels

[1]Bernoulli Institute for Mathematics, Computer Science, and Artificial Intelligence, University of Groningen,

[2]Informatics Institute, University of Amsterdam,
`rriesebos@hotmail.com`, `v.o.degeler@uva.nl`, `andres.tello@rug.nl`.

[3]A technology similar to classic Bluetooth but with significantly lower power consumption

to transmit BLE signals leads to severe received signal strength (RSS) variations. To mitigate these variations when collecting measurements, they used a time window of RSS measurements. Window sizes of around 0.5 to 2.0 seconds, for the measurements window used in the online stage, provided the best performance with a median positioning error of about 1 meter.

In 2016, Kriz et al. [3] combined BLE fingerprinting with Wi-Fi fingerprinting to improve the overall positioning accuracy. For each technology a separate set of fingerprints was collected and stored. To evaluate the positioning error, a leave-one-out cross-validation technique was applied on the collected fingerprints. From the set of 680 fingerprints, one was chosen in each iteration and its position was estimated based on the distance to the others. The results showed a 23% improvement when BLE beacons were used in addition to Wi-Fi access points, and yielded a median positioning error of 0.77 meters. But the mobile application was only capable of collecting fingerprint measurements, and the system was only evaluated using fingerprints that were constructed from a large number of RSSI samples — the 680 measurements consisted of 115,511 individual RSSI samples, each took 10 seconds to complete.

Later in 2016, Subedi et al. [4] published a paper that focused on using Weighted Centroid Localization (WCL) with BLE beacons. The log-distance path loss model estimated the distances between the receiver and the BLE beacons from the measured RSSI values. Before the distance was estimated, the RSSI measurements were filtered using a Kalman filter on top of a moving average filter. The developed system was evaluated in a 2.5 meters wide corridor in which a of total 14 beacons were deployed along the walls. The placement was done in pairs of two at a height of 2.5 meters, with a distance of 4.5 meters between each pair. The results showed that, out of the considered weight exponents of 0.5, 1.0, and 1.5, a weight exponents of 0.5 performed best for their test environment. The corresponding mean positioning error was about 1.8 meters when all measurement locations were averaged.

In 2019, Huang et al. [5] proposed an indoor positioning method that took advantage of the three separate BLE advertising channels. To separate the advertising channels, BLE beacons were configured to only broadcast on a single channel. For each advertising channel a series of RSS measurements was performed at distances between 0 and 19.2 meters, with 1.2 meter increments. Using these measurements, three channel-specific distance models were obtained by fitting the data. Before using these distance models for distance estimation, the RSS measurements that served as input to these models were filtered by taking the median of a sliding window. This data filtering step was performed for each advertising channel, leading to a separate distance estimation for each channel. These distance estimations were combined into a single, final distance estimate. Finally, weighted trilateration was used to convert the processed distance estimates into position estimates. The system was evaluated in two environments; a classroom measuring 5 by 10 meters, and an office room of 9 by 12 meters. In each environment four beacons were deployed, one at each corner of the environment. The proposed method achieved median positioning errors between 1.8 and 2.0 meters.

In 2020, L. Liu et al. [6] published a real-time indoor positioning method that fused positioning estimates obtained by using trilateration and fingerprinting. A Pedestrian Dead Reckoning (PDR) approach was explored, and the results from both the BLE-based method and the PDR method were fused using a Kalman filter. The initial position needed in the PDR method was provided by the BLE-based method. The BLE-based method used the log-distance path loss model to convert RSSI measurements to distance estimates. These distance estimates were fed directly into the trilateration positioning method, and the corresponding RSSI values were used in the fingerprinting method. To fuse both methods, a weighted average of both position estimates was taken. To evaluate their system, an about 2 meter wide corridor was used. In total 10 beacons were deployed along the edges of the corridor. In their experiments two different routes were traversed, and three experiments were performed per route. The results of all six experiments for the BLE-based method were averaged, resulting in a median position error of 2 meters.

TABLE I: Comparison with previous work

Ref.	Main positioning method	Median error	Environ-ment	BLE Beacons
[2]	Fingerprinting	1 m	600 m^2	19 (0 dBm, 50 Hz)
[3]	Fingerprinting (Wi-Fi + BLE)	0.77 m	2236 m^2	17 (0 dBm, 10 Hz)
[4]	WCL	1.8 m	$\sim$ 80 m^2	14 (4 dBm, 3.33 Hz)
[5]	(Weighted) Trilateration	1.8 m	50 m^2	4 (0 dBm, 10 Hz)
[6]	Trilateration	2 m	$\sim$ 90 m^2	10 (about -71 dBm, 1 Hz)
Ours	**Trilateration**	**1.48 m**	**61 m^2**	**10 (-59 dBm, 2 Hz)**

Whereas previous works mostly rely on a single positioning method, this paper extensively compares multiple different positioning methods. Similarly, multiple distance estimation models are explored, and the log-distance path loss model is compared to distance estimation models obtained by fitting experimental data. Furthermore, our work does not rely on fingerprinting but still has a comparatively low positioning error while being evaluated in a non-corridor environment using BLE beacons broadcasting at only 2 Hz.

III. IMPLEMENTATION

Our BLE-based IPS implementation consists of four steps: RSSI measurements, RSSI filtering, distance estimation, and positioning. Each step is discussed in a separate subsection.

A. RSSI measurements

In this paper, ten BLE beacons were used. These beacons use the iBeacon protocol, introduced by Apple in 2013 [7]. In accordance with this protocol, the beacons transmit a unique identifier and a transmission power (TX power) value indicating the signal power at a reference distance of 1 m.

To receive the advertising packets broadcast by the BLE beacons, a smartphone is used. In particular the OnePlus 6 is used, which supports Bluetooth 5.0 [8]. The scanning interval between measurements is 500 ms or 2 hertz, the maximum frequency supported by the available BLE beacons. To get an idea of the variance of the RSSI, we took 100 measurements of the RSSI at a static distance of one meter. We did this for all ten beacons. The resulting average RSSI at one meter ranged from -54.0 dBm to -57.7 dBm, with standard deviations between 1.49 dBm and 2.55 dBm.

B. RSSI filtering

The next step is to filter out the variance between the RSSI measurements previously observed. To do so, a sliding window of measurements is implemented, essentially acting as a buffer to store the last n number of measurements. Each beacon has its own measurements window, as illustrated in Figure 1. Here, the window size is five ($n = 5$). A window

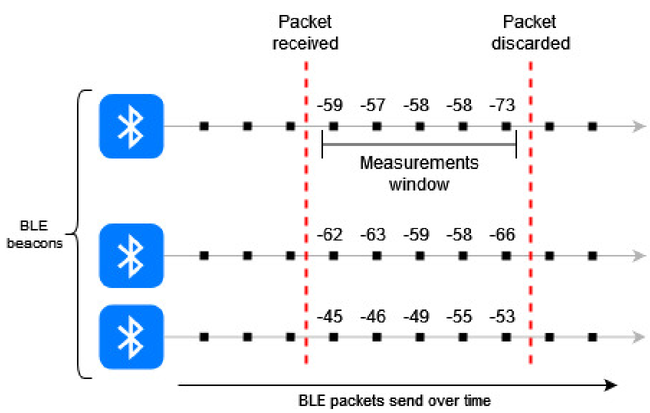


Fig. 1: Measurements windows for multiple BLE beacons

size of one ($n = 1$) means that no RSSI filtering occurs, and that the variance in the measurements is not reduced. On the other hand, changes in the RSSI are directly reflected in the distance estimation. Conversely, if the window size is too large, changes in the RSSI might have a delayed effect on the distance estimation, leading to a position estimation that lags behind on reality. To deal with the variance in the measurements, three methods to reduce the measurements to a single value were explored: the mean (average), the median and the mode. For the mode, if all measurements occur only once, the median is used as a fallback.

C. Distance estimation

The next step towards indoor positioning is distance estimation. To obtain distance estimates from (filtered) RSSI measurements, signal propagation models are used [9], [10]. These models rely on the fact that signals incur a loss in signal strength as they propagate through space. This is a consequence of the reduction in power density due to path attenuation, also referred to as path loss. The distance estimation step is arguably the most critical one, as it directly translates to accurate position estimation. We explored the log-distance path loss model and multiple models obtained by fitting logarithmic models to quantitative data.

1) The log-distance path loss model: A commonly used path loss model is the so-called log-distance path loss model [11], given by Equation 1,

$$\overline{PL}_{[dB]}(d) = \overline{PL}_{[dB]}(d_0) + 10n\log_{10}\left(\frac{d}{d_0}\right), \tag{1}$$

where $\overline{PL}$ refers to the average path loss, d_0 is a reference distance at which the path loss is known (usually one meter), n is the path loss exponent indicating the rate at which the path loss increases with distance (typical values for the path loss exponent range from 2.0 to 3.5 [11]), and d is the distance between the transmitter and receiver.

The path loss can be substituted by the RSSI, and the term $\frac{d}{d_0}$ can be simplified to just d when a reference distance of one meter is used. This results in the following equation:

$$\overline{RSSI} = \overline{RSSI}(d_0) + 10n\log_{10}(d). \tag{2}$$

Finally, rewriting this equation for the distance d gives us:

$$d = 10^{\frac{\overline{RSSI}-\overline{RSSI}(d_0)}{10n}}. \tag{3}$$

The RSSI at a reference distance d_0 of 1 m is called the transmission (TX) power, and is often included in the signal send by the transmitter. Instead of using the standard values, we chose to utilize the values obtained by the one meter experiments (Section III-C.2) because all beacons were preconfigured with a TX power value of -59 dBm, which does not account for differences between the individual beacons.

2) Fitted logarithmic models: Another approach to distance estimation is measuring the RSSI for a wide range of distances, and using these measurements to fit the data with a trendline to obtain a distance model. While such a model does encapsulate characteristics specific to the beacons, it also inadvertently captures qualities of the receiver. We measured the RSSI at 24 different distances, from 0.5 meters to 12 meters with increments of 0.5 meters. At each distance we took 100 measurements with Line-of-Sight (LOS) conditions, and 100 measurements with Non-Line-of-Sight (NLOS) conditions simulated by standing in front of the receiver. The results are shown in Figure 2. The dashed lines represent the fitted trendlines for the LOS, NLOS measurements, and the average of both. Each point represents the average of 100 measurements at the corresponding distance.

The fitted trendlines were obtained by fitting the data using a logarithmic least squares method. The resulting line equations are shown in Table II. The LOS and NLOS measurements are fit separately, and the average trendline is averaging the slope and intercept of both trendlines.

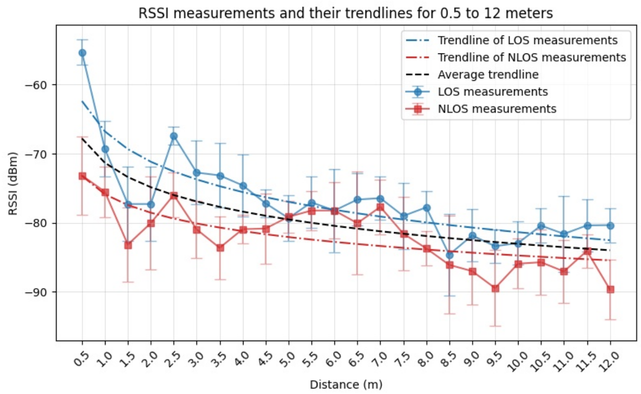


Fig. 2: Average RSSI measurements and their trendlines at distances between 0.5 and 12 meters

TABLE II: Equations of the fitted trendlines

Trendline	Fitted line equation
LOS	$-6.338\ln(d)-66.765$
NLOS	$-3.851\ln(d)-75.869$
Average	$-5.094\ln(d)-71.317$

D. Positioning

The final step towards locating the smartphone receiver is positioning itself. In this step the estimated distances from the previous step are used by a positioning method to estimate the receiver's position.

Three positioning methods were implemented: trilateration, Weighted Centroid Localization (WCL), and probability-based positioning.

1) Trilateration: The first method is trilateration. Using trilateration, a 2D position can be calculated based on the distances to the closest three transmitters (beacons).

For each transmitter, the set of possible positions of the receiver can be determined based on the distance between the transmitter and receiver. In two dimensions, the set of possible positions equates to a circle given by Equation 4,

$$d_i = \sqrt{(x_i - x)^2 + (y_i - y)^2}, \tag{4}$$

where d_i is the distance between transmitter i (Tx_i) and the receiver, and (x_i, y_i) is the known reference position of transmitter i.

To find the position of the receiver, the intersection of the three circles has to be calculated [12], [10]. This is done by solving the following system of equations,

$$d_i = \sqrt{(x_i - x)^2 + (y_i - y)^2}, \text{ for } i = 1,2,3. \tag{5}$$

Because the distance estimation is imperfect, there are three possible cases that can arise: (1) The three circles have a single intersection point. In this case the intersection point is used as the estimated position. (2) Only two of the circles intersect. In this case there are two intersection points to be considered. For the position estimate, the intersection point closest to the third beacon is used. (3) None of the circles intersect. In this case WCL is used. In reality the situation in case 1 rarely occurs, if ever. Case 2 is the most likely to arise, and case 3 only occurs when the three circles are non-overlapping, or when circles are contained in other circles.

2) Weighted Centroid Localization (WCL): The next method is a multilateration method called Weighted Centroid Localization (WCL). It utilizes all detected transmitters to estimate the target's position. It works by calculating the weighted mean of the known coordinates of nearby transmitters. Transmitters that are closer to the receiver are weighed higher and contribute more to the final predicted position. The position of the weighted centroid is defined by Equation 6 [13], [14].

$$(x, y) = \frac{\sum_{i=1}^{n} (x_i, y_i) \cdot w_i}{\sum_{i=1}^{n} w_i}, \tag{6}$$

where (x, y) is the predicted position, n is the number of considered transmitters, (x_i, y_i) are the coordinates of the i-th transmitter and w_i is the weight allotted to the i-th transmitter.

The weight is inversely proportional to the distance, and is given by Equation 7,

$$w_i = \frac{1}{d_i^g}, \tag{7}$$

where d_i is the distance to the i-th transmitter and g controls the weight drop off at larger distances.

3) Probability-based positioning: Finally, we have the probability-based positioning method, introduced by Knauth et al. [15]. This method requires the indoor environment to be divided into a grid of points [14], [15]. The probability-based positioning method makes use of a parametric probability density function $p(d, d_i)$. The function describes, for an estimated distance d_i to transmitter i, the probability p for the receiver to be at a distance d from the transmitter's position. A typical probability density function is defined in Equation 8 [14],

$$p(d, d_i) = \frac{1}{(d - d_i)^2 + c}, \tag{8}$$

where c is a parameter influencing the sharpness of the function. The probability is higher if the distance d is closer to the estimated distance d_i.

Equation 8 gives the probability for a single transmitter. To get the probability for all transmitters we multiply the probability of each transmitter to get a residual probability, as given by Equation 9,

$$p((x_j, y_j)) = \prod_{i=1}^{n} p(|(x_i, y_i) - (x_j, y_j)|, d_i), \tag{9}$$

where (x_j, y_j) are the coordinates at which the probability is calculated, n is the number of transmitters, (x_i, y_i) are the coordinates of the i-th transmitter and d_i is the estimated distance to the i-th transmitter.

Finally, we divide the floor plan into a grid of discrete coordinates. At each coordinate we calculate the residual probability given by Equation 9. After looping over all coordinates the point with the highest residual probability is chosen to be the predicted position.

IV. EXPERIMENTS

In this section, we discuss the setup and design of the experiments to evaluate our Indoor Positioning System.

A. Experiment setup

The experiments were conducted on the first floor of a residential building, consisting of a living room and a kitchen. A detailed floor plan of the first floor is given in Figure 3. The floor plan includes the furniture and a grid with cells of 20 by 20 centimeters. The total area of the first floor is about 61 m^2 and it has a bounding box of about 12 by 9.6 meters.

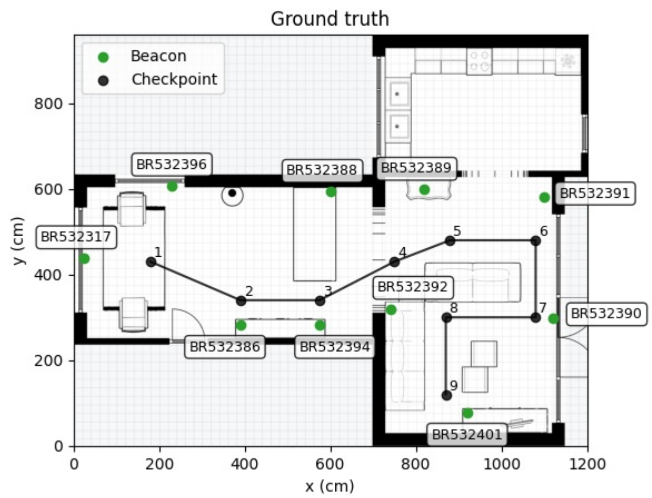


Fig. 3: Floor plan showing the beacon placement and ground truth

1) Beacon locations: The beacons were spread uniformly along the walls of the living room on the first floor, as shown in Figure 3. Each green dot represents a beacon, and the associated label indicates the beacon's name. Every beacon was placed at the same height in order to enable positioning in two dimensions, on the plane that intersects all beacons. If necessary, all methods discussed in Section III-D could be adapted to operate in three dimensions.

2) Ground truth: The ground truth is given by a path, or so-called trace, that is defined by nine checkpoints. These checkpoints are shown in Figure 3. The checkpoint numbers indicate the direction in which the ground truth path is traversed. The checkpoints were chosen in such a way that they represent a ground truth trace that covers the complete living room. To make sure that the ground truth path was followed, the checkpoints were carefully marked on the ground to guide the positioning subject. Furthermore, while traversing the ground truth path, the positioning subject walked in a straight line from checkpoint to checkpoint with a constant speed of about 5 km/h.

3) Ground truth interpolation: A problem with evaluating IPSs is that every single position estimate requires a complementary ground truth definition in order to calculate the positioning error. To combat this we used the dynamic evaluation method introduced by Osa et al [16]. It uses the predefined geometrical path shown in Figure 3. While traversing this path the positioning subject indicates when each checkpoint is reached in the Android application, recording the timestamps corresponding to when each checkpoint is reached. Now, for each position estimate, a corresponding interpolated checkpoint/ground truth point can be generated by determining between which checkpoints the position estimate falls and, using the timestamps of the position estimate and the checkpoints, linearly interpolating between the previous and upcoming checkpoints.

B. Experiment parameters

The RSSI filtering method, window size, distance model and positioning methods were described in detail in Section III. Table III lists all the different parameters explored in the experiments, along with the considered values. For the window size five different values are considered, capped at 20 measurements to avoid delays in the distance estimation. The values of the weight exponent and probability sharpness are capped at 3.5, since increasing these parameters further would have a diminishing impact on the resulting weights and probabilities.

TABLE III: Experiment parameters and the corresponding values

Parameter	Values
RSSI filtering method	Mean, median, mode
Window size	1, 5, 10, 15, 20 measurements
Distance model	Log-distance path loss model, fitted LOS, fitted NLOS, fitted average
Path loss exponent (n)	1.5 – 3.5, with 0.1 increments
Positioning method	Trilateration, Weighted Centroid Localization (WCL), probability-based positioning
Weight exponent (g)	0.5 – 3.5, with 0.5 increments
Probability sharpness (c)	0.5 – 3.5, with 0.5 increments

C. Replaying RSSI measurements

The parameters listed in Table III all affect the performance of the IPS. However, some parameters are also affected by changes in other, related parameters. For example, changes in the window size affect the filtering methods. This makes it hard to test changes in a parameter in isolation. Furthermore, RSSI measurements differ between experiments making it even more challenging to objectively compare results.

To account for these difficulties, a system was implemented that can replay the RSSI measurements as they were received by the smartphone. This is done by using the stored RSSI measurements and corresponding timestamps, along with the timestamps recorded for each position estimate. The system calculates the distance and position estimates exactly like the Android application, but it is not bound by time delays between the RSSI measurements, as all measurements are readily available. Consequently, it can apply different positioning techniques with arbitrary parameters to the same set of RSSI measurements — in a matter of seconds. Using this system, all parameter combinations can be efficiently explored and objectively compared. In total there are 4680 valid possible combinations of the parameters given in Table III.

V. RESULTS AND DISCUSSION

The ground truth path was traversed ten times, resulting in ten different sets of RSSI measurements. For each set of measurements, 4680 different parameter combinations were explored by replaying the RSSI measurements — resulting in a total of 46800 post-processed traces. For the final positioning error of each parameter combination, the ten positioning errors corresponding to each set of RSSI measurements were averaged. We discuss and briefly summarize the effect of each parameter on the positioning error, evaluating the best performing parameter combination and the overall performance of the IPS.

A. Parameter exploration

In order to evaluate the effect of each parameter on the positioning error, the discrete values of the parameters were used to create notched box plots. The notches represent the 95% confidence interval of the median, determined using a Gaussian-based asymptotic approximation [17]. Overlaid on the box plots are scatter plots of the corresponding data points. Each data point represent a unique parameter combination, where the specified parameter value is kept fixed. As such, the data points in the scatter plots are subsets of the 4680 different parameter combinations. For some parameter values, such as the log-distance path loss model distance model, related parameters (e.g. the path loss exponent) are explored resulting in more data points.

The positioning errors in Figure 4 are obtained using the median positioning error metric. To reduce overplotting, the data points are jittered. The wide spread of errors for every possible parameter combination is shown in Figure 4a. The best parameter combinations result in a median positioning error of about 1.5 meters, while the worst combinations result in errors of above 3 meters. The best combinations are most interesting, and are further explored in Section V-B. The median error of all parameter combinations is about 2.27 ± 0.027 m. This value is useful to contextualize whether a certain parameter value has a positive or negative effect on the overall positioning error, and is therefore explicitly shown as a red, dashed line in the sub-figures of Figure 4.

1) RSSI filtering method: The first parameter to be explored is the RSSI filtering method. The results for each method are presented in Figure 4b. It is evident that the mean filtering method performs significantly worse than the other two methods, with a median positioning error of about 2.51 ± 0.03 m and no data points with an error below 1.8 m. The median filtering method and the mode filtering method perform equally well; the median positioning error of the median filtering method is about 2.04 ± 0.03 m, and median error of the mode filtering method is about 2.03 ± 0.03 m.

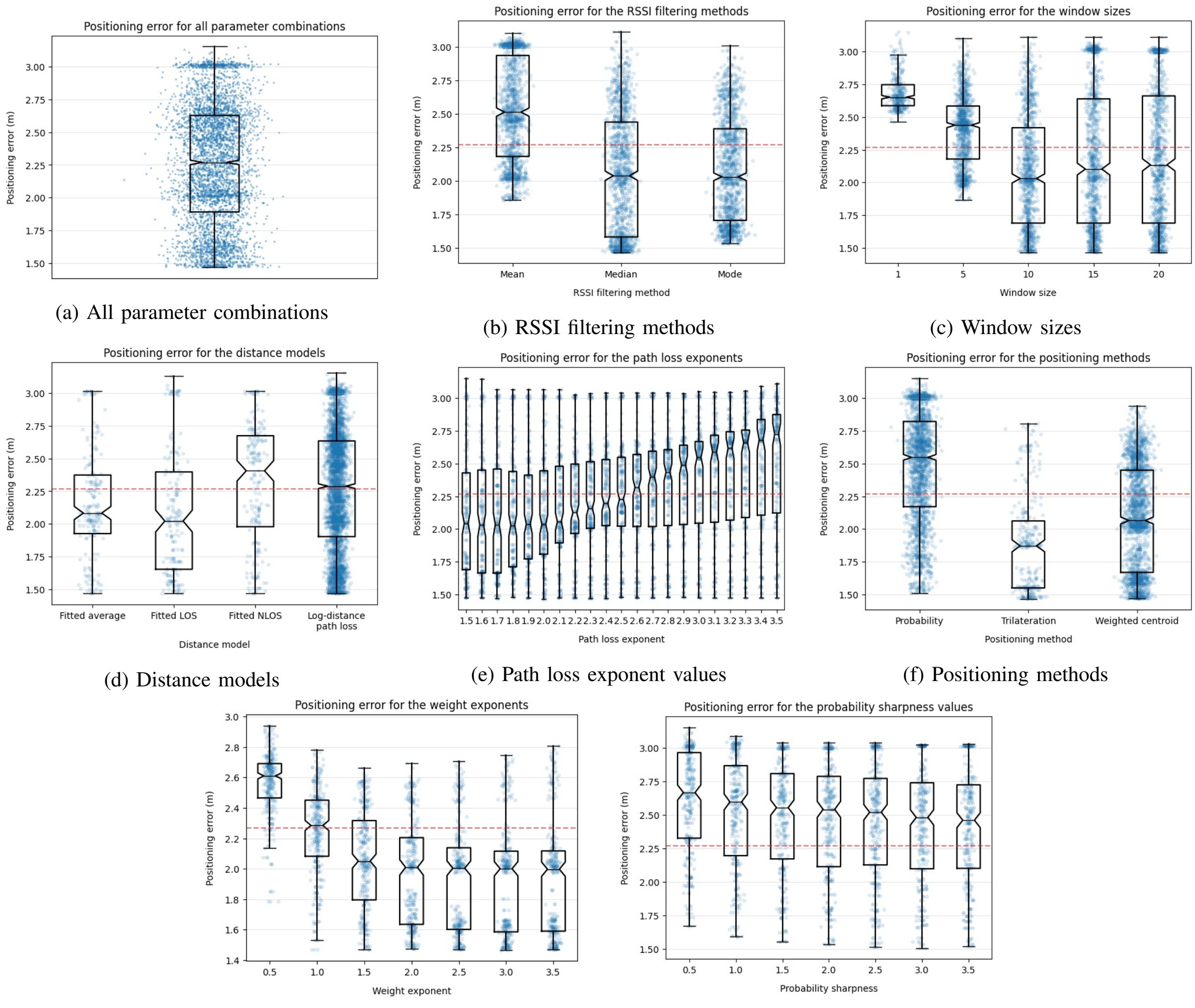
2) Window size: For the window size five different values were considered: 1, 5, 10, 15 and 20. In Figure 4c, the results for the different window sizes are shown. The median positioning error for parameter combinations with a window size of 1 is about 2.65 ± 0.01 m, which is well above the median of the other window sizes. Additionally, all parameter combinations with a window size of 1 have a positioning error above 2.45 meters, and the worst parameter combinations all have a window size of 1. These observations indicate that RSSI filtering is an effective way of reducing variances and, by extension, the positioning error. With a median position error of about 2.03 ± 0.04 m, a window size of 10 performs the best out of the explored values. Noteworthy however, is that the performance of the window size is related to the travelling speed. For the experiments a casual walking speed of around 5 km/h was maintained. At this speed the window sizes of 15 and 20 also perform relatively well, as they have a median positioning error of 2.10 ± 0.05 m and 2.13 ± 0.05 m respectively.

3) Distance model: Four distance models used in the IPS: the log-distance path loss model, and the models obtained by fitting distance – RSSI measurements. The results of using these distance models are shown in Figure 4d. The optimal distance method depends on the indoor environment; the log-distance path loss model or the fitted NLOS model might better suited for buildings with frequent LOS obstructions, while open-plan buildings are ideal for the fitted LOS model. The fitted average model is a compromise between both situations. For the indoor environment used in our experiments, the fitted LOS model performs the best. It has a median positioning error of 2.02 ± 0.07 m, which is considerably lower than the median error of the complete set of parameter combinations. The fitted average model performs relatively well with a median positioning error of 2.08 ± 0.05 m.

a) Path loss exponent: One of the parameters used in the log-distance path loss model is the path loss exponent. The positioning error for values between 1.5 and 3.5, with 0.1 increments, is shown in Figure 4e. The positioning error increases as the path loss exponent increases. This is consistent with the previous results that showed that the fitted LOS has the lowest positioning error since lower path loss exponents equate to a slower RSSI drop-off, as associated with LOS conditions [11]. The path loss exponent 1.8 results in the lowest positioning error with a median value of 2.03 ± 0.08 m, which is comparable to the median error using the fitted LOS and fitted average distance model.

4) Positioning method: Three positioning methods were implemented: probability-based positioning, trilateration and WCL, shown in Figure 4f. Trilateration has the best median performance with a positioning error of 1.87 ± 0.05 m. The probability-based positioning method has the worst median positioning error of 2.55 ± 0.02 m. When WCL is used, the median positioning error is 2.07 ± 0.03 m and the range of errors is similar to that of the trilateration method.

a) Weight exponent: An important parameter in WCL is the weight exponent, as discussed in Section III-D.2. For our experiments, six different values were explored: 0.5, 1.0,



(a) All parameter combinations

(b) RSSI filtering methods

(c) Window sizes

(d) Distance models

(e) Path loss exponent values

(f) Positioning methods

(g) Weight exponent values

(h) Probability sharpness values

Fig. 4: Average positioning error for the indicated parameters, data points are jittered to increases legibility

1.5, 2.0, 2.5, 3.0 and 3.5. The resulting positioning errors are shown in Figure 4g. The positioning error decreases as the weight exponent increases, indicating that more aggressive weighing of the beacon coordinates, based on the corresponding distances, improves the performance. The effect flattens off at weight exponents of 2.0 and above. The median positioning error corresponding to the weight exponent value of 0.5 is 2.61 ± 0.02 m, while the median positioning error for the weight exponent with a value of 2.0 is 2.01 ± 0.05 m — rivalling the median error obtained using trilateration.

b) Probability sharpness: The final parameter that we explored is the probability sharpness, used in probability-based positioning as discussed in Section III-D.3. Probability sharpness values between 0.5 and 3.5 were explored. The results are shown in Figure 4h. The median positioning error monotonically decreases as the probability sharpness increases. The decline in the positioning error is small, and the subsequent median positioning errors fall only just below the 95% confidence interval that corresponds to the previous median positioning error. The error of the probability sharpness with a value of 0.5 is 2.67 ± 0.05 m. On the other end of the explored value range, the median positioning error is 2.46 ± 0.06 m for the probability sharpness value of 3.5.

B. *Best results*

The best performing parameter combination is selected based on the average positioning error over the mean error, root-mean-square error, median error, 75$^{\text{th}}$ percentile error, and the 90$^{\text{th}}$ percentile error. There are three best parameter combinations that perform equally well because the performance of these parameter combinations is the same for the window sizes of 10, 15 and 20 due to the median filtering method. The error metrics in meters along with the parameter values are shown in Table IV. The window sizes are shown as a set of multiple values, corresponding to the parameter grouping. The median positioning error for the best parame-

TABLE IV: Positioning error metrics and parameter values for the best performing parameter combination

Mean	RMS	Median	75th Percentile	90th Percentile
1.59 ± 0.319	1.83 ± 0.408	1.48 ± 0.283	2.10 ± 0.434	2.68 ± 0.882

Filtering method	Window size	Distance model	Path loss exponent	Positioning method	Weight exponent	Probability sharpness
Median	{10, 15, 20}	Log-distance path loss	2.4	WCL	3.0	N/A

ter combination is 1.48 ± 0.283 meters. The positioning error sharply increases in the upper percentiles, indicating few increasingly bad predictions. Ironing these out would greatly reduce the mean and root-mean-square positioning errors. The values corresponding to the best performing parameter combination are in line with the observations in Section V-A. The median RSSI filtering method is used, the window sizes are exclusively above five, the log-distance path loss model is used and positioning is done using WCL.

VI. CONCLUSIONS

In this paper, an Indoor Positioning System (IPS) is implemented that runs locally on a smartphone and requires minimal setup before it is able to operate. At the core of this IPS are four main steps: collecting RSSI measurements, filtering these measurement, distance estimation, and positioning. To evaluate the performance of various methods and the IPS as a whole, several experiments were performed in which the position of the subject with the smartphone was estimated periodically while traversing a predefined path. Ground truth points were generated by interpolating between checkpoints with known timestamps using the timestamps of each received RSSI measurement.

The IPS has different parameters that affect the performance of the system. The experiment results showed that a window size of 10 significantly decreased the positioning error compared to smaller measurement windows. The median RSSI filtering method was the most effective in filtering the variance between RSSI measurements. The best performing distance estimation models were the fitted LOS model, and the log-distance path loss model using a path loss exponent between 1.5 and 2.0. The positioning methods with the lowest median positioning error were trilateration and WCL with a weight exponent between 2.0 to 3.5. The best performing parameter combinations had a median positioning error of about 1.48 ± 0.283 meters, and used the median filtering method, window sizes between 10 and 20, the log-distance path loss model, and Weighted Centroid Localization with a weight exponent between 2.0 and 3.5.

As a possible further improvement to this work, the Bluetooth 5.1 specification supports Angle of Arrival (AOA) measurements enabling triangulation techniques that could lead to large accuracy improvements. Evaluating the IPS using multiple ground truth paths and multiple indoor environments would result in more rigorous experiments and results. Other interesting avenues of research include optimal BLE beacon placement, the effects of varying the number of deployed beacons, and heuristics that could be used to dynamically adjust the window size.

The code and data of this paper are made publicly available[4]. Any use must include a citation to this paper.

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