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Improvement of Ultra-Wideband Based 3D Localization for Indoor Drone using Anchor Auto Calibration and Machine Learning Based Positioning

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Abstract. 3D localization is one of important part for indoor drone navigation systesm. 3D localization using Ultra-wideband (UWB) can be applied to solve GPS-denied environment problem. However, UWB has some disadvantages related to distance accuracy measurement, measurement fluctuation, and position estimation in 3-dimensional space. UWB measurement accuracy is affected by antenna delay. Antenna delay must be first 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 like trilateration, triangulation, or multilateration are effectively proven in 2-dimensional localization. While performing 3-dimensional localization, this method produced significant error, especially in Z-Axis. A new approach based on Machine Learning Convolutional Neural Network (CNN) is expected to solve complexity and nonlinearity in data measurement that arises in conventional methods. Data fluctuation problems due to UWB measurement during the position estimation process create large estimation errors. To solve these problems, a motion threshold is implemented after position estimation. Position changes that are too significant beyond the maximum drone velocity limit can be eliminated. Based on the experiment result, implementation of AAC in ML-based 3D localization with motion threshold significantly increases positioning accuracy up to 0.34 m, lowers standard deviation up to 0.12 m, and eliminates outliers caused by data fluctuation with maximum 1.07 m.

Keywords: Anchor auto-calibration; Indoor Drone; Machine Learning; Motion Threshold, Ultra-Wideband; 3D Localization.

1. Introduction

The use of 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 (Maria Elena Nenni, 2020) and construction (McCabe et al., 2017). Indoor drones, in particular, offer distinct advantages over traditional robots, including the ability to access difficult-to-reach areas, enhanced mobility, and a broader field of view. For safe and efficient operation, accurate 3D localization is essential for indoor drones (El-Sheimy and Li, 2021; Sesyuk et al., 2022). Precise positioning enables drones to navigate complex environments, avoid obstacles, and achieve their objectives with a high degree of accuracy.

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3D localization on drones allows drones to determine their position in 3D space. Global Positioning System (GPS) is a commonly used localization method, but it is not effective for indoor localization (Macoir et al., 2019; Niculescu et al., 2023; Shi et al., 2020; Shule et al., 2020; Yang et al., 2022). This is because the GPS signal is blocked by the building structure because GPS uses satellites to determine position, and this signal can be blocked by walls, ceilings, and other objects inside the building (Chang et al., 2023). In addition, 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). To overcome the weaknesses of indoor GPS, WiFi localization based on RSSI (Nina Hendrarini, 2022) or Ultra-Wideband (UWB) can be used. UWB offers a better solution for indoor drone 3D localization. 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 and transmit UWB signals. UWB has several advantages including high accuracy up to a few centimeters, and low latency (Dai et al., 2024; Nawaid Hasan, 2024). However, UWB itself also has several disadvantages, one of which is the problem of complexity. For the UWB localization system to work effectively, it is necessary to calibrate each anchor (Krapež and Munih, 2020), the anchor installation position (Gao et al., 2023), and the localization algorithm used (Chang et al., 2023; Joses S. Sorilla, 2024; Sandamini et al., 2023).

Problems related to the accuracy of distance measurement must first 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 (Gui et al., 2018; Liu et al., 2024). Antenna delay is a challenge in UWB-based distance measurement so this challenge has been attempted to be resolved by several previous studies. Efforts to reduce distance measurement errors have been carried out using several methods, including the Hybrid Compensation Model (Liu et al., 2023). The Hybrid Compensation Model is carried out with tests based on temperature and distance measurements. This method is equipped with a Kalman filter and several optimization algorithms. The Hybrid Compensation Model is quite good for use in static conditions. Multiple Simultaneous Ranging (MSR) introduces 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 Estimator method uses an automatic and real-time approach to calibrate antenna delay on UWB devices (Liu et al., 2024). This approach uses two estimators, namely coarse and fine adjustment. The LSTM method is also used to improve the accuracy and frequency of distance measurements with UWB (Liu and Bao, 2023). The first technique combines a convolutional neural network (CNN), a long short-term memory (LSTM) module, and a regression module to process data from the sensor. The second technique combines two random forest 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) in the localization system are quite effective in 2D space. Trilateration performs by measuring the distance between the object and a minimum of three reference sites, wherein the convergence of three spheres centred on these points establishes the object's location. Triangulation employs angular data between the object and reference points to ascertain its location, frequently utilised 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 utilised in navigation systems like radar and ultra-wideband (UWB). Several filter-based methods such as the Kalman Filter (Kim and Pyun, 2021), the Extended Kalman

Filter (Li et al., 2021; Tai Shie Teoh, 2023), to the unscented Kalman Filter (Fu et al., 2019; Kolakowski, 2020) have been applied to improve accuracy. However, when applied to 3D space, the accuracy will decrease drastically (Delamare et al., 2020). In general, 3D localization has a very high z-axis error due to the placement of anchors which are generally at almost the same height, causing a lack of vertical variation (Bao et al., 2024). This reduces the accuracy of height estimation. In addition, the reflection and multipath effects of UWB signals, especially in indoor environments, often cause inaccurate distance measurements in the z-axis. Another positioning technique developed is circle expansion to overcome the weakness of the absence of a circle intersection (Ibwe et al., 2023). To overcome the weaknesses of conventional methods, this paper proposes 3D localization using the CNN machine learning approach. Machine learning-based 3D localization can effectively handle complexity and non-linearity in measurement data (Gao et al., 2023; Nguyen et al., 2021, 2020). Where 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, while Kalman Filter requires a complex model. The actual position change is limited by the maximum speed, so if the estimated position change exceeds the distance that the drone can travel in a certain time, it can be considered as noise. To overcome this data fluctuation, this paper applies a motion threshold algorithm to limit the position change based on a realistic maximum speed, thereby improving the stability and accuracy of position estimation. Based on several advantages explained above, the contributions made in this paper include proposed anchor auto calibration for compensating antenna delay effect during distance measurement. This method succeeded in decreasing the error measurement range for each UWB sensor under 5 cm. This improvement has a significant impact on the final position estimation. Proposed machine learning-based 3D localization using 1DCNN based on measurement data between tag-anchor and previous position. This approach has less error than conventional positioning like trilateration, and multilateration. Implementing motion threshold to prevent fluctuated position estimation. Machine learning, such as 1D-CNN, improves UWB localisation by eliminating signal errors and improving the accuracy of position estimations. Anchor Auto-Calibration (AAC) provides reliable calibration through constant input and changes. To maintain the system's effectiveness, the 1D-CNN is optimised for real-time application with minimal latency, 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 needs to be improved first. This improvement is done by automatically calibrating the antenna delay on the UWB anchor. This procedure is called Anchor Auto Calibration (AAC). The distance measurement results are then entered into ML-based 3D localization using Convolutional Neural Network (CNN). For the last stage, a motion threshold has been implemented to eliminate fluctuating position estimation that is greater than the possible maximum drone velocity (0,2 m/s). The main proposed method of this paper is illustrated in Figure 1 below.

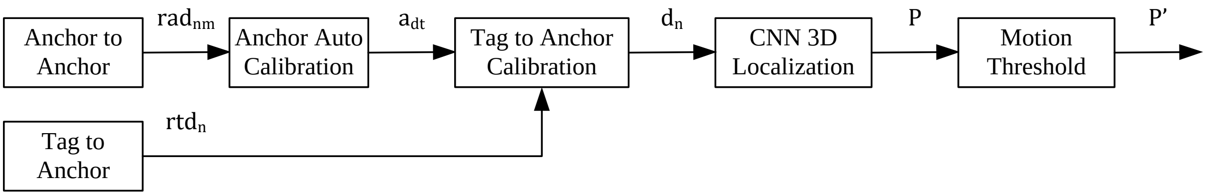
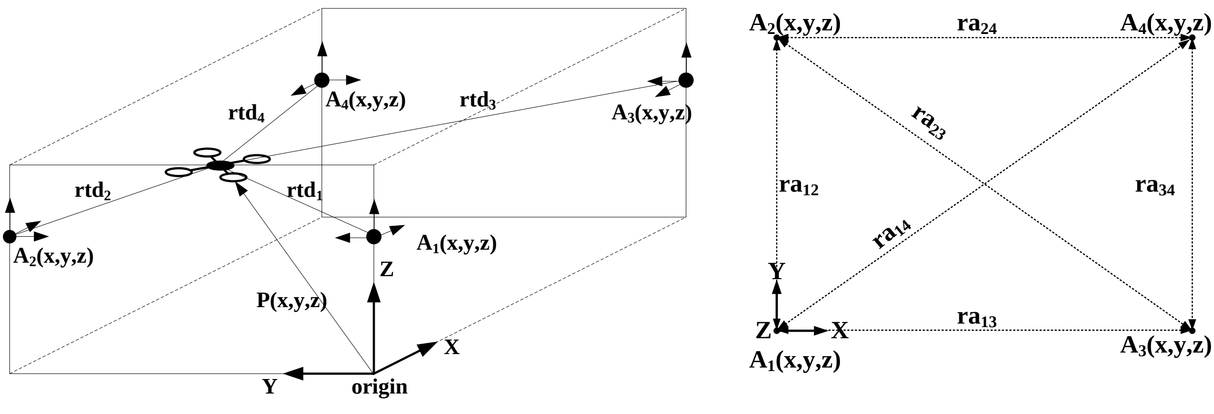


Figure. 1. Proposed Method Block Diagram

The raw data for determining the distance between anchors is referred to as rad_{nm}. The raw data is further calibrated using Anchor Auto Calibration (AAC) to generate calibrated anchor data (ad_t). The adt value is used as a calibration constant in 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 CNN 3D Localisation to ascertain 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 in situations where 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 starts 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. Position estimation can be calculated by trilateration based on the relative distance of the UWB tag with several UWB anchors. Basic indoor UWB-based 3D localization in this paper is illustrated in Figure 2.



(a) (b)

Figure. 2. Basic UWB 3D Localization for indoor drone (a) isometric view, (b) top view

The UWB module used in the test is the DW1000. The DW1000 is an Ultra-Wideband (UWB) transceiver developed by Decawave Ltd., a company based in Dublin, Ireland. The module has been equipped with an ESP32 microcontroller so that it can perform data acquisition and communication via wifi without additional devices. This module works at a frequency of 3774 MHz to 4243.2 MHz. This module is capable of measuring distances up to 100 meters and can be increased to more than 200 meters with additional antennas and lower working frequencies. However, in this study, no additional antennas were used considering that the room used only has a maximum length dimension of 20m.

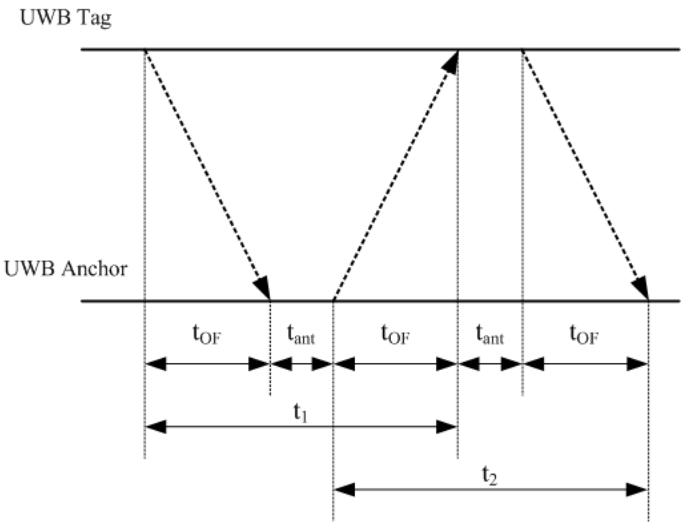


Figure. 3. Two-Way Ranging UWB Distance Measurement

To perform distance measurements, data acquisition is carried out using the Two Way Ranging (TWR) method. This method is quite good at eliminating errors caused by unsynchronization between modules. To run TWR, two UWB modules are needed, each of which functions 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 used as a reference point and is positioned statically. The measurement process begins with the tag sending data to the anchor and starting to calculate 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 data is received by the anchor, the anchor immediately sends data and an ACK signal to the tag. The time it takes for 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}). Furthermore, the time it takes for the signal to propagate from the anchor to the tag is tOF. The final stage of this process is carried out by the tag sending ACK2 to the anchor. This process requires data processing time of tant and tOF. TWR is illustrated in Figure 3.

$$t_1 + t_{ant} = t_{ant} + t_2 \quad (1)$$

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

$$t_{OF} = \frac{t_1 t_{ant} - t_{ant} t_2}{t_1 + t_2 + 2t_{ant}} \quad (3)$$

The process of converting tOF into distance estimation is done by multiplying tOF with electromagnetic wave velocity (c) of 3×10^8 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 may be fine-tuned to give the best possible range or location. Antenna delay will affect the calculation process of time t_1 and t_2 so that the error that appears due to antenna delay is formulated with (4). This paper has the main objective 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 method for 3D localization using UWB. 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 drone's position 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 done using the following 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 multilateration method as a conventional 3D positioning will be compared in performance with Machine Learning Based 3D Localization created using Convolutional Neural Network (CNN). So to get 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 accuracy of this measurement needs to be considered first. Distance measurement using UWB requires two UWB devices, each activated as a tag and anchor. Each device must be given a different address to avoid conflict. However, UWB devices cannot be activated as tags and anchors simultaneously at one time. So, a scheduling mechanism is needed to activate an anchor into a tag in a certain duration and time interval. In this paper, round-robin scheduling is proposed. This technique has the advantages of being simple, easy to implement, and starvation-free. The scheduling mechanism used is shown in Figure 4. This process begins by setting UWB A to be a tag, while the other three UWBs become anchors. This configuration is updated every 5 seconds and begins with an initialization process for 2 seconds 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 anchor-to-anchor distance measurement

2.3. Anchor auto-calibration algorithm

The Anchor Auto-Calibration (AAC) algorithm is an algorithm that improves the accuracy of distance measurements between anchors in a positioning system that utilizes anchors and tags. AAC begins with 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. Furthermore, the calibration coefficient is calculated by dividing the actual physical distance between anchors by the average value of the measurement distance. This coefficient functions as a multiplier in the calculation of the new antenna delay, where the initial antenna delay value is multiplied by the calibration coefficient. The updated antenna delay value is then 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, by actual physical conditions. The AAC process is explained in Algorithm in Table 1 below.

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 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 will decrease drastically. This is because the error on the z-axis is very high. In this paper, 3D localization is proposed using the CNN machine learning approach. This CNN is created by modeling all possible drone positions in its workspace. At each possible position, the ideal distance between the tag and anchor will be determined using trigonometry. These values are used as input for the CNN network created. Based on this modeling, the distance between the tag and anchor must be calculated for each possible position in the workspace. Assuming the UWB DW1000 has a default error of 10 cm, then 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 is the CNN architecture used in this paper.

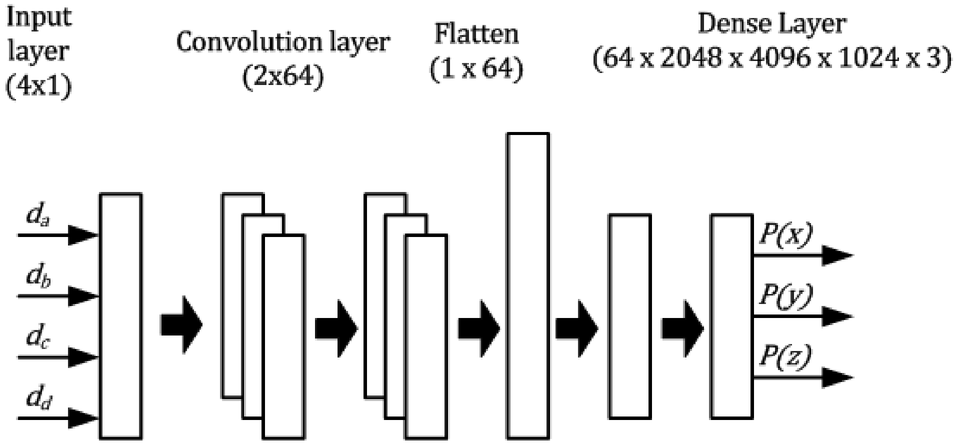


Figure. 5. CNN architecture for 3D Localization

2.5. Motion Threshold

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

In the evaluation of position methods, 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 smoothes out fluctuations and polynomial regression captures more complex data patterns. Multiple Simultaneous Ranging (MSR) improves simultaneous distance measurement by utilizing multiple sequence signals to improve accuracy by combining data from multiple sources, which helps identify and correct errors. Temperature Compensation (TC) includes temperature variables as compensation in distance measurement, ensuring accuracy is maintained 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 distance (d_a) and the measured distance (d_m). For position estimation measurements, the observed metrics are the Average Absolute Translation Error (ATE) value and its standard deviation. ATE is obtained from the root of the squared position difference on 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).

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

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

Where 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, zact is the actual position on the z-axis.

3. Results and Discussion

3.1. Distance Measurement Result

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

Table 3 Distance error measurement comparison 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

Testing is done by measuring the distance between the tag and each anchor used. The measurement results between the tag and anchor at each measurement distance are searched for the average value. The distances measured range from 1 m 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 m, 0.124 m, and 0.021. The proposed method also provides the smallest standard deviation value so that it can be claimed 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.

3.2. 3D Localization Result

3.2.1. Trained data

Before conducting experiments on 3D localization based on machine learning, the machine learning 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. In all experiments in this paper, up to 10 trainings were carried out. However, the data presented in this paper is only the model with the best training results. Historical training performance is shown in Figure 6. With a validation loss of 0.014, it is expected that the 3D localization results produced will also have good accuracy. In this training process, the variables observed are training loss and validation loss. Training loss measures how accurately a model learns from the dataset it was trained on, whereas validation loss evaluates the model's performance on an independent dataset that was not used during training. In figure 6, train loss is larger than validation loss because the data used is more diverse and complex.

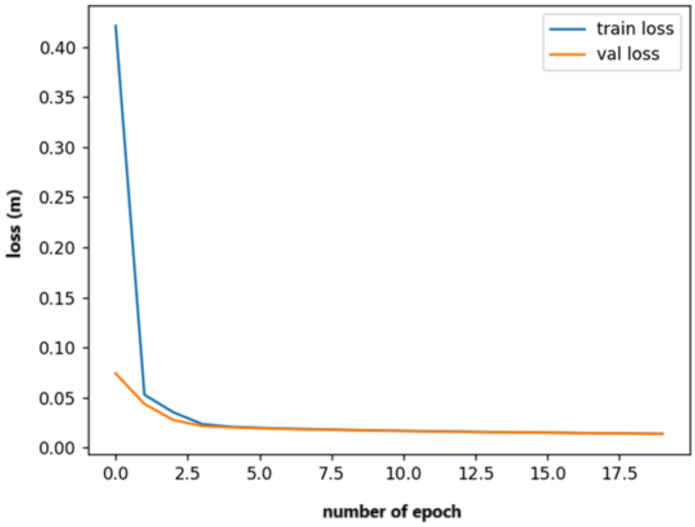


Figure. 6. Best Training Performance

3.2.2. Static Positioning

Static positioning testing is done by placing the UWB tag in a static position and a fixed coordinate. The limitation set in this experiment is that 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 Basic Trilateration method shows varying performance 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 around 1.35 m, with high stability, as indicated by the relatively low standard deviation. This indicates that Basic Trilateration 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 at the same number, which 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 reduce errors significantly.

Multilateration gives the most promising results, especially when combined with AAC and MSR, with average errors of 0.38 m 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 is still able to 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 m and 0.54 m, respectively. However, the very high maximum values indicate significant outliers, which have the potential to reduce the overall stability of this method. So the potential for outliers caused by data fluctuations needs to be minimized using the motion threshold algorithm.

The Basic Trilateration method shows varying performance 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 around 1.35 m, with high stability, as indicated by the relatively low standard deviation. This indicates that Basic Trilateration 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 at the same number, which 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 reduce errors significantly.

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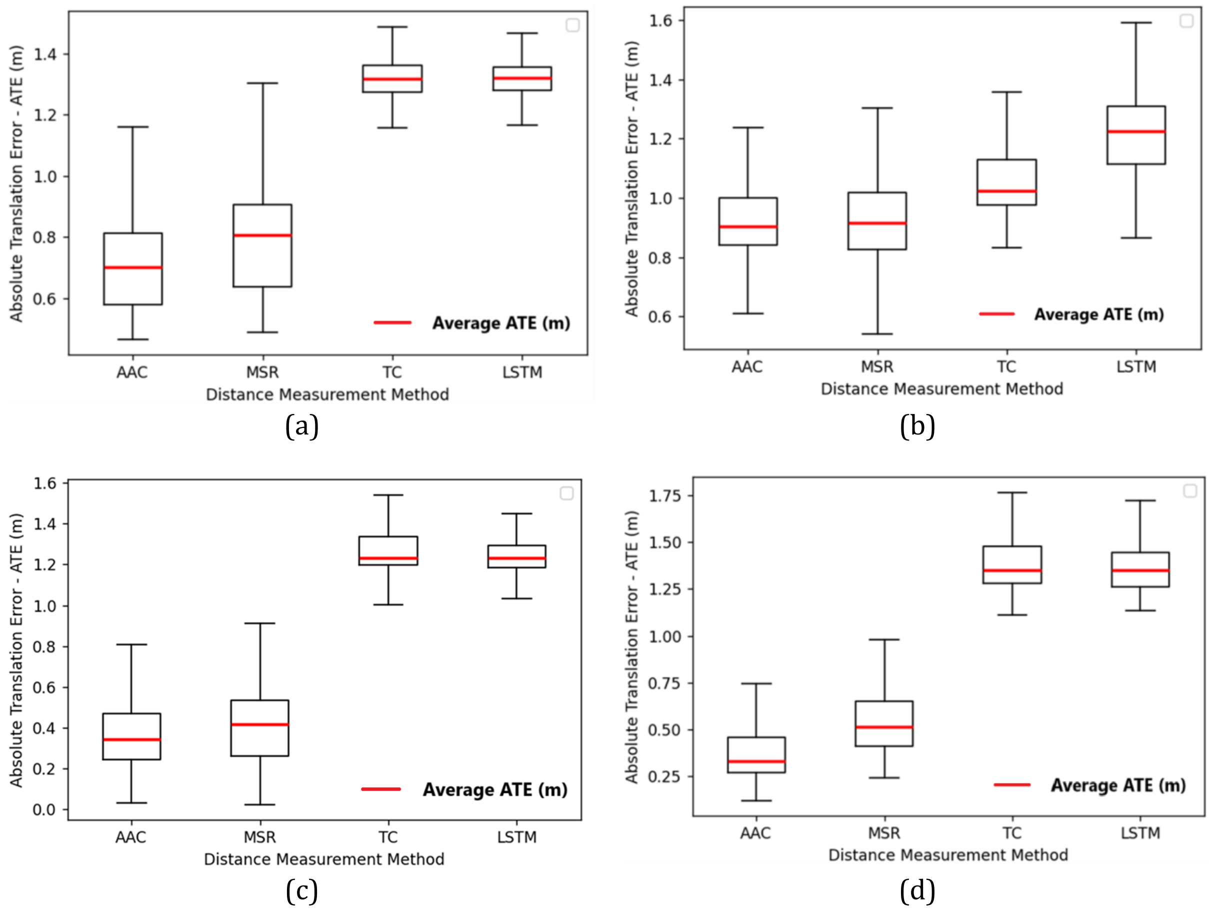

Figure. 7. 3D Localization Comparison (a) Basic Trilateration, (b) Expand circle Trilateration, (c) Multilateration, (d) Proposed Machine Learning-based 3D Localization

3.2.3. Motion Threshold Implementation

The application of motion threshold in the context of Machine Learning-based 3D Localization shows a significant impact on the performance of different measurement methods. Data analysis reveals that the application of motion threshold substantially improves 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 contributes to improving the measurement quality. This confirms that motion threshold is effective in filtering noise and improving the consistency and accuracy of the AAC and MSR methods. As seen in Figure 9, outliers that appear when applying a motion threshold can be minimized. Outliers are indicated by black circles. The addition of motion threshold successfully reduces the number of outliers. Absolute translate error is indicated by the red line.

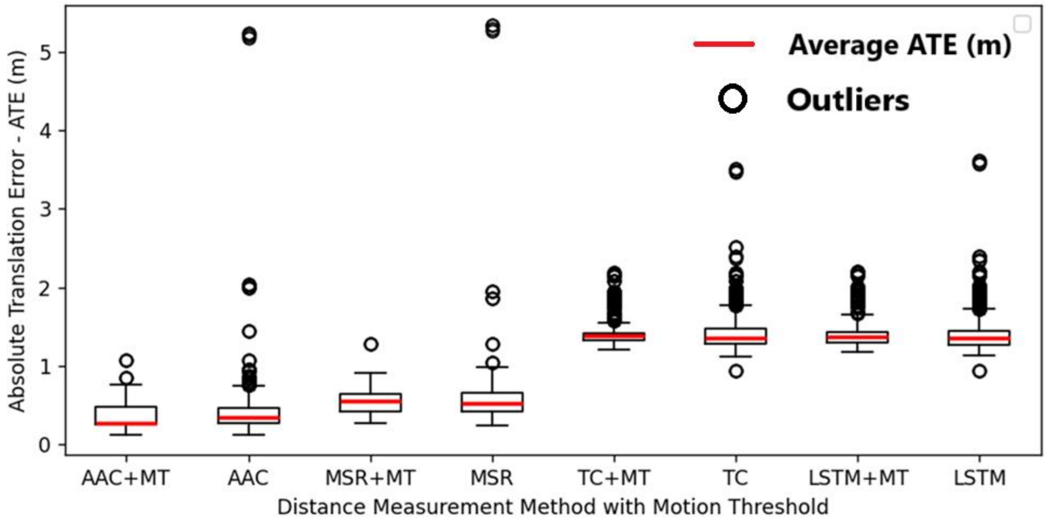

Figure. 8. Motion Threshold Implementation Result

4. Conclusions

This study successfully demonstrated that the measurement of distance between UWB devices using the Auto Anchor Calibration method is able to 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 Machine Learning based 3D Localization method has been proven effective in reducing the absolute translation error, which is significantly lower than 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 potential 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 compared to 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 conflict of interest.

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