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RIBATS: RSSI-based adaptive tracking system with ASEKF for indoor WSN

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ABSTRACT

Wireless indoor tracking systems face challenges due to environmental conditions and signal attenuation, affecting location accuracy, crucial in wireless sensor network (WSN) applications. Many tracking techniques rely on specific path loss models proposed by previous researches, but these models are susceptible to changes in environmental conditions, impacting estimation outcomes. In order to solve these problems, this paper propose adaptive tracking system using received signal strength indicator (RSSI) measurement parameter called as RIBATS. Adaptive in this system refers to the reliability of an algorithm for obtaining the accurate location without any path loss modelling at dynamic indoor environments. The enhancement of weighted centroid localization (eWCL) scheme calculates the location estimation only using RSSI data measurement without propagation characterisic determination. However, estimation result from eWCL still have high error at certain area. Hence, by defining a multiplier factor as adaptive scaled to the covariance matrix of EKF can eliminate distortion effects from eWCL called as adaptive scaled extended Kalman filter (ASEKF) algorithm. An effective variance estimation algorithm for adaptive indoor tracking system using eWCL and ASEKF combination achieve 0.82 meters mean square error (MSE) value with 55.67% error reduction. Then, without using multiplier scale factor at EKF algorithm only reduce previous eWCL at 3.78% with 1.78 meters MSE value.

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1. INTRODUCTION

Wireless sensor networks (WSN) provide many applications equipping a large number of sensor nodes interconnected wirelessly such as environmental monitoring, military surveilance, medical monitoring, object tracking, and vehicle navigation. All of these applications require accurate location information [1], [2]. Nevertheless, the accuracy performance of global positioning system (GPS) as location-based technology is only capable for outdoor tracking system applications and it is deteriorate rapidly in complex indoor environments [3]. Therefore indoor location-based services are still the main concern for many researchers due to incapability from existing technologies for achieving precision location information.

Several enabling technologies of indoor location-based services have been expanded using mobile wireless communication system such as Wi-Fi, ultrasound signal, Zigbee, ultra-wide band (UWB), LoRA, Bluetooth low energy (BLE), and Radio frequency identification (RFID) [4]–[11]. These technologies depend on its quality of measurement parameter as well as received signal strength indicator (RSSI), time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AoA) and frequency difference of arrival

(FDOA) [12], [13]. Compared to wireless communication indicator, RSSI have various advantages: low power consumption, simple hardware, and easy in data measurement. However its advantages of RSSI are directly proportional to its disadvantages as high sensitivity to environment. RSSI data measurement depends on the propagation characteristics represented as path loss exponent value (PLE). Many factors are used to consider the spesific PLE values including signal reflection, noise, multipath fading, scattering and interference effects. These factors can make inconsistent PLE values, while the spesific PLE values are required for determining distance estimation between anchor nodes as the transmitter and unknown node (UN) as receiver or target nodes from RSSI data measurement. Hence, establishing an accurate distance estimation based on RSSI measurement and PLE value is difficult which can also affect to the performance of indoor location-based services [6], [10].

In order to solve the problem related to the indoor location-based services using RSSI, many researchers proposed robust methods for minimizing the influence from the external environment variability. RSSI-based adaptive scheme is an effective solution to gain accurate locations in high complexity environment. The enhancement of weighted centroid localization (eWCL) is one of adaptive scheme in positioning system. Using eWCL scheme, the distance estimation can automatically calculate by RSSI measurement without determine PLE values [7], [14]. However, these schemes still have high errors distance in practical deployment up to 1.85 meters [15]. Therefore, improved algorithm should be added for minimizing the error estimation. Extended Kalman filter (EKF) as a statistic approach algorithm is appropriate for non-linear systems as well as fluctuating condition of RSSI [15]. EKF as the derivative algorithm of Kalman filter (KF) can be used for predicting the position of target node that recursively work for obtaining the convergence value from the variance of error measurement [15]–[24].

The dynamic states from RSSI data measurements can be influenced to the performance of KF algorithm in calculating estimated positions [25], [26]. Many researchers have been tried to modify the KF algorithm as adaptive filter scheme. Nie and Zhang [15] proposed effective scaled with self-adaptive scaling parameters which was called as unscented Kalman filter (UKF). Determination of scaling parameter values for UKF was important due to the estimation results is not as good as the EKF algorithm. As well as [18]–[21], [23], [24] have been proposed scaling parameters for EKF algorithm. The various schemes for calculating its parameters directly influenced the performance of the EKF results. Then, in [17] have been tried for modifying EKF using adaptive adjustment at its noise covariance values with scaling parameters also. Several approaches for determining the scaling parameter have been proposed before in [17]–[24] such as Fuzzy, least square, residual based and weighted.

This paper extends the conference paper [14], where we only proposed the eWCL algorithm for the indoor localization system without any refinement algorithm. Therefore, in this paper, we adopted previous research in [17]–[24] for using scaling parameter values for the EKF, which can be used to improve the result from [14]. In this paper, the scaling value was calculated using the eWCL algorithm as the weighted value from RSSI measurement data and then multiplied by the covariance matrix of the EKF. The contributions of this paper are: (i) the development of adaptive scheme for estimating position from RSSI data measurements automatically without determining the PLE value of each environment condition which called as RSSI-based adaptive tracking system (RIBATS); (ii) this paper presents the formulation algorithm of tracking system in detail with the addition of new scheme using the adaptive scaled Extended Kalman Filter (ASEKF) algorithm as the refinement process from initial estimation using eWCL algorithm to achieve accuracy result; (iii) the proposed scheme performance is verified through the realistic scenario of RSSI data measurement from Xbee S2 Pro transmission which were installed at the 3rd floor of EEPIS postgraduate building as indoor environment location.

In order to guarantee the effectiveness of this proposed system, this paper is organized as follows: the research methodologies are discussed in section 2, which involve the proposed scheme of RIBATS, as well as RSSI-based adaptive tracking system. This system utilizes the eWCL algorithm for initial estimation, followed by improvement with the ASEKF algorithm for final estimation. The experimental results based on real measurement data have been evaluated using mean square error (MSE) and accuracy percentage parameters to verify the proposed system results in section 3. Finally, we draw the conclusion and discuss possibilities of future work in section 4.

2. RESEARCH METHOD

2.1. RSSI-based adaptive tracking system

In this section, we explain in detail the process used to obtain the estimated route result in RSSI-based adaptive tracking system (RIBATS) at Figure 1. This process begins with the deployment of several nodes in a realistic environment, followed by RSSI measurement for estimating position and eWCL calculation as the input data for determining the estimated route using ASEKF algorithm. Estimated positions are obtained from RSSI measurements transmitted from XBee S2 Pro module, serving as the anchor node (AN) to the mobile UN. In this paper, we create a simulation that reflects a real-world scenario, implemented within the indoor environment of the EEPIS postgraduate building's 3rd floor. The simulations are performed using MATLAB software, and the relevant parameters for this system are provided in Table 1.

RSSI levels have been received by the UN using the Arduino Pro Micro module via the Xbee protocol. There are 18 anchor nodes deployed at the wall on the building walls at a height of 2.4 meters with 7 meters separations. The mobile UN moves to the 53 specified points at a height of 0.9 meters, as shown at Figure 2. The entire measurement process is conducted indoor area on the EEPIS campus, where several obstacles are present. The RSSI measurement phase starts at the first measurement point of the $UNs_{j\ (1,2,3\ldots\ n)}$, connecting to the nearest $ANs_{i\ (1,2,3\ldots n)}$ within a maximum serving distance of 10 meters. When the UN moves to the next point on its route and the distance is within 10 meters, the measurement process halts and shifts to measure the other ANs. This procedure repeats for each ANs located at the nearest point to the UNs route.

Table 1. Simulation parameter

Parameter	Value	Remarks
Operating frequency	2.4 GHz	
Transmit power	17 dBW	Xbee Pro (S2) module
Receiver sensitivity	-102 dBm	
Interval distance between anchor nodes (AN)	7 meters	Anchor nodes (AN) deployment
Calculating estimated position	2 meters	Unknown node (UN) movement

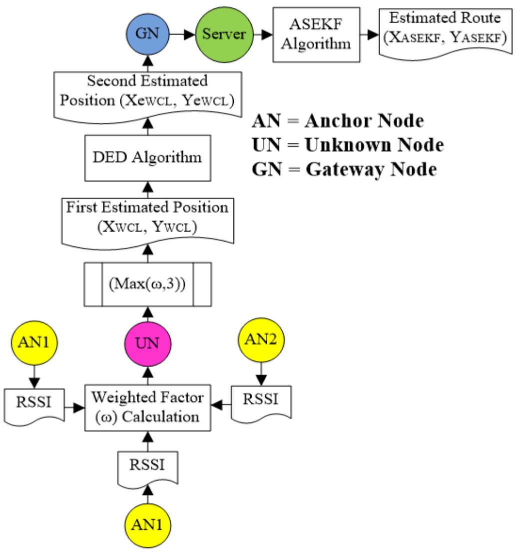


Figure 1. RSSI based adaptive tracking system methodology

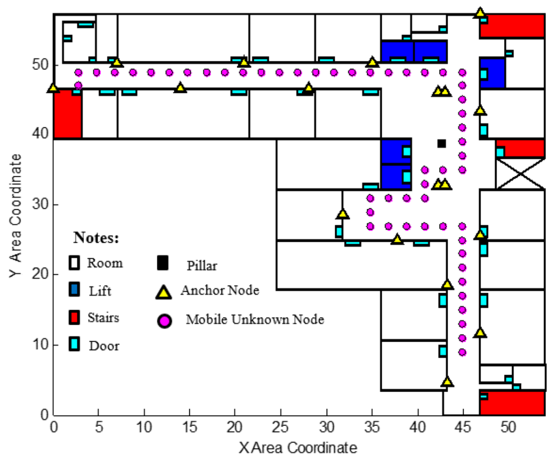


Figure 2. Assumed route scenario of mobile UN

Due to RSSI limitation and inconsistent data from Xbee transmission, the weighted factor value (ω) calculation is determined from three strongest RSSI level transmissions of ANs to the UNs. The weight factor based on RSSI can be express as [1], [14].

$$\omega_{ij} = \frac{\sqrt{(10^{RSSI_{ij}/10})^k}}{\sum_{i,j=1}^{n}\sqrt{(10^{RSSI_{ij}/10})^k}} \rightarrow \omega_{ij}' = \omega_{ij} \times N_{AN}^{2\omega_{ij}} \tag{1}$$

The weight value from (1) implies the influence in calculating the UNs estimated position. Therefore, previous weight factor value should be adjusted by k as the multiplier factor. The weight value is used to calculate the initial estimated position using the weighted centroid localization (WCL) algorithm, a refinement of the centroid localization (CL) method that enhances accuracy. The estimated position of UNs (x_j, y_j) based on WCL algorithm at (2) can be calculated using only the RSSI value and the coordinates of ANs, without the need for propagation value characteristics, as presented in [12], [15], [26]. This can be derived as [1], [14].

$$UN(x_{WCL}, y_{WCL}) = \frac{\sum_{i=1}^{n}(\omega_{ij}' \times (x_i, y_i))}{\sum_{i=1}^{n}\omega_{ij}'} \tag{2}$$

As illustrated in Figure 2, the next step involves using the weighted factor to reduce estimation errors without modifying the displacement positions of the UNs. To address this, the method from [23] was employed, incorporating the addition of the difference of estimated distance (DED) to achieve a uniform accuracy distribution across all UNs positions. The main requirement parameter of DED algorithm is distance, which is determined from estimated distance result of WCL algorithm, as shown in the (3).

$$d_{WCL_{AN_{i=1,2,3}}} = \sqrt[2]{\left(x_{WCL} - x_{AN_i}\right)^2 + \left(y_{WCL} - y_{AN_i}\right)^2} \tag{3}$$

The main idea of the DED algorithm is to determine the estimated position by calculating the difference in distances between the three nearest ANs and the position of the UNs. According to the distances of UNs to three nearest ANs, DED is multiplied with some weighted value as WCL algorithm (α, k). The weighted value of (k) can be adopted from adjusted result of WCL algorithm, while the (α) value should be adjusted again to obtain a better result for the DED algorithm. The (f) as the multiplication result between the weighted different distances to the three nearest coordinates of ANs can be calculated using (4-7).

$$f_{(x1,y1)} = (x_{AN1}, y_{AN1}) \times \left((d_{WCL2} - d_{WCL1})^k + (d_{WCL3} - d_{WCL1})^k + \frac{1}{d_{WCL1}{}^{\alpha}} + \frac{1}{d_{WCL2}{}^{\alpha}}\right) \tag{4}$$

$$f_{(x2,y2)} = (x_{AN2}, y_{AN2}) \times \left((d_{WCL2} - d_{WCL1})^k + (d_{WCL3} - d_{WCL2})^k + \frac{1}{d_{WCL2}{}^{\alpha}} + \frac{1}{d_{WCL3}{}^{\alpha}}\right) \tag{5}$$

$$f_{(x3,y3)} = (x_{AN3}, y_{AN3}) \times \left((d_{WCL3} - d_{WCL1})^k + (d_{WCL3} - d_{WCL2})^k + \frac{1}{d_{WCL1}{}^{\alpha}} + \frac{1}{d_{WCL3}{}^{\alpha}}\right) \tag{6}$$

$$F = 2 \times \begin{pmatrix} (d_{WCL2} - d_{WCL1})^k + (d_{WCL3} - d_{WCL1})^k + (d_{WCL3} - d_{WCL2})^k + \\ \frac{1}{d_{WCL1}{}^{\alpha}} + \frac{1}{d_{WCL2}{}^{\alpha}} + \frac{1}{d_{WCL3}{}^{\alpha}} \end{pmatrix} \tag{7}$$

The combination process of the WCL and DED algorithms is called as the enhancement of WCL (eWCL) algorithm. Therefore, estimated position result from eWCL can be calculated as (8).

$$(x_{eWCL}, y_{eWCL}) = \frac{f_{(x1,y1)} + f_{(x2,y2)} + f_{(x3,y3)}}{F} \tag{8}$$

The estimated position obtained from the WCL algorithm serves as the initial estimation, while the second estimation, derived from the eWCL algorithm, is processed at the UN. Subsequently, the UN directs this result to the gateway node (GN), which then forwards the data to the server. All communication links between the UN and GN, as well as between GN and the server, utilize the Wi-Fi protocol. The GN hardware consists of a Raspberry Pi 3B, while the server employs a laptop. The estimated route of UNs is determined through the ASEKF algorithm at the server, as it demands relatively high computational time. The specific process and calculations involved in the ASEKF algorithm are elaborated upon in the following section.

2.2. Adaptive scaled extended Kalman filter

This section provides a brief overview of extended Kalman filter (EKF) algorithm as the basic and conventional scheme before adding some multiplier scaled. The EKF, an advanced version of the Kalman filter (KF) is basically consist a series of measurement that allow for predicting uncertain information in a dynamic system [4]. Typically, EKF is well-known for solving the non-linear problems as well as tracking target locations through linearization process [10]. Indoor RSSI-based tracking systems produce diverse data, resulting in a non-linear nature. Consequently, the EKF algorithm can be utilized to enhance the initial estimates provided by the eWCL algorithm. Tracking systems typically use three types of EKF: the P-model (position), the PV-model (position and velocity), and the PVA-model (position, velocity, and acceleration) [27]. Given the RSSI-based positioning system, the P-model is the most suitable type of EKF for this application. In previous work [27], the P-model EKF determines the position based on results from the trilateration algorithm. The EKF algorithm involves three main phases: initialization, prediction, and update. The initial step performed by EKF algorithm is to declare input parameters (x_k, z_k) which are subsequently refined by the algorithm. The input state contains the estimated position data (x, y) from the previous algorithm calculation. Then, the prediction step, is processed the initialization state by utilizing the relationship between the state before and after from the posteriori and covariance (S_k, P_k). The update state ($P_{k|k-1}$, $Q_{k|k-1}$, $S_{k|k-1}$, $R_{k|k-1}$) process the output from the prediction state by adding the Kalman gain (K_k) as the main process for filtering the outlier data from initial estimation result. The expected estimation result of EKF are obtained from the posterior state ($x_{k|k-1}$) in the form of X_{EKF}, Y_{EKF} coordinates.

Referring to the EKF algorithm, the main process in the ASEKF algorithm is essentially the same, with only a few additional steps to improve the resulting accuracy of estimated position. The additional step is multiplying the update state by the weighted factor (ω) which have been calculated before at (1). Similar to the EKF algorithm, the three main processes of ASEKF, including the initialization, predict and update equations, are shown in Figure 3.

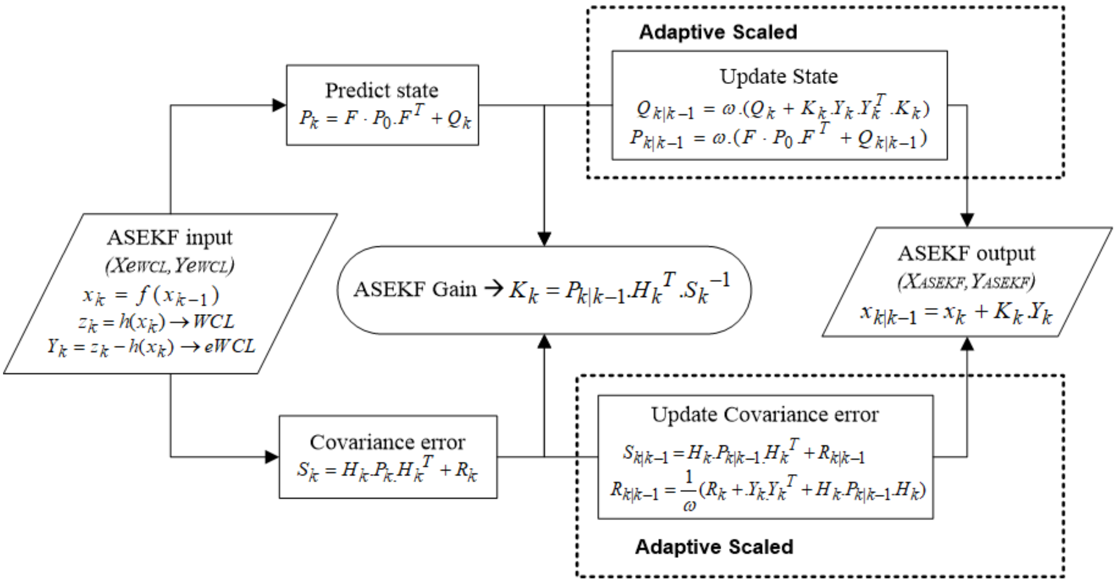


Figure 3. The main calculation processes of ASEKF algorithm

During the initialization phase of ASEKF, the estimated results from eWCL and WCL algorithm are used for data input of x_k, z_k, and Y_k, which are derived as (9 and 10).

$$x_k = f(x_{k-1}) \rightarrow [x_{ewcl} \quad y_{ewcl} \quad 0] \tag{9}$$

$$z_k = h\,(x_k) \rightarrow [d_{1_{wcl}} \quad d_{2_{wcl}} \quad d_{3_{wcl}}] \tag{10}$$

Since the function of the EKF algorithm is to smooth measurement noise, this paper adopts the EKF scheme to address the discrepancies in estimated distances between the eWCL and WCL algorithm outputs by using the three nearest references as measurement noise. Therefore, the value of Y_k can be written as (11).

$$Y_k = z_k - h(x_k) \rightarrow [d_{1_{wcl}} \quad d_{2_{wcl}} \quad d_{3_{wcl}}] - [d_{1_{ewcl}} \quad d_{2_{ewcl}} \quad d_{3_{ewcl}}] \tag{11}$$

Subsequently, the predicted state of ASEKF utilizes the EKF algorithm, incorporating an adjusted noise covariance value derived from the WCL and eWCL outputs, as illustrated by the (12 and 13).

$$P_0, Q_k = \begin{bmatrix} \sigma^2(x_{ewcl}) & 0 & 0 \\ 0 & \sigma^2(y_{ewcl}) & 0 \\ 0 & 0 & 0 \end{bmatrix}; F = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{12}$$

$$R_k = diag\left[\sigma^2 d_{1_{ewcl}} \quad \sigma^2 d_{2_{ewcl}} \quad \sigma^2 d_{3_{ewcl}}\right] \tag{13}$$

The covariance noise data parameters are processed into the Kalman gain (K_k) for determining the updated state during the correction process at ASEKF algorithm. Kalman gain is a key part of the Kalman filter which estimates the state of this system from the covariance noise data measurements as derived from (14).

$$H_k = \begin{bmatrix} x_{j_1} & y_{j_1} & 0 \\ x_{j_2} & y_{j_2} & 0 \\ x_{j_3} & y_{j_3} & 0 \end{bmatrix} \rightarrow x_{j_{i(1,2,3)}} = \frac{x_{ewcl_{(1,2,3)}} - x_{AN_{(1,2,3)}}}{d_{(1,2,3)_{ewcl}}}; y_{j_{i(1,2,3)}} = \frac{y_{ewcl_{(1,2,3)}} - y_{AN_{(1,2,3)}}}{d_{(1,2,3)_{ewcl}}} \tag{14}$$

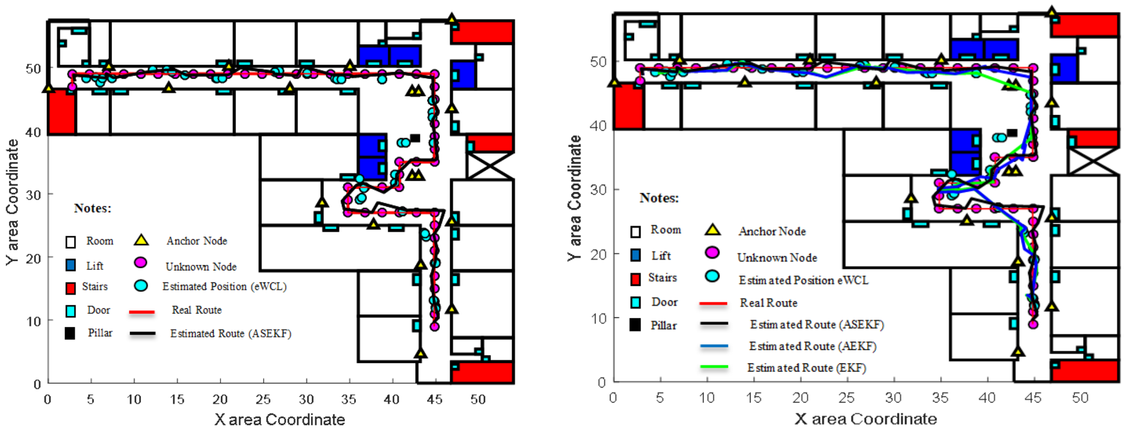
Its main function is to determine the optimal balance between the predicted state and the new updated state, based on their respective uncertainties. Therefore, by giving more weight as the scale factor to the updated covariance, ASEKF ensures the best possible to minimize estimation errors and adaptively improve accuracy over time. As shown at Figure 3, the updated state and updated covariance error are multiplied with ω as the scale factor which is adjusted to the weighted factor value from (1). Then, the output data from ASEKF algorithm as the final estimation result can be derived as $X_{k \mid k-1}$ in the form of (X_{ASEKF}, Y_{ASEKF}) coordinate.

3. RESULTS AND DISCUSSION

3.1. Performance analysis of estimation results

The RIBATS system provides two position estimation results. The first is obtained using the eWCL algorithm as the secondary estimation, and the second uses the ASEKF algorithm for the final route estimation. The initial estimation, which employs the WCL algorithm, is not discussed in detail here because both WCL and eWCL were covered in our previous work [14]. As illustrated in Figure 4, the initial position estimation obtained from the eWCL algorithm is refined using several algorithms, including ASEKF, AEKF, and EKF. The results indicate that the ASEKF algorithm produces route estimates that closely approximate the actual route, as shown in Figure 4(a). This demonstrates that ASEKF offers superior route estimation accuracy, particularly when compared to AEKF and EKF.

In contrast, combining the eWCL algorithm with the conventional EKF algorithm results in significant positional errors, leading to route estimates that diverge considerably from the actual route, as shown in Figure 4(b). Similarly, the combination of eWCL with the adaptive EKF (AEKF) algorithm, as previously studied in [17], where a constant multiplier of 0.3 was used and subsequently increased by up to 100 times, also produces route estimation data that significantly deviates from the actual route. This discrepancy is attributed to the suboptimal multiplier, which fails to achieve a balanced condition between the predict state and the update state, thereby resulting in less accurate estimations. This indicates that using an appropriate multiplier as a weighting factor for the EKF algorithm is crucial for improving the position estimation results from the eWCL algorithm. The highly variable and fluctuating signal strength measurements necessitate the use of adaptive weighting values based on the current data conditions. This is evidenced by the combination of eWCL and ASEKF, which produces significantly better route estimation results compared to the EKF algorithm without a multiplier or the AEKF algorithm that uses a constant multiplier. The results highlight that the adaptability of the ASEKF algorithm allows it to better handle the inconsistencies in signal strength, leading to more precise estimations and improved overall performance. The specific values of estimated error and accuracy percentages are detailed in the discussion section.



(a) (b)

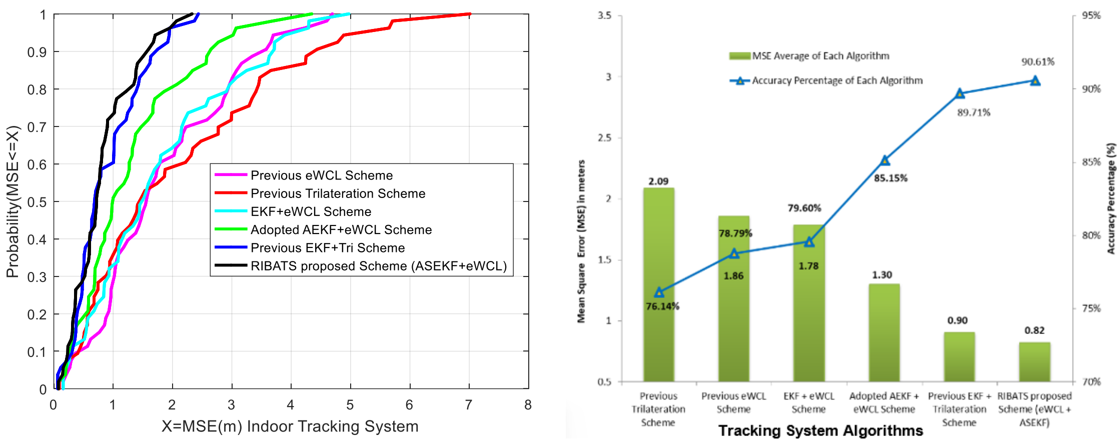
Figure 4. These figures are (a) estimated results from ASEKF algorithm and (b) comparison of estimated results from ASEKF, AEKF, and EKF algorithm

3.2. Discussion

In this paper, the primary evaluation focuses on position estimation, with the MSE being the key metric used to assess the performance of the algorithms. The MSE value reflects the accuracy of the position estimates, calculated as the average of the squares of the errors between the estimated and true positions, with lower values indicating better performance. This metric is derived from (15), which details the calculation process.

$$MSE = \sqrt[2]{\left(x_{Real} - x_{estimated\ position_{ASEKF}}\right)^2 + \left(y_{real} - y_{estimated\ position_{ASEKF}}\right)^2} \tag{15}$$

Figure 5 illustrates these results, with Figure 5(a) displaying the cumulative density function (CDF)-based analysis, which facilitates the understanding of the distribution of MSE values across different algorithms. Figure 5(b) presents a Pareto chart that compares accuracy percentages and MSE values, further simplifying the comparison of estimation errors produced by each algorithm. This research compares several algorithms, including the conventional trilateration algorithm based on RSSI and path loss exponent for distance and position estimation, the original EKF algorithm combined with trilateration, eWCL alone as adopted from previous research, eWCL combined with the original EKF, AEKF combined with eWCL, and finally, all existing and previously proposed algorithms are compared with the proposed RIBATS scheme, which integrates ASEKF and eWCL algorithms.



(a) (b)

Figure 5. These figures are (a) CDF graph of RSSI-based adaptive tracking system and (b) Pareto chart of RSSI-based adaptive tracking system

According to the Figure 5(a), shows that the highest MSE value performance is using conventional trilateration achieved MSE value up to 7.01 meters. This highlights the substantial influence of the PLE on the effectiveness of conventional trilateration for position estimation. The reliance on PLE-based methods results in a static position estimation system, necessitating environmental propagation mapping for accurate RSSI-based estimates across varying locations. The next largest MSE result is obtained from using eWCL alone without improvements, and the combination of eWCL with the original EKF algorithm, where the estimated MSE error is 4.69 meters for eWCL alone and 4.97 meters for the EKF and eWCL combination. This indicates that the standalone use of eWCL still results in relatively high estimation errors. Even when improvements are made, the use of an inappropriate correction algorithm can lead to high estimation errors. For instance, the EKF requires a balance between the prediction state and the update state, affecting the effectiveness of the data error filtering process. The combination of the eWCL algorithm with AEKF demonstrates a significant improvement in performance. According to the CDF distribution analysis, for the range from 0 to 0.8, the maximum MSE value reaches 2 meters, while for the range from 0.8 to 1, the maximum value is 4.34 meters. These findings confirm that the concept of using AEKF, as proposed by the research [17], is highly effective in improving eWCL estimation by applying a multiplication factor to the updated state. However, the reduction in MSE achieved is still not optimal, as the combination of EKF and conventional trilateration exhibits superior performance with an MSE range of 0.06 to 2.43 meters.

Nonetheless, this combination of trilateration and EKF cannot yet be classified as an adaptive scheme, as the RSSI estimation process still requires a PLE value that cannot be arbitrarily determined; accurate propagation measurement and mapping are necessary for each estimation process. When compared based on the data distribution using CDF, the proposed algorithms ASEKF and eWCL exhibit nearly identical performance within the CDF distribution range of 0 to 0.6, with an MSE of less than 1 meter. In the CDF range from 0.6 to 1, although the MSE differences are minimal, the use of ASEKF and eWCL successfully reduces the MSE to 2.32 meters. According to the average MSE values shown in Figure 5(b), the combination of eWCL with the ASEKF correction algorithm also achieves an average MSE of 0.82 meters, which is the smallest value, with an accuracy rate of up to 90.61%. Using the proposed algorithm RIBATS as illustrated at Figure 5(b), the average difference in MSE produced is only 0.08 meters. However, using RIBATS successfully reduces the resulting MSE and increases accuracy, albeit not significantly. On the other hand, using the ASEKF and eWCL algorithms has managed to create an adaptive scenario in the RSSI-based tracking system. When the object moves and receives the 3 strongest RSSI signals from several reference transmitters, the object can automatically estimate its position without preprocessing to determine the PLE value, which is highly dependent on environmental conditions. If the RSSI-based estimation process includes PLE, then when moving the node installation location, initial measurements are needed to determine the correct PLE value. In contrast, using the RIBATS scheme, the estimation process can be done automatically even if the environmental conditions are different.

4. CONCLUSION AND FUTURE WORK

In this paper, we introduce RIBATS, an RSSI-based adaptive tracking system. RIBATS is currently utilized for indoor position estimation, starting with the eWCL algorithm for initial position estimation. The results are then refined and the traversed route is displayed using the ASEKF algorithm. Eighteen anchor nodes continuously transmit RSSI information and reference coordinates via Xbee S2 Pro to the UN for position estimation. The adaptive aspect of RIBATS allows this RSSI-based estimation process to be performed automatically without needing the environmental propagation factor PLE, which is typically required for RSSI-based positioning systems. The addition of an adaptive multiplier or weighted factor in the EKF algorithm, referred to as ASEKF in this paper, successfully reduces the MSE value by up to 2 times compared to using the eWCL algorithm alone, and decreases the average MSE value by 0.08 meters compared to the combination of trilateration and EKF algorithm. This demonstrates that the ASEKF algorithm effectively enhances the eWCL algorithm’s adaptive estimation results without the need for PLE, and performs better compared to the trilateration and EKF algorithm that requires the PLE value.

In future work, we will utilize an RSSI-based adaptive multi-object tracking system through the LoRA protocol to expand coverage from indoor to outdoor environments. Additionally, we see several opportunities to use other non-linear algorithms to improve the accuracy of estimated positions and to enhance data privacy through security mechanisms.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Hendi Wicaksono Agung		✓				✓				✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

INFORMED CONSENT

This research does not involve human participants; therefore, informed consent was not required.

ETHICAL APPROVAL

This research does not involve human participants or animals; therefore, ethical approval was not required.

DATA AVAILABILITY

The data that support the findings of this research are available from the corresponding author upon reasonable request. The data consist of RSSI measurements collected using Zigbee S2 Pro modules and were used to evaluate the proposed algorithm.

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