A High Fidelity Indoor Navigation System Using Angle of Arrival and Angle of Departure*

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Abstract

Indoor location and micro-location systems are complicated by the lack of available GPS signals. This gap is being filled by Bluetooth and WiFi, but these systems have difficulty maintaining accuracy when the user is moving. This paper presents the results of an exploration of new features of Bluetooth 5.2, namely, *Angle of Arrival* and *Angle of Departure* using a Texas Instrument development board and Antenna Array. The research results are: 1) a novel prediction system for indoor positioning and navigation that performs at an accuracy of 0.23m (static), and 0.30m (moving); 2) a comparison and performance analysis of micro-location algorithms; and 3) an architectural model by which other researchers can extend our work on indoor positioning and navigation.

Keywords

beacons, high fidelity indoor localization, Angle of Arrival, Angle of Departure, micro-location, tracking in dynamic environments.

1. Introduction

Global Positioning Systems (GPS) are an integral part of our day to day lives. GPS signals assist us with road transportation, aviation, shipping, rail transportation, science, security, mapping and several other applications [1]. In ideal conditions (i.e., in the outdoors in a wide-open field), common mobile phone GPS receivers can provide an accuracy of 4.9 m (16 ft.) radius [2] which, in most cases, is sufficiently accurate. However, there are several factors that can cause radio interference and impact the accuracy of GPS such as buildings, bridges, trees and other obstructions [2]. This can cause significant issues in metropolitan areas and especially indoor environments where GPS signals can fluctuate significantly due to signal absorption, interference, reflection and/or diffraction [3]. Although GPS technologies have enabled estimates of a person's location, they do not provide the accuracy required for context-aware applications

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for indoor environments. An approach that addresses the limitations of GPS's inaccuracy is *micro-location* which uses technologies such as WiFi or Bluetooth to derive highly accurate location data [3]. Bluetooth beacons are one of the avenues being explored to enhance the accuracy of indoor micro-location [4]. These beacons have found some production level use cases in real world applications [4, 5]. Beacons have also been deployed in academic and research applications such as Robotic Path finding [6]. These devices have also found their way into commercial applications such as Macy's, to offer shoppers discounts and the Major League Baseball who has used beacons to navigate patrons to their seats [7]. Despite the widespread adoption of beacons, there are still unsolved issues with using them for highly accurate micro-location [5]. A significant problem lies in distance measurements using the Received Signal Strength Indicator (RSSI) [8]. The signal coming from a beacon is unstable especially in indoor environments with multiple obstacles, people and reflective surfaces [3]. As such, RSSI based location services require algorithms to improve the accuracy and reliability of the signal. Some studies have used smoothing algorithms (e.g., Particle Filter, Kalman Filter, etc.) to increase the accuracy of the RSSI which, in turn, has increased the accuracy of prediction of the location of a person or asset [3]. At this time, the reported accuracy of some typical indoor micro-location applications using beacons is 3.1m [4], 2.85m [9], 2.5m [3] and 2.21m [10]. However, in all of these studies, the user and assets are stationary. The outstanding challenge in this area is to design a micro-location system that can provide good accuracy in indoor environments while the user is in motion. Bluetooth 5.1 introduces a direction-finding feature in the core specification by using an antenna array system [11]. By calculating the *Angle of Arrival (AoA)* and *Angle of Departure (AoD)*, it offers the potential for high-degree accuracy for proximity and positioning systems [11]. In this research we used Texas Instrument's LAUNCHXL-CC26X2R1 development board and BOOSTXL-AOA Antenna Array for application in the indoor location and asset tracking spaces. We created an indoor navigation system that improves the beacon's RSSI signals and uses various algorithms to provide high accuracy location predictions in indoor environments. The main contributions of this work are:

1. A prediction system for indoor positioning and navigation that uses AoA and AoD and performs at an accuracy of 0.23m (when the asset is static) and 0.30m (when the asset is in motion),
2. A generalized indoor micro-location system that can be easily and rapidly deployed to new environments (within hours),
3. A comparison and performance analysis of micro-location algorithms, and
4. An architectural model by which other researcher can extend our work on indoor positioning and navigation.

This paper is structured as follows: section 2 provides a literature review of related work in this field, section 3 presents our methodology on the design, development and evaluation of our micro-location system, section 4 presents the findings, section 5 provides a discussion, and section 6 provides a conclusion and suggestions for future work.

2. Background

Indoor positioning systems have gained considerable attention in recent times. The application of indoor positioning can be adapted to indoor navigation and tracking of movement with sufficient amount of well placed Bluetooth Low Energy (BLE) beacons. A suitable dynamic positioning system to meet the desired goal of sub-2m accuracy in indoor environments would need to be able identify location of static BLE beacons and the dynamic location of the user (or asset) with respect to the beacons. There are numerous applications where this degree of accuracy is needed. For example, hospitals need to track the location of wheelchairs, patients and many pieces of medical equipment; warehouses need to track the movement of products and supplies; large educational institutes can benefit from students/teachers finding classes easily; geo-fencing around construction sites so workers do not go to certain areas without proper protection [12, 7, 13, 14]. There is a need across these sectors for a solution that provides a level of accuracy that is much higher than current solutions provide [4, 5]. Various studies have been conducted using technologies such as Wireless Local Area Network (WLAN) [12], BLE [15, 16], Radio Frequency Identification (RFID) [17], Ultrasonic waves, and ZigBee [18]. However, WLAN [19] and BLE [20] are the most popular due to the ease of deployment, cost, availability of technology on various devices. This section presents a comparison and analysis of the state-of-the-art in micro-location using the following techniques: Wi-Fi Based Indoor location, RFID Based Indoor location, and BLE beacons.

2.1. Wi-Fi based indoor location

Wi-Fi solutions use existing wireless networks and infrastructure within a facility to determine the location of an asset or person. Since most businesses already have this type of infrastructure, it is the easiest and most cost effective approach to deploy [21]. However, there are several issues with using Wi-Fi based systems such as the distance between existing wireless access points may be too large, the inability to move access points easily to improve location accuracy and the cost of enterprise level wireless access points [4, 8]. A recent study [22] showed an accuracy of 1.42m in a $8m$ x $8m$ x $3m$ room with 4 Access Points and 9 testing locations. However, the amount of data collection required was around 10,000 data points [22]. Unless the Wi-Fi access points are already deployed: the start up cost of Wi-Fi access points as location tracking system is considerably more than Bluetooth beacons (3-4 times more). For instance, the Gimbal beacons are $15-$20 USD [13].

2.2. RFID based indoor location

RFID solutions have two separate strategies for solving the problem of micro-location: *active* RFID and *passive* RFID [12]. Active RFID is an electronic device that either broadcasts or reads RFID signals, for example RFID reader/broadcast chips in modern smartphones [9, 23]. Passive RFIDs are commonly inert chips that use the build-up of electrical signal from an active RFID reader. Once an acceptable charge is established, the passive RFID emits a short broadcast. RFID stickers and swipe cards are a common example of this type of RFID technology [17]. Due to its restricted broadcast distance [24, 17], RFID is a poor choice of technology for micro-location research.

2.3. Bluetooth Low Energy beacons

BLE became part of the Bluetooth standard in 2010 with Bluetooth Core Specification 5.0 active since 2016 [25]. BLE enables a device to use Bluetooth networking at lower energy levels in an effort to reduce battery consumption [11]. A BLE beacon is a small device that emits a Bluetooth Low Energy signal. This differs from traditional Bluetooth in that the signal and device are essentially read only. There is no connection to these beacons as their purpose is exclusively to broadcast information [25]. The beacon sends out a packet, which is unique to each manufacturer. It contains specific information for the receiving device as shown in Fig. 1. Beacons can be

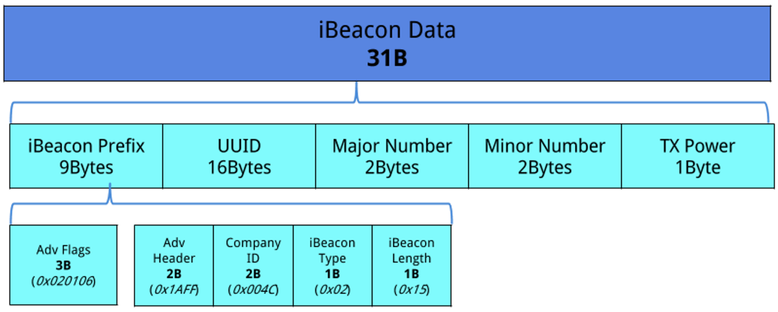

Figure 1: iBeacons advertisement frame (31 bytes)

incorporated into [1]micro-location systems using the beacon's configuration information and the RSSI. The RSSI is useful in approximating the distance from the transmitting device. For example, in the iBeacon protocol, this framework provides some interpretive measurements of distance using RSSI, and using three zones (i.e., Immediate, Near, and Far) [23]. Intended to provide an approximate guide for proximity, this approach is far from an accurate measurement and thus unsuitable for micro-location [23, 26]. The concept of indoor navigation presents some unique concepts and challenges. As the user is on the move and location is dynamically changing, it is difficult to accurately calculate the user's position. An approach to overcoming these challenges is to use algorithms that can quickly identify nearby beacons and use various formulas to determine the location. A recent study [27] explored various approaches to indoor navigation using Wi-FI and BLE using triliteration and a path-loss model in an office setting. The accuracy reported for BLE was around 6m [27].

2.4. BLE Beacon manufacturers: Assessment and evaluation

At the onset of this research, we recognized that there are only a few hardware companies that build iBeacon compliant beacons. Our aim was to select the most appropriate product for our purposes. Using the following criteria: 1) accuracy, 2) availability, 3) price, 4) well-designed and supported Software Development Kit (SDK) 5) secure use and communication, 6) ease of use and configuration, 7) data analytics, and 8) AoA and AoD. We reviewed the following beacon

[1]Micro-location is the process of pinpointing a person's placement to within a few inches or feet using various technologies. While GPS can only determine geo-location while outdoors, micro-location technology can determine location more precisely, both indoors and out.

products: Onyx Beacons [28], Bleu Station Beacon Series 100 [29], Estimote [30], Verve [31], Gimbal [13], Kontakt.io [32], and Texas Instrument's LAUNCHXL-CC26X2R1 development board. The results are presented in Table 1. Regarding micro-location and the accuracy of

Table 1
Evaluation of various beacon products

Criteria	Onyx	Bleu	Estimote	Verve	Gimbal	Kontakt.io	TI Dev Board
Accuracy	✓	✓	✓✓	✓	✓✓✓	✓✓✓	✓✓✓✓
Availability	✓	✓	✓	✓	✓	✓	✓
Price	✓	✓	✓✓	✓	✓✓	✓	✓✓
Well designed / supported SDK	✗	✗	✓✓✓	✓	✓✓	✓✓	✓
Secure use / communication	✓	✓	✓✓	✓	✓✓✓	✓	✓
Ease of use / configurable	✓✓	✓	✓✓	✓✓	✓	✓	✓
Data Analytics	✓	✗	✗	✓	✓✓✓	✓✓	✓✓
AoA and AoD	✗	✗	✗	✗	✗	✗	✓✓✓✓

✓: acceptable, ✓✓: good, ✓✓✓: very good, ✓✓✓✓: excellent, ✗: poor

beacons, equation 1 shows the relationship between RSSI and distance [33]. We used this equation to evaluate the accuracy of different beacon products when compared to ground truth (exact distance measurement from smartphone to beacon), where n represents a path-loss exponent that varies in value depending on the environment, d is the distance between the user and the beacon, d_0 is the reference distance which is 1 meter in our case, and C is the average RSSI value at d_0.

$$RSSI = -10n \log_{10}\left(\frac{d}{d_0}\right) + C \tag{1}$$

Bluetooth 5.1 introduced two new features called Angle of Arrival (AoA) and Angle of Departure (AoD) that allow for highly accurate positioning of Bluetooth devices [25]. AoA and AoD angles can be calculated from signal transmissions that land onto the receiving arrays (AoA), and for AoD, the departure angle emanating from the transmitter device. Bluetooth specification 5.2 and 5.3 provide no additional improvement with respect to AoA and AoD [25]. AoA allows a receiving device to determine the direction from which a signal is coming, while AoD allows a transmitting device to determine the direction to which a signal should be sent. This is achieved by using antenna arrays and measuring the phase difference between signals received by different antennas. By using AoA and AoD, Bluetooth devices can determine their precise location in three-dimensional space, enabling a wide range of applications such as indoor navigation, asset tracking, and proximity-based services [25]. The accuracy of this technology depends on the number of antennas used and the signal processing algorithms employed, but it has the potential to be substantially more accurate than other positioning technologies [25].

3. Methodology

The primary goal of this project was to create an indoor navigation system that predicts the user's location as accurately as possible if the user is standing or while the user is in motion.

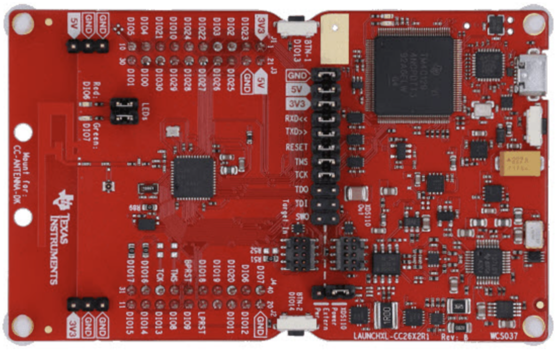

Figure 2: LAUNCHXL-CC26X2R1: Development board *(slave device - Transmitter)*

The secondary goal was to create a rapid deployment strategy that could be used in a variety of environments and scenarios without the need to have training data (i.e., as is the case of fingerprinting solutions). Our aim was to create a system that uses BLE beacons that consistently and accurately pinpoints the user's location in the sub 2m range while the user is moving. To our knowledge, there are no such systems that use BLE beacons that report this degree of accuracy. This section presents the methodology by which we created and evaluated our indoor navigation system: 3.1.Experiment setup: equipment and environment configuration; 3.2. Data collection strategy; 3.3. Static test; and 3.4. Moving test.

3.1. Experiment setup: Equipment & Environment configuration

We used hardware development kits designed by Texas Instruments to test AoA and AoD, and develop our system. Regarding the microcontroller, we used the LAUNCHXL-CC26X2R1 board. This microcontroller features an ARM Cortex-M4F processor, which runs at a speed of 48MHz, along with a wide range of peripherals such as a 128x128 LCD display, two user buttons, and an RGB LED. It also includes an integrated 2.4GHz radio, which supports Bluetooth Low Energy, Zigbee, and Thread protocols. Fig. 2 presents the LAUNCHXL-CC26X2R1 development board. For the antenna, we used BOOSTXL-AOA (Fig. 3). It is a direction finding antenna array board that allows users to determine the AoA of RF signals in the 2.4GHz band. The board features four antennas spaced at a known distance, which are used to determine the direction of incoming signals. In our experiments, we designated the BLE transmitter as a *slave device* and the antenna array as a *passive device*. For both slave and passive device, the TI LAUNCHXL development board was used with the exception of passive devices having the BOOSTXL board attached. The setup is presented in Fig. 4.

3.1.1. Angle Testing

Initially, we collected data on angle testing to figure out the best way to utilize the BOOSTXL-AOA antenna array. The board has two antenna arrays and when using it in single antenna array it provides a -45°to +45°angle. When using two antenna arrays at the same time the angle of arrival calculation goes from 0°to 100°on one side and 0°to -100°on the other side. This can be

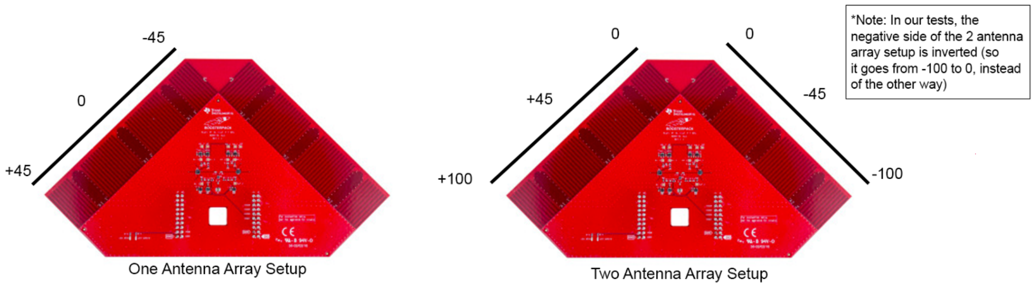

Figure 3: Antenna array setup on the BOOSTXL-AOA board *Passive device - Receiver*

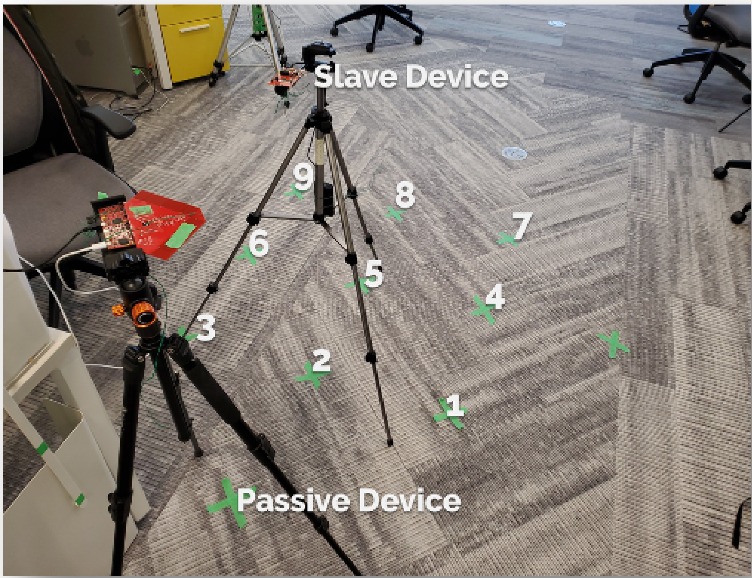

Figure 4: BLE passive and slave devices

seen on the Fig. 3

The slave device was set at 0°and 45°angles for various distances and error in angle was measured. For each experiment data was collected for 10 minutes and then averaged out. The experiment was done in an office room with Wi-Fi signals and other electronic components like computers, monitors and reflective surfaces to simulate real world scenarios. The test was performed in where the Bluetooth slave and passives devices will always be in a Line of Sight (LOS) scenario. Through the experiment we concluded that using 1 antenna set up yields the best result. The results can be seen from Table 2 where σ is the standard deviation of the error in angle received. Since the 2 antenna array results in worse results, for all the other experiments

Table 2
Error calculation for antenna array BOOSXL-AOA board

	Using 1 Antenna (Measured at 0°)			Using 2 Antennas (Measured at +45°)		
Distance (m)	**Received Angle(°)**	σ	**Error(°)**	**Received Angle(°)**	σ	**Error(°)**
0.50	-1.01	1.21	1.01	41.35	2.56	3.65
1.00	3.81	1.55	3.81	44.49	2.64	0.51
1.50	2.48	1.96	2.48	11.93	19.85	33.07
2.00	4.19	3.10	4.19	52.39	5.84	7.39
2.50	1.38	5.60	1.38	-5.65	27.23	50.65
3.00	-4.69	3.46	4.69	29.54	17.17	15.46

moving forward: the second array was disabled using the firmware options.

3.1.2. RSSI Calculation

From the TI passive device, we can get the value of RSSI. A Kalman filter was used to enhance the robustness, accuracy, and reliability of BLE signals which are often noisy. The RSSI value can be used to determine the distance from the transmitter. There are a few techniques to calculate RSSI with respect to calculating the distance. One of the ways to calculate distance is the outdoor propagation model using free space path loss (FSPL) formula in equation 2.

$$FSPL(dB) = 20\log_{10}(d_{km}) + 20\log_{10}(f_{GHz}) + 92.45 \tag{2}$$

However, for indoor transmission, it is difficult to use a specific model as the propagation varies drastically based on various factors. These include type of indoor environment, position of the transmitters within this environment, distance from walls, height of the transmitter compared to the ground and location of obstacles such as furniture [1]. From literature it can be found that [2-4] there are no accurate modelling for indoor propagation model. After testing some empirical models, we chose a statistical modelling of regression analysis to calculate the distance from RSSI values using the formula in equation 3.

$$y = Ax^B + C \tag{3}$$

The model uses a power regression analysis to calculate the constant values of A, B and C. With a base RSSI calculated at 1m distance, a ratio r is calculated for RSSI values at various distances. Using the RSSI, Ratio, and Actual Distance we can calculate the Predicted Distance. From our testing we were able to create the following model for 1 passive BLE device (equation 4).

$$0.59 * \left(\frac{RSSI}{-48}\right)^{6.7} - 0.14 \tag{4}$$

This formula provided the most accurate distance based on RSSI for our office indoor environment.

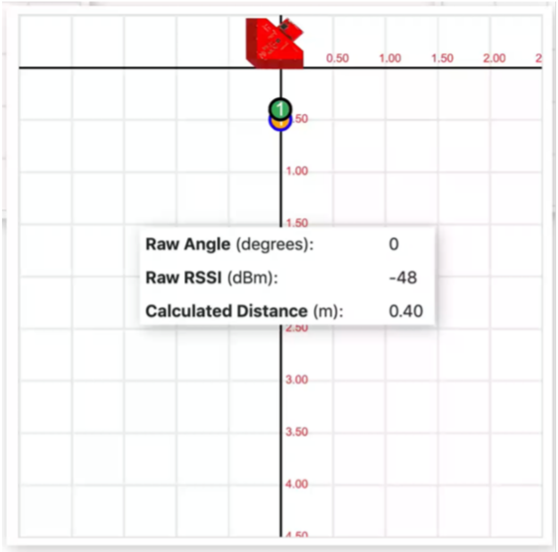

Figure 5: Web app results at 0.5m (1 passive and 1 slave)

3.2. Data collection strategy

In order to collect accurate angle of arrival data, we created a testing grid of 9 points across a 2m x 2m and 4m x 4m area. Fig. 4. illustrates a testing scenario where a 2m x 2m grid is used to collect AoA data using one antenna (passive device) and one Bluetooth receiver (slave device).

An optimum height of 1m from floor was used for all data collection processes. Data was collected for 5 minutes on each testing location. The results were then averaged over all 9 testing points for better reflection of accuracy. The data that was received form the Bluetooth Receiver (slave) is in the form of AoA and RSSI. The RSSI value gives us a radius of possible locations and the AoA value solidifies the position on that radius. The error in distance is calculated from finding the difference in positioning of actual testing point and measured location. We created a Web application that takes these measurements from the Bluetooth Receiver and plots them on a graph to show the real time location of the Bluetooth receiver. Fig. 5 shows the output when a receiver was placed 0.5m away at an angle of 0°.

3.3. Static Test

For the static test, the slave device was placed at various locations of our testing grid. The device was not moved for the duration of data collection. The initial testing was done with one slave device and one passive device. This gave us a baseline accuracy for AoA tests. Using the libraries available for the TI board we created a web application that shows the RSSI values in real time. We superimposed the figures of passive devices and created a grid with accurate distances in order to visualize location and signal directions that were received on the passive devices. Fig. 5 shows a screenshot from our web app for a static test at 0.5m distance.

To calculate the distance between the slave and Two, Three, or Four passives, the setup relies on using two passives' Points of Intersection. If there is no direct point of intersection, then the

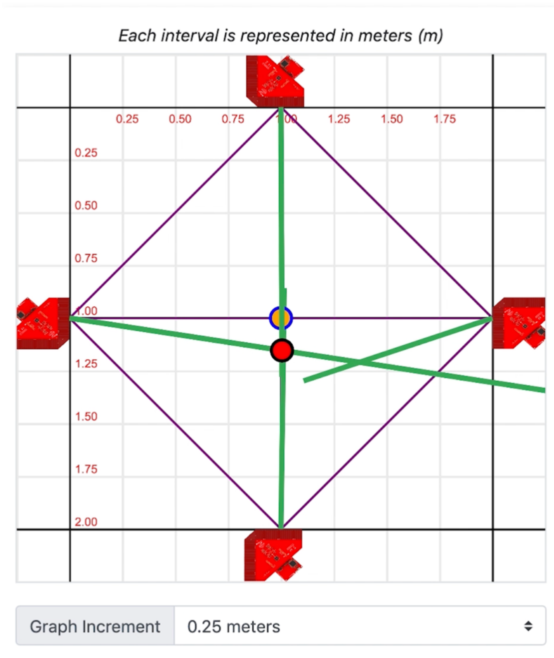

Figure 6: Web app results at 0.25m (4 passives and 1 slave)

application forces it to intersect. If 2 lines do not intersect, since 1 line may be shorter than the other, then it will force the shorter line to intersect with the other line. Fig 6 illustrates the process. In each of the testing grids, we used a different number of passive devices to calculate optimum number of Bluetooth sensors and their location.

3.4. Moving Test

The moving test involved the same setup, with the exception of the slave device being moved at a constant pace for the entire test. This can be visualized from the following Video on YouTube. We created a mini-robot using Lego Mindstorms EV3 to move at a constant speed through our testing locations. Data was collected for two scenarios: a) the robot stopped at the testing locations for two seconds and b) the robot moved from endpoint to endpoint without stopping. Data was collected every 0.25s and averaged out for better accuracy.

4. Finding and Discussion

Table 3 presents the results of our static and moving test results. The results are presented in terms of accuracy in metres for 2x2m and 4x4m grid environments with percentages representing the amount of change by adding more passives. The moving test results naturally are worse than static tests as signals experience Doppler effect, multi-path interference, reflections and scatterings [34]. The most obvious observation is that as we increase the number of passive devices, there is a diminishing return. Three passive devices produced the best results in our

Table 3
Static and Moving Test Results

	Static Test (metres)				Moving Test (metres)							
					With stop				Without stop			
	2x2 grid		4x4 grid		2x2 grid		4x4 grid		2x2 grid		4x4 grid	
1 passive	0.77		1.46		0.84		1.76		0.75		1.72	
2 passives	0.27	*65%*	0.77	*47%*	0.75	*11%*	0.73	*59%*	0.30	*60%*	0.69	*60%*
3 passives	0.23	*15%*	0.55	*29%*	0.52	*31%*	0.47	*36%*	0.41	*-37%*	0.58	*16%*
4 passives	0.31	*-35%*	0.70	*-27%*	0.66	*-27%*	0.59	*-26%*	0.41	*0%*	0.61	*-5%*

environment. The accuracy increased when increasing passive devices from 1 to 2 by 65%, whereas moving from 2 passive to 3 passive produced an increase of only 6.75% for the 2x2m grid. Similar results may be seen for the moving tests, however, the gain is not as large as the static tests. When the slave device was stopping at the testing locations, the greatest improvement in accuracy was the 3 passives scenario (i.e., an improvement of 32%). For moving tests, when the slave device did not stop and continued at a constant speed, the improvement was the most at 2 passives (60% at 2x2m grid). The results also show a similar pattern for the 4x4m grid configuration. The only exception was for the 2x2m grid and moving test, where there was no improvement for moving accuracy when adding an additional passive. Furthermore, there was no change for adding a 4^{th} passive device.

The main aim of this research was to create an indoor localization and navigation system that could be easily deployed with commonly available beacons and smartphones/tablets, while achieving a 2m level of accuracy while the user is in motion. Our system enables efficient real-time tracking of users or assets in indoor environments with a level of accuracy that is an improvement on previous work in this area.

4.1. Deployment considerations for real-world environments

The benefits of AoA/AoD have been well documented. There are improved navigation and augmented reality benefits [35], along with enhanced security [36], improved network efficiency and better user experience . However, all these studies, including ours, do not use a mobile device that can use AoA/AoD. At the time of this publication, the authors could not find any mobile devices that has the AoA/AoD antenna built in. Most current day smartphone have access to BLE 5.2 technology, but not the antenna array required to calculate AoA/AoD signals. Our research shows the benefit of utilizing the BLE antenna arrays for indoor navigation along with other aforementioned benefits.

4.2. Future Research

the research conducted demonstrates a framework for indoor localization using AoA and AoD. This can be scaled up for larger areas where the grid is limited to 4m x 4m area. Our test area was a normal office indoor environment. Future work could include different indoor environments like malls, warehouses and areas with obstacles and reflective surfaces. The idea would be to create a mathematical model that can be easily scaled to cater for various environments.

This can help in calculating how many passive devices would be necessary along with their positions.

5. Conclusion

In this work, we used a Texas Instrument development board and Antenna Array to conduct a thorough set of experiments exploiting AoA and AoD in BLE beacons. We created an indoor navigation system that improves the beacon's RSSI signals and uses various algorithms to provide high accuracy location predictions in indoor environments. Our work can be used in a variety of applications in indoor location and asset tracking. The main contributions of this work are:

1. An indoor positioning system that performs at an accuracy of 0.23m (when the asset is static) and 0.30m (when the asset is in motion),
2. A generalized indoor micro-location system that can be easily and rapidly deployed to new environments (within hours),
3. A comparison and performance analysis of BLE passive devices and how many passive is required depending on the scenario of different area and requirement of static or moving objects.
4. An architectural model by which other researcher can extend our work on indoor positioning and navigation.

In conclusion, we created a real-time context aware solution using BLE beacons with AoA and AoD for indoor environments that can track the user or asset while in motion.

In the spirit of furthering science, the source code for the apps, architectural designs, algorithms and datasets will be openly available on the publisher's website. We hope this will encourage others to extend our work.

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References

[1] H. Hoffman-Wellenhof, B., H. Lichtenegger, J. Collins, Global positioning system: theory and practice, Springer, New York, 2001.

[2] M. G. Wing, A. Eklund, L. D. Kellogg, Consumer-Grade Global Positioning System (GPS) Accuracy and Reliability, Journal of Forestry 103 (2005) 169–173. doi:10.1093/jof/103.4.169.

[3] F. Zafari, I. Papapanagiotou, M. Devetsikiotis, T. J. Hacker, Enhancing the accuracy of ibeacons for indoor proximity-based services, in: IEEE International Conference on Communications, IEEE, 2017, pp. 1–7.

[4] A. Booranawong, K. Sengchuai, N. Jindapetch, Implementation and test of an rssi-based indoor target localization system: Human movement effects on the accuracy, Measurement 133 (2019) 370–382.

[5] E. R. Sykes, A context-aware system using mobile applications and beacons for on-premise security environments, Journal of Ambient Intelligence and Humanized Computing 11 (2020) 5487–5511. URL: https://doi.org/10.1007/s12652-020-01906-2. doi:10.1007/s12652-020-01906-2.

[6] A. N. Raghavan, H. Ananthapadmanaban, M. S. Sivamurugan, B. Ravindran, Accurate mobile robot localization in indoor environments using bluetooth, in: 2010 IEEE international conference on robotics and automation, IEEE, 2010.

[7] H. O. Maycotte, Beacon technology: The where, what, who, how and why, 2015. URL: https://www.forbes.com/sites/homaycotte/2015/09/01/beacon-technology-the-what-who-how-why-and-where/#4baf7381aaf8.

[8] E. R. Sykes, S. Pentland, S. Nardi, Context-aware mobile apps using ibeacons: Towards smarter interactions, in: Proceedings of the 25th Annual International Conference on Computer Science and Software Engineering, ACM, USA, 2015, p. 120–129.

[9] X. Jiang, Y. Chen, J. Liu, Y. Gu, L. Hu, Fselm: fusion semi-supervised extreme learning machine for indoor localization with wi-fi and bluetooth fingerprints, Soft Computing 22 (2019) 3621–3635.

[10] T. Kawai, K. Matsui, Y. Honda, G. Villarubia, J. M. C. Rodriguez, Preliminary study for improving accuracy on indoor positioning method using compass and walking detect., in: International Symposium on Distributed Computing and Artificial Intelligence, 2018.

[11] M. Wooley, Bluetooth Core Specification Version 5.1 Feature Overview, report, Berkley, 2020. URL: https://www.bluetooth.com/bluetooth-resources/bluetooth-core-specification-v5-1-feature-overview/.

[12] O. Belmonte-Fernandez, A. Puertas-Cabedo, J. Torres-Sospedra, R. Montoliu-Colas, S. Trilles-Oliver, An indoor positioning system based on wearables for ambient-assisted living, Sensors 17 (2017).

[13] Gimbal, Gimbal proximity beacon series 21, 2021. URL: https://docs.gimbal.com/index.html.

[14] D. Giovanni, Luca, A. Machì, Towards accurate indoor localization using ibeacons, fingerprinting and particle filtering, in: International Conference on Indoor Positioning and Indoor Navigation, 2016.

[15] B. Benaissa, F. Hendrichovsky, K. Yishida, M. Koppen, P. Sincak, Phone application for indoor localization based on ble signal fingerprint, in: 2018 9th IFIP International Conference on New Technologies, Mobility and Security, 2018.

[16] A. De Blas, D. López-de Ipiña, Improving trilateration for indoors localization using ble beacons, in: 2nd International Multidisciplinary Conference on Computer and Energy Science, Springer, 2017.

[17] E. Hatem, B. El-Hassan, J.-M. Laheurte, S. Abou-Chakra, E. Colin, C. Marechal, Study the estimated distance error in indoor localization using uhf-rfid, 2018 IEEE Middle East and North Africa Communications Conference (2018).

[18] D. Konings, N. Faulkner, F. Alam, F. Noble, E. M. Lai, The effects of interference on the rssi values of a zigbee based indoor localization system, in: 24th International Conference on Mechatronics and Machine Vision, IEEE, 2017.

[19] S.-S. Jan, S.-J. Yeh, Y.-W. Liu, Received signal strength database interpolation by kriging for a wi-fi indoor positioning system, Sensors 15 (2015) 21377–21393.
[20] J. Zuo, S. Liu, H. Xia, Y. Qiao, Multi-phase fingerprint map based on interpolation for indoor localization using ibeacons, IEEE Sensors Journal 18 (2018) 3351–3359.
[21] E. L. Agustin-Blas, S. Salcedo-Sanz, P. A. Vidales, G. Urueta, A. Portilla-Figueras, Near optimal citywide wifi network deployment using a hybrid grouping genetic algorithm, Expert Syst. Appl. 38 (2011) 9543–9556. doi:10.1016/j.eswa.2011.01.141.
[22] H. K. Yu, S. H. Oh, J. G. Kim, Ai based location tracking in wifi indoor positioning application, in: 2020 International Conference on Artificial Intelligence in Information and Communication (ICAIIC), 2020, pp. 199–202. doi:10.1109/ICAIIC48513.2020.9065227.
[23] Apple, Apple ibeacon framework and technology, 2021. URL: https://developer.apple.com/ibeacon/.
[24] H. Kitayoshi, K. Sawaya, Long range passive rfid-tag for sensor networks., in: IEEE 62nd Vehicular Technology Conference, IEEE, 2005.
[25] M. Woolley, Bluetooth core specification v5.1, 2020. URL: https://www.bluetooth.com/wp-content/uploads/Files/Specification/1901_Feature_Overview_Brief_FINAL.pdf.
[26] X. Guo, N. Ansari, L. Li, H. Li, Indoor localization by fusing a group of fingerprints based on random forests, IEEE Internet of Things Journal 5 (2018) 4686–4698.
[27] R. Kaewpinjai, T. Chuaubon, A. Apavatjrut, On improving indoor navigation accuracy using bluetooth beacons, in: 2020 17th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), 2020, pp. 727–730. doi:10.1109/ECTI-CON49241.2020.9157901.
[28] Onyx, Onyx enterprise beacons, 2021. URL: http://roximity.com.
[29] Twocanoes, Bleu station beacon series 100, 2021. URL: http://twocanoes.com/bleu.
[30] Estimote, Estimote: Real-world context for your apps, 2021. URL: http://estimote.com.
[31] Verve, Verve beacons, 2021. URL: https://www.verve.com/products/beacons/.
[32] Kontakt.io, Simplifying enterprise internet of things, 2021. URL: https://kontakt.io.
[33] S. Kumar, S. Gil, D. Katabi, D. Rus, Accurate indoor localization with zero start-up cost, in: 20th annual international conference on Mobile computing and networking, ACM, 2014, p. 483–494.
[34] S. R. Theodore, et al., Wireless communications: principles and practice, 2002.
[35] M. Codina, D. Castells-Rufas, J. Carrabina, I. Salmon, N. Ayuso, A. Guerendiain, G. Alvarez, Augmented reality for emergency situations in buildings with the support of indoor localization, Multidisciplinary Digital Publishing Institute Proceedings 31 (2019) 76.
[36] M. Cominelli, P. Patras, F. Gringoli, Dead on arrival: An empirical study of the bluetooth 5.1 positioning system, in: Proceedings of the 13th international workshop on wireless network testbeds, experimental evaluation & characterization, 2019, pp. 13–20.