Do We Really Need UWB? Evaluating RSSI and UWB for Location-Aware Activity Recognition

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Abstract. Indoor positioning provides valuable contextual information for wearable activity recognition. Although ultra-wideband (UWB) enables accurate ranging, it increases hardware complexity and deployment costs. By contrast, Bluetooth Low Energy (BLE) received signal strength indication (RSSI) is widely available on commodity devices, but generally provides less reliable localization. We compare simultaneously collected RSSI and UWB measurements from a wearable activity recognition study to determine whether UWB's greater ranging accuracy provides meaningful benefits for location-aware activity recognition. Preliminary results show a strong correlation between RSSI and UWB-derived distance for many, but not all, participant–beacon combinations. This variation suggests that the suitability of RSSI depends on the application and deployment environment. We examine the trade-offs among localization accuracy, hardware cost, and practical feasibility in wearable sensing studies.

Keywords: Indoor Positioning · UWB · RSSI · HAR

1 Introduction

New sensors, communication protocols, and positioning technologies are developing rapidly. Yet these innovations often come with higher costs, compatibility problems with existing devices, and greater implementation complexity. Their benefits should therefore be assessed against those of simpler, established solutions. This trade-off is also relevant to indoor localization. Although Global Positioning System (GPS) is widely used outdoors, its availability and accuracy decrease indoors because building materials attenuate satellite signals.

Indoor localization supports navigation in airports, hospitals, shopping centers, and other complex buildings. It is also used to locate patients, personnel, equipment, and other assets in healthcare facilities and to support warehouse and intralogistics management [9,7,13].

Various technologies have been proposed for indoor localization, including Wi-Fi-based positioning, Bluetooth Low Energy (BLE) beacons, Ultra-wideband (UWB), radio-frequency identification, inertial measurement units, magnetic-field-based localization, ultrasound, visible-light positioning, camera-based systems, and hybrid approaches that combine multiple sensing modalities. These technologies differ substantially in positioning accuracy, cost, infrastructure requirements, scalability, and practical feasibility. Among them, recent developments in UWB have attracted particular attention because its time-based ranging methods can provide centimeter-level accuracy and perform reliably in multipath environments. However, the need for dedicated infrastructure and compatible devices may increase implementation costs and complexity.

This paper investigates whether the greater positioning accuracy offered by more advanced indoor positioning systems is necessary to improve application-level performance and whether such improvements justify the associated costs and implementation requirements. To address this question, we compare UWB- and Received Signal Strength Indicator (RSSI)-based indoor positioning within a human activity recognition (HAR) study.

2 Related Work

Indoor location information can improve HAR by distinguishing activities that involve similar movements but occur in different spatial contexts. Previous studies have combined wearable sensors with BLE beacons for activity recognition in healthcare, residential, and public environments. These systems demonstrate that relatively inexpensive RSSI-based proximity information can improve activity recognition despite its limited positioning accuracy [2,3,12,6].

UWB is commonly used when more precise ranging or fine-grained motion analysis is required. Prior work has applied UWB to gait analysis, physical activity monitoring, device-free activity recognition, and residential path tracking, reporting up to centimeter-level accuracy [10,1,11,8,14]. However, this accuracy requires dedicated hardware and greater deployment complexity.

Existing studies therefore demonstrate the applicability of both RSSI and UWB, but typically evaluate them in different systems, environments, and activity-recognition tasks. Consequently, it remains unclear whether the higher ranging accuracy of UWB provides meaningful application-level benefits over readily available RSSI measurements. We address this gap by comparing simultaneously collected RSSI and UWB data under identical experimental conditions in a location-aware HAR study.

3 Methods

The data used in this work originate from the SLICE (*Simulated Location-based Identification of Compulsive Events*) feasibility study, which investigated location-aware wearable activity recognition in a multi-room living laboratory at the Hasso Plattner Institute, Germany. Healthy participants performed scripted and natural daily activities while wearing wrist-mounted inertial measurement units (IMUs). Simultaneously, indoor positioning data were collected using BLE beacons supporting both RSSI and UWB. The study was approved by the Ethics Committee of the University of Potsdam (38/2022), and all participants provided written informed consent.

For the present analysis, only the simultaneously recorded RSSI and UWB measurements are considered. A detailed description of the study protocol, participants, sensor setup, and activity recognition dataset is provided in our previous work [4,5].

3.1 Data Collection

Indoor positioning data were collected as part of the SLICE feasibility study, for which complete sensor recordings from 12 healthy participants were available. Each participant completed an approximately one-hour session in a multi-room living laboratory while wearing IMUs on both wrists. Their position within the laboratory was recorded simultaneously using indoor positioning sensors. No researchers were present during the recording, and participants were free to decide when to perform the prescribed activities. The protocol included handwashing, table cleaning, and door checking, as these activities were selected based on the study hypotheses. Between these tasks, participants engaged in self-chosen everyday activities, such as reading, preparing food, or working on a laptop. However, no information about the specific activities they chose was recorded.

Indoor positioning data were recorded using Estimote beacons distributed throughout the lab, as shown in Appendix A. The system provided both BLE-based RSSI measurements and UWB ranging data. Although both modalities were recorded, only the UWB data were used in the original SLICE study analysis. The present work extends this analysis by comparing the simultaneously recorded RSSI and UWB measurements under the same experimental conditions.

RSSI represents the strength of a received signal in dBm. Less negative values indicate stronger signals and generally suggest greater proximity to a beacon, whereas more negative values indicate weaker signals. Although RSSI is inexpensive and widely supported by commodity devices, it is sensitive to obstacles, body occlusion, and other environmental factors, which can reduce localization accuracy. By contrast, UWB estimates the distance between devices using time-of-flight measurements and can typically achieve decimeter-level accuracy. This improved accuracy comes at the cost of specialized hardware and a more complex deployment.

3.2 Comparison Methodology

We compare RSSI and UWB measurements to investigate whether RSSI provides sufficient proximity information for location-aware HAR. Our analysis is guided by the following hypotheses:

- **H1:** RSSI is negatively associated with UWB distance, i.e., stronger RSSI values correspond to shorter UWB distances.
- **H2:** RSSI is more suitable for coarse proximity estimation than for exact nearest-beacon localization.
- **H3:** The agreement between RSSI and UWB varies across participants and beacon locations.

Valid paired RSSI and UWB location data of sufficient duration were available for 12 unique participants across all five beacon locations: Main Room, Bathroom, Hallway 1, Hallway 2, and Kitchen. For each participant–beacon pair, the RSSI and UWB streams were aligned by timestamp and aggregated into non-overlapping one-second windows using the median value per window. Only windows containing both RSSI and UWB measurements were included in the comparison.

We first quantified the relationship between RSSI and UWB distance using Spearman's rank correlation for each participant–beacon pair. Spearman's rank correlation coefficient is calculated as

$$\rho = \frac{\sum_{i=1}^{n}(R_i - \bar{R})(U_i - \bar{U})}{\sqrt{\sum_{i=1}^{n}(R_i - \bar{R})^2 \sum_{i=1}^{n}(U_i - \bar{U})^2}}, \tag{1}$$

where R_i is the rank of the ith RSSI measurement, U_i is the rank of the corresponding UWB distance measurement, and $\bar{R}$ and $\bar{U}$ are their respective mean ranks. The coefficient ranges from $\rho = -1$, indicating a perfect negative monotonic relationship, to $\rho = 1$, indicating a perfect positive monotonic relationship. A value of $\rho = 0$ indicates no monotonic relationship. In this analysis, a negative value means that stronger RSSI measurements, represented by less negative dBm values, tend to correspond to shorter UWB distances.

To assess location agreement, we then compared the UWB-nearest beacon with the beacon showing the strongest RSSI. We report Top-1 agreement, where both methods select the same beacon, and Top-2 agreement, where the UWB-nearest beacon appears among the two strongest RSSI signals.

4 Results

4.1 Signal-Level Comparison

Valid paired RSSI and UWB location data were available for 12 participants across all five beacon locations. Figure 1 shows the Spearman correlation between RSSI and UWB distance for each participant–beacon pair. Negative coefficients indicate that stronger RSSI values, meaning values closer to 0 dBm, tend to occur at shorter UWB distances.

The correlations were predominantly negative. Across all 60 participant–beacon pairs, the median correlation was $\rho = -0.58$. Fifty-seven pairs showed a negative association, and 39 met the threshold for a strong negative association ($\rho \leq -0.50$). Table 1 summarizes the results overall and by beacon location.

The predominance of negative correlations supports H1, indicating that RSSI generally became weaker as the distance from a beacon increased. However, the strength of this relationship differed across participants and locations. Individual coefficients ranged from $\rho = -0.88$ to $\rho = 0.76$. At the location level, Kitchen showed the strongest median negative correlation ($\rho = -0.67$), whereas Hallway 2 showed the weakest ($\rho = -0.43$). This variation is consistent with H3.

Table 1. Summary of Spearman correlations between RSSI and UWB distance.

Location	Pairs	Negative	$\rho \leq -0.50$	Median ρ
Main Room	12	11	8	-0.62
Bathroom	12	12	10	-0.63
Hallway 1	12	11	8	-0.65
Hallway 2	12	12	5	-0.43
Kitchen	12	11	8	-0.67
Overall	60	57	39	-0.58

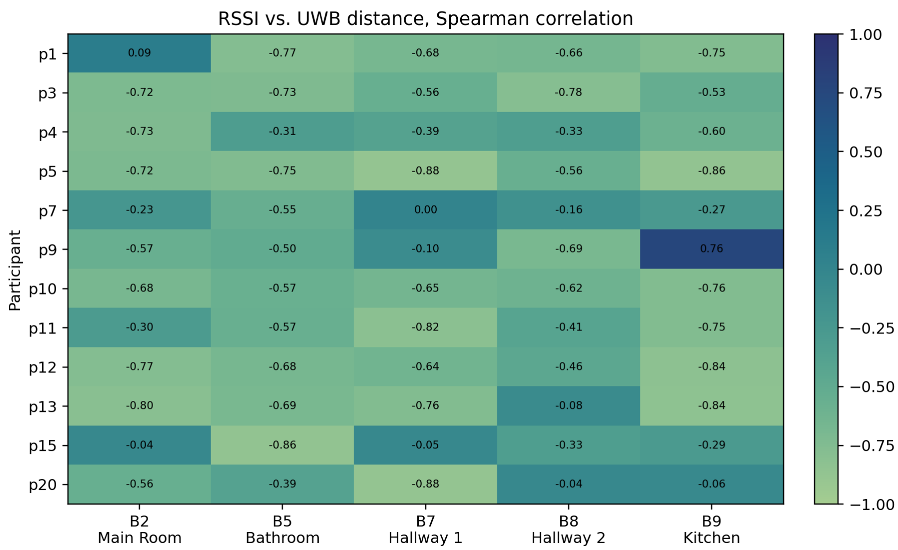

Fig. 1. Spearman correlation between RSSI and UWB distance for each participant–beacon pair. Negative values indicate that stronger RSSI measurements tend to correspond to shorter UWB distances.

The participant-level results are shown in Figure 1, and the raw paired measurements for each location are provided in Appendix B.1.

Spearman correlation describes the monotonic relationship between RSSI and distance, but it does not directly show whether RSSI can distinguish practically relevant proximity states. We therefore conducted an additional analysis in which UWB distance was used as the reference to classify measurements as near or far from a beacon. The ability of RSSI to distinguish these states was evaluated using the area under the curve (AUC). Participant–beacon-level results for this analysis are provided in Appendix B.2.

4.2 Impact on Activity Recognition

For location-aware activity recognition, correlation alone is insufficient because it does not show whether RSSI can identify which beacon is closest. We therefore evaluated nearest-beacon agreement within each one-second window. The beacon with the shortest UWB distance was used as the reference, and the available beacons were ranked by RSSI from strongest to weakest.

Two agreement criteria were applied. Top-1 agreement was counted as a match when the UWB-nearest beacon also had the strongest RSSI signal. The median Top-1 agreement was 0.47, meaning that, for the median participant, the two methods identified the same beacon in 47% of comparable windows.

Top-2 agreement was counted as a match when the UWB-nearest beacon had either the strongest or the second-strongest RSSI signal. The median Top-2 agreement was 0.87, indicating that the UWB-nearest beacon was usually among the two highest-ranked RSSI signals, even when it was not ranked first.

Together, these results are consistent with H2. RSSI appears more suitable for identifying a small set of nearby beacons than for selecting the exact nearest beacon. Ranked or soft RSSI features may therefore be more appropriate for location-aware activity recognition than assigning each window to a single beacon. However, because Top-2 agreement is less strict and depends on the number of available beacons, its higher value should be interpreted cautiously. The variation in agreement across participants (see Figure 2) is also consistent with H3.

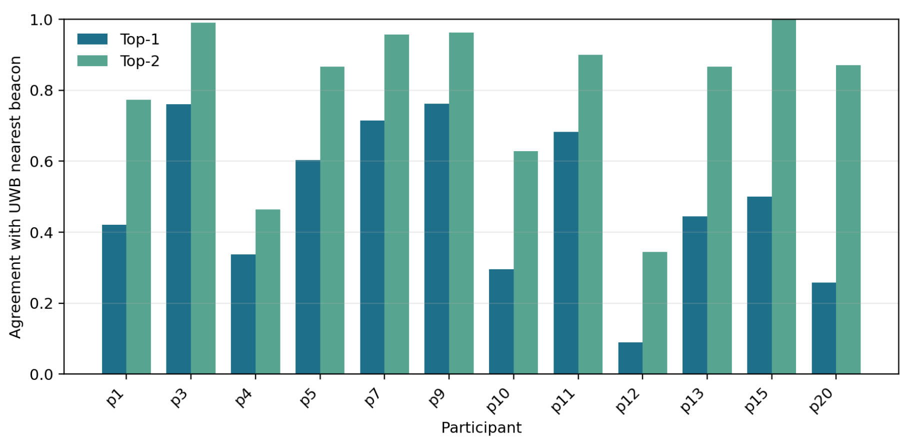

Fig. 2. Agreement between the UWB-nearest beacon and the beacon estimated from RSSI, reported using Top-1 agreement and Top-2 agreement.

4.3 Calibration of RSSI-Derived Distance Estimates

We further evaluated whether RSSI could be converted into metric distance estimates using the TxPower path-loss model:

$$\hat{d} = 10^{\frac{P_0 - \mathrm{RSSI}}{10n}}, \tag{2}$$

where $\hat{d}$ is the estimated distance in metres, P_0 is the expected RSSI at a reference distance of one metre, and n is the path-loss exponent describing how quickly the signal weakens in the environment. The default model used $P_0 = -59\,\mathrm{dBm}$ and $n = 2$. Because these parameters depend on the hardware and propagation environment, we also evaluated globally calibrated, beacon-specific, and leave-one-participant-out variants.

Figure 3 compares these variants using UWB distance as the reference. The default parameters produced the largest errors, whereas calibration reduced both mean absolute error (MAE) and root mean squared error (RMSE). Beacon-specific calibration produced the lowest errors, indicating that the relationship between RSSI and distance differed across beacon locations. These results suggest that RSSI can provide approximate metric distances, but requires calibration for the specific deployment. This finding complements H2 by showing that uncalibrated RSSI is more suitable for coarse proximity estimation than for direct distance estimation. Additional scatter plots in Appendix B.3 illustrate the deviation of the default estimates from the UWB reference distances.

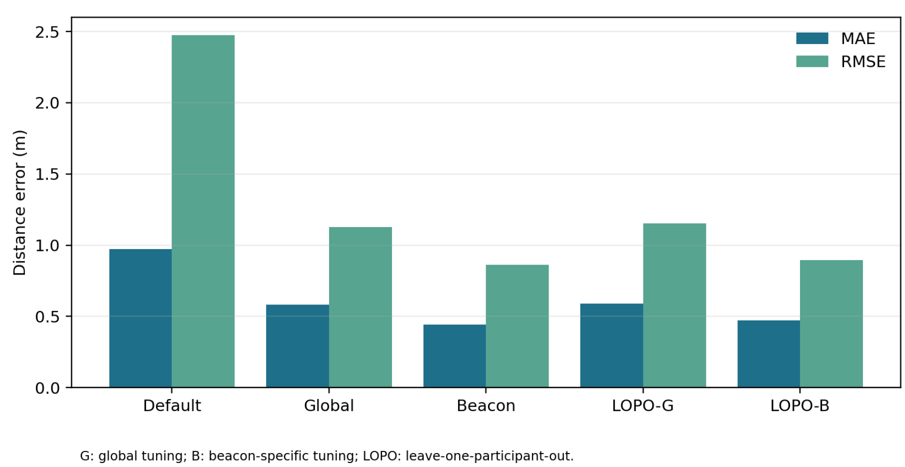

Fig. 3. Distance error of RSSI-derived distance estimates compared with UWB distance for the default, globally tuned (Global), beacon-specific tuned (Beacon), leave-one-participant-out globally tuned (LOPO-G), and leave-one-participant-out beacon-specific tuned (LOPO-B) TxPower formula variants.

5 Discussion and Limitations

The results show that RSSI provides meaningful proximity information but does not reproduce UWB-based ranging. H1 was supported by the predominantly negative associations between RSSI and UWB distance. Their variation across participants and beacon locations supports H3 and indicates that RSSI is sensitive to deployment conditions.

For location-aware HAR, RSSI appears more suitable for coarse proximity estimation than for precise localization. The moderate Top-1 agreement showed that the strongest RSSI signal did not consistently identify the UWB-nearest beacon. The higher Top-2 agreement indicates that this beacon was often among the two strongest RSSI signals, supporting H2. However, Top-2 agreement is influenced by the number of available beacons and should be interpreted cautiously. The results suggest that RSSI may be more useful as soft or ranked proximity information than as a hard location label.

The TxPower analysis supports this interpretation. The default formula produced large distance errors, while calibration, particularly beacon-specific calibration, improved agreement with UWB. The usefulness of RSSI-derived distance estimates depends on the deployment and availability of calibration data. RSSI may offer a lower-cost alternative when coarse room-level or activity context is sufficient, whereas applications requiring robust metric distances or exact nearest-beacon localization are more likely to benefit from UWB.

The analysis was limited to 12 participants, five fixed beacon locations, and a single living-laboratory deployment. The results may not generalize to other layouts, beacon placements, devices, or populations. Effects of body orientation, occlusion, reflections, and other environmental conditions were not isolated. Moreover, UWB was treated as the reference despite being susceptible to measurement errors, particularly under non-line-of-sight conditions. Finally, the analysis evaluated signal-level and proximity agreement rather than downstream HAR performance. Future work should compare activity-recognition models using no location features, RSSI, UWB, and combined representations to determine whether the observed differences affect activity classification.

6 Conclusion

This work compared simultaneously collected RSSI and UWB beacon measurements in a location-aware HAR study. The results indicate that RSSI provides useful coarse proximity information, but does not consistently match UWB for exact nearest-beacon localization or uncalibrated metric distance estimation. Calibrated RSSI may therefore be sufficient for low-cost context-aware activity recognition, while UWB remains preferable when precise and robust indoor ranging is required.

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Appendix

A SLICE Study Floor Plan

Fig. 4. Floor plan of the sensor-equipped residential research lab used in the SLICE study, adapted from our previous description of the study [4]. Estimote BLE beacons supporting both RSSI and UWB were installed at key locations. This work considers only the measurements from beacons B2, B5, B7, B8, and B9, which simultaneously transmitted both RSSI and UWB. The figure also includes legacy BLE beacons that broadcast RSSI only; their measurements were not included in the present analysis.

B Additional Results

B.1 RSSI vs. UWB Scatter by Beacon

Figure 5 shows the paired RSSI and UWB measurements for each of the five beacon locations: Main Room, Bathroom, Hallway 1, Hallway 2, and Kitchen. Under ideal propagation conditions, RSSI is expected to decrease approximately logarithmically with increasing distance, producing a downward-curving relationship. Across the five locations, stronger RSSI values, that is, values closer to 0 dBm, generally correspond to shorter UWB distances. However, the spread and shape of the point clouds vary between locations. Hallway 1 showed a strong median negative correlation ($\rho = -0.65$), while Kitchen showed the strongest median negative correlation overall ($\rho = -0.67$). Hallway 2 showed the weakest median association ($\rho = -0.43$). These differences suggest that the relationship between RSSI and physical distance is influenced by factors such as beacon placement, room geometry, body occlusion, and local signal propagation.

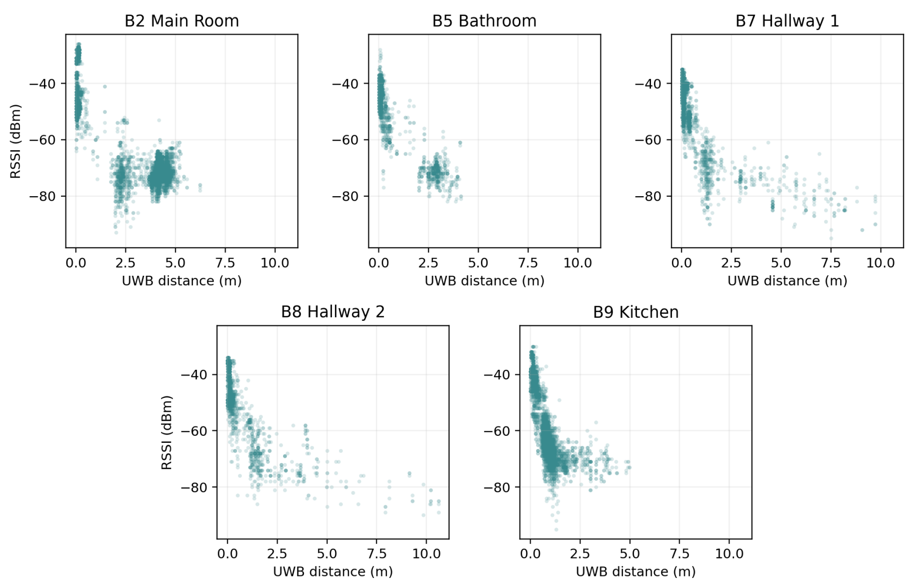

Fig. 5. Relationship between RSSI and UWB distance across beacon locations.

B.2 Distance Prediction from RSSI

The heatmap shows how well RSSI distinguishes whether a participant was near a beacon based on the UWB reference distance. For each participant–beacon pair, RSSI and UWB measurements were aligned in one-second windows, and UWB distance was classified as near or far using a 1m threshold. Each cell shows the AUC for predicting this label from RSSI. Values near 1.0 indicate strong separability. Blank cells indicate undefined AUC values because all valid windows belonged to one class.

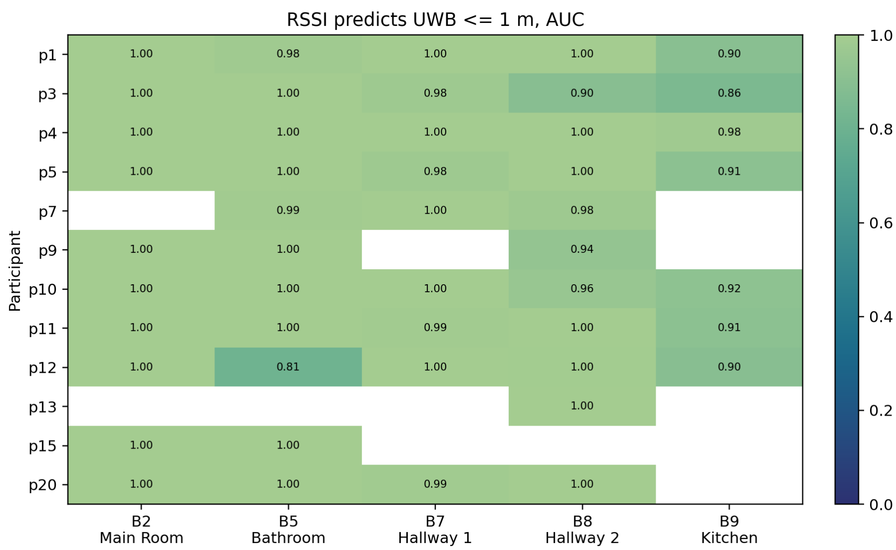

Fig. 6. AUC for classifying near beacon states from RSSI, using UWB as reference.

B.3 Default TxPower vs. UWB Scatter

Figure 7 compares distance estimates obtained from the default TxPower path-loss formula with the corresponding UWB reference distances. The dashed identity line indicates perfect agreement between the RSSI-derived distance estimate and the UWB distance. While the estimates broadly preserve the expected ordering, many points deviate substantially from this line, especially at short distances. The horizontal bands reflect the discrete nature of RSSI measurements, where repeated signal-strength values are mapped to the same distance estimate by the formula. Overall, this indicates that the off-the-shelf TxPower formula is not sufficiently calibrated for this deployment without further parameter tuning.

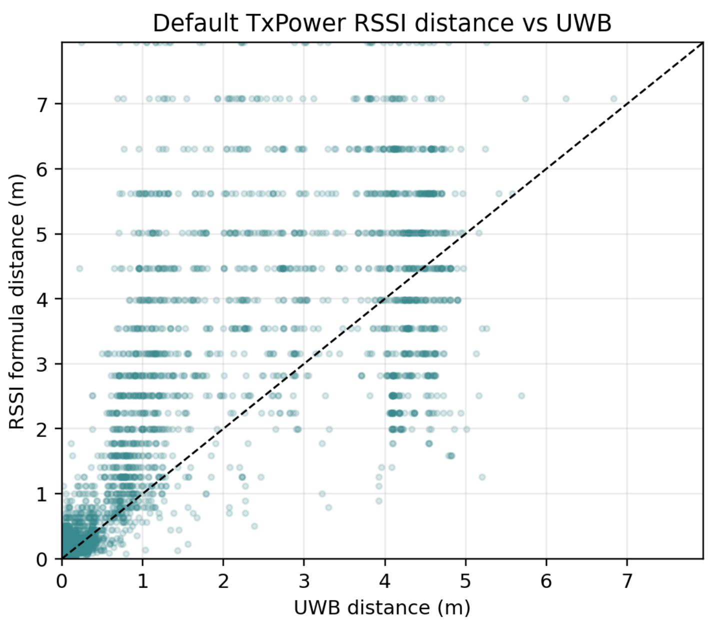

Fig. 7. Default TxPower formula distance estimates derived from RSSI compared with UWB distance. The dashed line indicates perfect agreement.

B.4 Calibration of RSSI-Derived Distance Estimates

Metric distance was estimated from RSSI using the log-distance path-loss model

$$\hat{d} = 10^{\frac{P_0 - \mathrm{RSSI}}{10n}}, \tag{3}$$

where $\hat{d}$ is the estimated distance in metres, P_0 is the expected RSSI at a reference distance of one metre, and n is the path-loss exponent describing how quickly the signal weakens with distance. The analysis used the paired median RSSI and UWB measurements from the non-overlapping one-second windows.

The model parameters were calibrated by grid search. The reference signal strength P_0 was varied from -85 to -35 dBm in steps of 1 dBm, and the path-loss exponent n was varied from 1.0 to 5.0 in steps of 0.1. For each parameter combination, RSSI-derived distances were calculated using Equation 3 and compared with the corresponding UWB distances. The combination with the lowest MAE was selected. Estimated distances were constrained to a minimum of 0.01 m. Table 2 summarizes the five evaluated variants.

Table 2. TxPower path-loss calibration variants.

Variant	Parameters	Calibration data	Evaluation data
Default	$P_0 = -59$ dBm; $n = 2$	None	All observations
Global	One fitted parameter pair	All participants and beacons	Calibration data
Beacon-specific	One fitted pair per beacon	All participants, separated by beacon	Calibration data
LOPO global	One fitted pair per fold	Remaining 12 participants	Held-out participant
LOPO beacon-specific	One fitted pair per beacon and fold	Remaining 11 participants, separated by beacon	Held-out participant

The global and beacon-specific variants provide in-sample estimates because the same observations were used for calibration and evaluation. They therefore describe the fit achievable when deployment-specific reference data are available. The leave-one-participant-out variants provide a more conservative estimate of performance for participants not included during calibration. Performance was evaluated using MAE and RMSE, with UWB distance treated as the reference.

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