

Indoor positioning with trilateration using orientation-based FSPL model selection

Dominik Csík^{1,2}, Ákos Odry², Peter Sarcevic²

With the rise of Industry 4.0, wireless sensor networks (WSN) are increasingly vital, particularly in indoor positioning applications using various positioning techniques. Radiocommunication-based technologies such as WiFi and Bluetooth Low Energy (BLE), Ultra-Wideband (UWB) technologies are receiving growing attention in this area. The Free Space Path Loss (FSPL) model establishes a relationship between signal attenuation during propagation and distance. Previous studies have demonstrated that considering the angle between individual modules, i.e., their orientation, can significantly impact the accuracy of distance estimation. In this paper, an orientation-based positioning method is proposed. The appropriate FSPL model is selected based on the orientation of both the anchors and the station unit to compute the distance, followed by position determination using trilateration. This method was compared to a generalized FSPL model approach. In the tested scenario, the proposed orientation-based method demonstrated superior performance, achieving a 13% relative improvement in the average of the Mean Absolute Error (MAE).

Keywords: trilateration, Free Space Path Loss (FSPL) model, radiocommunication-based technologies, indoor positioning, received signal strength indicator

1 Introduction

Positioning is a critical task in many applications and many areas (mobile robotics, trajectory planning, automated warehouses etc.). The positioning systems used in outdoor environments are not able to perform indoor positioning tasks. The widely used Global Navigation Satellite Systems (GNSS) [1-4] such as the European Galileo, the Chinese BeiDou, the American Global Positioning System (GPS) [5] and the Russian GLONASS do not fulfil the requirements for indoor applications [2, 6]. The basic requirement for their application is a direct line of sight (LOS) between the transmitter and the receiver, which is not possible indoors. The signals are often obstructed or attenuated by various structural elements such as walls, ceilings, floors, and even large objects or machinery. This obstruction leads to weakened signals or complete signal loss, which in turn results in significant inaccuracies in position estimations. Additionally, the signal propagation indoors is further complicated by factors such as multipath effects and variations in the dielectric properties of building materials, which can alter signal strength and travel paths. Other methods and tools must be used indoors [2,3].

Indoors, several methods can be used to perform positioning. There are methods that can calculate absolute position, while other methods are suitable for

relative positioning. During relative positioning, such as dead reckoning with encoders [4] or Inertial Measurement Units (IMU) [4], the error accumulates over time, and it is necessary to correct or fuse with an absolute positioning method [7]. The absolute position can be determined by different technologies. These include voice-based systems, radio communication-based technologies [2, 3, 8, 9, 10], magnetic field monitoring systems [6], optical systems, and camera systems [11]. Each technology presents a unique set of advantages and limitations, which affect their suitability for indoor localization depending on factors such as precision, cost, and environmental conditions. Camera systems, for instance, offer extensive coverage but are typically more expensive, requiring significant lighting and substantial computational resources. Conversely, optical systems deliver high accuracy but are also associated with high costs due to the advanced equipment they necessitate [11]. Systems based on radio communication technologies are more and more widely used. Indoor Positioning Systems (IPS) are composed of sensor nodes, which are called Wireless Sensor Networks (WSN). The sensor nodes monitor various parameters of the environment with their sensors. The structure of WSNs can be diverse based on topology. The most commonly used topologies are the point to point, star, mesh, hybrid and the tree topology [12]. The nodes are also able to change information between each

¹ Doctoral School of Applied Informatics and Applied Mathematics, Óbuda University, Budapest, 1034 Hungary

² Department of Mechatronics and Automation, Faculty of Engineering, University of Szeged, Szeged, 6724 Hungary
 csikd@mk.u-szeged.hu

other through wireless technologies. The most common radio communication-based technologies used in WSNs are the Radio Frequency Identification (RFID) [13], ZigBee [14], UWB [15], BLE [8-9], WiFi [4, 10, 16], [17], LoRa [18]. These technologies make absolute positioning possible.

The methods which are capable of positioning can be divided into two groups: range-based methods and range-free methods. Range-based methods require the knowledge of the distance between modules and rely on techniques such as Received Signal Strength Indicator (RSSI) [2,9,18], Time of Flight (TOF) [4], Round Trip Time (RTT) [4,10], Angle of Arrival (AOA) [15], or Time Difference of Arrival (TDOA) [19]. These techniques provide distances or angles that can be used to determine the position. The methods, which can be utilized to calculate position are probabilistic methods, area-based techniques (e.g., min-max and sum-dist) [8], geometric-based approaches (e.g., triangulation, trilateration, and multilateration) [2, 3, 8, 9]. However, range-based systems that rely on time measurements tend to be expensive due to the additional hardware required and the need for clock synchronization between transmitter and receiver modules. Despite their cost, these systems are generally more accurate than those based on RSSI measurements, which, while simpler and cheaper, are highly susceptible to environmental factors such as temperature, humidity, and the presence of obstacles [2]. Range-free methods, on the other hand, do not require the determination of distance for localization. Among these methods, Distance-Vector hop (DV-Hop) [20] and fingerprinting techniques are the most widely used [16,21].

Positioning using RSSI measurements can be achieved through the fingerprinting technique or by determining the distance and then using trilateration. The disadvantage of fingerprinting is that it requires measurements to be taken at specific points within the space at a defined resolution before positioning can occur. This process is known as the offline phase, during which a database is created. The resolution of these measurements directly affects the accuracy of the positioning. Various machine learning algorithms can be used in fingerprinting, including Decision Trees (DT), K-Nearest Neighbor (KNN), Weighted KNN (WKNN), Support Vector Machines (SVM), Random Forest (RF), and Artificial Neural Networks (ANN), such as Multi-layer Perceptron (MLP), Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN) [16], and Deep Q-Networks (DQN) [22, 23]. In contrast, trilateration does not involve an offline phase. Instead, the measured RSSI values are converted into distances using a specific model. One of the most used model for this purpose is the FSPL model next to the Log-Normal Shadowing Model (LNSM) [2] and the International Telecommunication Union (ITU) model [8].

The path loss models used in RSSI-based positioning are not the theoretical FSPL model. Instead, the empirical LNSM (5) is used. The parameters of this model can be determined by fitting the model to real-world measurements taken within the specific target environment. These empirical parameters effectively aggregate the average signal loss caused by fixed obstructions, walls, and mean multipath effects. Our work is built upon this established empirical methodology, seeking to refine it further.

While classical positioning methods like trilateration remain widely used due to their simplicity, recent state-of-the-art methodologies have achieved significant accuracy improvements. These include Deep Learning (DL) approaches, which have enhanced fingerprinting by using complex architectures like hybrid Convolutional and Recurrent Neural Networks (CNN-RNN/LSTM) to learn signal patterns [24], or by comparing CNN performance against other machine learning models in complex environments [25].

Other advanced techniques focus on advanced filtering and sensor fusion, which are crucial for handling the noisy, time-varying nature of RSSI, as highlighted in comprehensive reviews [26]. This involves using filtering algorithms like the Kalman Filter (KF), Extended Kalman Filter (EKF), and Particle Filters (PF) to fuse RSSI data with other sensors, such as Inertial Measurement Units (IMUs) for Pedestrian Dead Reckoning (PDR) [27]. Furthermore, Simultaneous Localization and Mapping (SLAM) techniques, typically using cameras, are also being integrated with radiofrequency data for robust fusion [28].

However, these methods often introduce trade-offs. DL, for instance, requires massive offline data collection and significant computational resources. SLAM and advanced filtering require more complex and power-hungry hardware (e.g., cameras). Our work, in contrast, focuses on improving the foundational accuracy and robustness of the classical, model-based trilateration method itself, providing a valuable, low-cost, and infrastructure-light alternative for applications where complexity and power consumption are primary constraints.

In [2], a novel trilateration method was proposed, which uses a Taylor series to reduce the complexity of the previous algorithms. The data was filtered by a Gaussian filter before it was used for trilateration. CC2250 modules were used to test the algorithm. The parameters of the propagation model were determined using the least squares curve fitting. The experimental results show that the proposed method outperformed the other, previously used methods.

The authors of [14] proposed Particle Swarm Optimization (PSO) to determine the parameters of the FSPL model. For the evaluation, measurements were con-

ducted in a $9 \text{ m} \times 12 \text{ m}$ room, where the anchors were positioned in the four corners of the room. During the evaluation, the position was determined using the K-Nearest Neighbor (KNN) algorithm. The results indicate that the proposed method outperforms the traditional approach. The positioning error ranged from 3.30 m to 4.17 m.

Reference [29] introduced a sensor fusion framework aimed at reducing localization errors by combining pedestrian dead reckoning (PDR) and WiFi RSSI with Kalman filter. The proposed system achieved a maximum position error of 1.6 m, representing a significant improvement compared to the PDR-only system, which had a maximum error of 2.9 m and the WiFi-only system, which had a maximum error of 2 m.

Previous research shows that FSPL models created for different orientations significantly improve distance estimation instead of using a generic model [30]. While that work focused on the empirical validation of this distance-level improvement, the new scientific contribution of this paper is the validation of the complete 3-phase positioning algorithm (detailed in Section 2.4) that utilizes this model framework. The aim is to investigate how much the position estimation can be improved if the orientation of the modules is considered. In this work an orientation-based positioning system is proposed, the positioning algorithm is trilateration. To determine the position, the distances are first given using a general FSPL model from the measured RSSI values. The resulting approximate position is further refined using the relative orientation of the anchor nodes at the reference points and the station module. To validate the effectiveness of this approach, its performance was benchmarked directly against the standard baseline method: trilateration using a single, generalized FSPL model that does not account for orientation. The results were validated in a simulation environment, where the RSSI values were simulated using real measurements. The assumption is that the positioning can be made more precise by taking the orientation into account.

The remainder of this paper is organized as follows. Section 2 describes the principles used, the operation of the positioning algorithm, and provides insight into the measurements. Section 3. presents the results for the different cases. Section 4 provides the future work plans

2 Materials and methods

2.1 Distance determination

The strength of the signal is reducing as it travels in the free space between the transmitter and the receiver. The Friis outdoor transmission Eqn. (1) describes the signal strength at a given distance [31].

$$P_{received}(d) = P_{tr} \cdot A_{tr} \cdot A_{rc} \left(\frac{\lambda}{4\pi d} \right)^2 \cdot \frac{1}{C}, \quad (1)$$

where $P_{received}(d)$ indicates the measured signal power (in W) at distance d , P_{tr} represents the power fed into the antenna (in W), A_{tr} and A_{rc} are the antenna gain factors (in m), λ is the wavelength (in m), d is the distance between the antennas (in m), and C represents the circuit loss factor (in m).

The FSPL phenomena can be derived from Eqn. (1) [9].

$$PL = \left(\frac{4\pi df}{c} \right)^2, \quad (2)$$

where f is the frequency of the signal (in Hz) and c is the speed of light (in m/s). The power of 2 represents the propagation in vacuum. Fluctuations, reflections, diffractions and refractions affect the propagation. This can be generalized for any environment In Eqn. (3) [9].

$$PL = \left(\frac{4\pi df}{c} \right)^N, \quad (3)$$

where N marks the propagation constant, which is usually between 1.6 and 4 depending on the environment. The path loss can be given in dB in Eqn. (4).

$$PL = 10 N \log_{10}(d) + 10 N \log_{10} \left(\frac{4\pi f}{c} \right), \quad (4)$$

From Eqn. (4), the RSSI can be determined as

$$RSSI = -10 N \log_{10}(d) + RSSI_{ref}, \quad (5)$$

where $RSSI_{ref}$ indicates the reference RSSI, which is given at 1 meter distance from the transmitter module. The distance can be calculated from RSSI value [9]:

$$d = 10^{-\frac{RSSI + RSSI_{ref}}{10N}}. \quad (6)$$

Next to the empirical FSPL model, different models can be found in the literature. ITU has recommendations for different scenarios [32]. The site-specific basic model can be given as

$$PL_{total} = PL(d_0) + N \log_{10} \left(\frac{d}{d_0} \right) + PL_f(n), \quad (7)$$

where $PL(d_0)$ is the basic transmission loss at the reference distance d_0 , $PL_f(n)$ represents the floor penetration loss factor, n is the number of floors between the modules.

LNSM is the generalized version of the FSPL model. The reference distance can be any distance. In this case the distance can be determined using (8) [2]:

$$d = d_0 + 10^{-\frac{RSSI + RSSI(d_0)}{10N}}. \quad (8)$$

2.2 Trilateration

Trilateration is a mathematical method employed to determine the position of an object by using the distances from multiple known reference points. The process begins by measuring the distance between the object and each reference point. These distances can be obtained using techniques such as TOF or RSSI. Each distance corresponds to the radius of a sphere, with the center of each sphere located at the coordinates of the respective reference point. The equations of the spheres are (9):

$$\begin{aligned} (x - x_1)^2 + (y - y_1)^2 + (z - z_1)^2 &= d_1^2 \\ (x - x_2)^2 + (y - y_2)^2 + (z - z_2)^2 &= d_2^2 \\ &\vdots \\ (x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2 &= d_i^2 \end{aligned} \quad (9)$$

where (x_i, y_i, z_i) are the coordinates of the reference points, and d_i is the radius, representing the distance from the reference point. The position is found at the intersection of these spheres. However, due to noise and inaccuracies in the measurements, the spheres may not intersect perfectly at a single point. To address this, techniques such as the least squares method are employed to estimate the coordinates [33]. This section defines the standard mathematical tool used for position estimation. The complete, multi-phase algorithmic framework that utilizes this tool is detailed in Section 2.4.

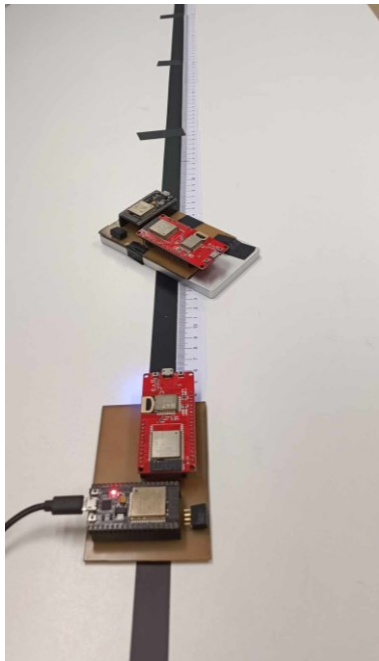
2.3 Measurement system and data collection

The measurement system utilized wireless technologies capable of measuring RSSI. The setup included two ESP32 modules, with one configured as an Access

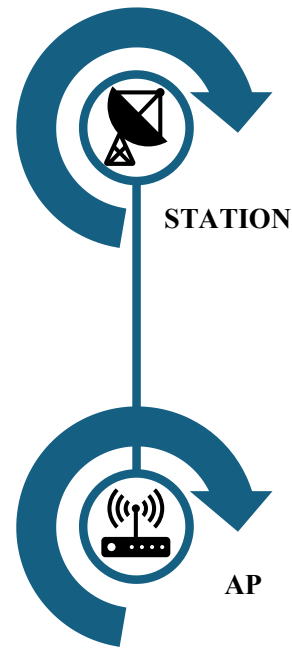
Point (AP) and the other as a Station (STATION), which can be seen in Fig. 1. Data collection was conducted over a 4-meter segment, with measurements taken at every 20 cm and in multiple orientations. At each measurement point, 10 measurements were taken for every orientation. The average of these 10 measurements was used for further analysis to reduce the impact of noise. The position of the AP module remained stationary throughout the experiment, but its orientation was altered by 90° increments. Meanwhile, the STATION module moved along the predefined path, with its orientation adjusted every 45°. The data was collected by a laptop through Message Queuing Telemetry Transport (MQTT) protocol. Node-red managed the storage of incoming data.

The measurements were conducted in a university laboratory. A significant portion of one wall of the room consisted of glass windows. The room was furnished with a long table, which was used for the measurement path, several metal chairs, and other laboratory equipment (PLC stations, power supplies) located along the walls. This represents a realistic, non-ideal indoor environment rich in metal objects and potential multi-path sources.

All rotations were performed only in the 2D horizontal plane, as described. This experimental setup was chosen to simulate the typical operating conditions of indoor mobile robots and pedestrians, where movement occurs on a planar surface. The data collection was automated, and no researchers were present in the room during the sampling process, eliminating any potential human-body shadowing effects.



(a)



(b)

Fig. 1. (a) The modules during measurement, and (b) the conception of the measurement

2.4 Orientation based positioning

The standard model (5) is a simplification that assumes ideal, isotropic antennas. In practice, the integrated PCB antennas on low-cost modules like the ESP32 are highly anisotropic; they possess complex, non-uniform 3D radiation patterns. This anisotropy means that the effective antenna gain (A_{tr} and A_{rc}) in the Friis transmission equation (1) is not constant. It changes significantly depending on the relative orientation (angle and rotation) between the transmitting and receiving modules [34]. This physical phenomenon introduces a systematic, orientation-dependent bias to the RSSI, which the generalized FSPL model treats as random noise, leading to large distance estimation errors. The proposed method addresses this by replacing the single generalized model with an empirically derived model selection framework. This framework is not a single complex equation, but a collection of multiple distinct, simple FSPL models as defined in (5).

The proposed method has three phases. The conception of the method can be seen in Fig. 2.

In the first phase, the multiple distinct, orientation-specific FSPL models are created. As justified above, this is an offline, empirical process. The two parameters (N and A) for each of the models are determined by applying the PSO optimization algorithm to the extensive measurement dataset (described in Section 2.3). This optimization, detailed in our prior work [35], finds the optimal parameters that best fit the real-world data for each specific orientation combination.

In the second phase, a preliminary position Estimation is performed using trilateration. For this initial step, the distances from all anchors are calculated using the single generalized FSPL model.

In the third phase, the bearing angle (relative orientation) to each anchor module is calculated using the obtained approximate position. This calculated angle, combined with the station's known heading, is used to select the correct, specific FSPL model from the multiple-model framework for each anchor. With these more accurate orientation-based models, new distances are specified. From these refined distances, the final position is determined by trilateration.

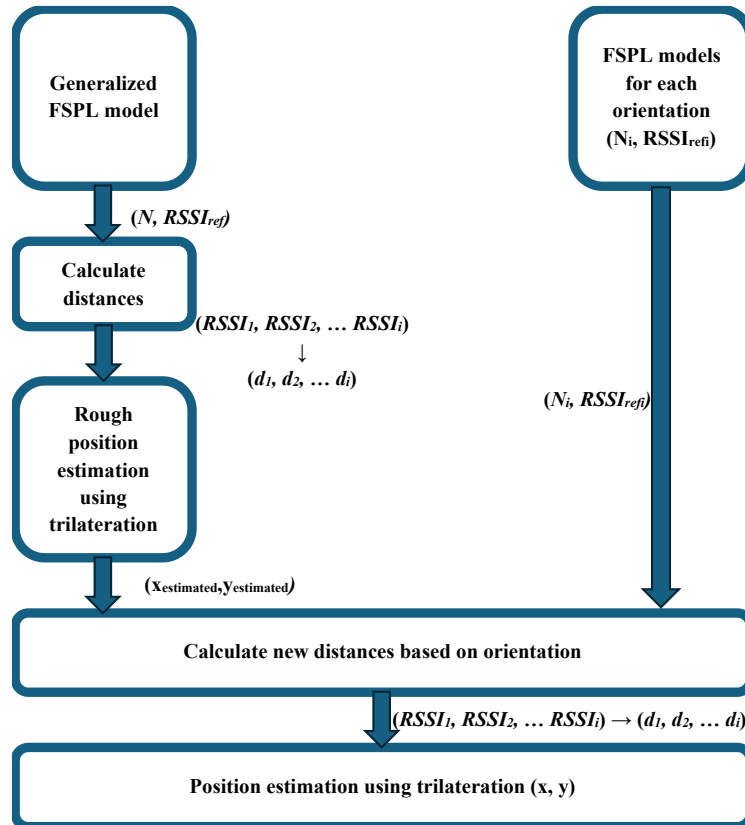


Fig. 2. The conception of the proposed method

3 Results

To validate the proposed method, a model-based simulation was performed. The parameters for the models were empirically derived from the real measured data collected in the experiment described in Section 2.3.

Validation of the performance of the positioning algorithm (the three-phase trilateration) is enabled by this approach in a controlled and repeatable environment that accurately reflects the real-world, orientation-dependent signal behaviour. For testing purposes, 25 randomly selected test points were used with known, randomly chosen orientations of the measurement module. For this simulation, the RSSI values were first calculated based on the orientation of both the measurement module at the test points and the anchor modules at the reference locations in conjunction with the FSPL model. To simulate the stochastic nature of a real-world wireless channel, we introduced signal variations using the standard LNSM. This model accounts for large-scale signal fluctuations caused by environmental clutter (e.g., furniture, human presence) that are not captured by the deterministic FSPL model. This approach aligns with our experimental methodology, where small-scale multipath fading was mitigated by averaging 10 measurements at each point.

This shadowing effect was implemented by adding a zero-mean Gaussian random variable, to the calculated mean RSSI (in dBm) (10):

$$RSSI_{simulated} = \overline{RSSI} + X_{\sigma}, \quad (10)$$

where X_{σ} is drawn from a normal distribution $N(0, \sigma^2)$. Based on our experimental observations, a standard deviation of $\sigma = 6$ dBm was used.

The results were analyzed in MATLAB environment. The objective function used in the optimization process was calculated using the MAE as defined by equation (11):

$$O = \frac{1}{m} \sum_{i=1}^m |d_{calc} - d|, \quad (11)$$

where m is the number of measurement points, d_{calc} represents the calculated distance and d marks the real distance. The hyperparameters of the optimization process are shown in Tab. 1. The calculated parameters (path loss exponent and reference RSSI) can be seen in a previous work [35]. A total of 32 models were

considered, derived from the combination of 8 possible orientations of the station and 4 possible orientations of the anchor module.

Simulation was performed using 4 anchor modules. These modules were positioned at the corners of a room with dimensions of 10 m by 5 m. The coordinates of the anchor modules, given in meters, are as follows:

- anchor1 (0, 0)
- anchor2 (0, 5)
- anchor3 (10, 0)
- anchor4 (10, 5)

The positioning error was given by MAE (12):

$$MAE = \frac{1}{N} \sum_{i=1}^N \sqrt{(y_{calc} - y_i)^2 + (x_{calc} - x_i)^2}, \quad (12)$$

where N is the number of test points, y_{calc} and x_{calc} are the calculated coordinates and y_i and x_i represent the real coordinates.

Table 1. Hyperparameters of PSO algorithm

Hyperparameters of PSO	Value
Number of searched parameters	2
Number of particles	5000
Social component weight	2
Cognitive component weight	2
Initial factor	0.5
Maximum number of iterations	1000

3.1 Baseline method: Positioning using the generalized FSPL model

In the case of applying the generalized FSPL model, the value of PLE was 4.09 and the value of $RSSI_{ref}$ was -59.02 dBm. These values belong to the 0° orientation. When the anchor and the station are parallel to each other. Under these parameters, the average positioning error was 2.15 m. In 4 out of 25 cases the MAE exceeded 4 m, and in 9 cases, it was greater than 2 m. The maximum error observed was 7.63 m, the minimum error was 0.16 m, and the median MAE was 1.47 m. The cumulative distribution function (CDF) is presented in Fig. 3.

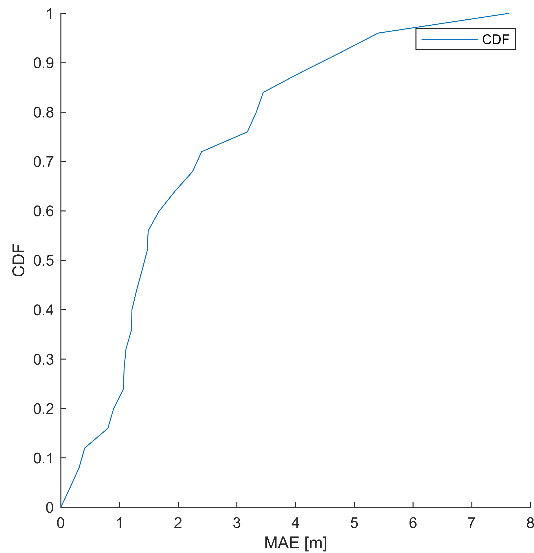


Fig. 3. CDF using generalized FSPL model

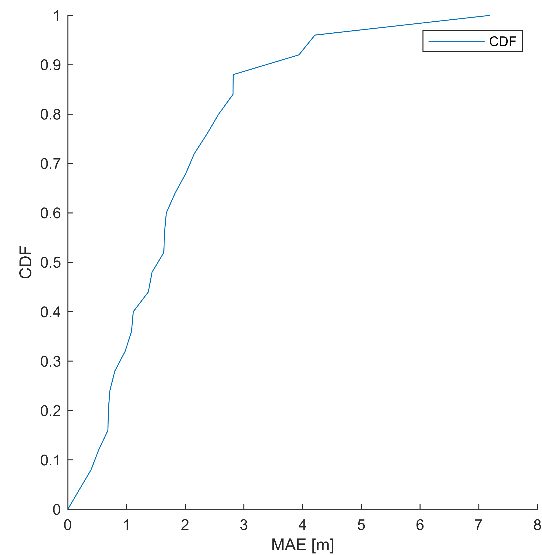


Fig. 4. CDF using orientation-based FSPL model

3.2 Proposed method: Positioning using orientation-based FSPL model selection

In the other case, the FSPL model was selected considering the orientation. It is important to mention that the orientation of the station module is assumed to be known. It could be determined by using different technologies, such as IMUs. The first step is to perform a position estimation with the generalized FSPL model. The station, whose orientation is known, is placed in the estimated position. Since the orientation of the anchors is also known, it is possible to enter relative orientations. First, the orientation value for the anchor module was determined. Afterwards, the orientation value of the station module was determined using the angle between the station module and the anchor module. The orientation values were rounded to the nearest 90° in the case of anchor and 45° in the case of the station modules. With the help of these, the appropriate FSPL model was selected. The comparison of the methods can be seen in Table 2. In this case the average MAE value was 1.87 m. In 2 out of the 25 cases the MAE exceeded 4 m, and in 9 cases, it was greater than 2 m. The maximum error was 7.19 m, the minimum error was 0.20 m and the median error was 1.64 m. The CDF is presented in Fig. 4.

The proposed orientation-based positioning method reduced the average MAE, yielding an improvement of 0.29 m, which corresponds to a relative improvement of 13%. This method outperformed the other in 15 out of 25 cases. The most significant improvement observed was 3.25 m, representing a relative improvement of 60%. Additionally, there was a reduction in the number of major errors, with only 2 instances where the error exceeded 4 m, compared to 4 instances in the previous approach.

Table 2. Comparison of positioning performance

Metric	Baseline method	Proposed method	Improvement
Mean MAE (m)	2.15	1.87	0.28
Median MAE (m)	1.47	1.64	-0.17
Max error (m)	7.63	7.19	0.44
Min error (m)	0.16	0.2	-0.04
Errors >4 m	4 cases	2 cases	50% reduction
Errors >2 m	9 cases	9 cases	No change

4 Conclusion

The research introduced an orientation-based positioning method using adaptive FSPL model selection and trilateration. Simulations were conducted to validate the proposed method. Two scenarios were analyzed: in the first scenario, a generalized FSPL model was utilized to estimate the distances between the anchors and the station module while in the second scenario, the FSPL model was selected based on the orientation of the modules. The results demonstrate that considering orientation can enhance positioning accuracy. It is important to note that while the specific parameters are unique to this test environment, the methodology of applying an orientation-aware, multi-model framework to correct the errors of a single generalized model is broadly generalizable to other complex indoor settings.

Future work will focus on several key areas: expanding the system to address 3D rotations (pitch and roll) and the dynamic antenna-tuning effects present in tracking applications (e.g., wearable devices), conducting more extensive real-world measurements in diverse environments, integrating the orientation-aware model into hybrid sensor fusion frameworks to enhance the accuracy and investigating the method's performance in specific Non-Line-of-Sight (NLOS) scenarios and outdoor environments to further isolate the impact of orientation from multipath fading.

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References

- [1] C. Becker Westphall, I. Pozniak-Koszalka, E. Borcoci, D. Krstic, and International Academy, Research, and Industry Association, Eds., *ICWMC 2015: the Eleventh International Conference on Wireless and Mobile Communications: October 11-16, 2015, St. Julians, Malta*. Red Hook, NY: Curran Associates, Inc, 2015.
- [2] B. Yang, L. Guo, R. Guo, M. Zhao, and T. Zhao, "A Novel Trilateration Algorithm for RSSI-Based Indoor Localization," *IEEE Sensors J.*, vol. 20, no. 14, pp. 8164–8172, Jul. 2020, doi: 10.1109/JSEN.2020.2980966.
- [3] M. E. Rusli, M. Ali, N. Jamil, and M. M. Din, "An Improved Indoor Positioning Algorithm Based on RSSI-Trilateration Technique for Internet of Things (IOT)," in *2016 International Conference on Computer and Communication Engineering (ICCCCE)*, Kuala Lumpur, Malaysia: IEEE, Jul. 2016, pp. 72–77. doi: 10.1109/ICCCCE.2016.28.
- [4] B. Zhou, Z. Wu, Z. Chen, X. Liu, and Q. Li, "Wi-Fi RTT/Encoder/INS-Based Robot Indoor Localization Using Smartphones," *IEEE Trans. Veh. Technol.*, vol. 72, no. 5, pp. 6683–6694, May 2023, doi: 10.1109/TVT.2023.3234283.
- [5] D. P. Kun, E. Baksáné Varga, and Z. Tóth, "Ontology based Indoor Navigation Service for the ILONA System," *Infocommunications journal*, no. 3, pp. 20–29, 2018, doi: 10.36244/ICJ.2018.3.4.
- [6] X. Liu, L. Chen, Z. Jiao, and X. Lu, "Robust Pedestrian Dead Reckoning Integrating Magnetic Field Signals and Digital Terrestrial Multimedia Broadcasting Signals," *Remote Sensing*, vol. 15, no. 13, p. 3229, Jun. 2023, doi: 10.3390/rs15133229.
- [7] I. Sharp and K. Yu, "Sensor-based dead-reckoning for indoor positioning," *Physical Communication*, vol. 13, pp. 4–16, Dec. 2014, doi: 10.1016/j.phycom.2013.11.013.
- [8] V. Cantón Paterna, A. Calveras Augé, J. Paradells Aspas, and M. Pérez Bullones, "A Bluetooth Low Energy Indoor Positioning System with Channel Diversity, Weighted Trilateration and Kalman Filtering," *Sensors*, vol. 17, no. 12, p. 2927, Dec. 2017, doi: 10.3390/s17122927.
- [9] R. Bembenik and K. Falcmán, "BLE Indoor Positioning System Using RSSI-based Trilateration," *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications*, vol. 11, no. 3, pp. 50–69, 0 2020, doi: 10.22667/JOWUA.2020.09.30.050.
- [10] C. Gentner, M. Ulmschneider, I. Kuehner, and A. Dammann, "Wi-Fi-RTT Indoor Positioning," in *2020 IEEE/ION Position, Location and Navigation Symposium (PLANS)*, Portland, OR, USA: IEEE, Apr. 2020, pp. 1029–1035. doi: 10.1109/PLANS46316.2020.9110232.
- [11] Y. Li, Z. Ghassemlooy, X. Tang, B. Lin, and Y. Zhang, "A VLC Smartphone Camera Based Indoor Positioning System," *IEEE Photon. Technol. Lett.*, vol. 30, no. 13, pp. 1171–1174, Jul. 2018, doi: 10.1109/LPT.2018.2834930.
- [12] S. Sharma, D. Kumar, and K. Kishore, "Wireless Sensor Networks - A Review on Topologies and Node Architecture," *Int. J. Comp. Sci. Eng.*, vol. 1, no. 2, pp. 19–25, Oct. 2013.
- [13] Z. Xiong, Z. Y. Song, A. Scalera, F. Sottile, R. Tomasi, and M. A. Spirito, "Enhancing WSN-Based Indoor Positioning and Tracking through RFID Technology," in *2012 Fourth International EURASIP Workshop on RFID Technology*, Torino, Italy: IEEE, Sep. 2012, pp. 107–114. doi: 10.1109/RFID.2012.26.
- [14] H. Guo, H. Li, J. Xiong, and M. Yu, "Indoor positioning system based on particle swarm optimization algorithm," *Measurement*, vol. 134, pp. 908–913, Feb. 2019, doi: 10.1016/j.measurement.2018.12.038.
- [15] S. Sung, H. Kim, and J.-I. Jung, "Accurate Indoor Positioning for UWB-Based Personal Devices Using Deep Learning," *IEEE Access*, vol. 11, pp. 20095–20113, 2023, doi: 10.1109/ACCESS.2023.3250180.
- [16] A. Alitalieshi, H. Jazayeriy, and J. Kazemitabar, "EA-CNN: A smart indoor 3D positioning scheme based on Wi-Fi fingerprinting and deep learning," *Engineering Applications of Artificial Intelligence*, vol. 117, p. 105509, Jan. 2023, doi: 10.1016/j.engappai.2022.105509.
- [17] J. Bi et al., "PSOSVRPos: WiFi indoor positioning using SVR optimized by PSO," *Expert Systems with Applications*, vol. 222, p. 119778, Jul. 2023, doi: 10.1016/j.eswa.2023.119778.
- [18] A. Strzoda, R. Marjasz, and K. Grochla, "LoRa Positioning in Verification of Location Data's Credibility," *Infocommunications journal*, vol. 14, no. 4, pp. 56–61, 2022, doi: 10.36244/ICJ.2022.4.8.
- [19] P. Wu, S. Su, Z. Zuo, X. Guo, B. Sun, and X. Wen, "Time Difference of Arrival (TDoA) Localization Combining Weighted Least Squares and Firefly Algorithm," *Sensors*, vol. 19, no. 11, p. 2554, Jun. 2019, doi: 10.3390/s19112554.
- [20] Y. Wu, C. Zhang, L. Tong, and X. Shi, "Location Optimization Based on Improved 3D DV-HOP Algorithm in Wireless Sensor Networks," *IEEE Access*, vol. 11, pp. 85525–85536, 2023, doi: 10.1109/ACCESS.2023.3303569.

- [21] A. O. De Sá, N. Nedjah, and L. De Macedo Mourelle, "Distributed efficient localization in swarm robotic systems using swarm intelligence algorithms," *Neurocomputing*, vol. 172, pp. 322–336, Jan. 2016, doi: 10.1016/j.neucom.2015.03.099.
- [22] D. Li and Z. Niu, "A Wireless Fingerprint Positioning Method Based on Wavelet Transform and Deep Learning," *IJGI*, vol. 10, no. 7, p. 442, Jun. 2021, doi: 10.3390/ijgi10070442.
- [23] R. Safwat, E. Shaaban, S. M. Al-Tabbakh, and K. Emara, "Fingerprint-based indoor positioning system using BLE: real deployment study," *Bulletin EEI*, vol. 12, no. 1, pp. 240–249, Feb. 2023, doi: 10.11591/eei.v12i1.3798.
- [24] Z. Turgut and A. G. Kakisim, "An explainable hybrid deep learning architecture for WiFi-based indoor localization in Internet of Things environment," *Future Generation Computer Systems*, vol. 151, pp. 196–213, Feb. 2024, doi: 10.1016/j.future.2023.10.003.
- [25] L. Rissmann, J. Wittmann, C. Huber, and S. Meissner, "Application of Machine Learning for 3D Localization using RFID-Tag RSSI Values in Logistics Environments," in *Proceedings of the 26th International Conference on Harbor, Maritime and Multimodal Logistic Modeling & Simulation*, CAL-TEK srl, 2024, doi: 10.46354/i3m.2024.hms.004.
- [26] C. Agualimpia-Arriaga, S. Govindasamy, B. Soni, C.-I. Páez-Rueda, and A. Fajardo, "RSSI-Based Indoor Localization Using Machine Learning for Wireless Sensor Networks: A Recent Review," in *2024 IEEE ANDESCON*, Cusco, Peru: IEEE, Sep. 2024, pp. 1–6, doi: 10.1109/ANDESCON61840.2024.10755908.
- [27] Y. Zhu, X. Luo, S. Guan, and Z. Wang, "Indoor Positioning Method Based on WiFi/Bluetooth and PDR Fusion Positioning," in *2021 13th International Conference on Advanced Computational Intelligence (ICACI)*, Wanzhou, China: IEEE, May 2021, pp. 233–238, doi: 10.1109/ICACI52617.2021.9435887.
- [28] Z. Liu, Z. Li, A. Liu, K. Shao, Q. Guo, and C. Wang, "LVI-Fusion: A Robust Lidar-Visual-Inertial SLAM Scheme," *Remote Sensing*, vol. 16, no. 9, p. 1524, Apr. 2024, doi: 10.3390/rs16091524.
- [29] A. Poulouse, O. S. Eyobu, and D. S. Han, "A Combined PDR and Wi-Fi Trilateration Algorithm for Indoor Localization," in *2019 International Conference on Artificial Intelligence in Information and Communication (ICAIIIC)*, Okinawa, Japan: IEEE, Feb. 2019, pp. 072–077, doi: 10.1109/ICAIIIC.2019.8669059.
- [30] D. Csik, A. Odry, R. Pesti, J. Sarosi, and P. Sarcevic, "A novel orientation-based FSPL model parameter optimization method using PSO for indoor localization," in *2023 IEEE 21st World Symposium on Applied Machine Intelligence and Informatics (SAMI)*, Herl'any, Slovakia: IEEE, Jan. 2023, pp. 000201–000206, doi: 10.1109/SAMI58000.2023.10044514.
- [31] H. T. Friis, "A Note on a Simple Transmission Formula," *Proc. IRE*, vol. 34, no. 5, pp. 254–256, May 1946, doi: 10.1109/JRPROC.1946.234568.
- [32] "Recommendation ITU-R P.1238-12 (08/2023) Propagation data and prediction methods for the planning of indoor radiocommunication systems and radio local area networks in the frequency range 300 MHz to 450 GHz".
- [33] M. N. Rahman, M. T. Ir. A. T. Hanuranto, and S. T. M. T. R. Mayasari, "Trilateration and iterative multilateration algorithm for localization schemes on Wireless Sensor Network," in *2017 International Conference on Control, Electronics, Renewable Energy and Communications (ICCREC)*, Yogyakarta, Indonesia: IEEE, Sep. 2017, pp. 88–92, doi: 10.1109/ICCEREC.2017.8226710.
- [34] Y. Cao, H. Kandula, and X. Li, "Measurement and Analysis of RSS Using Bluetooth Mesh Network for Localization Applications," *Network*, vol. 1, no. 3, pp. 315–334, Dec. 2021, doi: 10.3390/network1030018.
- [35] D. Csik, Á. Odry, R. Pesti, and P. Sarcevic, "Impact of antenna orientation on localization accuracy using RSSI-based Trilateration," *Analecta*, vol. 18, no. 2, 2024.

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