Journal of Advanced Research in Computational Thinking and Data Science 8, Issue 1 (2025) 23-34

KARYA ILHAM PUBLISHING
CONNECTING MINDS, BRIDGING IDEAS, INSPIRING READERS

International Journal of Advanced Research in Computational Thinking and Data Science

Journal homepage:
https://karyailham.com.my/index.php/ctds/index
ISSN: 3030-5225

Indoor Self-Aware Positioning Robot using Bluetooth Low Energy (BLE)

Akram Abdul Azid[1,*], Ahmat Izhar Ahsan[1], Syed Mohd Fairuz Syed Mohd Dardin[1], Asnor Mazuan Ishak[1]

[1] Department of Electrical & Electronics Engineering, Faculty of Engineering, National Defence University of Malaysia, Kem Sg Besi, 57000 Kuala Lumpur, Malaysia

ARTICLE INFO

Article history:
Received 8 December 2025
Received in revised form 31 January 2026
Accepted 2 February 2026
Available online 5 February 2026

Keywords:
Autonomous robot; BLE; indoor positioning system; obstacle avoidance; RSSI; trilateration; fingerprinting; ESP32

ABSTRACT

This paper presents the development of an autonomous indoor mobile robot utilizing Bluetooth Low Energy (BLE) technology for self-aware localization and navigation. The proposed system features a distributed hardware architecture, employing a standard ESP32 for motor control and BLE signal processing, alongside an ESP32-CAM to host a real-time web-based Graphical User Interface (GUI). Localization is achieved through Received Signal Strength Indicator (RSSI) trilateration and fingerprinting, enhanced by a Kalman filter to mitigate multipath interference and signal noise. Experimental results demonstrate a positioning accuracy of 74.27% in static conditions and 72% during autonomous movement. While the ultrasonic sensor system achieved a 100% success rate in detecting static obstacles of varying materials (cloth, glass, cardboard) within a 25 cm range, the reliability of the obstacle avoidance maneuver was limited (20% success rate) due to orientation drift inherent in the open-loop motor control mechanism. The system offers a scalable, cost-effective prototype for indoor navigation with potential applications in environments such as warehouses and smart buildings, subject to further domain-specific validation.

1. Introduction

The demand for self-operating robots in the service and manufacturing industries has sparked a large amount of research in sensor technology and robotics. However, traditional Global Positioning System (GPS) based location does not work indoors because the signal is lossy and blocked. It is obvious that alternative indoor positioning systems (IPS) need to be developed. One popular alternative is Bluetooth Low Energy (BLE) which is relatively low power and nowadays fairly ubiquitous in modern microcontrollers (e.g. the ESP32) and also in many devices (from tracking labels over smartwatches to fitness trackers).

There are three objectives that were focused in this research; to develop an autonomous robot capable of detecting and avoid obstacles by itself within an indoor environment; to integrate a Bluetooth Low Energy (BLE)-based Indoor Positioning System (IPS) into the robot; and to evaluate

* *Corresponding author.*
E-mail address: akram@upnm.edu.my

the BLE-based Indoor Positioning System and robot navigation performance for accuracy, and precision.

The system uses trilateration and fingerprinting techniques to estimate the position of the robot from RSSI measurements reported by stationary ESP32 BLE beacons. We use a Kalman filter to improve localization accuracy by removing noise and multipath interference. Kalman Filter is a numerical system used to estimate the state of a system from noisy measurements over time, in this project the received signal strength (RSSI). The RSSI is then used to estimate the distance between the two-point using the Free Space Path Loss which mathematical models how the strength of a wireless signal decreases when it travels through space. The robot communicates with the beacons in a direct manner via Wi-Fi, enabling efficient and secure real-time data transfer. Users are given a web-based interface hosted by the ESP32-CAM module to see the location of the robot in real time. Obstacle detection is an extremely important feature for autonomous robots navigating through dynamic environments. Sensor technologies have been explored for this purpose like the ultrasonic [1].

Ultrasonic sensors are favored due to their affordability, extensive range, and consistency in varied environmental conditions [2]. The sensor emits high-pitched sound waves and measures the time for echo to return, enables accurate distance measurement even when there is dust or darkness [3]. Ultrasonic sensors are less affected by ambient light than other sensors like IR and LiDAR and provide consistent readings at extended ranges [4]. However, they may struggle with soft, bent, or small things that do not shine well [5]. Despite these, ultrasonic sensors remain a good choice for real-time obstacle detection for autonomous indoor robots [6]. LiDAR provides spatial high-resolution information at a more expensive and computational demanding [7]. There have been research that demonstrated effective obstacle avoidance with sensor fusion techniques including ultrasonic, LiDAR, and encoder sensors in order to provide smooth navigation without stop [8][9]. For this project, ultrasonic sensors were used because they are cheap, dependable, and appropriate for real-time applications indoors [10].

Autonomous robot navigation involves real-time decision-making algorithms allowing the robot to adjust its path based on sensor input. There have been researches that demonstrated effective autonomous navigation programs based on sensor fusion techniques [11]. Localization is an important role played by autonomous robots to determine their position in the environment. Techniques employed include fingerprinting, triangulation, and trilateration [10]. Trilateration is preferred owing to its simplicity and scalability for wide areas under the utilization of Bluetooth Low Energy (BLE) Received Signal Strength Indicator (RSSI) values [12]. Trilateration determines the position of the robot based on distances obtained from RSSI values reported by at least three stationary BLE beacons [13]. while building a signal characteristic map at different known locations in an environment.

Fingerprinting, another popular approach, forms a signal characteristic map at different known locations and enables the robot to estimate its location by comparing real-time observations with previously collected data [14]. As there is noise and multipath interference indoors, filtering procedures such as Kalman filtering may be employed to increase localization accuracy [15]. Such provides a database whereby a device or robot can understand its location through comparison between observations from the current instance and those that were obtained previously.

2. Methodology

The proposed system for autonomous indoor navigation is based on a distributed architecture consisting of two primary components: a mobile robotic platform and a network of stationary Bluetooth Low Energy (BLE) beacons. The overall methodology integrates hardware selection, system software development, and algorithmic implementation to achieve robust localization and navigation. This section details the hardware architecture of the robot and beacons, the implementation of the Received Signal Strength Indicator (RSSI)-based localization algorithms, the mechanism for ultrasonic obstacle avoidance, and the design of the real-time communication protocol and user interface for positioning.

2.1 Autonomous Robot

The autonomous robot is fundamentally composed of two primary components, hardware and software. The term hardware refers to the physical elements of the robot that make up for the robot itself. In this case, the robot is equipped with two microcontrollers, the ESP32-CAM and a standard ESP32. Both microcontrollers are strategically mounted onto the robot's chassis as shown in Figure 1. The standard ESP32 serves as the central processing unit, managing data and operations while also broadcasting a Bluetooth Low Energy (BLE) signal to facilitate communication with other devices. Meanwhile, the ESP32-CAM plays a dual role, in addition to providing capabilities for image capture and processing, it also functions as a Wi-Fi access point. This setup allows the ESP32-CAM to host a web user interface (WebUI), which is essential for remote monitoring of the robot's activities.

The purpose of integrating two microcontrollers into a single robot is to reduce the processing load. The system is performance optimized by appointing one microcontroller to control the movements of the robot and the other to host the web user interface (WebUI) and serve as a Wi-Fi access point. The combination of hardware components allows the robot to function independently while giving users real-time access to its operational status through the hosted web interface. This task division helps keep any one component from becoming overloaded.

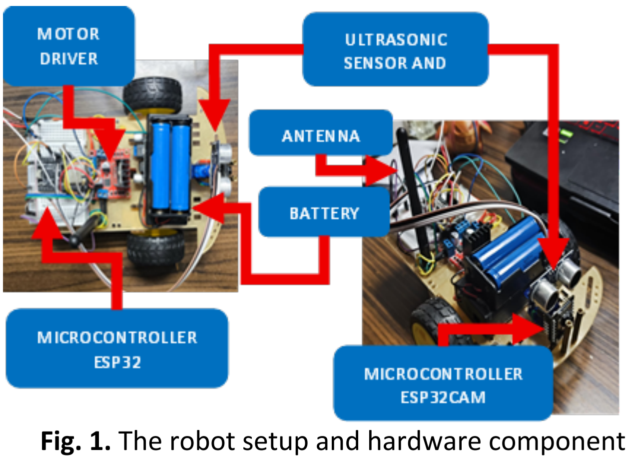


Fig. 1. The robot setup and hardware component

The software side of the robot entails a code uploaded through the Arduino IDE that facilitates direct communication protocols between the various microcontrollers. the generic ESP32 and ESP32-CAM on the robot and three ESP32-C3 supermini modules being used as reference points. This setup is necessary to enable the microcontrollers to receive RSSI (Received Signal Strength Indicator) readings, which characterize signal strength and are utilized to calculate the location of the robot.

The processed RSSI information is transferred to a web user interface (WebUI) to enable users to monitor the operational status and location of the robot in real time. The Web User Interface (WebUI), as shown in Figure 2 is hosted directly on the ESP32-CAM module mounted on the robot. The WebUI is developed using light coding languages such as HTML, CSS, and JavaScript to ensure that the design is kept light in order not to cause unnecessary network overload. The design is intentionally made simple for quick access and response. The live camera feed is at the center of the WebUI, that provides real-time feedback of the surrounding environment of the robot. In addition, the interface also shows a basic two-dimensional map which is designed based on the physical structure of the indoor environment where the robot is intended to be utilized. The WebUI further includes a convenient download feature, enabling users to download Received Signal Strength Indicator (RSSI) values for all three reference points and the history of the last ten positions. The downloaded data is in structured JSON format, a more organized data for convenient processing

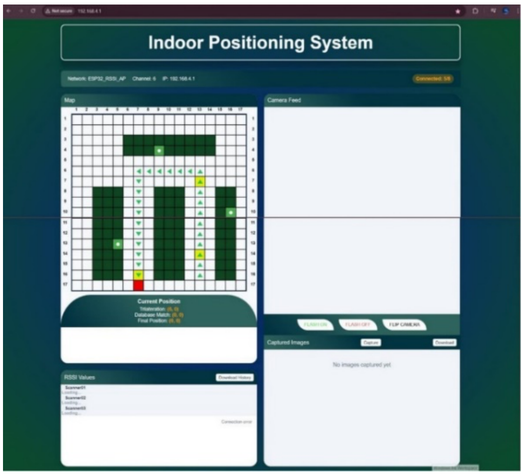


Fig. 2. The Web UI that shows the interface of the monitoring system

The robot process flow is shown as Figure 3. The process begins with the initialization of the monitoring system, which establishes communication between the robot and BLE beacons via Wi-Fi. The robot sends a BLE signal that is picked up by the reference points (BLE beacons), and they reply by sending RSSI values to the robot. The RSSI values are used to estimate the robot's position by using both trilateration and fingerprinting techniques.

Once the robot has determined its position, it proceeds to plan its path to the given location. During movement, the robot continuously updates its position and reports to a web-based platform for real-time monitoring. When encountering any obstacle during movement, the robot activates its obstacle avoidance system. The robot scans left and right using an ultrasonic sensor interfaced with a servo motor, compares the distances, and steer accordingly to avoid collision. Having avoided the obstacle, the robot resumes its journey until it reaches the predetermined destination, where the process terminates.

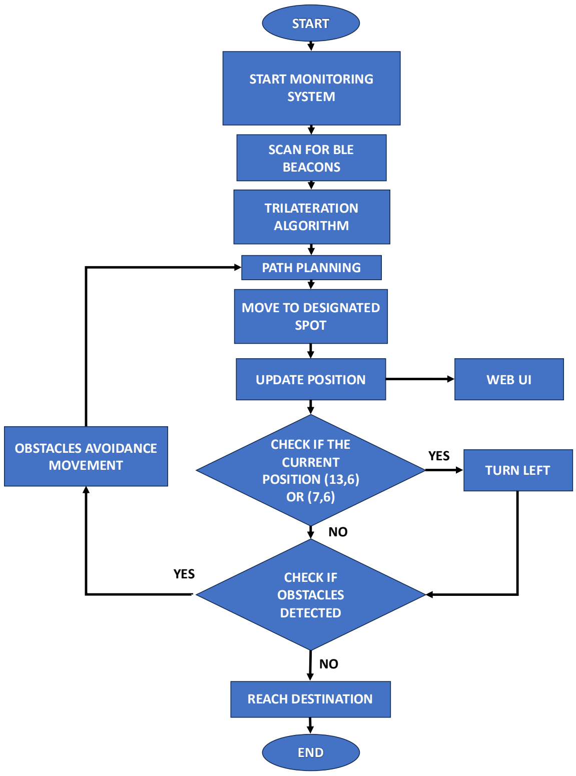


Fig. 3. The autonomous robot system flowchart

2.2 Communication Protocol

The research utilizes two wireless communication technologies, Bluetooth Low Energy (BLE) and Wi-Fi. BLE is primarily used to collect Received Signal Strength Indicator (RSSI) values between the robot and fixed ESP32 beacons for real-time localization [16], while Wi-Fi is employed to enable seamless data communication between microcontrollers with assured reliability and low latency [17]. This includes sending BLE RSSI values and enabling direct communication to prevent data loss and enable real-time monitoring. The ESP32-CAM on the robot handles the task of establishing this Wi-Fi network and serves as a web server to host the web interface for monitoring.

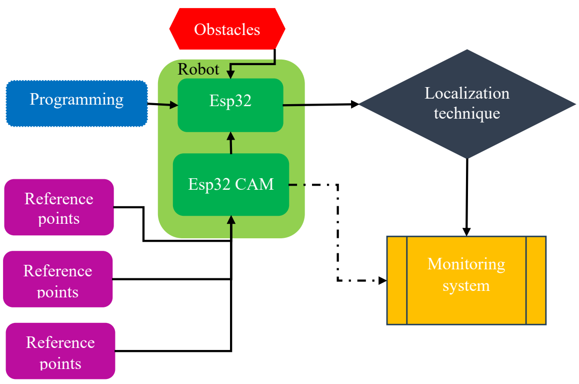


Fig. 4. The communication protocol for the wireless communication between the robot, beacons, and the esp32CAM

The complete system communication architecture is illustrated in Figure 4. Multiple ESP32 devices are paired with the robot's ESP32 via BLE to receive their respective RSSI values, which are then transmitted to the ESP32-CAM for distance calculation and position estimation. All the information collected is presented on the web interface, which can be viewed by any device connected to the same network.

2.3 Obstacles Detection and Avoidance

The obstacle detection and avoidance of the robot consists of two distinct modules, the detection phase and the avoidance phase. The primary objective of obstacle detection is the detection of obstacles' existence only and not the calculation of their precise distance or dimension. As it is, the sensor is not needed to be very accurate or have numerical readings in detail, it is sufficient for the ultrasonic sensor to be able to detect the presence of an obstacle. The sensor is also mounted on top on a 180-degree servo, optimizing the robot's detection coverage. It allows the robot to maintain efficiency in its operation while still being able to respond to obstacles in real time. Thus, the system prioritizes reliable detection over precision. For robot obstacles avoidance, the robot will perform a series of pre-programmed movement uploaded to the robot as below:

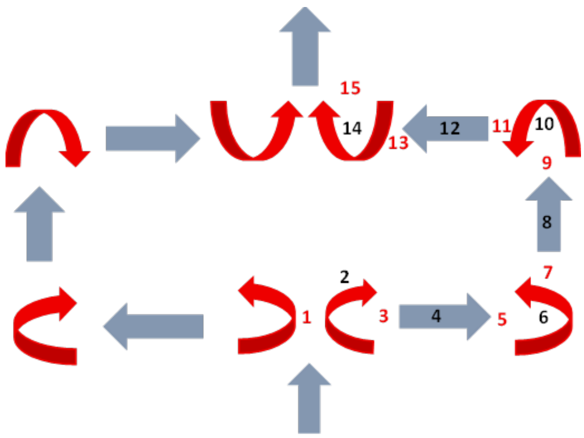


Fig. 5. Robot obstacles movement

The robot is programmed to have a predetermined series of movements from 1 to 15. Every movement corresponds to an action that the robot performs within its environment. Movements 1, 3, 5, 7, 9, 11, 13, and 15 are reserved for stopping both wheels of the robot's motor, effectively stopping it at various locations along its track. This action allows the robot to come to a halt because of changes in its environment or because an obstacle is detected, thus ensuring safety and control during movement. Conversely, movements labeled 2, 6, 10, and 14 are crafted for the robot to rotate its motors, allowing it to turn either left or right. This turning capability is crucial in allowing the robot to navigate around corners and obstacles. The other movements in the sequence offer straight forward motion, this structured movement sequence enhances the robot's ability of moving efficiently while avoiding the obstacles.

2.4 Positioning

For the positioning of the robot, using the BLE’s RSSI value to determine the distance between the robot (beacon) and the reference points. The positioning is done in a control environment with the position desks and the beacon is fixed.

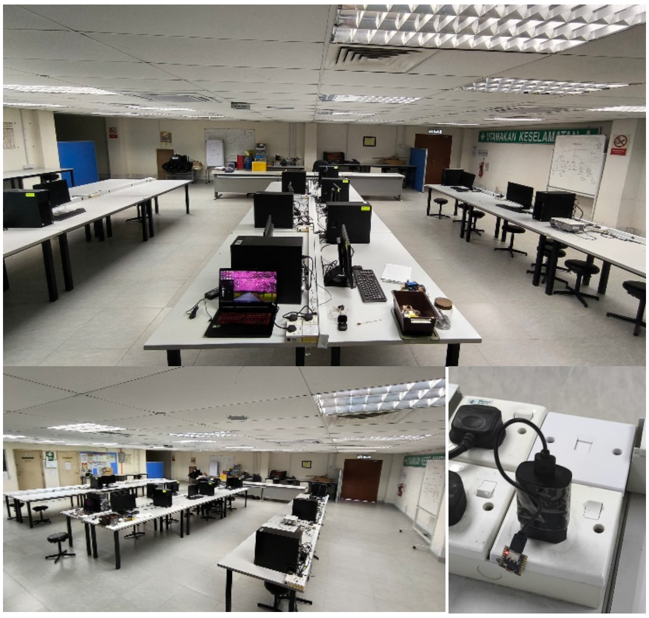


Fig. 6. Layout for indoor positioning and how the beacon is placed

The formula used to calculate the distance between the two is derived from the Free Space Path Loss (FSPL) model, which describes how electromagnetic waves propagate through space without obstacles or interference.

The derive formula is:

$$RSSI(d) = RSSi(d_0) - 10nlog10(\frac{d}{d_0}) \tag{1}$$

where,

- d_0 is the is the known signal strength at a 1 meter
- n is the path loss exponent in free space
- d is the distance that obtain from the calculation

The variable *n* quantifies the rate of signal decay and is influenced by the surrounding environment. Higher values of *n* suggest a denser environment that includes furniture, walls, and other obstacles that can absorb or reflect the signal. In this project, the indoor environment consists primarily of tables and chairs, leading us to set *n* to 3. This is a reasonable choice, as a typical value of 2 is used for open environments with no obstructions. The formula can further simplify to,

$$d = 10^{\frac{referenceRSSI - RSSI}{10n}} \tag{2}$$

Since the position is calculated using BLE'RSSI in real world application, they are bound to be noise from the surroundings that can affect the actual reading. To cope with this problem, a filter is a must to increase the reliability of the system. Kalman filter is employed to tackle this problem, Kalman filter can adjust the filtered values and can learn to give out less noise output. The Kalman filter formula used for this project is a variant of the filter with only accounted for one dimensional unit as shown below:

$$x_{|k} = x_{k|k-1} + K_k\left(z_k - x_{k|k-1}\right) \tag{3}$$

Where,
- $x_{|k}$ the value of the new estimate
- $x_{k|k-1}$ the value of the previous estimate
- K_k Kalman gain
- z_k the measured RSSI value

The value of Kalman gain can be calculated using formula:

$$K_k = \frac{P_{k|k-1}}{P_{k|k-1}+R} \tag{4}$$

Where,
- $P_{k|k-1}$ predicted estimate error
- R measurement noise

The predicted estimate formula:

$$P_{k|k-1} = P_{k-1} + Q \tag{5}$$

Where,
- P_{k-1} Kalman estimate error
- Q process noise

Under calibration, the filter is run several times to be able to accommodate environmental factors such as ambient temperature and noise, values of Q and R then set at 8 and 5, respectively. Because the signal is very noisy, both values have been adjusted to the higher numbers to be able to make allowance for unreliability of raw data. Since the robot is constantly in the moves, it is critical for the filtering system to be able to distinguish quickly between good signals and noise. Due to the ambient noise and multipath effects, the filtering technique was used to reduce errors and enhance localization accuracy [18]. The Kalman filter used for this reason may respond too late in dynamic conditions since it relies on previous estimates [19]. To overcome this limitation, the Kalman gain is reset for each 30 cycles in runtime so that the filter would be able to learn quicker to changes in RSSI and respond better to environment noise [20]. The filter would be able to respond better to changes in RSSI values dynamically with dynamic adjustment of the Kalman gain while running, which makes it responsive to the environment noise.

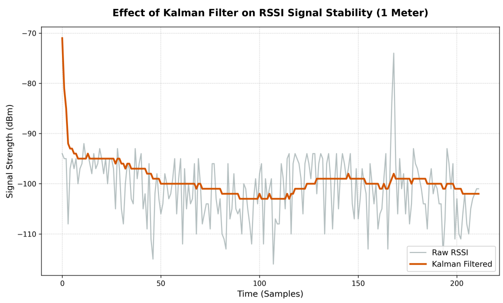


Fig. 7. The raw and filtered values of the received signal strength

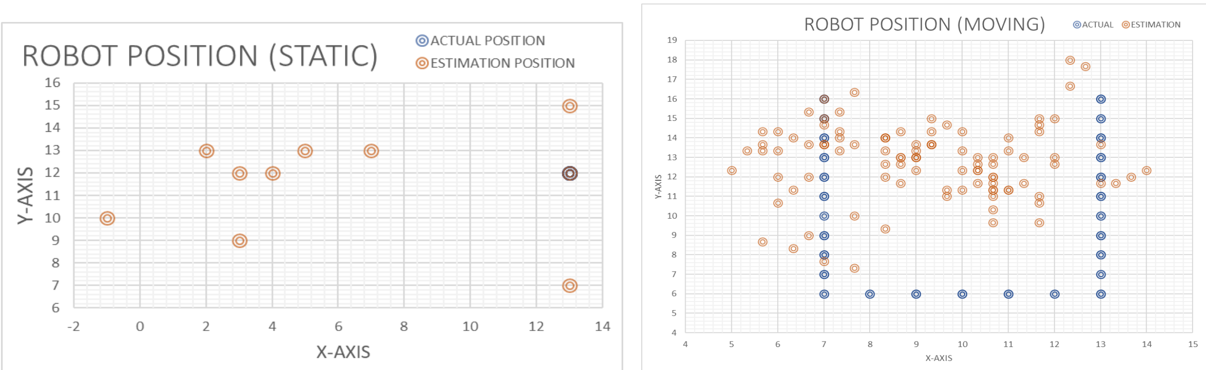
Figure 7 above shows a sample of both raw and filtered RSSI values at 1 meter distance. The graph shows the comparison between the before and after the application of Kalman filter. A filtered reading showing a smoother signal curve compared to raw data.

3. Results and Discussion

3.1 Results

The outcomes of this experiment focused on the accuracy and reliability of Bluetooth Low Energy (BLE) in determining the robot's position, as well as the robot's ability to detect and avoid obstacles. For positioning, we assess accuracy both when the robot is stationary and when it is in motion toward its designated location.

Figure 8 compares the robot's estimated position against its actual position in static and dynamic scenarios. Accuracy is quantified using the Root Mean Square Error (RMSE) relative to the grid size.



(a) (b)

Fig. 8. The actual position of the robot compared to the estimation position during both (a) static and (b) moving movement

The accuracy is then computed using Euclidean distance to determine the error, which in this context refers to the difference between the two points, applying the following formula:

$$d = \sqrt{\left(x_{actual\ position} - x_{estimate\ position}\right)^2 + \left(y_{actual\ position} - y_{estimate\ position}\right)^2} \tag{6}$$

The distance acquired from the formula above is the error between the two points. The larger the magnitude of the distance indicates the larger error occurred. Root Mean Square Error can be calculated using this formula:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} d_i^2} \tag{7}$$

Where, n is the number of samples.

The accuracy percentage is defined by normalizing the error against the maximum possible distance (d_{max}) in the grid:

$$Accuracy = \left(1 - \frac{RSME}{d_{max}}\right) \times 100\% \tag{8}$$

Where, d_{max} is the maximum possible error relative to grid size which can be calculated using formula:

$$d_{max} = \sqrt{17^2 + 17^2} = 24.0416$$

where, 17 is the maximum value for the *x* and *y* axis. The average accuracy of the robot during static and dynamic movement are as below:

Table 1
Comparison of localization accuracy in static and dynamic conditions

Condition	Sample Size (*n*)	RSME (m)	Average Accuracy (%)
Static	5	6.18	74.27
Moving	3	6.78	72.00

The average accuracy of the robot position during stationary is 74.27%. while the average accuracy during moving is 72%.

For the obstacles detection, the result is as follows:

Table 2
Obstacle detection success rates across different materials (Distance ≈ 25 cm)

Material Type	Total Trials	Successful Detections	Success Rate (%)
Cloth	5	5	100
Water bottle	5	5	100
Cardboard	5	5	100
Glass	5	5	100

The ultrasonic sensor demonstrated a 100% success rate in detecting static obstacles (cloth, water bottle, cardboard, glass) at a distance of approximately 25 cm (Table 2). However, the obstacle avoidance maneuver showed significant limitations as shown in Table 3.

Table 3
Reliability analysis of obstacle avoidance maneuvers

Test Scenario	Trials	Successful Recovery	Main Cause of Failure	Accuracy (%)
Obstacle avoidance	10	2	Orientation drift (Open-loop control)	20

The accuracy of the robot's obstacle avoidance capabilities is lower than desired due to the robot's orientation after each turn. Out of ten trials the accuracy rate is 20%.

3.2 Discussion

On the positioning aspect, the robot achieved a positioning accuracy of 74.27% when static, decreasing slightly to 72% during motion. While the Kalman filter successfully smoothed the raw RSSI data (as evidenced by the reduction in signal variance in Figure 7), the remaining error highlights the inherent challenges of BLE-based positioning, such as signal fluctuation and multipath effects. It is important to note that while the filter improved signal stability, a direct quantitative comparison of positioning accuracy with and without the filter was not conducted in this study. The current accuracy is dependent on the grid size; larger environments may introduce higher absolute errors. The loss of accuracy in movement indicates potential issues the system faces in varying scenarios. Since the raw RSSI values have noise introduced by environmental factors such as ambient temperature, magnetic fields, and the indoor space layout itself, some form of filtering is required to obtain more consistent and reliable values for distance estimation. The Kalman filter used here can fail because it must learn from past values in making a prediction on the next outcome. However, this does take time and gets in the way of computation.

For the obstacle detection, the robot is 100% accurate in sensing various materials, including cloth, water bottles, cardboard, and glass, which is an indication of its good sensor capabilities. The 100% accuracy resulted from the detection range set for this project, which is approximately 25 cm. This range is perfect and allows the robot to pass over obstacles without tripping. The materials used are not of a specific type either. For instance, a thin material may remain unnoticed by the ultrasonic sensor as the ultrasonic sound can merely pass through it.

While detection was reliable across various materials, the avoidance system failed in 80% of trials. This low success rate is directly checking attributed to the open-loop control system. The robot relies solely on motor timing to determine turn angles. In the absence of feedback sensors (such as wheel encoders or gyroscopes), factors like tire traction, battery voltage drop, and floor friction cause orientation drift. A slight error in the turn angle accumulates, preventing the robot from returning effectively to its original path.

Several limitations affect the system's robustness. First, BLE signals are highly susceptible to environmental interference (human bodies, metal furniture), leading to RSSI instability despite filtering. Second, the open-loop motor control renders the navigation prone to cumulative errors, making it unsuitable for precision-critical tasks without hardware upgrades. Finally, the scalability of the current trilateration approach may be limited in very large or complex environments where line-of-sight to beacons is obstructed.

4. Conclusions

The implementation of an indoor self-sensing positioning robot based on Bluetooth Low Energy (BLE) represents a significant development in autonomous navigation research. Through the integration of ultrasonic sensors for obstacle detection and BLE for real-time positioning, the system demonstrates a viable alternative to GPS for indoor environments. The combination of trilateration techniques with a Kalman filter effectively stabilized signal readings, resulting in an average positioning accuracy of approximately 74% in static conditions.

While the positioning results demonstrate potential, the obstacle avoidance system requires substantial improvement. The 20% success rate in avoidance maneuvers highlights the inadequacy of open-loop control for precise navigation. Future work will prioritize the integration of wheel encoders and an Inertial Measurement Unit (IMU/Gyroscope) to provide closed-loop feedback, directly addressing the orientation drift issue. Additionally, exploring advanced sensor fusion algorithms could further mitigate BLE signal instability. With these enhancements, the system architecture shows promise for applications in smart buildings and warehousing logistics.

References

[1] Leong, Pui Yee, and Nur Syazreen Ahmad. "LiDAR-based obstacle avoidance with autonomous vehicles: A comprehensive review." *IEEE Access* (2024). https://doi.org/10.1109/ACCESS.2024.3493238

[2] Rathod, Shusmita M., and S. K. Apte. "Obstacle detection using sensor based system for an four wheeled autonomous electric robot." In *2019 International Conference on Communication and Electronics Systems (ICCES)*, pp. 493-497. IEEE, 2019. https://doi.org/10.1109/ICCES45898.2019.9002065

[3] Oh, Sung Hyun, and Jeong Gon Kim. "DNN based WiFi positioning in 3GPP indoor office environment." In *2021 International Conference on Artificial Intelligence in Information and Communication (ICAIIC)*, pp. 302-306. IEEE, 2021. https://doi.org/10.1109/ICAIIC51459.2021.9415207

[4] Tang, Jintao, Lvqing Yang, Jiangsheng Zhao, Yishu Qiu, Yihui Deng, and Shaoqin Shen. "Research on RFID indoor positioning algorithm based on attention." In *2021 IEEE International Conference on Electronic Technology, Communication and Information (ICETCI)*, pp. 140-143. IEEE, 2021. https://doi.org/10.1109/ICETCI53161.2021.9563444

[5] Neyaz, Hera, Muhammad Inamullah, and MM Sufyan Beg. "Machine learning based indoor positioning system using Wi-Fi fingerprinting dataset." In *2024 International Conference on Electrical, Computer and Energy Technologies (ICECET*, pp. 1-5. IEEE, 2024. https://doi.org/10.1109/ICECET61485.2024.10698116

[6] Gao, Mingyu, Jindi Tang, Yuxiang Yang, Zhiwei He, and Yu Zeng. "An obstacle detection and avoidance system for mobile robot with a laser radar." In *2019 IEEE 16th International Conference on Networking, Sensing and Control (ICNSC)*, pp. 63-68. IEEE, 2019. https://doi.org/10.1109/ICNSC.2019.8743288

[7] Hutabarat, Dony, Muhammad Rivai, Djoko Purwanto, and Harjuno Hutomo. "Lidar-based obstacle avoidance for the autonomous mobile robot." In *2019 12th International Conference on Information & Communication Technology and System (ICTS)*, pp. 197-202. IEEE, 2019. https://doi.org/10.1109/ICTS.2019.8850952

[8] Jabade, Vaishali, Udit Nahata, Nipun Jain, Anvesh Pandey, and Tanmay Paratkar. "Obstacle detection and walkable path detection." In *2022 IEEE Delhi section conference (DELCON)*, pp. 1-5. IEEE, 2022. https://doi.org/10.1109/DELCON54057.2022.9753182

[9] Kiran, B., S. Karthikeyan, MA Suhel Pasha, K. N. Manjunatha, S. Manoj Kumar, and Sharvin Vivian Moras. "Design and development of autonomous mobile robot for mapping and navigation system." In *2022 IEEE Pune Section International Conference (PuneCon)*, pp. 1-5. IEEE, 2022 https://doi.org/10.1109/PuneCon55413.2022.10014944

[10] Anusha, T. R., S. Selva Kumar, and S. Panday. "*ROS Based Obstacle Detection Robot Using Ultrasonic Sensor and FMCW RADAR.*" In 3rd International Conference on Electronics and Sustainable Communication Systems (ICESC), (2022). https://doi.org/10.1109/ICESC54411.2022.9885346

[11] Petrov, Plamen, Veska Georgieva, Stiliyan Nikolov, and Antonia Mihaylova. "Real-time laser obstacle detection system for autonomous mobile robot navigation." In *2019 X National Conference with International Participation (ELECTRONICA)*, pp. 1-4. IEEE, 2019. https://doi.org/10.1109/ELECTRONICA.2019.8825623

[12] Xia, Jingbo, Yanting Wang, Baoxiang Jiang, and Guancheng Xiong. "Research on indoor positioning system based on BLE-AOA/UWB technology." In *2022 41st Chinese Control Conference (CCC)*, pp. 5100-5105. IEEE, 2022. https://doi.org/10.23919/CCC55666.2022.9902552

[13] Alsmadi, Laial, Xiaoying Kong, Kumbesan Sandrasegaran, and Gengfa Fang. "An improved indoor positioning accuracy using filtered RSSI and beacon weight." *IEEE Sensors Journal* 21, no. 16 (2021): 18205-18213. https://doi.org/10.1109/JSEN.2021.3085323

[14] Chen, Xin, Ao Peng, and Biyu Tang. "Automatic radio map adaptation for wifi fingerprint positioning systems." In *2020 5th International Conference on Communication, Image and Signal Processing (CCISP)*, pp. 64-69. IEEE, 2020. https://doi.org/10.1109/CCISP51026.2020.9273484

[15] Huang, Yung-Fa, Shu-Wai Chang, and Yung-Hoh Sheu. "Performance of Adaptive Offset Cancellation Method for UWB Indoor Positioning System." In *2023 International Conference on Consumer Electronics-Taiwan (ICCE-Taiwan)*, pp. 589-590. IEEE, 2023. https://doi.org/10.1109/ICCE-Taiwan58799.2023.10226622

[16] Saravanan, M., P. Satheesh Kumar, and Amit Sharma. "IoT enabled indoor autonomous mobile robot using CNN and Q-learning." In *2019 IEEE International Conference on Industry 4.0, Artificial Intelligence, and Communications Technology (IAICT)*, pp. 7-13. IEEE, 2019. https://doi.org/10.1109/ICIAICT.2019.8784847

[17] Siddiqa, Asima, Satyanarayana Sahoo, and K. Saraswathi. "Design and implementation of indoor positioning using uwb positioning algorithm for indoor navigation." In *2022 IEEE 3rd Global Conference for Advancement in Technology (GCAT)*, pp. 1-7. IEEE, 2022. https://doi.org/10.1109/GCAT55367.2022.9971871

[18] Li, Zhitian, Wuhao Yang, Linhui Xiao, Xingyin Xiong, Zheng Wang, and Xudong Zou. "Integrated wearable indoor positioning system based on visible light positioning and inertial navigation using unscented kalman filter." In *2019 11th International Conference on Wireless Communications and Signal Processing (WCSP)*, pp. 1-6. IEEE, 2019. https://doi.org/10.1109/WCSP.2019.8928098

[19] Madleňák, Matúš, and Erika Skýpalová. "Experimental Testing of Received Signal Strength in Indoor Positioning System." In *2024 International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA)*, pp. 1-4. IEEE, 2024. https://doi.org/10.1109/HORA61326.2024.10550904

[20] Phutcharoen, K., M. Chamchoy, and P. Supanakoon. "*Accuracy Study of Indoor Positioning with Bluetooth Low Energy Beacons.*" In 2020 Joint International Conference on Digital Arts, Media and Technology with ECTI Northern Section Conference on Electrical, Electronics, Computer and Telecommunications Engineering (ECTI DAMT and NCON), (2020). https://doi.org/10.1109/ECTIDAMTNCON48261.2020.9090691