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Research Article

Improvement of Ultra-Wideband-Based 3D Localization for Indoor Drones Using Anchor Auto Calibration and Positioning Based on Machine Learning

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Abstract: 3D localization is an important parts of indoor drone navigation systems. 3D localization using ultra-wideband (UWB) can be applied to solve the GPS-denied environment problem. However, UWB has some disadvantages related to measurement accuracy, measurement fluctuation, and position estimation in 3-dimensional space. The UWB measurement accuracy is affected by the antenna delay. The antenna delay must be calibrated for each anchor before measurement is performed. Performing an automatic calibration for antenna delay can significantly increase the consistency and efficiency of measurement systems. Conventional localization methods, such as trilateration, triangulation, or multilateration are effectively proven in 2-dimensional localization. This method produced significant error while performing 3-dimensional localization, especially in Z-axis. A new approach based on ML CNN is expected to solve the complexity and nonlinearity in data measurement that arise in conventional methods. Data fluctuation problems due to UWB measurement during the position estimation process result in large estimation errors. A motion threshold is implemented after position estimation to solve these problems. Position changes that are significantly greater than the maximum drone velocity limit can be eliminated. Based on the experimental results, the implementation of AAC in ML-based 3D localization with a motion threshold significantly increased the positioning accuracy up to 0.34 m, lowered the standard deviation up to 0.12 m, and eliminated the outliers caused by data fluctuation with a maximum of 1.07 m.

Keywords: 3D localization; Anchor auto-calibration; Indoor drone; Machine learning; Motion threshold; Ultra-wideband

1. Introduction

Drone technology has seen significant growth in recent years, becoming a crucial tool in various industries, such as warehousing (Ekici et al., 2023; Shen et al., 2021), indoor livestock management (Krul et al., 2021), medical (Nenni et al., 2020), and construction (McCabe et al., 2017). In particular, indoor drones offer distinct advantages over traditional robots, including the ability to access difficult-to-reach areas, enhanced mobility, and a broader field of view. Accurate 3D localization is essential for safe and efficient operation of indoor drones (Sesyuk et al., 2022; El-Sheimy and Li,

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2021). Precise positioning enables drones to navigate complex environments, avoid obstacles, and achieve their objectives with high accuracy.

3D localization on drones allows them to determine their position in 3D space. The global positioning system (GPS) is a commonly used localization method, but it is not effective for indoor localization (Niculescu et al., 2023; Yang et al., 2022; Shi et al., 2020; Shule et al., 2020; Macoir et al., 2019). This is because the building structure blocks the GPS signal because GPS uses satellites to determine position, and walls, ceilings, and other objects inside the building can block this signal (Chang et al., 2023). In addition, the GPS accuracy is generally around 1-3 meters, which is not enough for some indoor drone applications because it is considered less precise (Patrik et al., 2019). WiFi localization based on RSSI (Hendrarini et al., 2022) or ultra-wideband (UWB) can be used to overcome the weaknesses of indoor GPS. UWB offers a better solution for 3D localization of indoor drones. The UWB uses high-frequency signals with a wide band to measure the distance between the drone and the anchor point. Anchor points are stationary devices installed in indoor environments that transmit UWB signals. UWB has several advantages, including high accuracy (up to a few centimeters) and low latency (Dai et al., 2024; Hasan et al., 2024). However, UWB itself has several disadvantages, one of which is the complexity problem. For the UWB localization system to work effectively, each anchor (Krapež and Munih, 2020), the anchor installation position (Gao et al., 2023), and the localization algorithm used must be calibrated (De Guzman et al., 2024; Chang et al., 2023; Sandamini et al., 2023).

First, problems related to the accuracy of distance measurement must be resolved. This problem is caused by the antenna delay (t_{ant}), which is the time required for a UWB device to process the received data and send it back to the previous data sender (Liu et al., 2024; Gui et al., 2018). Antenna delay is a challenge in UWB-based distance measurement, and several previous studies have attempted to resolve this challenge. Efforts have been made to reduce distance measurement errors using several methods, including the hybrid compensation model (Liu et al., 2023). The hybrid compensation model is carried out with temperature and distance measurements. The proposed method is equipped with a Kalman filter and several optimization algorithms. The hybrid compensation model is suitable for use in static conditions. Multiple simultaneous ranging (MSR) is a new calibration system that measures the antenna delay of the anchor node in a real-time UWB-based distance measurement system (Shah et al., 2022). After calibration, the anchor node measured by this system provides more accurate distance measurements in LOS conditions. The two-evaluator method uses an automatic and real-time approach to calibrate the antenna delay on UWB devices (Liu et al., 2024). This approach uses two estimators: coarse adjustment and fine adjustment. The LSTM method has also been used to improve the accuracy and frequency of distance measurements with UWB (Liu and Bao, 2023). The first technique combines a CNN, a long short-term memory (LSTM) module, and a regression module to process sensor data. The second technique combines two RF models to improve the accuracy of the measurement results.

Conventional localization methods, such as trilateration, triangulation (Guo et al., 2022), and multilateration (Djosic et al., 2022), are quite effective in 2D space. Trilateration is performed by measuring the distance between the object and a minimum of three reference sites, where the object's location is established by the convergence of three spheres centered on these points. Triangulation employs angular data between the object and reference points to ascertain its location, which is frequently used in camera and laser systems. Conversely, multilateration ascertains location using the time difference of arrival (TDOA) of signals from several reference sites, rather than direct distance, rendering it extensively utilized in navigation systems such as radar and ultra-wideband (UWB). Several filter-based methods, such as the Kalman Filter (Kim and Pyun, 2021), the Extended Kalman Filter (Teoh, 2023; Li et al., 2021), and the Unscented Kalman Filter (Kolakowski, 2020; Fu et al., 2019), have been applied to improve accuracy. However, the accuracy will decrease drastically when applied to 3D space (Delamare et al., 2020). In general, 3D localization has a very high z-axis error due to anchor placement, which is generally at almost the same height, causing a lack of vertical variation (Bao et al., 2024). This reduces the height estimation accuracy. In addition, the reflection and multipath effects of UWB signals, especially in indoor environments, often cause inaccurate distance measurements along the z-axis. Circle expansion is another positioning technique developed to overcome the weakness of the absence of a circle intersection (Ibwe et al., 2023). This paper proposes 3D localization using the CNN machine learning approach to overcome the weaknesses of conventional methods. Machine learning-based 3D localization can effectively handle the complexity and nonlinearity of measurement data (Gao et al., 2023; Nguyen et al., 2021; 2020). These advantages cannot be achieved by simple geometric models such as trilateration, triangulation, and multilateration.

Distance estimation from UWB sensors often fluctuates due to noise and environmental disturbances (Bregar, 2023), thus requiring data smoothing filters such as moving average (MA) or Kalman filter (KF) (Borhan et al., 2023; Huang and Qian, 2023; Liu and Li, 2019). However, MA is less responsive to rapid changes, whereas the Kalman filter requires a complex model. The actual position change is limited by the maximum speed; therefore, if the estimated position change exceeds the distance that the drone can travel in a certain time, it can be considered as noise. This study applies a motion threshold algorithm to limit the position change based on a realistic maximum speed to overcome this data fluctuation, thereby improving the stability and accuracy of position estimation. Based on the advantages explained above, the contributions made in this paper include the proposed anchor auto-calibration for compensating the antenna delay effect during distance measurement. This method succeeded in decreasing the error measurement range for each UWB sensor to less than 5 cm. This improvement significantly impacts the final position estimation. Proposed machine learning-based 3D localization using 1DCNN based on the measurement data between the tag-anchor and the previous position. This approach has less error than conventional positioning, such as trilateration and multilateration. Implementing a motion threshold to prevent fluctuating position estimation. Machine learning, such as 1D-CNN, improves UWB localization by eliminating signal errors and improving position estimation accuracy. AAC provides reliable calibration through constant input and changes. The 1D-CNN is optimized for real-time application with minimal latency to maintain the system's effectiveness, and its integration with a Kalman filter further improves accuracy without increasing complexity.

2. Methods

To obtain accurate 3D localization results, the distance measurement between the UWB tag and anchor must first be improved. This improvement is achieved by automatically calibrating the antenna delay on the UWB anchor. This procedure is called AAC. The distance measurement results are then entered into ML-based 3D localization using a CNN. In the last stage, a motion threshold was implemented to eliminate fluctuating position estimation that is greater than the possible maximum drone velocity (0,2 m/s). The main method proposed in this paper is illustrated in Figure 1.

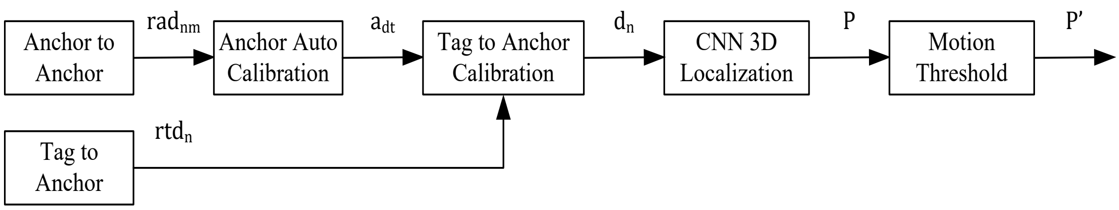

Figure 1 Block diagram of the proposed method

The raw data for determining the distance between anchors is referred to as rad_{nm}. The raw data are further calibrated using AAC to generate calibrated anchor data (ad_t). The adt value is used as a calibration constant in the tag-to-anchor calibration. This aims to convert the raw data from measuring the distance between tags and anchors (rtd_n) into calibrated data (d_n). Then, dn is input into the CNN 3D Localization to ascertain the position (**P**). The estimated location P may still provide outliers; therefore, a motion threshold is implemented to achieve a more refined position estimate (**P′**).

2.1. Basic Ultra-Wideband Based 3D Localization

The issue of inaccurate 3D localization arises when the GPS signal is weak or lost, particularly during indoor drone flights. This challenge can be effectively solved through UWB-based 3D localization. This technique begins by measuring the relative distance between the UWB tag and the UWB anchor. A minimum of 3 UWB anchors is required to estimate a 2D position, while for a 3D position estimation, a minimum of 4 UWB anchors is essential. The position estimation can be calculated by trilateration based on the relative distance of the UWB tag with several UWB anchors. Figure 2 illustrates the basic indoor UWB-based 3D localization in this paper.

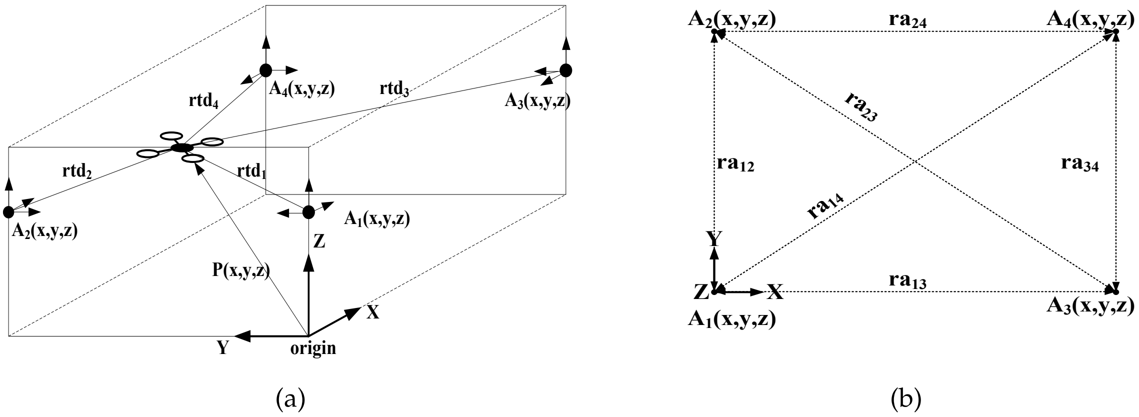

Figure 2 Basic UWB 3D Localization for indoor drones: (a) isometric view and (b) top view

The DW1000 UWB module used in the test The DW1000 is an UWB transceiver developed by Decawave Ltd., a company based in Dublin, Ireland. The module is equipped with an ESP32 microcontroller so that it can perform data acquisition and communication via Wi-Fi without the need for additional devices. This module operates at a frequency of 3774–4242 MHz. This module can measure distances up to 100 m and can be increased to more than 200 m with additional antennas and lower working frequencies. However, in this study, no additional antennas were used, considering that the room only had a maximum length dimension of 20 m.

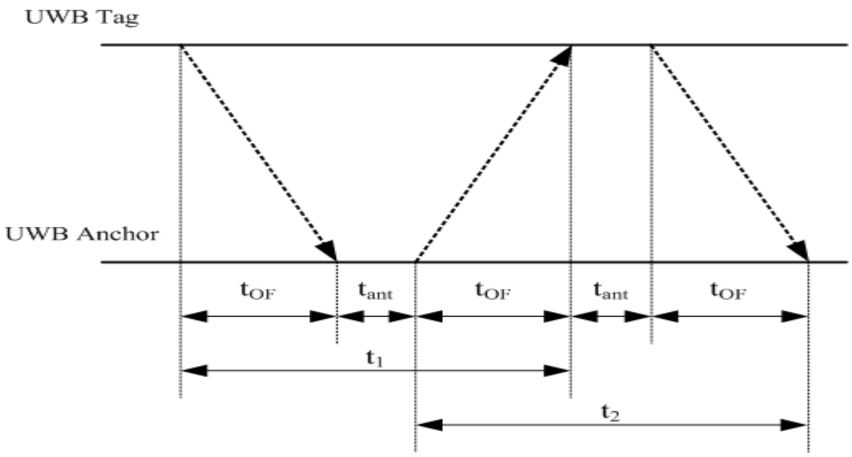

Figure 3 Two-Way Ranging of UWB Distance Measurement

To perform distance measurements, data acquisition is carried out using the TWR method. This method effectively eliminates errors caused by unsynchronization between modules. Two UWB modules are needed to run TWR, each function as a tag and an anchor. A tag is a UWB device that is attached to a moving object as well as a position measurement point, while an anchor is a UWB device that is positioned statically and used as a reference point. The measurement process begins with the tag sending data to the anchor and calculating the time (t_1). The time it takes for the data to reach the anchor is usually called the time of flight (tOF). After the anchor receives the data, it immediately sends data and an ACK signal to the tag. The time taken by the anchor to process the data until the signal is transmitted is called the time process. In the UWB DW1000, this time is called the Antenna delay (t_{ant}). The time it takes for the signal to propagate from the anchor to the tag is tOF. The final stage of this process is performed by the tag sending ACK2 to the anchor. This process requires tant and tOF data processing time. The TWR is illustrated in Figure 3.

$$t_1 + t_{ant} = t_{ant} + t_2 \tag{1}$$

$$t_1 t_{ant} - t_{ant} t_2 = 2TOF(t_2 + t_{ant}) \tag{2}$$

$$t_{OF} = \frac{t_1 t_{ant} - t_{ant} t_2}{t_1 + t_2 + 2t_{ant}} \tag{3}$$

The process of converting tOF into distance estimation is performed by multiplying tOF with electromagnetic wave velocity (c) of 3x10^8 m/s. t_{OF} is calculated based on (3), where the values of t_1 to t_2 are calculated using (1) and (2). However, a common problem is the inaccuracy of time calculation, especially the processing time or antenna delay on the DW1000. The DW1000 antenna delay can be fine-tuned to provide the best possible range or location. Antenna delay will affect the calculation process of time t_1 and t_2 such that the error due to antenna delay is expressed with (4). This study mainly aims to improve the accuracy of antenna delay values automatically. The accuracy of tant values is determined by the automatic calibration process based on equation (5) where d is the tag-anchor actuation distance, and c is the electromagnetic wave velocity.

$$t_{ant} = \frac{t_1 + t_2 - 4t_{OF}}{2} \tag{4}$$

$$t_{ant} = \frac{t_1 + t_2 - (\frac{4d}{c})}{2} \tag{5}$$

Multilateration is the most widely used UWB method for 3D localization. The distance between the drone and the UWB anchor is denoted by (rtd_n). The rtdn value is obtained from the square root of the sum of the differences in the position of the drone on each axis (6). To implement 3D localization, a minimum of 4 anchors are required.

$$\begin{bmatrix} rtd_1^2 \\ rtd_2^2 \\ \vdots \\ rtd_n^2 \end{bmatrix} = \begin{bmatrix} (x_d - x_1)^2 & (y_d - y_1)^2 & (z_d - z_1)^2 \\ (x_d - x_2)^2 & (y_d - y_2)^2 & (z_d - z_2)^2 \\ & \vdots & \\ (x_d - x_n)^2 & (y_d - y_n)^2 & (z_d - z_n)^2 \end{bmatrix} \tag{6}$$

Position estimation (**P**) based on the distance between the tag and anchor can be performed using Equation (7).

$$\boldsymbol{P} = \begin{bmatrix} P_x \\ P_y \\ P_z \end{bmatrix} = (A^T.A)^{-1} A^T.B \tag{7}$$

Where the values A and B are described in (8) and (9) respectively.

$$A = \begin{bmatrix} (x_n - x_1) & (y_n - y_1) & (z_n - z_1) \\ (x_n - x_2) & (y_n - y_2) & (z_n - z_2) \\ & \vdots & \\ (x_n - x_{n-1}) & (y_n - y_{n-1}) & (z_n - z_{n-1}) \end{bmatrix} \tag{8}$$

$$B = \frac{1}{2} \begin{bmatrix} r_{i,1}^2 - r_{i,k}^2 + x_k^2 - x_1^2 + y_k^2 - y_1^2 + z_k^2 - z_1^2 \\ r_{i,2}^2 - r_{i,k}^2 + x_k^2 - x_2^2 + y_k^2 - y_2^2 + z_k^2 - z_2^2 \\ \vdots \\ r_{i,k-1}^2 - r_{i,k}^2 + x_k^2 - x_{k-1}^2 + y_k^2 - y_{k-1}^2 + z_k^2 - z_{k-1}^2 \end{bmatrix} \tag{9}$$

In this paper, the performance of the multilateration method as a conventional 3D positioning is compared with that of machine learning-based 3D localization created using convolutional neural network (CNN). To obtain the **P** value, it is done by entering the rtd_n value into the CNN feed forward network.

2.2. Anchor-to-anchor distance measurement

Accurate distance measurement is the most important part, so the measurement accuracy needs to be considered first. The distance measurement using UWB requires two UWB devices, each activated as a tag and anchor. Each device must be assigned a different address to avoid conflict. However, UWB devices cannot be simultaneously activated as tags and anchors. Therefore, a scheduling mechanism is needed to activate an anchor into a tag in a certain duration and time interval. This paper proposes round-robin scheduling. This technique is simple, easy to implement, and starvation-free. The used scheduling mechanism is shown in Figure 4. This process begins by setting UWB A to be a tag, while the other three UWBs are used as anchors. This configuration is updated every 5 s and begins with an start process for 2 s for UWBs that experience a function transition.

<table>
<tr><th>Time (s)</th><th>1-2</th><th>2-5</th><th>6-7</th><th>8-10</th><th>11-12</th><th>13-15</th><th>16-17</th><th>18-20</th></tr>
<tr><td>UWB A</td><td>Tag init</td><td>Tag</td><td>Anchor init</td><td colspan="5">Anchor</td></tr>
<tr><td>UWB B</td><td colspan="2">Anchor</td><td>Tag init</td><td>Tag</td><td>Anchor init</td><td colspan="3">Anchor</td></tr>
<tr><td>UWB C</td><td colspan="4">Anchor</td><td>Tag init</td><td>Tag</td><td>Anchor init</td><td>Anchor</td></tr>
<tr><td>UWB D</td><td>Anchor init</td><td colspan="5">Anchor</td><td>Tag init</td><td>Tag</td></tr>
</table>

Figure 4 Round-robin scheduling for measurement of anchor-to-anchor distance

2.3. The anchor auto-calibration algorithm

The AAC algorithm improves the accuracy of distance measurements between anchors in a positioning system that uses anchors and tags. AAC begins by measuring the distance between anchors through a round-robin scheduling mechanism, where each anchor takes turns measuring the distance to each other. At this stage, the initial antenna delay (t_{ant}) value of 16580 is used as the initial parameter. After all measurements are completed, the distance values obtained are averaged to produce an estimate of the average distance between anchors. The calibration coefficient is calculated by dividing the actual physical distance between anchors by the average measurement distance. In the calculation of the new antenna delay, this coefficient functions as a multiplier, where the initial antenna delay value is multiplied by the calibration coefficient. Then, the updated antenna delay value is implemented in the system to be used in subsequent distance measurements between tags and anchors. By updating the antenna delay value based on this calibration, the system can perform more accurate and consistent distance measurements under actual physical conditions. The AAC process is explained in the Algorithm in Table 1.

Table 1 Anchor auto calibration algorithm

Step	Algorithm
1:	pd= physical distance, md=measurement distance
2:	for anchor=1 to 4
3:	for i=1 to n UWB
4:	for t=1 to 3
5:	md[t]=anchor to anchor distance
6:	coeff = average pd / average md
7:	new antenna delay = last antenna delay * coeff
8:	anchor antenna delay update
9:	end

2.4. Machine Learning Based on 3D Localization

The use of trilateration and multilateration in localization is quite effective in 2D space. However, when applied to 3D space, the localization accuracy decreases drastically. This is because the z-axis error is very high. In this study, 3D localization is proposed using the CNN machine learning approach. This CNN is created by modeling all possible drone positions in its workspace. The ideal distance between the tag and anchor will be determined at each possible position using trigonometry. These values are used as input for the CNN network. The distance between the tag and anchor must be calculated for each possible position in the workspace based on this modeling. Assuming that the UWB DW1000 has a default error of 10 cm, the possible positions calculated are 10 cm intervals in the entire workspace. Each measurement distance and possible position are used as input and target in the dataset. Figure 5 shows the CNN architecture used in this study.

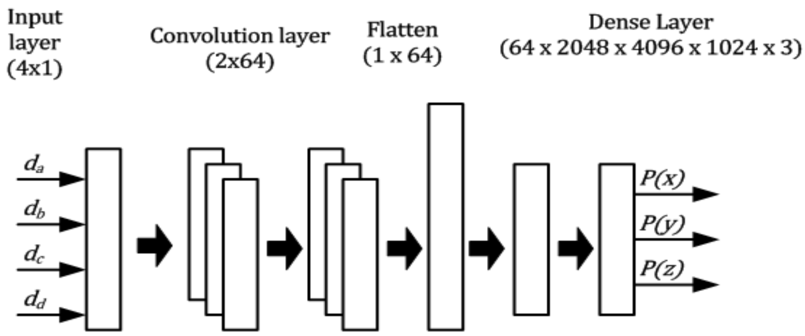

Figure 5 CNN architecture for 3D localization

2.5. Motion Threshold

Rapid changes in the distance reading between the tag and the anchor can decrease the accuracy of the position estimation of the drone. This decreased accuracy often results in significant positioning errors in the drone. Given the drone's speed limitations, such large changes in position in a short period should be unlikely. Therefore, when a large change appears, it can be considered an anomaly or estimation error. The accuracy of the position estimation can be improved and unnecessary errors can be minimized by eliminating these excessive changes. This error elimination process is called the motion threshold with the following algorithm (Table 2).

Table 2 Motion threshold algorithm

Step	Algorithm
1:	P= Position Estimation
2:	v_{th}=motion threshold (0.2 m/s)
3:	v=$\sqrt{(P_n(x)-P_{n-1}(x))^2+(P_n(y)-P_{n-1}(y))^2+(P_n(z)-P_{n-1}(z))^2}$/dt
4:	if v>vth:
5:	$P_n=P_{n-1}$
6:	else:
7:	$P_n=P_n$

2.6. Evaluation Metrics and Benchmarks

Techniques and filters, such as moving average and polynomial regression, are used to improve measurement accuracy by reducing noise in the data, where moving average smoothest out fluctuations and polynomial regression captures more complex data patterns. Multiple simultaneous ranging (MSR) improves simultaneous distance measurement by combining data from multiple sources to improve accuracy by utilizing multiple sequence signals, which helps identify and correct errors. Temperature compensation (TC) includes temperature variables as compensation in distance measurement, ensuring accuracy despite changes in ambient temperature. In conducting distance measurements, the observed metric is the distance error value

(d_e) in meters. The distance error (10) is obtained from the difference between the actual (d_a) and the measured distance (d_m). For position estimation measurements, the observed metrics are the ATE value and its standard deviation. ATE is obtained from the squared position difference in each axis. The smaller the ATE value, both the average and the standard deviation, the better the position estimation system. The ATE value is calculated using (11).

$$d_e = d_a - d_m \tag{10}$$

$$ATE = \sqrt{(x_{est} - x_{act})^2 + (y_{est} - y_{act})^2 + (z_{est} - z_{act})^2} \tag{11}$$

Here, de is the distance error, da is the actual distance, dm is the measured distance, xest is the estimated position on the x-axis, xact is the actual position on the x-axis, yest is the estimated position on the y-axis, yact is the actual position on the y-axis, zest is the estimated position on the z-axis, and zact is the actual position on the z-axis.

3. Results and Discussion

3.1. Distance measurement results

The accuracy of distance measurement is one of the main factors in UWB-based position estimation. In this paper, the performance of the UWB-based measurement system is first tested using the AAC algorithm. The AAC algorithm is the method proposed in this paper. This test was also carried out by comparing the proposed method with several conventional algorithms, such as moving average (MA) and polynomial regression (PR), and comparing it with previous research algorithms, namely LSTM-based (Liu and Bao, 2023), MSR (Shah et al., 2022), and TC (Liu et al., 2023).

Testing is performed by measuring the distance between the tag and each anchor used. The average value of the measurement results between the tag and anchor at each measurement distance is searched. The measured distances ranged from 1 to 10 m with an interval of 1 m. Based on the test in Table 1, the proposed method produces the smallest average error value of 0.011 m, smaller than LSTM, TC, and MSR, which are each worth 0.027, 0.124, and 0.021 m, respectively. The proposed method also provides the smallest standard deviation value so that the proposed method has good precision. The proposed method is the method proposed in this paper, while the benchmark method is a comparative method that has been carried out by previous research.

Table 3 Comparison of distance error measurement with other methods

Distance (m)	Distance Error (m)					
	MA	PR	LSTM**	TC**	MSR**	AAC *
1	0.315	0.017	0.002	0.217	0.010	0.008
2	0.245	0.047	0.005	0.152	0.006	0.004
3	0.290	0.043	0.015	0.192	0.140	0.058
4	0.211	0.034	0.016	0.113	0.009	0.004
5	0.142	0.073	0.068	0.091	0.010	0.005
6	0.214	0.059	0.038	0.129	0.010	0.009
7	0.183	0.025	0.011	0.085	0.007	0.007
8	0.156	0.067	0.035	0.076	0.006	0.004
9	0.149	0.063	0.027	0.064	0.007	0.006
10	0.156	0.128	0.056	0.125	0.003	0.006
Average	0.206	0.056	0.027	0.124	0.021	**0.011**
Std Dev	0.061	0.031	0.022	0.050	0.042	**0.017**
Min	0.142	0.017	0.002	0.064	0.003	0.004
Max	0.315	0.128	0.068	0.217	0.140	0.058

* Proposed method
** Benchmark method

3.2. 3D Localization Results

3.2.1. Trained data

Before conducting experiments on 3D localization based on ML, the ML model to be used is first prepared. The model is first trained using the prepared dataset. The model is trained until the smallest validation loss is obtained. Up to 10 trainings were carried out in all experiments in this paper. However, the data presented in this paper is only the model with the best training results. Figure 6 shows the historical training performance. With a validation loss of 0.014, the 3D localization results produced are expected to have good accuracy. In this training process, the observed variables are training loss and validation loss. Training loss measures how accurately a model learns from the dataset on which it was trained, whereas validation loss evaluates the model's performance on an independent dataset that was not used during training. In Figure 6, the train loss is larger than the validation loss because the data used are more diverse and complex.

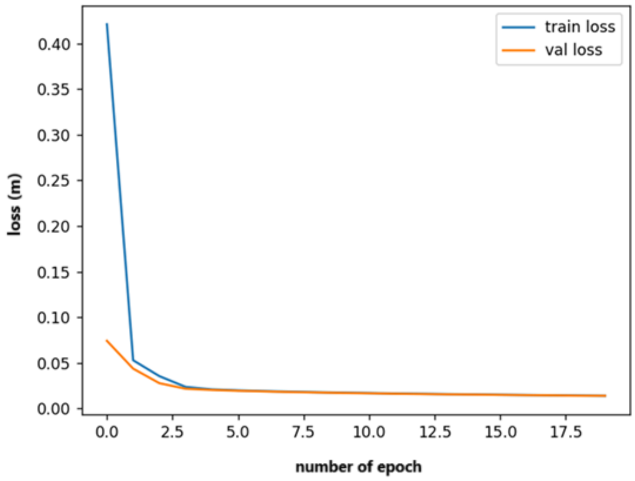

Figure 6 Best Training Performance

3.2.2. Static Positioning

Static positioning testing is performed by placing the UWB tag in a static position and a fixed coordinate. In this experiment, the UWB tag position is always within the square area between the four UWB anchors. This experiment was conducted by applying the AAC distance measurement method and several benchmarks, including TC, MSR, and LSTM. The performance of the basic trilateration method varies depending on the distance measurement method used. AAC and MSR provide lower average errors, with values of 0.71 m and 0.81 m, respectively. However, when the TC and LSTM methods are used, the average error increases to approximately 1.35 m, with high stability, as indicated by the relatively low standard deviation. This indicates that BT performs better when combined with AAC and MSR compared to TC and LSTM.

Furthermore, trilateration with the Expand Circle method shows slightly better results than basic trilateration, especially when combined with AAC and MSR. The average error for both methods is 0.95 m. However, this combination still shows an increase in error compared to the multilateration method, indicating that the development of the trilateration method with this circle expansion is not yet effective enough to significantly reduce errors.

Multilateration yields the most promising results, especially when combined with AAC and MSR, with average errors of 0.38 and 0.42 m, respectively. The relatively low standard deviation indicates that this method is not only more accurate but also more consistent in producing precise measurements. Even when using TC and LSTM methods, which generally show larger errors, Multilateration can still maintain a better level of accuracy than other localization methods. The ML-based method shows competitive results, especially when used with AAC and MSR, with average errors of 0.39 and 0.54 m, respectively. However, the very high maximum values indicate significant outliers, which can potentially reduce the overall stability of this method. Therefore, the actantial for outliers caused by data fluctuations must be minimized using the motion threshold algorithm.

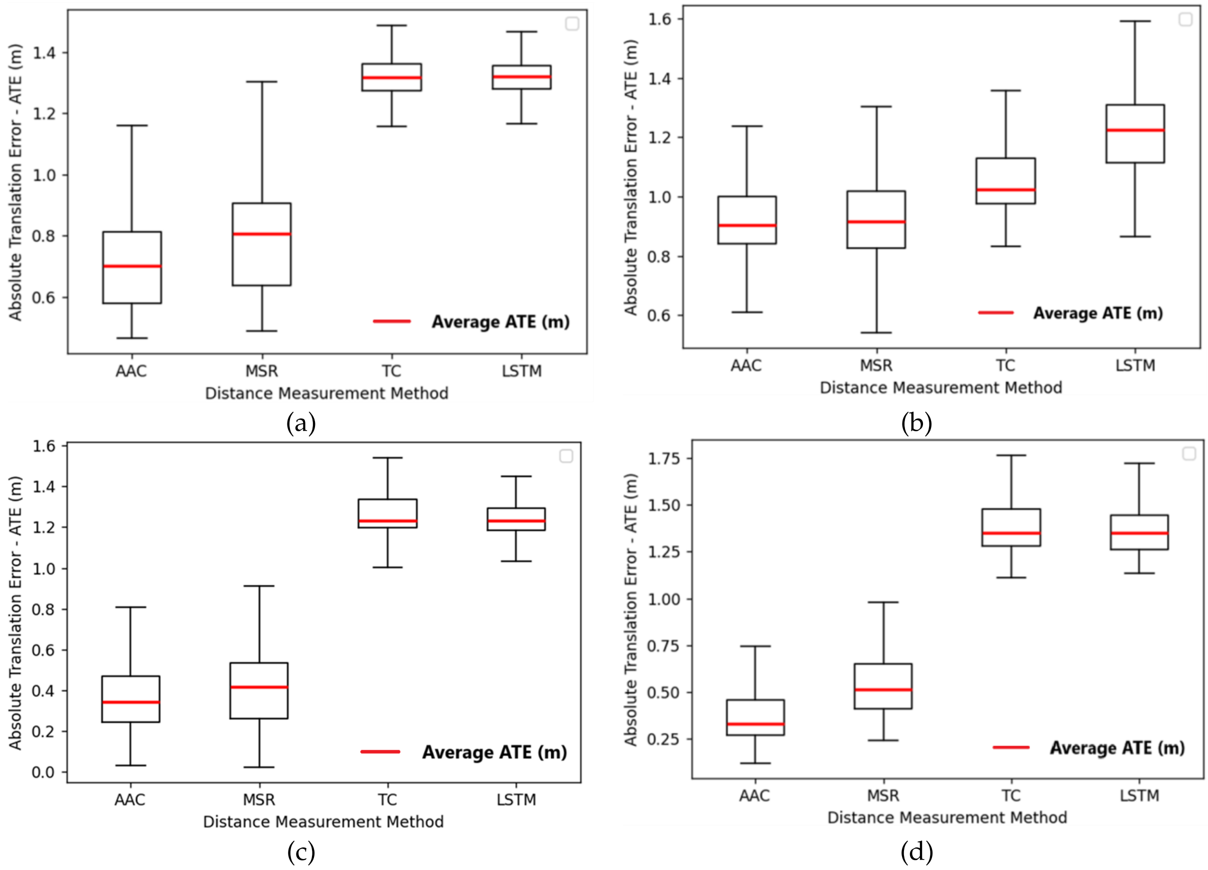

Figure 7 3D Localization Comparison (a) Basic Trilateration, (b) Expand circle Trilateration, (c) Multilateration, (d) Proposed Machine Learning-based 3D Localization

The performance of the basic trilateration method varies depending on the distance measurement method used. AAC and MSR provide lower average errors, with values of 0.71 m and 0.81 m, respectively. However, when the TC and LSTM methods are used, the average error increases to approximately 1.35 m, with high stability, as indicated by the relatively low standard deviation. This indicates that BT performs better when combined with AAC and MSR compared to TC and LSTM.

Furthermore, trilateration with the Expand Circle method shows slightly better results than basic trilateration, especially when combined with AAC and MSR. The average error for both methods is 0.95 m. However, this combination still shows an increase in error compared to the multilateration method, indicating that the development of the trilateration method with this circle expansion is not yet effective enough to significantly reduce errors.

Multilateration yields the most promising results, especially when combined with AAC and MSR, with average errors of 0.38 and 0.42 m, respectively. The relatively low standard deviation indicates that this method is not only more accurate but also more consistent in producing precise measurements. Even when using TC and LSTM methods, which generally show larger errors, Multilateration can still maintain a better level of accuracy than other localization methods. The ML-based method shows competitive results, especially when used with AAC and MSR, with average errors of 0.39 and 0.54 m, respectively. However, the very high maximum values indicate significant outliers, which can potentially reduce the overall stability of this method. Therefore, the actantial for outliers caused by data fluctuations must be minimized using the motion threshold algorithm.

3.2.3. Implementation of motion threshold

The application of motion threshold in the context of ML-based 3D localization has a significant impact on the performance of different measurement methods. The data analysis revealed that the application of motion threshold substantially improved the accuracy of the AAC and MSR methods. In this case, the motion threshold successfully reduces the average error, decreases the standard deviation, and limits the maximum error value, which overall improves the measurement quality. This confirms that the motion threshold is effective in filtering noise and improving the consistency and accuracy of the AAC and MSR methods. Figure 9 shows that outliers that appear when applying a motion threshold can be minimized. Outliers are indicated by black circles. The addition of the motion threshold successfully reduces the number of outliers. The absolute translation error is indicated by the red line.

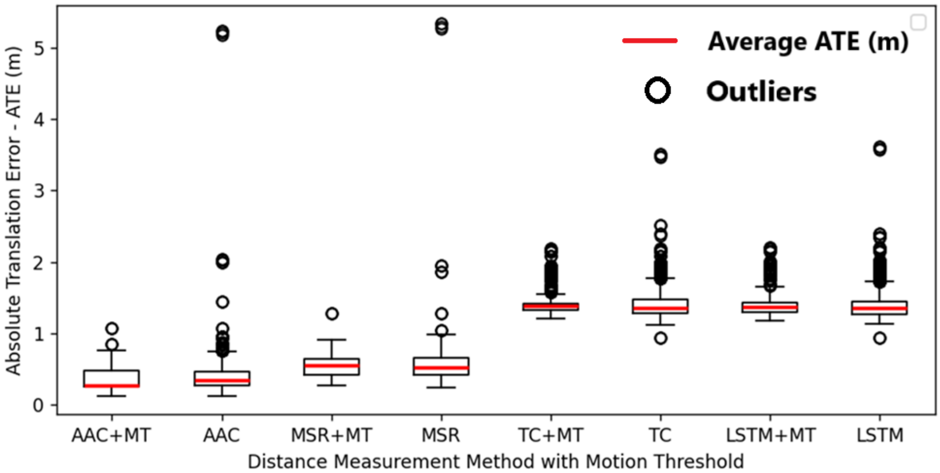

Figure 8 Results of motion threshold implementation

4. Conclusions

This study successfully demonstrated that using the auto anchor calibration method to measure the distance between UWB devices can achieve a very high level of accuracy, with a measured error below 2 cm and a standard deviation of 1.7 cm. Furthermore, the application of the ML-based 3D localization method has been proven effective in reducing the absolute translation error, which is significantly lower than that of conventional methods such as trilateration and multilateration. The application of motion threshold in the filtering process of 3D localization results based on machine learning also shows superior ability in eliminating unrealistic position estimates, especially estimates that exceed the maximum actantial speed of the drone. Overall, these results indicate that the proposed approach not only improves the accuracy but also the reliability of the drone navigation system, making it a more optimal solution than previous methods.

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Author Contributions

Riza Agung Firmansyah contributed to designing the testing platform, data acquisition, and writing the original draft. Tri Arief Sardjono contributed to methodology, writing, review, supervision, and editing. Ronny Mardiyanto contributed to supervision, analysis, data validation, and review.

Conflict of Interest

The authors declare no conflicts of interest.

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