"Where Am I": Characterization of Ultra-Wide Band Real Time Location System in Line of Sight

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***Abstract*—Absolute position measurement is a necessity in an Autonomous Indoor Mobile Robot (AiMR) built as to compensate the systematic and non-systematic errors caused by the odometry. This paper is set out to characterize the range bias of DecaWave Trek 1000 in Line of Sight (LOS). DecaWave Trek 1000 is a commercially available Real Time Location System (RTLS) based on Ultra-Wide Band (UWB) technology. The main advantage of using such a system is it provide quick solution with best-in-class accuracy of up to ±10 cm. The system also compliant with IEEE802.15.4-2011 standards and implemented based on CMOS technology. To validate its performance, four distinct environment scenarios were selected based on their spatial occupancies to represent both favourable and non-favourable operating conditions. A total of 120,000 positioning data were measured and recorded throughout this study. Firstly, the collected data were compared to the ground truth and subjected to statistical analysis to determine whether environment factors significantly influenced ranging errors. Then the range error the results confirm that while the system performs within its specified accuracy under favourable conditions, the non-favourable condition on the other hand shows a drop of 20% in ranging accuracy. Throughout this extensive characterization, a systematic error model and noise estimation were formulated, providing a critical foundation for integrating UWB RTLS measurements into advanced probabilistic localization framework. Looking forward, the developed characterization function, offers strong potential for fusion with filtering algorithm such as Bayesian filters to enhance indoor navigation reliability for an AiMR application.**

***Keywords*—real time location system, ultra-wide band, range error, characterization**

I. INTRODUCTION

Accurate positioning has become significantly important in the development of an Autonomous Indoor Mobile Robot (AiMR). Traditionally, AiMR rely on its odometry for navigating and positioning. It makes used information from encoders to measure wheel rotations and steering orientation. However, the integration of incremental data can lead to unbound position errors due to systematic and non-systematic odometry errors [1]. This can significantly hinder the full potentials of an AiMR. Alatise and Hancke [2], and Niloy et al. [3] also stated that the current set of on boards sensors used is still unable to deliver exceptional navigation performance. A solution to this is to fuse the odometry data with an absolute position measurement data for a better and reliable position estimation.

Among various technologies available for the intended purpose is an Ultra-Wide Band (UWB). UWB have gained significant attention since its open for public application for their capability to provide cm level accuracy [4], making it a promising solution for an indoor application. In addition to UWB, there are several other technologies used by researchers and practitioners within the field, such Wi-Fi, Bluetooth, Zigbee and Radio Frequency Identification (RFID) [5]. These technologies however often fall shorts in delivering the required accuracy and robustness especially in demanding complex indoor environment [6]. Wi-Fi based positioning leverages on existing wireless infrastructure with room level accuracy. Its performance however is often affected by signal interference and multipath effect. Bluetooth technology have a unique cost advantage due to their low in price and ease of deployment. With an accuracy of meter level, it is suitable for low precision application. RFID technology offers high accuracy and commonly used for asset tracking but its operating range is limited. UWB technology has emerged as a promising solution, offering high resolution ranging capabilities and resilience against multipath interference, making it particularly suitable for an indoor positioning task [7].

UWB technology is a wireless communication method that uses a wide frequency spectrum to transmit data over short distances. It occupies a wide bandwidth typically greater than 500 MHz which enables high data transfer rates and extremely precise distance and position measurements. The formal standardization of UWB by the Institute of Electrical and Electronics Engineering (IEEE) in 2007, marked a significant milestone that catalysed widespread research and development activities in UWB based indoor positioning system [8]. Fig. 1 shows a typical configuration of an Ultra-Wide Band Real Time Location System (UWB RTLS). In a standard setup, anchors are strategically placed at a known reference coordinate within the environment, while tags are attached to the object being tracked. The position weather in two dimensional (2D) or three dimensional (3D) is determined by calculating its distance from multiple anchors, a process known as trilateration or multitrilateration method [9].

Depending on specific application and system requirements, different position estimation techniques can be employed. These methods can be categorized into two schemes. A summary of these schemes is shown in Table 1.

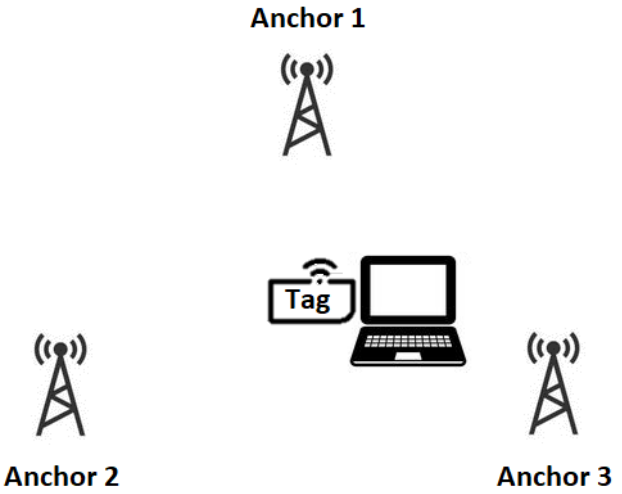

Fig. 1. General UWB RTLS setup.

Although UWB is known to have high penetrability, various literature shows than an inaccuracy could still occurred due to multipath effect [9-11]. To combat this issue, system characterization can be done prior to system integration to capture the dynamic nature of the UWB range error [12-14]. Based on previous works, the range error can be investigated by two factors: Distance to anchor and Environment conditions.

TABLE I. ESTIMATION TECHNIQUE COMPARISON [10]

	Signal Strength Based Schemes	Time Based Schemes
Distance estimation	Measuring the attenuation of signal strength	Measuring the time it takes for the radio signal to travel between the transmitter and the receiver
Accuracy	Low	High
Computational requirements	Low	High
Technique	RSSI fingerprinting	Time of Arrival (TOA), Time Delay of Arrival (TDOA), Two-Way Ranging (TWR)
Example application	Asset tracking, rough proximity detection	Autonomous navigation, robotics, and industrial applications

Despite this, there remains a gap in understanding the dynamic nature of UWB ranging error. Existing studies have primarily focus on single environment scenarios, which doesn't fully capture the complexities and variabilities of real-world application, which eliminate the needs of proper characterization to be considered. Hence this study aims to evaluate and characterize the ranging error of UWB RTLS in various indoor settings. Ranging measurement were obtained under controlled line of sight (LOS) condition. The data were then compared to the ground truth to quantify the influence of these factors on ranging accuracy. Subsequently, a representative transfer function that captures the observe error behaviour is derived.

II. EXPERIMENTAL SETUP

To systematically characterized the ranging performance of the UWB RTLS under varying indoor spatial density, a controlled experiment was developed using Decawave Trek1000 development boards. This boards provide Two-Way Ranging (TWR) capabilities and allow flexible configuration as either an anchors or tags. Four development boards were used in this study, three of the boards were configured as an anchor and one as a tag. The configuration of the boards was done through DIP switch settings. Fig. 2 shows the DIP switch configurations for an anchor and tag respectively.

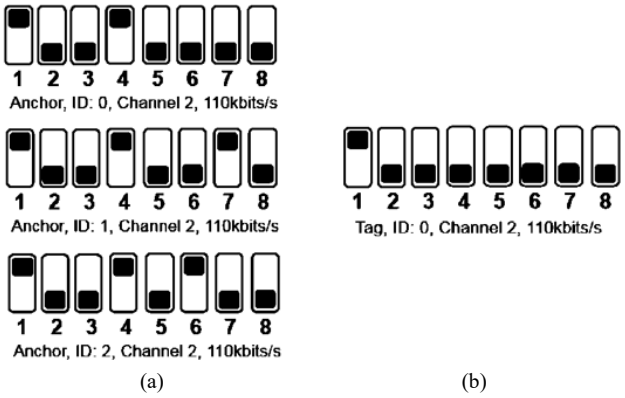

Fig. 2. DIP switch setting (a) anchor DIP switch setting; (b) tag DIP switch setting [15].

Each device was mounted at a fixed height of 71cm above floor surface to minimize vertical variation and ensure consistent LOS alignment. To access the performance of the system, four indoor environments with distinct spatial density were selected to represent the favourable and non-favourable operating conditions. The setups are as shown in Fig. 3(a) and Fig. 3(b). Fig. 3(a) represent the favourable operating environments which comprise of an open space room (E1), with <10% spatial density on the left and postgraduate room (E2), with <50% spatial density. Fig. 3(b) represent the non-favourable operating conditions which comprise of a narrow walkway (E3) on the left and machine shop (E4), with >80% spatial density. This classification is to represent a normal working environment for an AiMR to be deployed.

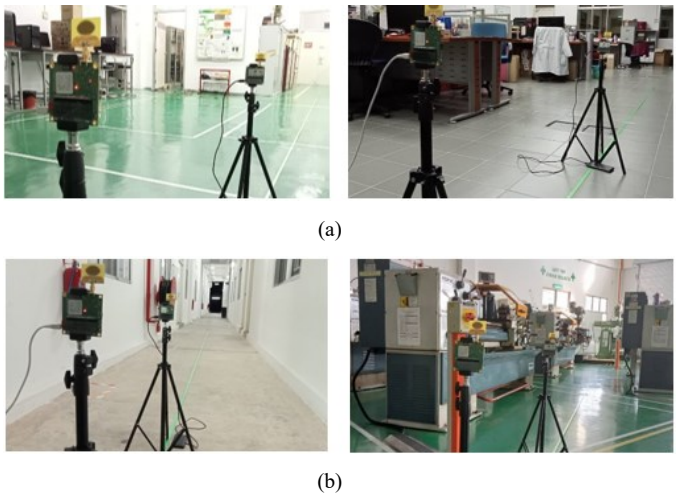

Fig. 3. Different environment with varying spatian density used for evaluation (a) favourable conditions; (b) non-favourable conditions.

III. RESULT AND DISCUSSION

A. Statistical Analysis

To validate the consistency and reliability of the ranging performance, one-way ANOVA was conducted. The main objective of this analysis is to determine whether statistically significant differences exist between the means of ranging data collected. Three ranges were chosen for this analysis which is

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1m 5m and 10m. This range value was chosen in order to assess the effect of distance between the tag and anchor on the range bias. A comprehensive datasheet for statistical analysis was provided by the 12000 individual range measurements required for each of the ranges involved. Table ll summarizes the outcome of the one-way ANOVA performed for each position.

TABLE II. ONE FACTOR ANOVA RANGE BIAS AT DISTANCE OF 1M, 5M, AND 10M AT $\alpha = 0.05$

Distance (m)		1	5	10
N		12000	12000	12000
Mean		- 0.0180	0.0880	0.0667
Std. Deviation		0.0237	0.0278	0.0292
SS	Between groups	0.0273	0.3362	0.1819
	Within groups	0.6472	0.5909	0.7249
df	Between groups	3	3	3
	Within groups	1196	1196	1196
MS	Between groups	0.0091	0.1121	0.0606
	Within groups	0.0005	0.0005	0.0006
F		16.8341	226.8434	100.0346
$p-value$		< 0.00001	< 0.00001	< 0.00001

The result shows compelling evidence of statistically significant differences in the mean range bias across selected environments at a 95% confident level. This is indicated by extremely low $p-value$ of < 0.00001, which are well below the significant threshold. The low $p-value$ means that the observed differences in range error are not due to random coincidence. Examining the F values further support this conclusion. Nevertheless, at 1m, the F value remains small suggesting that closer distances have less range bias. This is consistent with theoretical expectations of lower signal degradation at a shorter range. At 5m, the F value is remarkably high, indicating a strong environment effect on range bias. At 10m, a substantial F value is also observed, albeit slightly lower than previous distance.

While one-way ANOVA revealed that statistically significant differences exist among the means of the selected distances, the test itself does not identify which specific pairs of positions differ significantly. To further validate the statistical significance and understand the extend of mean differences between specific environment pairs, a Tukey's HSD test was conducted. Table lll shows the result of pair wise comparisons (PWC) between different environment at three distances (1m, 5m and 10m). At 1m, significant differences exist primarily between E1 and other environments. However, the observed mean differences are small and the Q values, while statistically significant, are much lower than at longer distances, which indicates a marginal impact. At 5m, strong differences are observed across nearly all environment pairs, exceeding the HSD threshold considerably. The largest discrepancy was present at E1:E4 comparison (Q = 35.14), suggesting that environment changes dramatically impact range measurements. At 10m, although some environment pairs show small mean differences, E2:E4 and E3:E4 show substantial bias still present at a longer distance.

B. Characterization Model

Since the chosen system uses three different anchors for coordinate trilaterion calculation, each of the anchor reading with the tag were plotted to illustrate the overall system variations. Fig. 4 shows the bias vs range for each of the anchors in all four selected environment and the resulting average of system bias. A careful examination of the graph reveals that anchor 1 (A1) and anchor 2 (A2) exhibited nearly identical bias curvatures in favourable environments, with the exception of anchor 0 (A0). On the other hand, the non-favourable conditions resulted in much more dynamic variations in the graph curvature. This is as expected since [4] stated that the system could experience greater multipath effect due to the presents of additional structures or equipments within the environment. The analysis reveals that the system was able to perform well within the specified accuracy of $\pm$10cm in the favourable conditions but experienced a drop in accuracy in the non-favourable conditions of up to 20%.

Fig. 5(a) shows the average graph for each of the environment. The favourable conditions only have slight variations at the beginning and towards the end of the system range but differ greatly with the non-favourable conditions. After carefully analyse the result, a function model to determine the range has been formulated. The model breaks down into several distinct components, each of which is assigned a unique probability distribution as shown in equation (1).

$$d_{uwb} = d_{true} + f(d) + n, n \sim (0, \sigma^2), \quad (1)$$

where:

d_{uwb} = distance reading

$f(d)$ = systematic error model

n = measurement random noise (σ^2)

TABLE III. TUKEY HSD TEST AT $Q_{0.5}(3.63)$ FOR RANGE BIAS MEASUREMENT OF 1M $HSD_{0.5} = 0.0049$), 5M $HSD_{0.5} = 0.0047$) AND 10M $HSD_{0.5} = 0.0052$)

PWC	1m			5m			10m		
	Means	HSD	Q	Means	HSD	Q	Means	HSD	Q
E1:E2	$M_1 = -0.03$ $M_2 = -0.02$	0.01	4.47	$M_1 = 0.06$ $M_2 = 0.09$	0.03	19.64	$M_1 = 0.09$ $M_2 = 0.10$	0.01	8.51
E1:E3	$M_1 = -0.03$ $M_3 = -0.01$	0.01	9.46	$M_1 = 0.06$ $M_3 = 0.10$	0.04	27.35	$M_1 = 0.09$ $M_3 = 0.10$	0.01	7.39
E1:E4	$M_1 = -0.03$ $M_4 = -0.01$	0.01	7.52	$M_1 = 0.06$ $M_4 = 0.11$	0.05	35.14	$M_1 = 0.09$ $M_4 = 0.07$	0.02	13.23
E2:E3	$M_2 = -0.02$ $M_3 = -0.01$	0.01	4.99	$M_2 = 0.09$ $M_3 = 0.11$	0.01	7.71	$M_2 = 0.10$ $M_3 = 0.10$	0.00	1.13
E2:E4	$M_2 = -0.02$ $M_4 = -0.01$	0.00	3.05	$M_2 = 0.09$ $M_4 = 0.11$	0.02	15.51	$M_2 = 0.10$ $M_4 = 0.07$	0.03	21.74
E3:E4	$M_3 = -0.01$ $M_4 = -0.01$	0.00	1.94	$M_3 = 0.10$ $M_4 = 0.11$	0.01	7.79	$M_3 = 0.10$ $M_4 = 0.07$	0.03	20.61

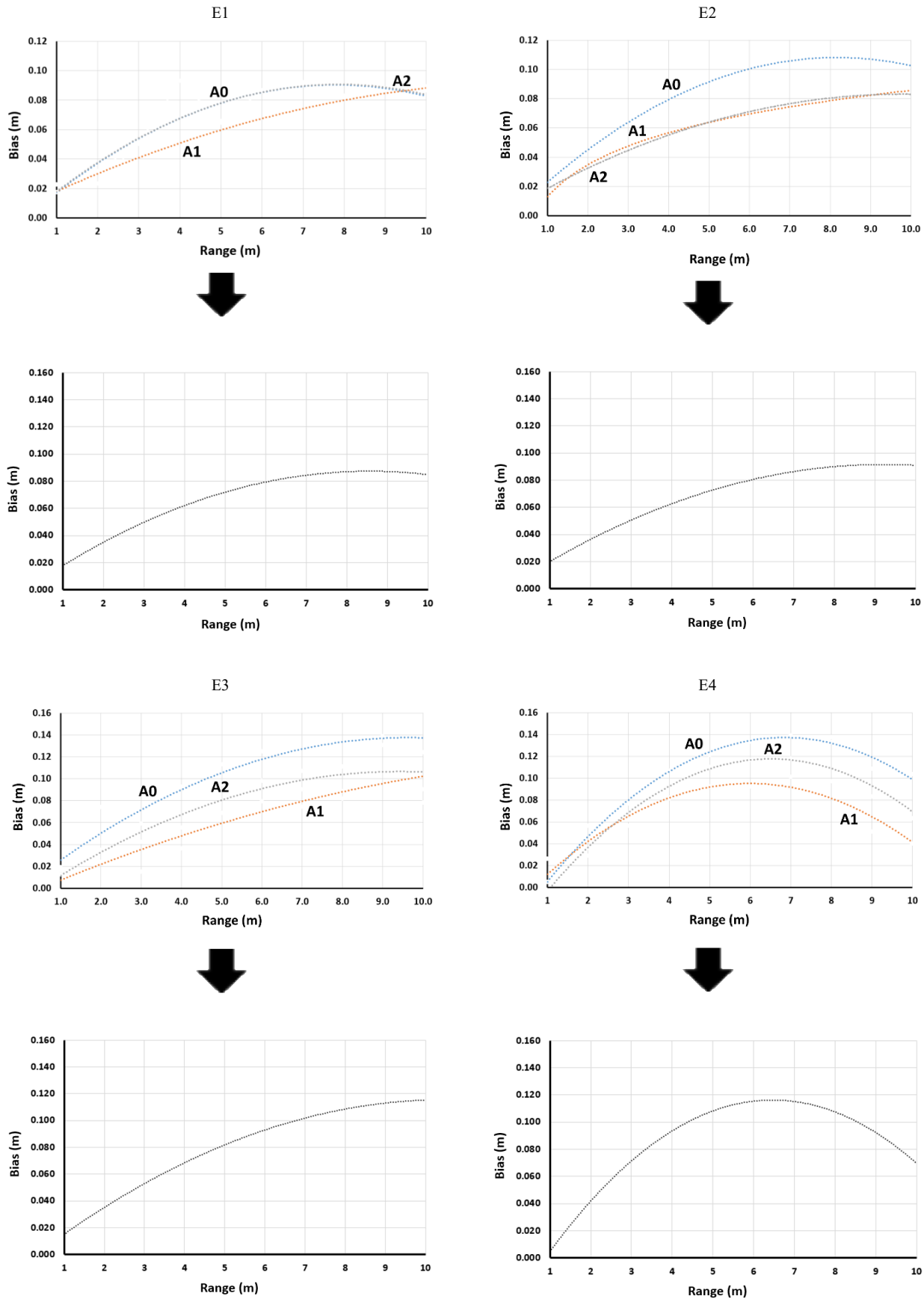

Fig. 4. Variations of bias vs. range between 3 different anchors used in four different environment conditions and combination bias average in each environment.

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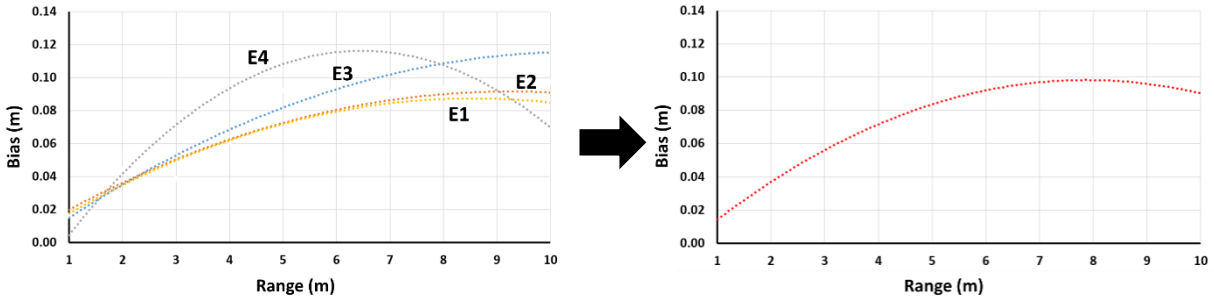

(a) (b)

Fig. 5. System bias average (a) average bias comparison between all environment scenarios; (b) overall average system bias performance.

Based on previous calculations shown in Table II, the average standard deviation value of σ is determined to be 0.0269 m. This is slightly better compared to the findings of the research by Flueratoru et al. [14]. Fig. 5(b) shows the average performance of the entire system, which serves as a crucial tool for characterizing the system's behaviour. Notably, an exponential relationship between the bias and range measurements has been derived by equation (2).

$$f(d) = 0.0018d^2 + 0.028d - 0.0119 \quad (2)$$

This improvement suggests that the system is capable of delivering more consistent and reliable distance measurements, which is vital for applications requiring high spatial accuracy. This enables more accurate calibration and compensation techniques, thereby enhancing the overall performance and reliability of the system in practical deployment scenarios. The findings underscore the potential of this system to outperform existing models, particularly in environments where precise range estimation is critical.

IV. Conclusion

This study is set out to answer a fundamental question: does this off-the-shelf UWB RTLS exhibit significant variations in its ranging accuracy across multiple spatial densities of an indoor environment, which covers both favourable and non-favourable conditions? While this may seem like a technical and dry endeavour, it carries broader implications for the development of UWB tracking systems in real-world scenarios where environmental conditions are rarely ideal. From the analysis being done, the system shows it capabilities to meet its advertised accuracy of $\pm$10 cm under favourable conditions. However, in more complex non-favourable conditions, accuracy degradation of up to 20% was observed. The findings affirm that, characterizing the ranging behaviours of UWB RTLS is essential in understanding the system limitations but serves as a prerequisite for the development of robust correction strategies. Importantly, this study provides critical foundation for the next stage of development which is the integration of empirically derived characterization functions with advance filtering algorithm such as Bayesian estimators within a probabilistic localization framework. Looking ahead, future work should expand the experimental scope to include non-line of sight (NLOS) conditions and dynamic obstacles to better access system performance.

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