Improved Indoor Localization Mechanism for Automated Guided Robots Using Bluetooth Beacons

1st Fakih Irsyadi
Departement of Electrical Engineering and Informatics
Universitas Gadjah Mada
Sleman, Indonesia
fakih.irsyadi@ugm.ac.id

2nd Jans Hendry
Departement of Electrical Engineering and Informatics
Universitas Gadjah Mada
Sleman, Indonesia
jans.hendry@ugm.ac.id

3rd Joko Slamet Saputro
Departement of Electrical Engineering
Universitas Sebelas Maret
Surakarta, Indonesia
jssaputro89@staff.uns.ac.id

4th Aji Bambang Sasongko
Departement of Electrical Engineering and Informatics
Universitas Gadjah Mada
Sleman, Indonesia
aji.bambang.sasongko@mail.ugm.ac.id

5th Muhammad Harrys Gumay
Departement of Electrical Engineering and Informatics
Universitas Gadjah Mada
Sleman, Indonesia
muhammad.harrys.gumay@mail.ugm.ac.id

*Corresponding author: fakih.irsyadi@ugm.ac.id
Received: April 03, 2025; **Accepted:** April 23, 2025

***Abstract*—Robot localization is essential for successful navigation, particularly in indoor environments where Global Positioning System (GPS) devices are ineffective. Bluetooth Low Energy (BLE) beacons provide a promising solution by transmitting 2.4GHz signals that can be interpreted by nearby robots. The trilateration method, utilizing Received Signal Strength Indicator (RSSI) values from BLE beacons at predefined locations, enables position estimation. However, RSSI values are highly susceptible to fluctuations and environmental interference, leading to significant errors. This research addresses these challenges by developing a low-cost beacon device using an ESP32 microcontroller and implementing a Kalman filter to minimize RSSI fluctuations. A curve fitting method is applied to convert filtered RSSI data into distance estimates, offering improved accuracy compared to the path loss model. The trilateration approach determines the robot's position based on three dominant BLE beacons, selected for their signal strength. Results demonstrate that the proposed localization system is effective, with the integration of the Kalman filter and beacon selection mechanism significantly enhancing positional accuracy. This study contributes to the advancement of indoor localization by providing a robust and cost-efficient system suitable for autonomous mobile robot navigation.**

Keywords*—*Indoor Localization, BLE, Trilateration, Multilateration, RSSI.

I. Introduction

Amidst the advancements of the industrial era, the field of robotics has advanced and is widely applied in various human activities. Autonomous Mobile Robots (AMRs) have been extensively used in industrial environments and other applications due to their high levels of efficiency and productivity[1], [2]. Recently, AMRs with differential drive wheels have gained increasing attention and have been widely implemented due to their advantages, such as flexible mobility, simple structure, and lower production costs [3]. AMRs, which are an evolution of Automated Guided Vehicles (AGVs), have been utilized in modern industries as tools for moving materials more flexibly compared to conventional conveyors.

AMRs interact with their environment through sensors to move and function autonomously. The robot's movement cycle begins with perception and localization. Once the robot's location is estimated and compared to a global map, the next action to be taken is determined (cognition). The robot then moves and navigates through the environment until it reaches its target position (movement control) [4]. Localization is one of the most challenging problems in robot motion research. The inability of Global Positioning System (GPS) devices to function in indoor environments makes this topic intriguing for ongoing research.

In essence, various studies on mobile robot localization have been conducted to date. Odometry is one of the most used localization mechanisms for mobile robots. Odometry utilizes encoder data installed on the robot's wheels to determine the distance traveled by the robot (from its initial position) by calculating the rotation and/or steering angle of the robot's wheels [5]. Odometry is often used because it is simple, inexpensive, and easy to implement. However, this method is highly prone to errors, both systematic and non-systematic. Systematic errors can often be resolved by adding error compensation, as error profiles tend to follow patterns. For non-systematic errors, additional external sensors are required to minimize these errors. In the study by Chen & Zhang [6], an electronic compass was added to help the robot minimize non-systematic errors.

Another method that can be used for localization is through Bluetooth Low Energy (BLE) beacons. The process of location identification is carried out by measuring the signal strength emitted by BLE beacons installed along the track. The signal strength values, or Received Signal Strength Indicators (RSSI), are inversely proportional to the distance between the transmitter and receiver. By using several BLE beacons placed statically at various locations, the relative position of the robot can be determined and used to establish the global location by utilizing the beacon location information. One method that can be used to estimate the robot's location is the trilateration algorithm [7].

However, RSSI values are highly susceptible to fluctuations and environmental interference, leading to significant localization errors [8], [9]. To address these challenges, this study proposes the development of a low-cost beacon device using an ESP32 microcontroller and the implementation of a Kalman filter to minimize RSSI fluctuations. A curve fitting method is utilized to convert the filtered RSSI data into distance estimates, providing improved accuracy compared to traditional path loss models. The trilateration approach is further refined by selecting three dominant BLE beacons based on signal strength, ensuring more reliable position estimation.

This study aims to demonstrate the effectiveness of integrating the Kalman filter and beacon selection mechanism in improving positional accuracy for indoor localization. By providing a robust and cost-efficient system, this research contributes to advancing indoor localization, particularly for autonomous mobile robot navigation in challenging environments.

II. METHOD

A. Localization Sustem Based on Bluetooth Low Energy (BLE) Beacons

BLE is a Bluetooth 4.0 technology operating at a 2.4 GHz frequency band. Similar to classic Bluetooth technology, BLE is also used as a medium for transmitting limited-capacity data with very low power consumption. In this study, BLE operates with an advertising event protocol, which allows receivers to receive data packets and measure RSSI values for localization mechanisms [10]. The robot's location is determined using a trilateration mechanism involving three dominant BLE beacons while ignoring others with low RSSI values at a given position. In this study, four BLE beacons are placed at all corners of the robot arena, as shown in Fig. 1.

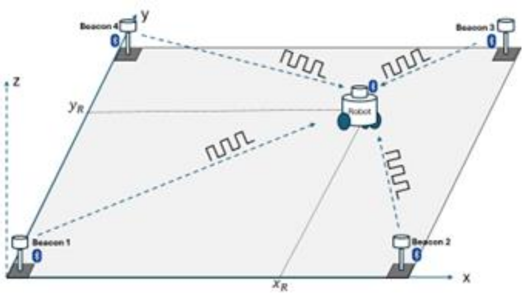

Fig. 1. Ilustration of Localization System Based on BLE Beacon.

B. RSSI Data Preprocessing Mechanism

Data preprocessing focuses on improving data quality by addressing noise during measurement. Several types of filters, including the Median filter, EMA (Exponential Moving Average) filter, and Kalman filter, will be implemented and their performances compared in this study. The Kalman Filter is an estimation algorithm used to predict the true value of a measured variable. It employs the Linear Minimum Mean Square Error Prediction (LMMSE) and Linear Recurrence Updating system, aiming to minimize estimation errors by optimally accounting for noise distribution [11]. In the context of RSSI, the Kalman Filter smooths signal variations caused by noise or fluctuations in communication between beacons.

The EMA (Exponential Moving Average) filter is a signal processing filter used to reduce fluctuations in RSSI values. This filter assigns exponentially greater weights to recent data, making it more responsive and effectively reducing temporary fluctuations [12][13]. Another type of filter implemented in this study is the Median Filter. In the research titled *“A Novel Distance Estimation Algorithm for Bluetooth Devices Using RSSI”*, the Median Filter is used to remove outliers in RSSI caused by noise due to multipath fading in indoor scenarios [8].

C. RSSI Data Conversion Mechanism

Data conversion is the process of transforming RSSI values into distance values, which are then used as inputs in position estimation equations. The first mechanism is the Path Loss Model, a mathematical model used to estimate attenuation or signal power loss occurring as a radio signal travels through a medium or depends on environmental conditions. The Path Loss Model employed in this study is the Log-Distance model, which provides more optimal attenuation estimation by incorporating an exponent factor as an environmental factor value. The path loss exponent used, based on the experimental environment, is 2.7 for Urban area cellular radio conditions [9].

In addition to the Path Loss Model, another method applied involves curve-fitting the average RSSI values at each experimental distance to derive an equation better suited to the system. Curve-fitting is performed using an exponential system, as radio signals experience exponential attenuation with increasing or decreasing distance from the signal source due to multipath fading effects [14], [15].

D. Positioin Estimation Mechanism

Trilateration is a method for estimating a position by utilizing distances measured from three reference points with known locations [16][17]. The trilateration equation is fundamentally based on the equation of a circle, as follows (1).

$$\cdot\, dn^2 = (x - x_n)^2 + (y - y_n)^2 \tag{1}$$

If all three beacons are used, the following three equations are obtained.

$$d_1{}^2 = (x - x_1)^2 + (y - y_1)^2 \tag{2}$$

$$d_2{}^2 = (x - x_2)^2 + (y - y_2)^2 \tag{3}$$

$$d_3{}^2 = (x - x_3)^2 + (y - y_3)^2 \tag{4}$$

Next, subtracting (3) and (4) from (2) results in:

$$A_1 = -2(x_1 - x_2) \tag{5}$$

$$A_2 = -2(x_1 - x_3) \tag{6}$$

$$B = d_1{}^2 - d_2{}^2 - (x_1{}^2 + y_1{}^2) + (x_2{}^2 + y_2{}^2) \tag{7}$$

$$C_1 = -2(y_1 - y_2) \tag{8}$$

$$C_2 = -2(y_1 - y_3) \tag{9}$$

$$D = d_1{}^2 - d_3{}^2 - (x_1{}^2 + y_1{}^2) + (x_3{}^2 + y_3{}^2) \tag{10}$$

To find x and y, the solution is calculated using (11) and (12).

$$x = \frac{B.C_2 - D.A_2}{A_1.C_2 - C_1.A_2} \qquad (11)$$

$$y = \frac{B - A_1.x}{A_2} \qquad (12)$$

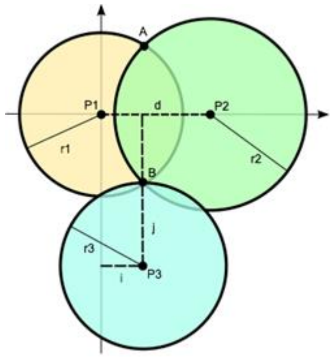

Fig. 2. Ilustration of Position Estimation with Trilateration.

In multilateration, the concept is similar to trilateration. However, in multilateration, the system can use multiple measured position distances from reference points without limitations [18]. The underlying equation is also based on the circle equation to obtain the distance from the reference point. Multilateration can be defined by the following equation.

$$\mathbf{A} = 2\begin{bmatrix} (x_{i=1} - x_{i+1}) & (y_{i=1} - y_{i+1}) \\ (x_{i=1} - x_{i+2}) & (y_{i=1} - y_{i+2}) \\ \vdots & \vdots \\ (x_{i=1} - x_n) & (y_{i=1} - y_n) \end{bmatrix} \qquad (13)$$

$$\mathbf{X} = \begin{bmatrix} x_{est} \\ y_{est} \end{bmatrix} \qquad (14)$$

$$\mathbf{B} = \begin{bmatrix} \left(({d_{i+1}}^2 - {d_{i=1}}^2) - ({x_{i+1}}^2 + {y_{i+1}}^2) + ({x_{i=1}}^2 + {y_{i=1}}^2)\right) \\ \left(({d_{i+2}}^2 - {d_{i=1}}^2) - ({x_{i+2}}^2 + {y_{i+2}}^2) + ({x_{i=1}}^2 + {y_{i=1}}^2)\right) \\ \vdots \\ \left(({d_n}^2 - {d_{i=1}}^2) - ({x_n}^2 + {y_n}^2) + ({x_{i=1}}^2 + {y_{i=1}}^2)\right) \end{bmatrix} \qquad (15)$$

Matrix X is the result of the estimation and can be solved using the following (16), utilizing (13) and (15).

$$\mathbf{X} = (\mathbf{A}^{\mathbf{T}}.\mathbf{A})^{-1}\mathbf{A}^{\mathbf{T}}.\mathbf{B} \qquad (16)$$

III. Results and Discussion

The position estimation mechanism consists of several stages including data acquisition, data preprocessing, data conversion, and position estimation system.

A. Data Acquisition

RSSI values will be measured against distance changes from zero to 5 meters with an interval of 0.5 meters. At each distance point, 500 data samples are taken for processing, and the standard deviation is calculated. The RSSI sample data for a distance of 1 meter is shown in Fig. 3 shows that the measured RSSI data fluctuates due to noise. Table 1 shows all measurement data with fluctuation levels represented by the standard deviation of 500 data samples for each distance. Based on the measurement results, it is observed that the data is more stable at closer distances and tends to be more fluctuating at greater distances.

TABLE I. RSSI and Standard Deviation for Distances 0-5 Meter

Distance (m)	Lower RSSI (dB)	Upper RSSI (dB)	Mean	Std. Deviation
~0	-18	-16	-17.04	0.21
0.5	-59	-42	-44.80	3.13
1	-73	-47	-64.30	4.36
1.5	-81	-47	-69.48	6.66
2	-79	-71	-75.62	1.58
2.5	-83	-70	-76.92	3.39
3	-85	-73	-79.44	3.20
3.5	-83	-74	-79.60	2.10
4	-98	-74	-83.84	4.67
4.5	-98	-74	-79.45	5.38
5	-102	-79	-87.23	7.01

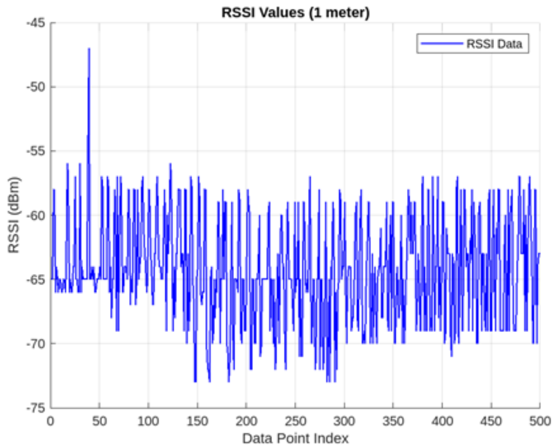

Fig. 3. RSSI value at 1 Meter.

This can also be observed from the standard deviation values of every 500 data samples at each distance. Data conditioning mechanisms are needed so that the data can be used for the position estimation process.

B. Data Preprocessing

Fig. 4(a) shows the results of applying three types of filters to the RSSI data for a distance of 1 meter, and Fig. 4(b) shows the comparison of signal standard deviation values from the three filters for all distance combinations.

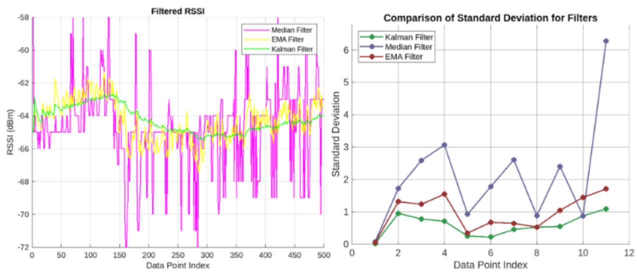

Fig. 4. (a) Filtering Results, (b) Graph of Filters Standard Deviation

The results show that the Median filter produces the largest and most unstable signal fluctuations, although it can dampen some extreme signal spikes. The EMA filter produces smoother signals compared to the Median filter. This method gives exponential weights to historical data, thus reducing signal fluctuations. However, some fluctuations are still noticeable in some parts. The Kalman filter shows the most stable and smooth results compared to the other two methods. This filter works by predicting the signal value based on a statistical model and correcting this prediction using actual measurements, resulting in a smoother signal with the highest standard deviation value of 1.092 and the lowest at 0.017. Fig. 4(b) shows that the system has increasing standard deviation values as the distance increases. In the Median filter, the standard deviation is higher compared to the other two filters, and the best result is obtained with the Kalman filter, which has a lower average standard deviation value than the other two filters. Therefore, the Kalman filter will be used in the position estimation process to achieve results with smaller distance errors.

C. Data Conversion

At this stage, the use of the path loss model is compared with the results of exponential curve-fitting using Matlab software, with the RMSE (Root Mean Square Error) value for the average RSSI values at distances from 0 to 5 meters, with an interval of 0.5 meters. The path loss model, log distance, has the following equation.

$$RSSI(d) = RSSI(d_0) + 10n \log 10 \left(\frac{d}{d_0}\right) \tag{17}$$

Thus, the RSSI to distance conversion equation is as follows:

$$d = d_0 10^{\left(\frac{RSSI(d_0) - RSSI(d)}{10n}\right)} \tag{18}$$

In Fig. 5(a), the model has a pattern similar to the measurement pattern. The RMSE for each point is 0.5945. In the curve-fitting results, the equation and variable values are as follows:

$$d = ae^{bRSSI(d)} \tag{19}$$

$$a = 0.0165 \tag{20}$$

$$b = -0.0662 \tag{21}$$

In Fig. 5(b), the fitted curve graph pattern has a higher degree of similarity compared to the path loss model in Fig. 5(a) proven by the RMSE value for each sample, which is 0.3427. The result shows that the fitted exponential curve method is more optimal and will be used to generate input data for the location determination process.

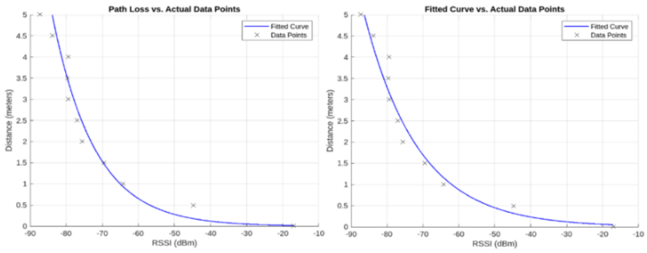

Fig. 5. (a) Path Loss Model Graph, (b) Fitted Curve Graph

D. Position Estimation

Trilateration and multilateration methods are used for location determination. In trilateration (after beacons selection mechanism), the system will only use three of the four beacons with dominant RSSI values for each iteration. The results of the trilateration and multilateration estimation are shown in Table 2 and 3 below.

TABLE II. RESULT OF TRILATERATION

True Position (x, y in cm)	Estimated Position Trilateration (x, y in cm)	Distance Error Trilateration (cm)
(0, 0)	(0, 0)	0
(250,250)	(273.05, 239.08)	25.50
(-250, 250)	(-312.56, 239.83)	63.38
(-250,-250)	(-239.85, -210.11)	41.16
(250,-250)	(464.79,-273.57)	216.08
(0, 250)	(0, 144.94)	105.06
(-250, 0)	(-204.23, -38.77)	59.98
(0, -250)	(-26.06, -111.22)	141.20
(250, 0)	(150.11, 60.34)	116.70

TABLE III. RESULT OF MULTILATERATION

True Position (x, y in cm)	Estimated Position Multilateration (x, y in cm)	Distance Error Multilateration (cm)	Distance Error Difference (Multilateration-Trilateration)
(0, 0)	(-281.68, -281.68)	281.68	281.68
(250,250)	(193.35, 159.39)	75.56	50.06
(-250, 250)	(-283.43, 181.58)	53.85	-9.53
(-250,-250)	(-626.03, -596.28)	361.46	320.30
(250,-250)	(433.61, -257.98)	129.95	-86.13
(0, 250)	(-119.27, 25.67)	179.65	74.59
(-250, 0)	(-108.48, 56.98)	107.88	47.90
(0, -250)	(-97.29, 31.24)	210.43	69.23
(250, 0)	(129.99, 40.23)	89.49	-27.20

The trilateration result for position (0, 0) shows perfect accuracy with a distance error of 0, while other positions show varying errors, with the largest error being 216.08 cm at position (250, -250). On the other hand, the multilateration results show very large inaccuracies. This is because there is no selection mechanism before the calculation. The smallest distance error occurs at the point (-250, 250) with a value of 53.85 cm, and the smallest difference is -9.53. The largest distance error occurs at the point (-250, -250) with a value of 361.46 cm, and the difference from trilateration is 320.30 cm. The results show that the trilateration after beacons selection system performs better than multilateration.

IV. CONCLUSION

Based on the experimental results, it was found that the design of a robot localization mechanism in an indoor environment using BLE beacons was successfully implemented. The fluctuation of the measured RSSI signals can be conditioned using filters, and in this study, the Kalman filter showed the highest effectiveness in reducing signal fluctuations. Furthermore, for the data conversion mechanism, the exponential curve-fitting method demonstrated better performance compared to the path loss model.

The position estimation results indicated that the trilateration method with a beacon selection system achieved higher accuracy compared to the multilateration method. This highlights the potential of using BLE beacons for position estimation in robots, with further optimization possible in the future.

ACKNOWLEDGMENT

This research was made possible by funding from the Hibah Dana Masyarakat (Damas) of the Vocational School of Universitas Gadjah Mada for the fiscal year 2024. The authors would like to express their gratitude to all those

including for the team members from Universitas Sebelas Maret for the contribution in this study.

References

[1] M. T. Ballestar, Á. Díaz-Chao, J. Sainz, and J. Torrent-Sellens, “Knowledge, robots and productivity in SMEs: Explaining the second digital wave,” J. Bus. Res., vol. 108, pp. 119–131, 2020.

[2] F. Rubio, F. Valero, and C. Llopis-Albert, “A review of mobile robots: Concepts, methods, theoretical framework, and applications,” Int. J. Adv. Robot. Syst., vol. 16, no. 2, p. 1729881419839596, 2019.

[3] N. T. T. Van, N. M. Tien, N. C. Luong, and H. T. K. Duyen, “Energy Consumption Minimization for Autonomous Mobile Robot: A Convex Approximation Approach,” J. Robot. Control, vol. 4, no. 3, pp. 403–412, 2023.

[4] F. A. X. Da Mota, M. X. Rocha, J. J. P. C. Rodrigues, V. H. C. De Albuquerque, and A. R. De Alexandria, “Localization and navigation for autonomous mobile robots using petri nets in indoor environments,” IEEE access, vol. 6, pp. 31665–31676, 2018.

[5] R. Haq, “Kendali posisi mobile robot menggunakan sistem proportional integral derivative (pid) dengan metode odometry,” J. Inov. Fis. Indones., vol. 6, no. 3, 2017.

[6] W. Chen and T. Zhang, “An indoor mobile robot navigation technique using odometry and electronic compass,” Int. J. Adv. Robot. Syst., vol. 14, no. 3, p. 1729881417711643, 2017.

[7] A. Handojo, T. Octavia, R. Lim, and J. K. Anggita, “Indoor positioning system using BLE beacon to improve knowledge about museum visitors.” Petra Christian University, 2020.

[8] J. Huang, S. Chai, N. Yang, and L. Liu, “A novel distance estimation algorithm for Bluetooth devices using RSSI,” in 2017 2nd International Conference on Control, Automation and Artificial Intelligence (CAAI 2017), 2017, pp. 379–381.

[9] A. L. Imoize and A. I. Oseni, “Investigation and pathloss modeling of fourth generation long term evolution network along major highways in Lagos Nigeria,” Ife J. Sci., vol. 21, no. 1, pp. 39–60, 2019.

[10] U. M. Qureshi, Z. Umair, Y. Duan, and G. P. Hancke, “Analysis of bluetooth low energy (ble) based indoor localization system with multiple transmission power levels,” in 2018 IEEE 27th International Symposium on Industrial Electronics (ISIE), 2018, pp. 1302–1307.

[11] Z. Kaibi, Z. Yangchuan, and W. Subo, “Research of RSSI indoor ranging algorithm based on Gaussian - Kalman linear filtering,” Proc. 2016 IEEE Adv. Inf. Manag. Commun. Electron. Autom. Control Conf. IMCEC 2016, no. 3, pp. 1628–1632, 2017, doi: 10.1109/IMCEC.2016.7867493.

[12] M. H. P. Swari, I. P. S. Handika, and I. K. S. Satwika, “Comparison of simple moving average, single and modified single exponential smoothing,” in 2021 IEEE 7th Information Technology International Seminar (ITIS), 2021, pp. 1–5.

[13] I. B. Setyawan, A. K. Huda, F. H. Nashrullah, I. D. Kurniawan, S. I. Frans, and J. Hendry, “Noise Removal in The IMU Sensor Using Exponential Moving Average with Parameter Selection in Remotely Operated Vehicle (ROV),” in 2022 8th International Conference on Science and Technology (ICST), 2022, vol. 1, pp. 1–5.

[14] Y. A. Zakaria, E. K. I. Hamad, A. S. A. Elhamid, and K. M. El-Khatib, “Developed channel propagation models and path loss measurements for wireless communication systems using regression analysis techniques,” Bull. Natl. Res. Cent., vol. 45, pp. 1–11, 2021.

[15] D. Puccinelli and M. Haenggi, “Multipath fading in wireless sensor networks: Measurements and interpretation,” in Proceedings of the 2006 international conference on Wireless communications and mobile computing, 2006, pp. 1039–1044.

[16] N. Pakanon, M. Chamchoy, and P. Supanakoon, “Study on accuracy of trilateration method for indoor positioning with BLE beacons,” in 2020 6th international conference on engineering, applied sciences and technology (ICEAST), 2020, pp. 1–4.

[17] J. Luomala and I. Hakala, “Adaptive range-based localization algorithm based on trilateration and reference node selection for outdoor wireless sensor networks,” Comput. Networks, vol. 210, p. 108865, 2022.

[18] L. S. De Oliveira, O. K. Rayel, and P. Leitao, “Low-cost indoor localization system combining multilateration and kalman filter,” in 2021 IEEE 30th International Symposium on Industrial Electronics (ISIE), 2021, pp. 1–6.