Journal of Computing Theories and Applications ISSN:3024-9104

Research Article

Indoor Positioning using Smartphones: An Improved Time-of-Arrival Technique

Thang C. Vu [1], Trung H. Nguyen [1], Mui D. Nguyen [2], Dung T. Nguyen [1], Tao V. Nguyen [1], Long Q. Dinh [1], Minh T. Nguyen [2,*]

[1] Thai Nguyen University of Information and Communication Technology, Thai Nguyen 24000, Viet Nam; e-mail : vcthang@ictu.edu.vn; trungnh.hgg@gmail.com; ntdungcndt@ictu.edu.vn; nvtao@ictu.edu.vn; dqlong@ictu.edu.vn
[2] Department of Electrical Engineering, Thai Nguyen University of Technology, Thai Nguyen 24000, Viet Nam; e-mail : ducmui@tnut.edu.vn; nguyentuanminh@tnut.edu.vn
* Corresponding Author : Minh T. Nguyen

Abstract: Indoor positioning technology based on smartphones plays an important role in the current technological development context. Especially in applications such as warehouses, supermarkets, hospitals, or buildings. While the global positioning system (GNSS) is popular and effective outdoors, it has several limitations when operating in enclosed spaces, such as indoors, due to the complexity of these environments. Smartphones have many built-in sensors (such as light sensors, sound sensors, gyroscopes, accelerometers, and magnetic sensors) and support the connection of various types of wireless communication technologies such as Wi-Fi and Bluetooth. However, such sensors were not initially developed for positioning applications. This study addresses the positioning problem using the MUSIC technique in conjunction with the Time of Arrival (ToA) method. The effectiveness of the positioning solution is evaluated through the signal-to-noise ratio (SNR) index. The absolute error and squared error indices are evaluated through the cumulative distribution function (CDF) to indicate the effectiveness of the proposed solution. Additionally, we propose a Pedestrian Dead Reckoning method to determine a person's position in indoor environments continuously. Based on the segmentation of the moving process by turns, the direction measurements in each segment are processed using a Kalman filter, which is designed to enhance the results achieved by the system. We also discuss the challenges and some future research directions in the field of smartphone-based indoor positioning.

Keywords: Indoor Positioning; Smartphone; Time of Arrival; MUSIC Algorithm; Pedestrian Dead Reckoning; Kalman Filter; Sensor Fusion; Signal to Noise Ratio.

Received: June, 26th 2025
Revised: July, 17th 2025
Accepted: July, 20th 2025
Published: July, 22nd 2025

1. Introduction

Positioning is a key component of today's most advanced technologies, particularly in the Internet of Things, artificial intelligence, and unmanned vehicles [1]–[3]. GNSS positioning systems work well outdoors but have difficulty in indoor environments. The main reason is that indoor spaces are complex and have diverse structures. The signals are weak and attenuated, so accurate and efficient real-time positioning remains a major challenge [4]–[7]. Nowadays, Smartphones are equipped with a few advanced sensors (such as light sensors, sound sensors, gyroscopes, accelerometers, and magnetic sensors). Measurements from these sensors are often used for positioning, particularly in complex and dynamic environments, such as indoor settings. Some of the popular positioning methods today include Pedestrian Dead Reckoning, visual positioning, and acoustic positioning.

The Pedestrian Dead Reckoning method is relatively simple yet effective, as it utilizes the built-in sensors of smartphones. However, this method is susceptible to interference from indoor environments. Therefore, to improve the positioning efficiency, it can be combined with other positioning algorithms to improve direction estimation and reduce cumulative errors [8]. Smartphone visual localization primarily relies on monochrome cameras and image matching methods, where the position is determined by comparing the current image with an image database. Techniques such as density matching and structure from motion (SFM) help improve accuracy. Additionally, methods utilizing gyroscopes and visual distance measurement are employed to determine the direction of movement [9], [10]. However, these methods struggle to navigate through sharp turns or in environments with limited features.

Visible LED positioning technology uses visible light. It is light whose characteristics fall within the range visible to the human eye. Light source modulation [11] and pattern matching are two popular methods in visible light positioning (VLP). The basic principle is based on the characteristics of time and frequency of light, which enables the collection of a fingerprint database to support positioning. The method, which involves measuring the time of arrival and departure of ultrasonic waves from the transmitter and receiver, is also widely applied. The two most popular ultrasonic positioning systems are Active Bat [12] and Cricket [13], which are the two most popular ultrasonic positioning systems today. The positioning accuracy of the Active Bat system is within 9 cm with a 95% confidence level. However, most current smartphones do not have ultrasonic transceivers, so the application of smartphones in ultrasonic positioning is still rarely deployed [14].

The common time-based positioning methods are TOA and TDOA.TOA is to calculate the time it takes for a signal to travel from the transmitter to the receiver and then use the measured data to determine the distance and locate the object. The signal used is usually radio waves, light, or ultrasound waves, which are transmitted from a fixed point to a mobile station or vice versa. Knowing the speed of the signal in the medium and the time it takes to travel, we can calculate the distance between the transmitter and the receiver. Typically, there is only one transmitter, and multiple receivers are required to share data and cooperate with each other to determine the transmitter's location. Compared to other algorithms, this cooperation requires a larger bandwidth [15].

Multiple Signal Classification is a signal processing algorithm used to estimate the Direction of Arrival (DOA) of electromagnetic or acoustic signals when they arrive at an array of antennas or microphones. In [16], Music technique is used to detect the signals from pedestrians reflected to the receiver for positioning in an indoor environment and distinguish them from the reflections from static objects. The research was conducted using Intel 5300 Wi-Fi cards and achieved an average accuracy of less than 0.6 meters. A 2D MUSIC technique enhanced by a cross-linear antenna array to improve positioning accuracy is presented in [17]. This technique aims to extend to 3D positioning, while solving the problem of unknown departure times. Accuracy is achieved at the centimeter level even when the transmitter and receiver are not completely synchronized.

Indoor location also plays a crucial role in accurately planning the path of a mobile robot. An accurate location enables the robot to avoid collisions and perform tasks efficiently in environments with numerous obstacles [18], by measuring the signal propagation time and knowing the propagation speed of the wave. When combining ToA with the MUSIC algorithm, the accuracy in determining these angles of arrival is greatly improved thanks to the high-resolution capability of MUSIC, especially in environments with multiple signal sources or signals coming from close directions. After accurately determining the packet transmission times from multiple antenna locations or receiving stations using MUSIC. The ToA method can be applied to calculate the location of the intersection point, which is the location of the signal source. In this research context, the main goal is to achieve high positioning accuracy in multipath signal environments while ensuring real-time deployment with a limited number of devices.

The rest of this work is organized as follows. Section 2 presents the MUSIC and ToA algorithms for indoor positioning. The Pedestrian Dead Reckoning method for calculating continuous position information is presented in Section 3. Section 4 provides some simulation results. Finally, Section 5 addresses conclusions and discussion on this topic.

2. MUSIC algorithm combined with Time of Arrival

2.1. MUSIC technique

The ToA algorithm is used to estimate the location of the STA, with the characteristics of the environment, including multipath effects, affecting the positioning accuracy. ToA is calculated using the MUSIC super-resolution method to classify complex and diverse signal patterns. The model includes one STA and three APs. The performance of the positioning method based on the signal-to-noise ratio (SNR) is compared and evaluated. The formula of the MUSIC algorithm:

$$P_{MUSIC}(\theta) = \frac{1}{a(\theta)^H E_n E_n^H a(\theta)} \quad (1)$$

Where $a(\theta)$ is the steering vector (the vector the signal points to); E_n is the matrix of undisturbed vectors
Formula for calculating SNR:

$$\mathrm{SNR} = \frac{P_{signal}}{P_{noise}} \quad (2)$$

Or in dB (decibels):

$$\mathrm{SNR\ (dB)} = 10 \times \log_{10}\left(\frac{P_{signal}}{P_{noise}}\right) \quad (3)$$

The effect of SNR index on signal quality is explicitly described in Table 1 below.

Table 1. Meaning of SNR values [19].

Signal-to-noise ratio (dB)	Signal quality
< 0 dB	Poor
0 – 10 dB	Weak
10 – 20 dB	Average
20 – 30 dB	Good
> 30 dB	Very Good

2.2. Time of Arrival (ToA) Measurement

The distance between the AP and the mobile device is related to the power/travel time variation. The distance is expressed in a specific mathematical expression related to the range and intersection of the AP coverage area. For 2D measurements, there will be two intersections, so there will be two cases considered, with the location to be determined. To accurately determine the location, an AP is needed; the intersection of these ranges (expressed by a mathematical equation) will accurately determine the location of the mobile device, as shown in Figure 1. In a 3D environment (x, y, z), at least four APs are used to determine the object's location [20] accurately.

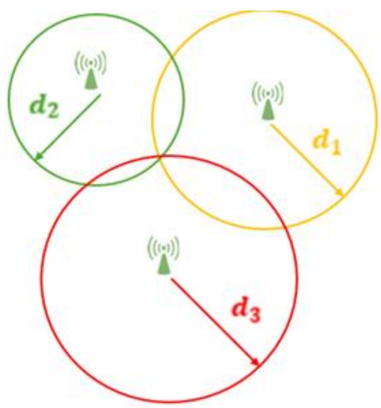


Figure 1. Triangle positioning.

ToA is often used to estimate location through differential measurements (received signal strength/time of arrival). Differential measurements are used to reduce the impact of environmental changes. In this case, metrics such as unspecified transmit power (UTP) and time of arrival of an unspecified access point (TOA) are used for location [23]–[28]. When combining these two methods, ToA provides distance information, while MUSIC helps determine the direction to the signal source more accurately, thereby minimizing the effects of multipath signals —a common problem in indoor environments but less prevalent outdoors.

Determining the distance between the STA and the AP is done by recording the timestamp of the NDP packet. The STA records the time t_1 that it transmits the uplink NDP. The AP then records the time t_2 that it receives it and records the time t_3 that it transmits the downlink NDP. The STA then records the time t_4 (DL ToA) at which it receives the DL NDP. The diagram illustrates the measurement probe phase between STA and a single AP, as shown in Figure 2 below.

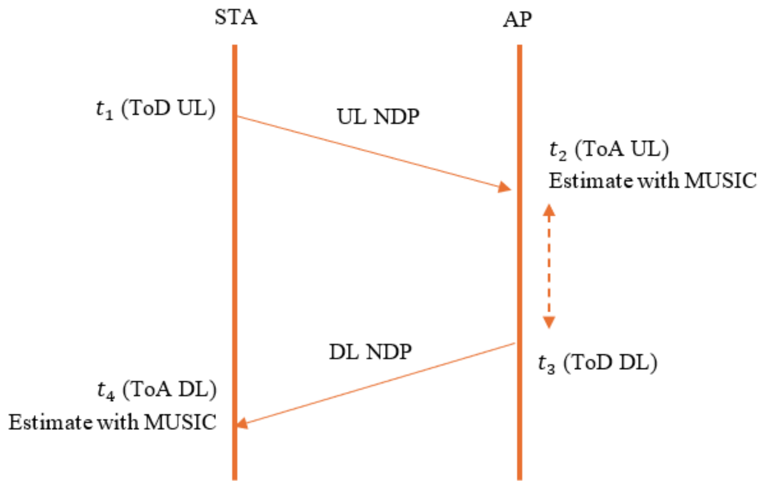


Figure 2. NDP Diagram of calculating NDP packet transmission time points.

T_{RTT} is the round-trip time (RTT) for receiving and transmitting packets is calculated by combining the timestamps.

$$T_{RTT} = (t_4 - t_1) - (t_3 - t_2) \quad (4)$$

Then, calculate the distance d between the STA and AP using the following equation. $d = T_{RTT} * c/2$ where c is the speed of light. Where t_2 and t_4 are estimated using MUSIC super-resolution, following the steps described in Figure 3, as follows.

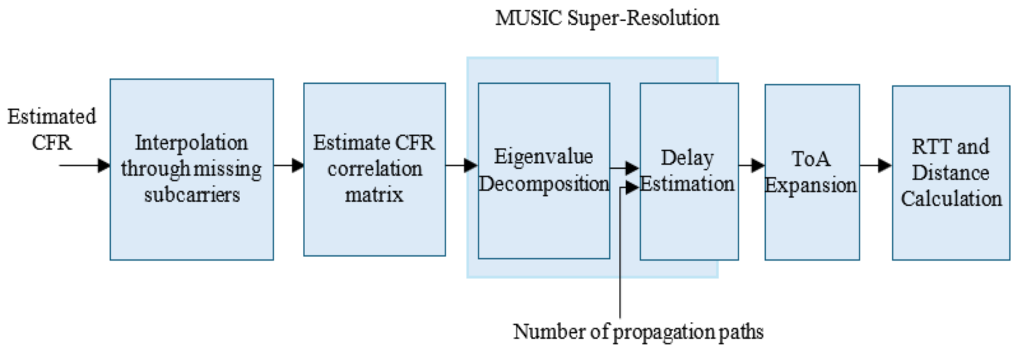


Figure 3. NDP Steps to estimate time t_2, t_4.

3. Pedestrian Dead Reckoning on a Smartphone

Pedestrian Dead Reckoning is a positioning method that allows continuous location estimation. This technique utilizes sensors built into smartphones. The Pedestrian Dead Reckoning method works according to the following basic process: (1) Step detection based on the accelerometer that counts the number of steps the user takes while walking; (2) Step length estimation based on the accelerometer data, which can be user-dependent; (3) Heading estimation based on the magnetic sensor and gyroscope. The process of calculating the coordinates of each step is described in Figure 4.

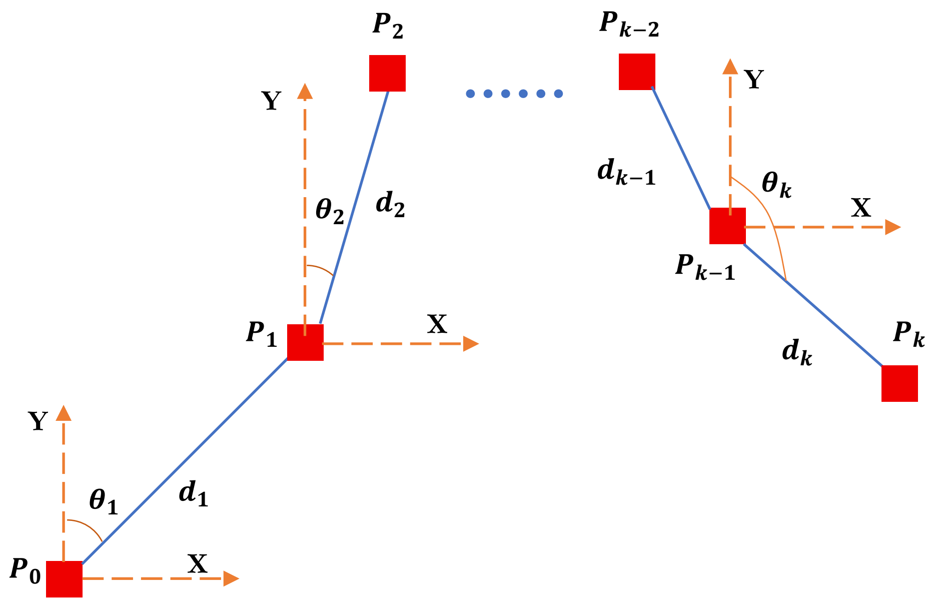


Figure 4. Calculate the coordinates of each step.

The proposed method can determine the walking direction and stride length at each step based on the starting point P_o. At step k, the cumulative result of the previous $k-1$ steps allows us to determine the coordinates of the point $P_k(x_k, y_k)$. Equation (5) shows how to determine the coordinates of the position P_k:

$$x_k = x_0 + \sum_{n=1}^{k} d_n \sin\theta_n$$
$$y_k = y_0 + \sum_{n=1}^{k} d_n \cos\theta_n \quad (5)$$

The advantage of the Pedestrian Dead Reckoning method is that it does not require indoor positioning devices (such as Wi-Fi AP or BLE). However, to determine an absolute position and establish the initial state, the method can be implemented using the sensors built into the smartphone device. The sensors, including an accelerometer, gyroscope, and magnetic sensor built into the smartphone, will collect the necessary data. As shown in Figure 5, these sensors refer to three rotations (including the X-axis, Y-axis, and Z-axis). However, a limitation can be noticed that the results obtained from the sensors may be inaccurate. This will lead to cumulative errors, especially during the direction estimation process.

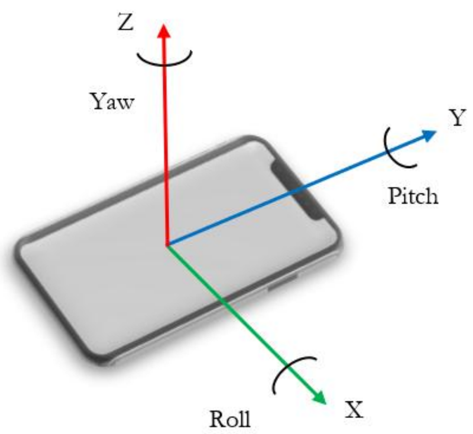


Figure 5. The axes of the smartphone.

The user's step count is determined based on data from the smartphone's accelerometer. The sensor continuously records acceleration values along three axes (X, Y, Z) in space, from which the magnitude of the acceleration vector is calculated. The acceleration vector magnitude values are plotted as a waveform over time with peaks and valleys corresponding to different phases of a step (e.g., foot lift, foot touch). A step is detected based on two consecutive peaks or the time difference between them. The difference in amplitude (between peaks and valleys) and time must be greater than a certain threshold to eliminate results that do not reflect real steps. To increase the reliability of the results, a peak is only confirmed as valid if there is a continuous increase (at least two consecutive times) before reaching the peak. Finally, the results are converted from raw acceleration data into step count information. In equation (6), variables a, b can be adjusted appropriately to determine the stride length.

$$L = a * f + b \tag{6}$$

where parameter f represents the current step frequency.

The accuracy of the sensors built into smartphones can lead to errors in the results. Therefore, the direction error will accumulate quickly, and it becomes especially serious after the user changes the direction of walking. This results in the estimated trajectory being significantly different from the actual one (as shown in Figure 6). Although the direction parameter can vary greatly, in most cases, the pedestrian will move linearly and at a relatively stable speed before turning. Therefore, the solution segments the entire pedestrian trajectory into straight-line segments based on the turning locations.

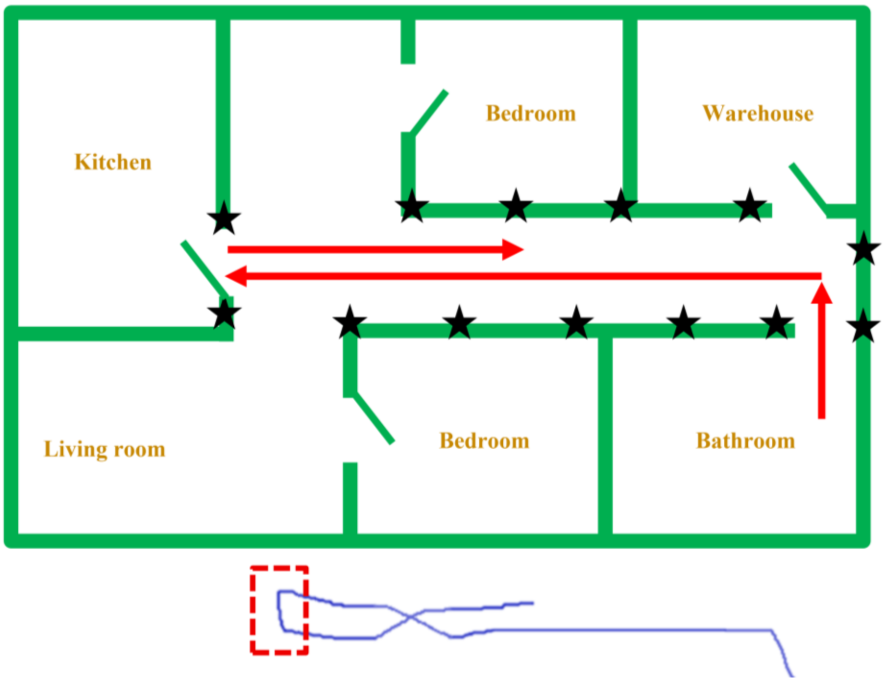


Figure 6. Yaw after turning.

The turn location detection method is performed according to the following procedure: Turns are determined based on data obtained from the gyroscope. At the turn locations, the angular velocity often increases suddenly, thereby creating distinct peaks on the waveform. The system identifies these special peaks to determine the turn location; additionally, a tolerance value is set to ensure accuracy. Finally, the segments are separated to determine the user's walking trajectory.

The movement in each segment is assumed to be linear and relatively stable. Therefore, a Kalman filter is applied separately to each segment to reduce the cumulative error in direction. The state variables are set to estimate the positioning direction (θ) and angular velocity (φ) in each segment (Eq. 7).

$$\hat{X}_k = \begin{bmatrix}\theta_k \\ \varphi_k\end{bmatrix} = F_k \hat{X}_{k-1} = \begin{bmatrix}1 & \Delta t \\ 0 & 1\end{bmatrix}\begin{bmatrix}\theta_{k-1} \\ \varphi_{k-1}\end{bmatrix}$$
$$P_k = F_k P_{k-1} F_k^T + Q \tag{7}$$

where, $\hat{X}_k$ is the state vector at time k; P_k represents the covariance matrix at time k; Q represents the random error; Δt represents the time of angular velocity change.

For linear motion, the angular velocity change (at the last time) is assumed to be the same as the current angular velocity. This simplifies the Kalman filter model. Next, the state vector of the system (containing and φ) is continuously updated through the Kalman filter update equations. The result is a filtered and more accurate position direction value θ at each time k of each segment. Since the motion of the two segments has a difference in direction, the covariance matrix P_k of the Kalman filter is reset to a unit matrix. This helps to eliminate the influence of the accumulated error from the previous segment on the current segment. The association processing of STA and each AP is described in detail below (Figure 7).

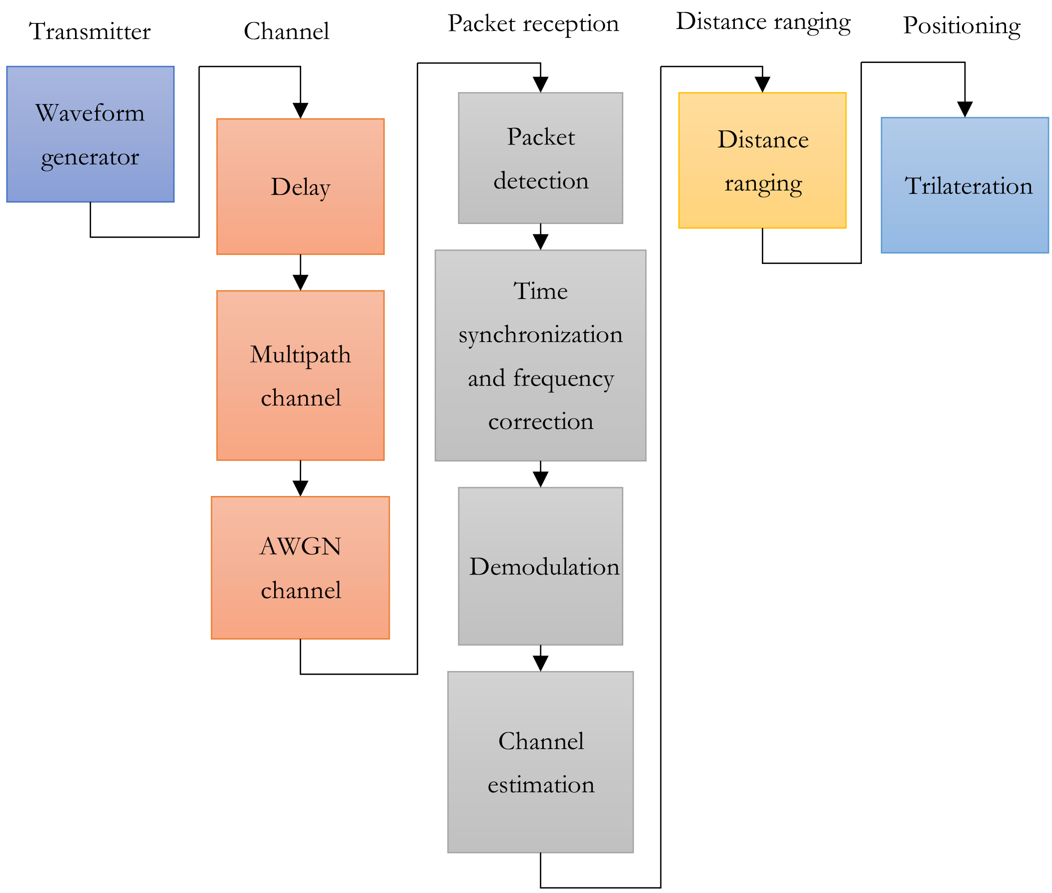


Figure 7. Processing of each associated STA-AP

4. Simulation Results

To perform the simulation, we set the following parameters: the number of iterations is 50, the number of access points (AP) is 3, the number of transmitting antennas is 2, and the number of receiving antennas is 2. Assume the user will move at 0.5m/s in the setup environment. AP1, AP2, and AP3 have coordinates (x, y) of (-52.34, 81.84), (35.19, 47.11), and (11.97, -78.30), respectively. The area of space is 100m x 100m. The multipath model is set up with basic parameters, including: breakpoint distance 5m, RMS delay spread 15ns, Maximum delay 80ns, and the number of clusters is 2. Our MATLAB simulation results (shown in Figure 8) compare the packet transmission time and power in practice with those obtained when using MUSIC.

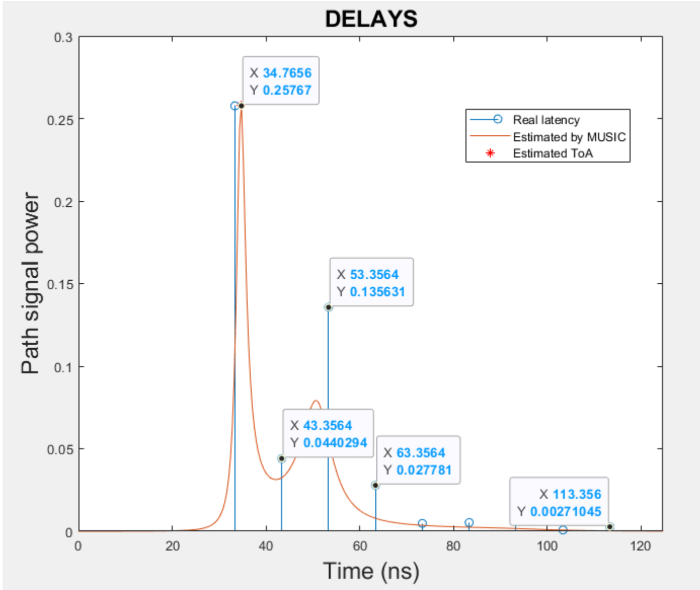
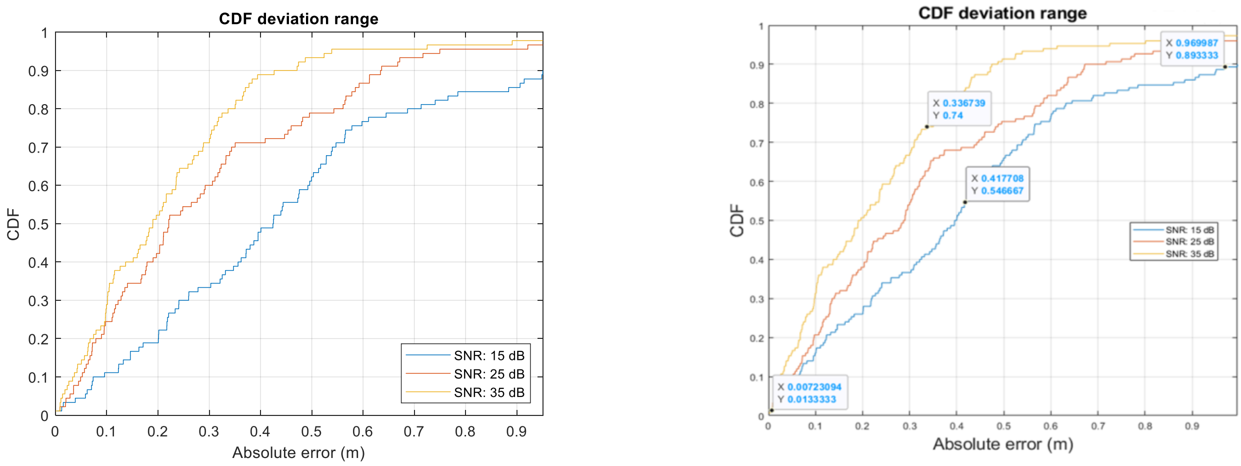


Figure 8. Comparison of the time and power of actual packet transmission and when using MUSIC.

The results show the correlation between the time and power of the actual packet transmission and when using MUSIC. The ToA calculated by Music is approximately 103 ns compared to the actual time of 113 ns. At 53 ns, there is a relatively large difference in transmission power, 0.135 of the actuals, compared to 0.078 estimated by MUSIC. Figure 9(a) shows the simulation results of the CDF values with absolute errors for different SNR values without applying the MUSIC algorithm, and Figure 9(b) shows the result with the MUSIC algorithm.



(a) (b)

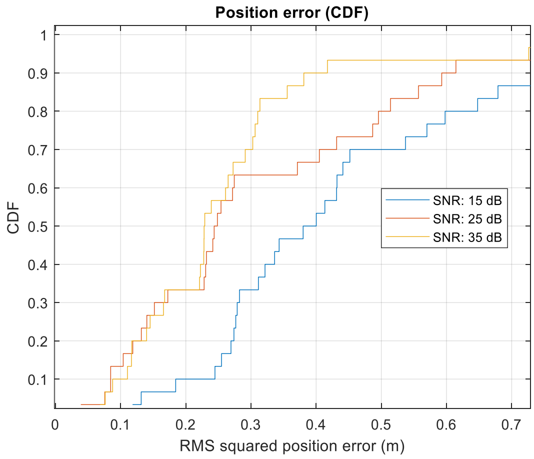
Figure 9. CDF of absolute error for different SNR values (**a**) ToA; (**b**) ToA and Music.

The results in Table 2 show that, for small SNR values, the positioning quality decreases. With decreasing absolute error and CDF becoming larger (approaching 100%).

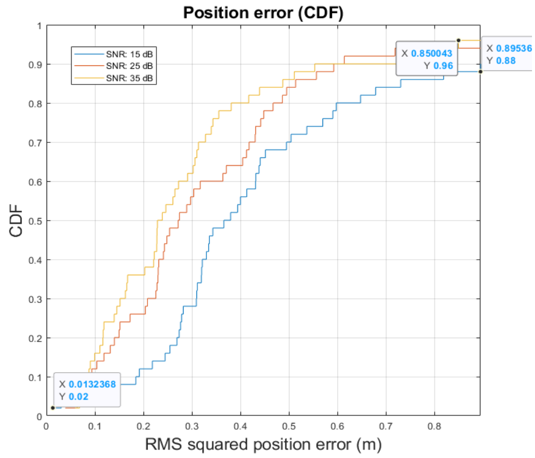
Table 2. Positioning quality based on Average Absolute Error and SNR.

SNR (dB)	Average Absolute Error (m)
15	0.66
25	0.52
35	0.30

Simulation results of CDF value of root mean square (RMS) absolute error with SNR value when using ToA only (Figure 10a) and when combining ToA and Music (Figure 10b).



(a)



(b)

Figure 10. CDF of squared error with different SNR values (**a**) ToA; (**b**) ToA and Music.

The results in Table 3 evaluate the CDF through the squared error as shown in the figure above. The results clearly demonstrate the dependence of positioning quality on SNR. For indoor navigation applications for pedestrians or service robots in large environments such as supermarkets, hospitals, and shopping malls, an error of less than 0.5 m is considered to meet the operating standards well. The CDF, when evaluated through the RMS of the model using only ToA, is smaller when combining ToA and Music, especially at RMS values below 0.2. It effectively demonstrates the ability to improve the positioning accuracy when combining ToA and Music.

Table 3. Evaluate the CDF through the squared error.

SNR (dB)	Average Absolute Error (m)
15	0.66
25	0.52
35	0.30

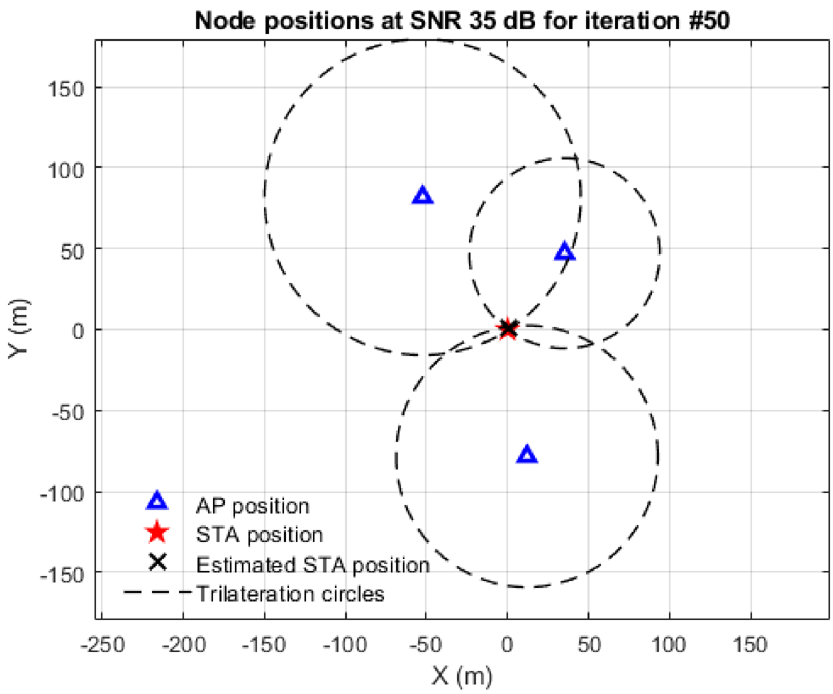


Figure 11. Estimated position results of STA and actual position when there are 03 Aps

Figure 11 shows the estimated location results of STA and the actual location when there are three APs at an SNR value of 35 dB. The results show that at iteration 50, the actual location of the STA and the estimated location are very good. The APs have a maximum distance of up to 100m. The results are obtained when the STA is within the impact area of all three given APs.

As mentioned, indoor positioning is a key technology in the IoT and AI era, particularly when combined with the integration of robots and humans. Based on our research and analysis, the following prominent trends can be mentioned: First, the trend of combining multiple technologies (sensor fusion) is gradually becoming a popular solution to improve the accuracy and stability of positioning. Multi-floor positioning is also a promising research direction, enabling the accurate determination of a user's location not only according to the 2D plan but also according to the floors within the building. This research direction can be seen as combining height data from the phone's barometer and AI for automatic stratification. Additionally, developing methods to automatically create signal maps (radio maps) based on crowdsourced data and AI is another potential direction. It helps to reduce the cost and effort of deploying large-scale positioning systems in large projects. Security and privacy issues in the collection and processing of location data are also important research topics. Data encryption solutions, on-device processing, and new protocols are being proposed to address security issues.

5. Conclusions

This paper points out that indoor positioning using smartphones is a current trend in positioning technology. This work has identified some popular indoor positioning technologies that utilize smartphones today. The MUSIC technique and the ToA method are chosen to address the problem of locating a mobile device and evaluate their effectiveness through the SNR and CDF of the absolute error and the square of the error, providing a clearer understanding of this issue. In addition, to continuously determine the position in an indoor environment, we propose a Pedestrian Dead Reckoning method. Based on the segmentation of the moving process by turns, the Kalman filter is applied to the direction measurements in each segment to improve the results achieved by the system. Although the proposed method requires time synchronization between access points (APs), it offers advantages over the Fingerprinting method, which is limited by the need for frequent data collection and updates, along with lower accuracy. This solution still demonstrates advantages in terms of stability and practical applicability. Meanwhile, convolutional neural network (CNN)-based positioning methods can achieve high accuracy and good adaptability, but they require a large amount of training data, high computational cost, and high latency, making it difficult to deploy on devices with limited resources. Therefore, the solution proposed in this study is considered suitable for current indoor positioning conditions. The author expects that the article will provide a useful reference and contribute to the orientation of further studies in selecting technologies, approaches, and optimizing positioning solutions suitable for each type of environment and different practical applications.

Author Contributions: Conceptualization: Trung H. Nguyen, Long Q. Dinh and Minh T. Nguyen; methodology: Long Q. Dinh and Dung T. Nguyen; software: Mui D. Nguyen and Minh T. Nguyen.; validation: Tao V. Nguyen, Thang C. Vu; formal analysis: Tao V. Nguyen, Long Q. Dinh; investigation: Minh T. Nguyen; resources: Dung T. Nguyen; data curation: Thang C. Vu.; writing—original draft preparation: Dung T. Nguyen; writing—review and editing: Minh T. Nguyen; visualization: Thang C. Vu, Dung T. Nguyen; supervision: Thang C. Vu; project administration: Tao V. Nguyen and Long Q. Dinh; funding acquisition: Minh T. Nguyen. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding

Data Availability Statement: Data can be shared based on any requests to the corresponding authors.

Acknowledgments: The author would like to thank Thai Nguyen University of Information and Communication Technology, Thai Nguyen University, Ministry of Education and Training Viet Nam (Project B2025-TNA-04).

Conflicts of Interest: The authors declare no conflict of interest

References

[1] M. Zhang, S. Zhang, and J. Cao, "Fusing Received Signal Strength from Multiple Access Points for WLAN User Location Estimation," in *2008 International Conference on Internet Computing in Science and Engineering*, Jan. 2008, pp. 173–180. doi: 10.1109/ICICSE.2008.24.

[2] M. L. Trinh, D. T. Nguyen, L. Q. Dinh, M. D. M. T. Nguyen, D. R. I. M. Setiadi, and M. D. M. T. Nguyen, "Unmanned Aerial Vehicles (UAV) Networking Algorithms: Communication, Control, and AI-Based Approaches," *Algorithms*, vol. 18, no. 5, p. 244, Apr. 2025, doi: 10.3390/a18050244.

[3] Đ. Q. Long, N. H. Công, D. P. Tuấn, N. Q. Vịnh, and N. T. Minh, "A Comprehensive Study of Mobile Robot Navigation and Obstacle Avoidance Schemes," *TNU J. Sci. Technol.*, vol. 228, no. 14, pp. 302–312, Nov. 2023, doi: 10.34238/tnu-jst.8978.

[4] J. Singh, N. Tyagi, S. Singh, F. Ali, and D. Kwak, "A Systematic Review of Contemporary Indoor Positioning Systems: Taxonomy, Techniques, and Algorithms," *IEEE Internet Things J.*, vol. 11, no. 21, pp. 34717–34733, Nov. 2024, doi: 10.1109/JIOT.2024.3416255.

[5] G. N. Tran, S. Q. Nguyen, M. T. Nguyen, and S. Kim, "Optimal Power Allocation for Non-Orthogonal Multiple Access Visible Light Communications with Short Packet and Imperfect Channel Information," in *2022 International Conference on Advanced Technologies for Communications (ATC)*, Oct. 2022, pp. 234–238. doi: 10.1109/ATC55345.2022.9943006.

[6] T. C. Vu, M. T. Nguyen, V. T. Nguyen, and Q. C. Le, "Approach New Framework of Compressive Sensing Based Secret Sharing in Wireless Sensor Network: Theory and Applications," in *Advances in Information and Communication Technology*, 2024, pp. 26–34. doi: 10.1007/978-3-031-50818-9_4.

[7] A. Coboi, M. T. Nguyen, V. N. Pham, T. C. Vu, M. D. Nguyen, and D. T. Nguyen, "Zigbee Based Mobile Sensing for Wireless Sensor Networks," *Comput. Networks Commun.*, Dec. 2023, doi: 10.37256/cnc.1220233923.

[8] Z.-A. Deng, G. Wang, D. Qin, Z. Na, Y. Cui, and J. Chen, "Continuous Indoor Positioning Fusing Wi-Fi, Smartphone Sensors and Landmarks," *Sensors*, vol. 16, no. 9, p. 1427, Sep. 2016, doi: 10.3390/s16091427.

[9] M. T. Nguyen, H. M. La, and K. A. Teague, "Compressive and collaborative mobile sensing for scalar field mapping in robotic networks," in *2015 53rd Annual Allerton Conference on Communication, Control, and Computing (Allerton)*, Sep. 2015, pp. 873–880. doi: 10.1109/ALLERTON.2015.7447098.

[10] L. Ruotsalainen, H. Kuusniemi, M. Z. H. Bhuiyan, L. Chen, and R. Chen, "A two-dimensional pedestrian navigation solution aided with a visual gyroscope and a visual odometer," *GPS Solut.*, vol. 17, no. 4, pp. 575–586, Oct. 2013, doi: 10.1007/s10291-012-0302-8.

[11] A. Ganick and D. Ryan, "Light positioning system using digital pulse recognition," US 8,248,467 B1, 2012 [Online]. Available: https://patents.google.com/patent/US8248467B1/en

[12] A. Ward, A. Jones, and A. Hopper, "A new location technique for the active office," *IEEE Pers. Commun.*, vol. 4, no. 5, pp. 42–47, 1997, doi: 10.1109/98.626982.

[13] N. B. Priyantha, A. Chakraborty, and H. Balakrishnan, "The Cricket location-support system," in *Proceedings of the 6th annual international conference on Mobile computing and networking*, Aug. 2000, pp. 32–43. doi: 10.1145/345910.345917.

[14] F. Ijaz, H. K. Yang, A. W. Ahmad, and C. Lee, "Indoor positioning: A review of indoor ultrasonic positioning systems," in *2013 15th International Conference on Advanced Communications Technology (ICACT)*, 2013. [Online]. Available: https://ieeexplore.ieee.org/document/6488379

[15] C. N. Reddy and B. R. Sujatha, "TDOA Computation Using Multicarrier Modulation forSensor Networks," *Int. J. Comput. Sci. Commun. Networks*, vol. 1, no. 1, pp. 85–89, 2011.

[16] X. Li, S. Li, D. Zhang, J. Xiong, Y. Wang, and H. Mei, "Dynamic-MUSIC: accurate device-free indoor localization," in *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, Sep. 2016, pp. 196–207. doi: 10.1145/2971648.2971665.

[17] P. P. Hassan, I. Marsland, R. Smith, R. Kerr, E. Iun, and I. Lambadaris, "3D Indoor Positioning Using the 2D-MUSIC Algorithm," in *GLOBECOM 2024 - 2024 IEEE Global Communications Conference*, Dec. 2024, pp. 1881–1887. doi: 10.1109/GLOBECOM52923.2024.10901003.

[18] H. Belaidi and F. Demim, "NURBs Based Multi-robots Path Planning with Obstacle Avoidance," *J. Comput. Theor. Appl.*, vol. 1, no. 4, pp. 478–491, May 2024, doi: 10.62411/jcta.10387.

[19] N. Iwakiri and T. Kobayashi, "Ultra-Wideband Time-of-Arrival and Angle-of-Arrival Estimation Using Transformation Between Frequency and Time Domain Signals," *J. Commun.*, vol. 3, no. 1, Jan. 2008, doi: 10.4304/jcm.3.1.12-19.

[20] K. Langendoen and N. Reijers, "Distributed localization in wireless sensor networks: a quantitative comparison," *Comput. Networks*, vol. 43, no. 4, pp. 499–518, Nov. 2003, doi: 10.1016/S1389-1286(03)00356-6.

[21] L. Lin, H. C. So, and Y. T. Chan, "Accurate and simple source localization using differential received signal strength," *Digit. Signal Process.*, vol. 23, no. 3, pp. 736–743, May 2013, doi: 10.1016/j.dsp.2012.12.020.

[22] N. Chang, R. Rashidzadeh, and M. Ahmadi, "Robust indoor positioning using differential Wi-Fi access points," *IEEE Trans. Consum. Electron.*, vol. 56, no. 3, pp. 1860–1867, Aug. 2010, doi: 10.1109/TCE.2010.5606338.

[23] S. M. M. Dehghan, H. Moradi, and S. A. A. Shahidian, "Optimal path planning for DRSSI based localization of an RF source by multiple UAVs," in *2014 Second RSI/ISM International Conference on Robotics and Mechatronics (ICRoM)*, Oct. 2014, pp. 558–563. doi: 10.1109/ICRoM.2014.6990961.

[24] F. Liu, J. Wang, J. Zhang, and H. Han, “An Indoor Localization Method for Pedestrians Base on Combined UWB/PDR/Floor Map,” *Sensors*, vol. 19, no. 11, p. 2578, Jun. 2019, doi: 10.3390/s19112578.
[25] M. Ridolfi, S. Van de Velde, H. Steendam, and E. De Poorter, “Analysis of the Scalability of UWB Indoor Localization Solutions for High User Densities,” *Sensors*, vol. 18, no. 6, p. 1875, Jun. 2018, doi: 10.3390/s18061875.
[26] A. Sesyuk, S. Ioannou, and M. Raspopoulos, “A Survey of 3D Indoor Localization Systems and Technologies,” *Sensors*, vol. 22, no. 23, p. 9380, Dec. 2022, doi: 10.3390/s22239380.
[27] J. Choliz, M. Eguizabal, A. Hernandez-Solana, and A. Valdovinos, “Comparison of Algorithms for UWB Indoor Location and Tracking Systems,” in *2011 IEEE 73rd Vehicular Technology Conference (VTC Spring)*, May 2011, pp. 1–5. doi: 10.1109/VETECS.2011.5956174.
[28] J. Liu, “Survey of wireless based indoor localization technologies,” Washington University, 2014. [Online]. Available: https://www.cse.wustl.edu/~jain/cse574-14/ftp/indoor/index.html