Peer-To-Peer UWB Ranges as a Source of Training Data for Estimating BLE RSSI Path-Loss Exponents

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Abstract

This paper presents a practical indoor positioning approach to improve short-range distance estimation using Bluetooth received signal strength (RSSI) and precise ultra-wideband (UWB) range measurement. The conventional distance estimation technique from Bluetooth RSSI uses a classical path loss model that is environment specific. The model faces challenges in determining suitable path loss factors to estimate distance accurately. A curve-fitting function on BLE RSSI values with actual distance shows that the distance estimation error increases with increasing distance. UWB provides a precise range measurement in line of sight (LOS) condition indoors. Therefore, this paper investigates the feasibility of using UWB range as a source of training data for BLE RSSI range estimation. The experimental results show that a line-fitting model of RSSI values using a UWB range gives similar performance compared to the actual distance for short ranges in a complex indoor environment.

Keywords

BLE-RSSI, Ultra-wideband, Indoor Positioning

1. Introduction

Bluetooth low energy (BLE) has recently emerged as a low power, low cost, low complexity solution for determining the distance between two BLE equipped devices and has been identified as a favored method for electronic contact tracing in the context of the ongoing Covid-19 pandemic [1]. BLE can indeed determine if two devices have been in proximity, the ability to estimate the actual range between the devices is limited by the difficulty in converting an observed signal power observation into a distance measurement. This conversion depends both on estimating an appropriate path loss exponent for the environment and identifying obstructions and obstacles in the line-of-sight [2]. Most mobile phones in the market today are equipped with Bluetooth radios and can measure Received Signal Strength Indicator (RSSI). However, the available BLE-based contact tracing apps on them do not give an accurate and reliable measured distance from BLE RSSI, as apps do not consider hardware and environmental factors [3].While it is most often used for nearest-beacon proximity and fingerprinting methods [4]–[8]. RSSI can be used to directly estimate range through estimation of a path-loss exponent or application of other path-loss models, however, this suffers from drawbacks due to varying devices and propagation environments [9], [10] . Consequently, Bluetooth localization using RSSI-based ranges is not commonly used as it requires a large amount of training data in order to be useful [11].

The latest Apple's iPhone series supports an ultra-wideband (UWB) ranging radio chip (U1), which is 802.15.4z compliant, computes distances based on asymmetric double sided flight time between two UWB enabled devices. UWB ranges have up to centimetre-level precision in line-of-sight (LOS) conditions [12], [13] and generally allow for decimetre level accuracies.

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Our long-term objective is to develop a concept where a small group of devices or users equipped with UWB ranging systems can be used to train low-cost systems that rely on BLE alone including relative pedestrian navigation and smartphone-based contact tracing applications.

This paper proposes and presents preliminary results of using peer-to-peer UWB ranges as a source of training data to fit path-loss models to Bluetooth RSSI measurements and assesses the accuracy of UWB-trained path-loss to that obtained using a reference or truth range obtained through laser range finding.

The rest of the paper is organized as follows. Section 2 describes the fundamentals of system: Bluetooth and UWB technology in brief. Section 3 presents the proposed system. Section 4 discusses preliminary experimental results. Finally, Section 5 summarizes current work and describes the scope of future work.

2. Background

We propose to use Bluetooth Low Energy and a low-cost solution as it is already widely deployed. Ultrawideband will serve as a source of more accurate training data.

Bluetooth RSSI-based indoor localization is the most attractive and widely used technology due to low cost, low power consumption, small size, and ease of deployment [14]–[16]. Many manufacturers have introduced BLE-based indoor positioning solutions [17]. The technology uses three advertising channels primarily for discovery purposes: channel 37 (2402 MHz), channel 38 (2426 MHz), and channel 39 (2480 MHz). When one BLE device measures RSSI values of another, these will differ on each channel due to different channel gain and multipath fading. Some researchers and systems have simply used all available RSSI values while others have noted that there is less variably when BLE channels are considered separately instead of considering the aggregated channel's RSSI [18], [19].

The signal strength of the transmitted radio wave attenuates as it travels away from the transmitter. In three-dimensional free space that can be modelled as one over range squared [20]. However, in real environments the loss may be more severe, due to attenuation, or less due to constructive interference or wave-guide effects. If the path loss can be modelled as a function of distance, then the distance between the transmitter and the receiver can be estimated from a received signal strength measurement. The Free Space Friis Model is used as a basis to form a simplified standard log-distance path loss model in an indoor environment.

$$\mathbf{RSSI = RSSI\ (}\boldsymbol{d_0}\mathbf{)\ -\ 10nlog}\frac{\boldsymbol{d}}{\boldsymbol{d_0}} + \boldsymbol{X_\sigma} \tag{1}$$

where RSSI(d_0) represents a reference RSSI value at the reference distance d_0, typically 1 m, X_σ and n represent the observation error and path loss exponent value respectively, and d is the distance between transmitter and receiver. The path loss exponent is environment specific and usually determined by either choosing a standard value or by fitting a line to training data [21], [22].

Ultra-wideband (UWB) is an emerging precise indoor positioning method that uses low power, but very high time resolution signals to achieve centimetre to level precision and decimetre level accuracy ranging allowing for very precise indoor positioning in both one-way and two-way modes [23]. The difficulty with UWB is that while the cost of UWB radios has decreased significantly in the past decade, they are still not commonly found in consumer electronics. But in the near term only a small fraction of mobile phones will be equipped with UWB ranging radios.

3. Proposed System Model

We propose to test peer-to-peer line of sight ranging between mobile users. In this work-in-progress paper, out goal is to assess if UWB can provide sufficiently precise peer-to-peer ranges to determine a BLE RSSI path-loss exponent along the same path. If successful, we will then investigate more complex RSSI to range models and methods, including using large quantities of UWB data to train artificial networks to convert BLE RSSI values to ranges. The assumption is that a small number of UWB-equipped users will be able to provide enough training data to enable BLE RSSI-based ranging for most of the users who do not have UWB radios.

The project uses two DWM1001-DEV (Decawave, Dublin, Ireland) developmental kits [24]. The development kit includes both an nRF52832 BLE radio and a DW1000 UWB module and thus can be used as both a BLE source and a UWB transceiver. A separate nRF52840 development kit (Nordic semiconductor, Norway) [25], co-located with the second DWM1001-DEV, is used as a BLE receiver, logging RSSI values at 50ms rate, and the two DWM1001-DEVs perform double sided two-way ranging at 100ms rate. To explore the performance of the proposed system, an experiment is performed in a narrow corridor (2.4 m wide by 10 m in length) located on the third floor in the CCIT building of the University of Calgary illustrated in Figure 1

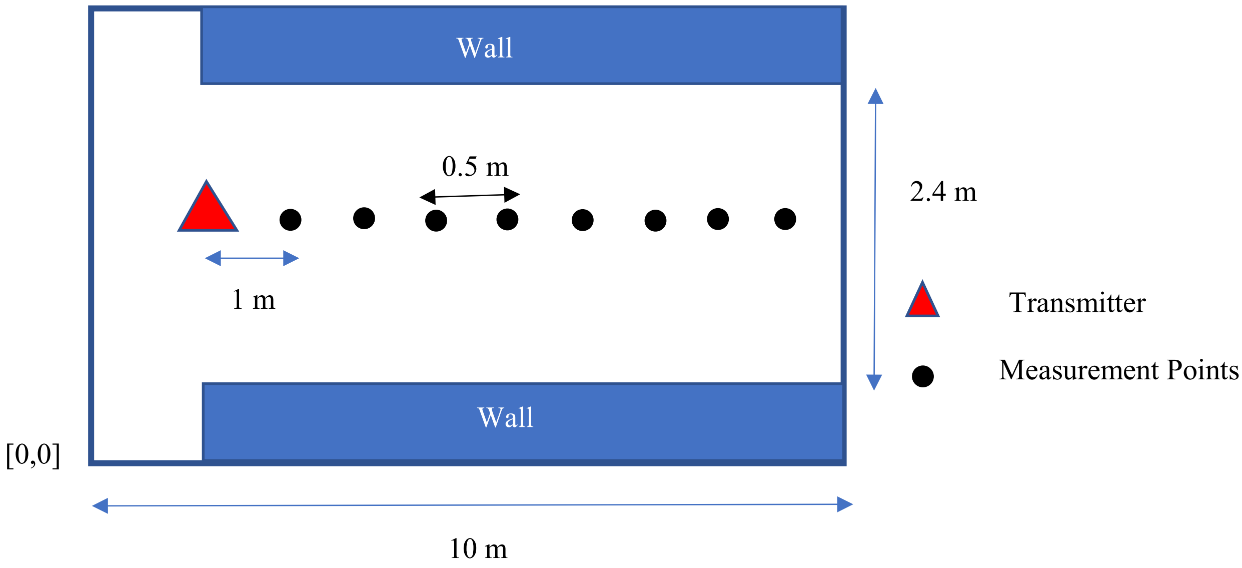


Figure 1*:* Environmental Scenario (not to scale)

4. Preliminary Results

Measurements were collected in static mode over a number of distances ranging from 1 to 5 metres. Even in static mode, the raw BLE RSSI measurements show significant fluctuations. In contrast, the UWB range shows no fluctuation and gives precise measurements of the line-of-sight range. Figure 2 shows the raw RSSI values observed over a 1 m range as well as a filtered version of the Channel 37 RSSI values and a histogram of each channel. Figure 3 shows the distribution of UWB range measurements at 1 metre and 2-metre distance. We log both the BLE RSSI and UWB range in our experiments together. Then, we consider the samples of RSSI

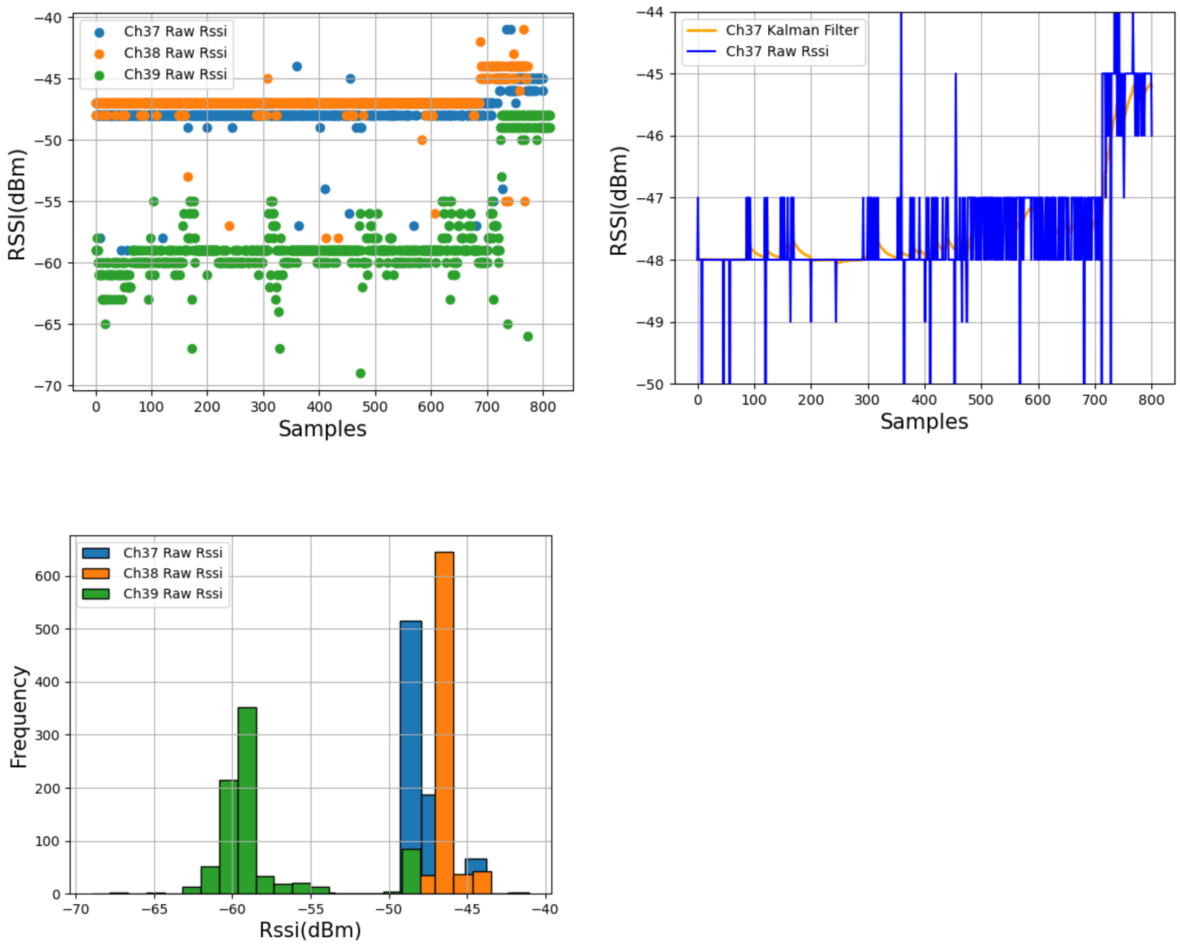


Figure 2 (a): Raw received signal strength indicator (RSSI) values, (b) Kalman Filter output of Channel 37 (c) Histogram plot of raw RSSI at a fixed place showing the spread of RSSI.

and range for all the matched time instants. Subsequently, a Kalman filter is applied to filter out each BLE channel's raw RSSI values to remove outliers and obtain more stable RSSI data. We measure RSSI values from 1 metre to 5-metre distance (logging data for more than 15 minutes in each location).

It is observed that the RSSI values observed over more than 5 metres often show constructive interference and a change in the path-loss exponent and for this reason we conducted the experiment up to 5 m. In addition, the variability in the RSSI values increases with distance. A simple line fit model was applied to the RSSI values using both a true (laser range finder) and UWB distance for the x-axis. The resulting models were then evaluated for each RSSI measurement to determine a residual range error for each RSSI measurement. The linear models, shown in Figure 4, do not fit particularly well as can be seen from the histograms of the corresponding RSSI-based range errors shown in Figure 6. This performance can be improved if the line fit is limited to distances of 3 metres or less as shown in Figure 5 and the corresponding RSSI range residuals better than 15 cm shown in Figure 7. In both cases, the use of true (laser range finder) ranges results in line fits that lead to slightly better RSSI-based ranges, however the UWB-based line fits are very similar to those obtained with the true ranges, demonstrating the feasibility of using UWB to gather training data for RSSI path-loss models.

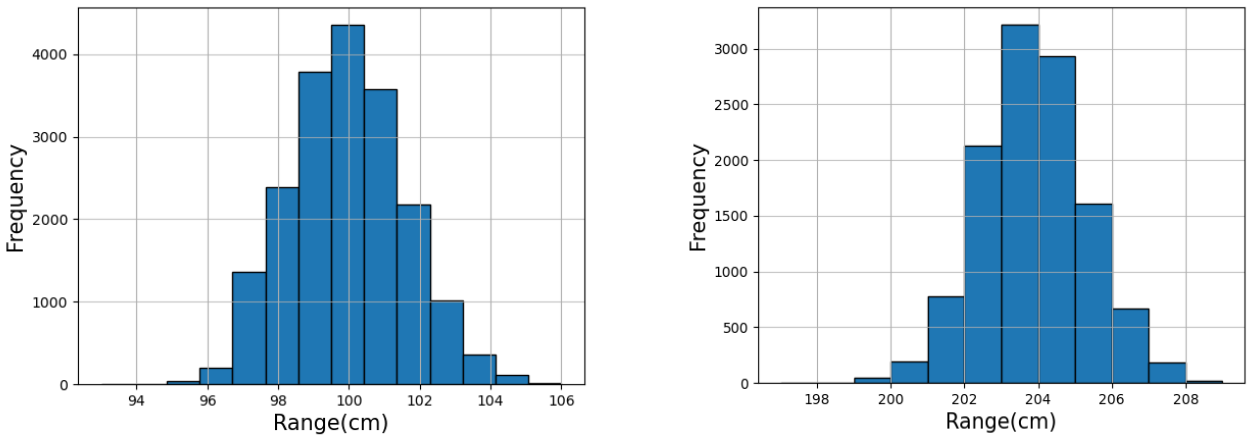


Figure 3: UWB Range distribution at (a) 1-metre and (b) 2-metre LOS distance in complex indoor environment

Table 1: Channel 38 filtered RSSI and UWB measurements at LOS in complex indoor environment.

Actual Distance (m)	Lowest RSSI Value (dBm)	Highest RSSI Value(dBm)	Average UWB Distance (m)
1	-41.4	-40.8	0.99
1.5	-44.2	-43.2	1.46
2	-50.02	-49.3	2.01
2.5	-58	-54.1	2.48
3	-61.2	-58.4	3
4	-55.5	-54	4.05
5	-47.8	-46.6	5.03

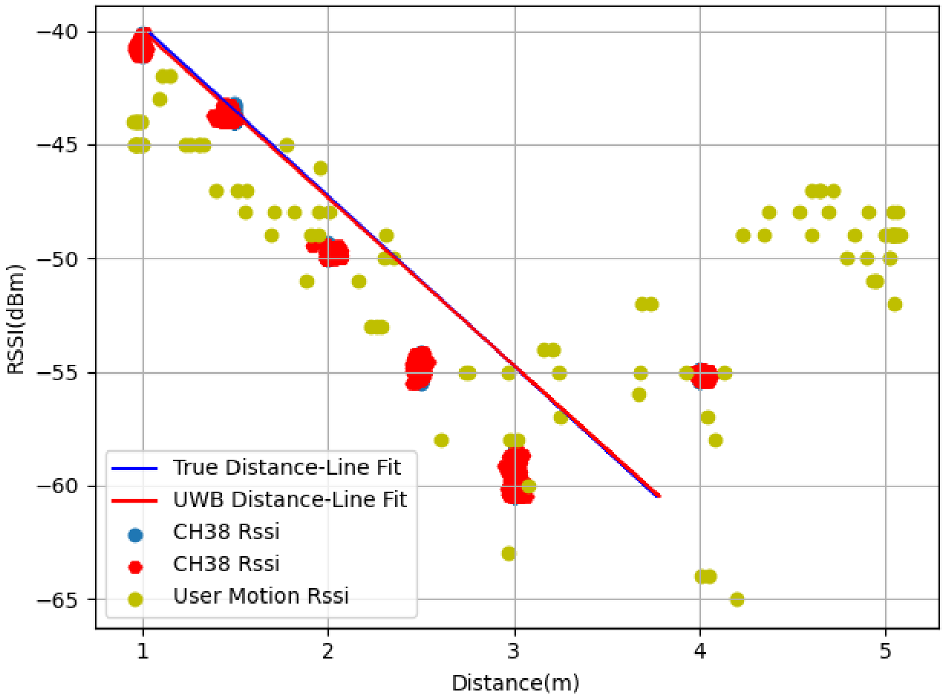


Figure 4: Distance vs RSSI Line fit by plotting cluster of RSSI points up to 5m using true and UWB distance.

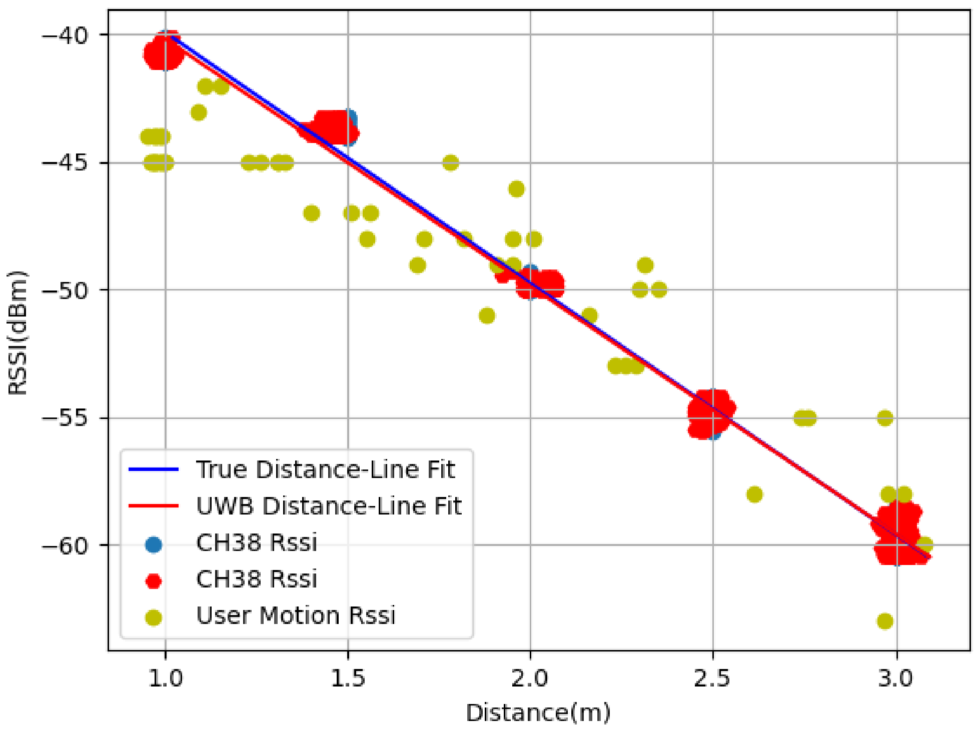


Figure 5: Distance vs RSSI Line fit by plotting cluster of RSSI points up to 3m using true and UWB distance.

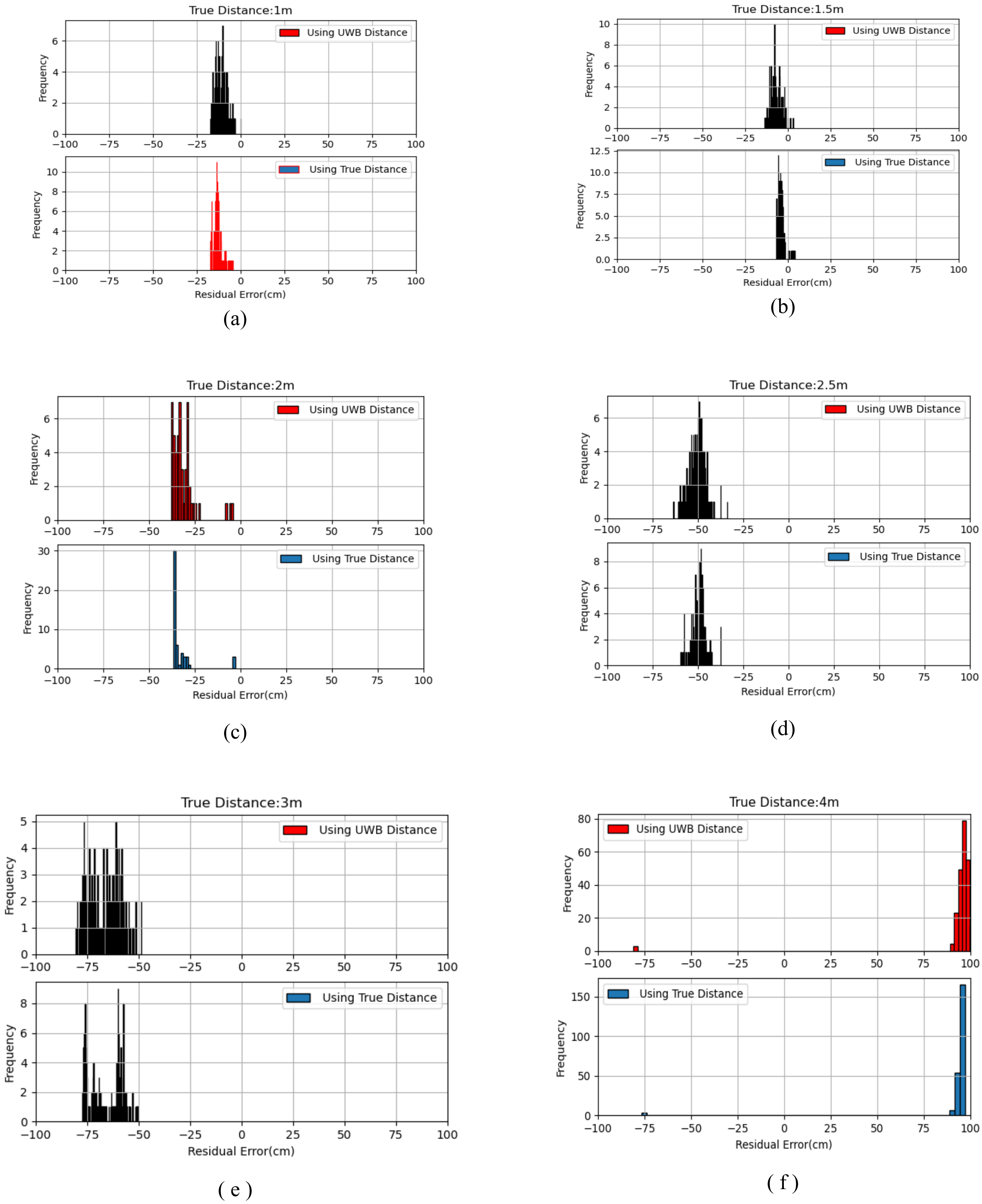
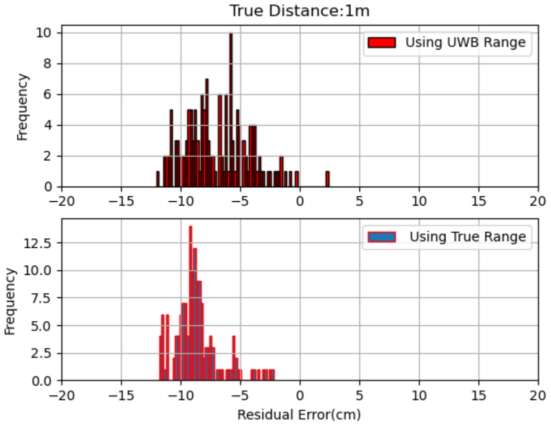
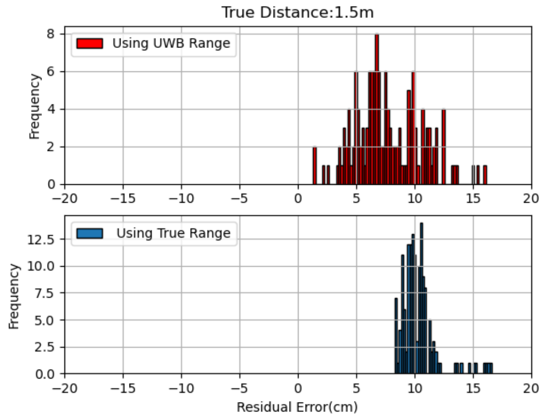


Figure 6: Residual error of distance estimation using a 6-point line fit model with true and UWB distance at a) 1m, b) 1.5m, c) 2m, d) 2.5m, e) 3m, and f) 4m respectively



(a)



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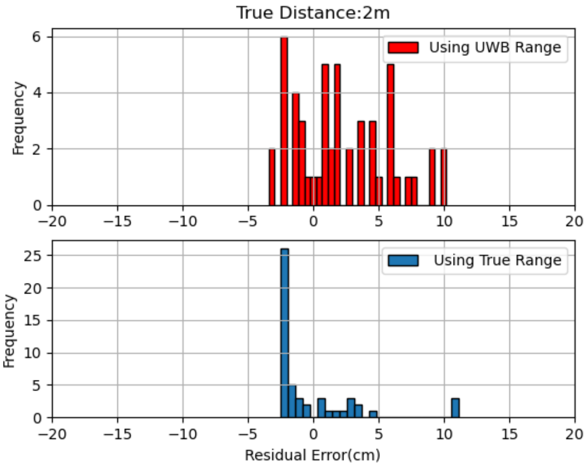

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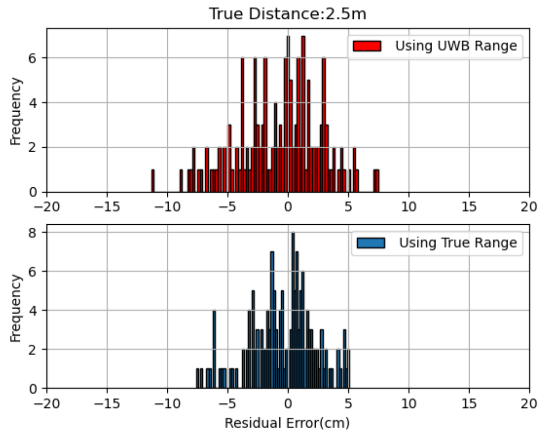

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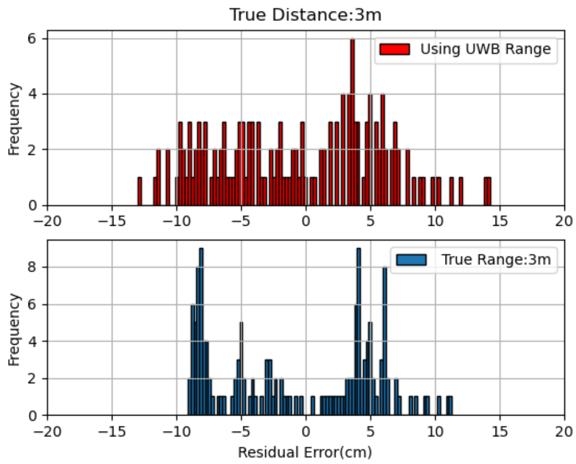

(e)

Figure 7: Residual error of distance estimation using a 5-point line fit model with true and UWB distance at a) 1m, b) 1.5m, c) 2m, d) 2.5m, e) 3m respectively.

5. Conclusion and Future Plans

This work demonstrated that UWB can provide precise ranges in order to fit a line to RSSI values. The log-distance model for distance estimation depends very highly on the environment. The BLE advertising channels have different transmission power levels due to carrier frequency, channel gain, multipath, and fading. The preliminary experiments show that a simple line fit model is suitable for estimating a short-range from RSSI values with an error less than 15 cm is feasible up to 3 metress. The error in distance estimation increases after 3 metres as the impact of constructive interference begins to change the path-loss exponent.

The next step in this work will be to collect more and varied training data, in the form of BLE RSSI and corresponding UWB ranges, and then compare fitting more and multiple lines to determine difference path loss exponents for many different environments with using artificial intelligence to develop implicit models for converting RSSI into range for each of these environments.

More investigation is required to understand the nature of the environments and the amount of training data needed for AI to learn patterns from the data. The applicability of models developed in one environment to data gathered in different environments also needs to be assessed. Finally, we hope to understand if BLE RSSI from low-cost general mobile users can be used to determine the precise proximity between two BLE-enabled devices in any future critical pandemic situations.

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