An Indoor to Outdoor RSSI Based Positioning System Using EKF with Different Distance Correction Algorithm

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Abstract—**Locating the target nodes of indoor environment using the received Signal Strength Indicator (RSSI) measurement, often applies in several field areas. With the rise of location services applications, the need for positioning extends from indoor to outdoor areas, using same indicator in estimated position process. To address these challenges, this paper aims to propose indoor to outdoor positioning system using RSSI-based technique from Bluetooth Low Energy (BLE) transmission as a low-cost method in localization. By combining an Extended Kalman Filter (EKF) with Different Distance Correction (DDC) as the position estimation algorithm, it shows that the position accuracy result from the conventional multi-lateration based four RSSI measurement references can be significantly increased. To comprehensively evaluate the system performance, experiments are carried out in laboratory campus as the indoor environment and hallway outside the laboratory as the outdoor environment. The experimental results show that the proposed system using EKF-DDC can achieve error estimation only in 0.34 meters and the accuracy reaches up to 95.9% compared with only using conventional multi-lateration reached high error estimation up to 8.15 m at indoor to outdoor environment.**

Keywords—**indoor to outdoor positioning system, Signal Strength Indicator (RSSI), Extended Kalman Filter-Different Distance Correction (EKF-DDC), multi-lateration, Bluetooth Low Energy (BLE)**

I. Introduction

The continued growth of ubiquitous computing system accompanied by the widespread integration of Internet of Things (IoT) into various fields has resulted in an increasing need for precise and reliable positioning systems. Location information of everything is an essential component in most IoT applications which has significant role in improving the IoT services performances [1]. Accurate positioning system as part of Location-Based Services (LBS) is critical for numerous applications such as patient tracking in healthcare monitoring, visitor navigating inside mall building, asset tracking, and fraud detection [2–4]. A commonly technology for determining location information is Global Positioning System which refers to Global Navigation Satellite System (GNSS) technique [5]. However, satellite signals utilized by Global Positioning System (GPS) can be attenuated by obstacle reflection or building walls diffraction, limiting their availability to outdoor environments. Due to this limitation, indoor positioning technology requires alternative methods beyond GPS and satellite signals [6]. Therefore, indoor positioning system becomes a challenging issue for many researchers with concern related to the accuracy, expense, and feasibility computational system and methods [7].

Nevertheless, several issues were exclusively focused on the indoor environment as the testing location for positioning system. In fact, some technologies require seamless connectivity and communication between users at all environments, both indoor and outdoor. As a result, many researchers have been developed technologies based on indoor environment as an alternative solution to resolve the integration of indoor to outdoor location issue such as infrared, A Wireless local-Area Network (WLAN), Bluetooth, Radio Frequency Identification (RFID), Ultra-Wideband (UWB) and Inertial Navigation System (INS) [8–10]. However, each technology still has limitation in positioning system. According to these technologies, Inertial Navigation System (INS) provides better positioning accuracy and also resistance to noise signal due to its mechanism which is integrating position, velocity and orientation by dead reckoning calculation. INS installation and maintenance involve high cost which is not appropriate for multi object positioning system. As well as INS, infrared also has high positioning accuracy, but it cannot pass through an obstacle, so it can only cover small area with line-of-sight condition [11].

WLAN, Bluetooth and UWB as the wireless technology allow to be easily distracted by various disturbances such as signal interference, multipath fading or signal attenuator that can influence to the accuracy of

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positioning system. Based on these three wireless technologies, Bluetooth Low Energy (BLE) as Bluetooth derivative technology is small, portable, low power consumption and easy to distribute widely. While, WLAN is highly responsive to nearby devices utilizing Wi-Fi signal, that also affected to the positioning performance. For UWB, Received Signal Strength Indicator (RSSI), Time of Arrival (ToA), Time Difference of Arrival (TDOA), and Angle of Arrival (AoA) are the most frequently used for determining position. Usually, UWB is used in high-level tracking system to map position with high precision, both indoors and outdoors [12]. Unfortunately, UWB implementations tend to consume more power compared to BLE technology. This can be a critical factor, especially in battery powered devices or small sensors that require low power. Furthermore, BLE technology also features RSSI, similar to UWB, which can be utilized for predicting and analyzing position information [13].

Several previous studies have utilized Bluetooth Low Energy (BLE) technology to achieve precise location information, with an average error range within 2 meters, particularly in small spaces like rooms, ensuring high-quality and real-time responsiveness [13–21]. Therefore, BLE has a potential possibility of being implemented in the indoor to outdoor positioning systems. However, another limitation still exists in BLE is that signal quality depends on many structures such as room layout, signal propagation and high risk of multipath fading which is the common problem in indoor environment. Hence, many researches develop on BLE-based positioning system aim to achieve high accuracy in various ways, including integration with technologies such as GPS for outdoor location detection, using INS/MEMS/UWB as a fusion system. Additionally, diverse algorithmic approaches such as tri or multi-lateration, weighted, K-Nearest Neighbors (KNN), Principal Component Analysis (PCA), Fingerprinting, Kalman Filter (KF) and its derivatives, centroid, linear or non-linear regression and others, with the purpose of obtaining optimal results in precise location information [18–23].

Previous work in the most of indoor and outdoor seamless positioning system only realize the positioning preference and the seamless of accuracy, ignoring the hardware cost, ease of use, implementation and deployment especially for multi object positioning system. Using integration from Global Navigation Satellite System (GNSS), INS and BLE technology have been proposed by [18] to build indoor and outdoor seamless positioning system. Several previous studies also used a combination of several technologies such as Wi-Fi, BLE for indoor area and GNSS, Inertial Measurement Unit (IMU) for outdoor area, which can improve accuracy and enable seamless of indoor and outdoor positioning system [24–27]. Therefore, to reduce the hardware cost but still ensure the positioning accuracy in transition environment between indoor and outdoor, this paper using only BLE technology as the indicator measurement of RSSI transmission for determining position estimation. Then, combining reliable algorithm for reducing the error estimation in non-linear condition using extended Kalman Filter (EKF) with different distance correction scheme, aims to reduce loss effect in the form of estimated distance result from RSSI. The initial estimated position was carried out using multi-lateration with four references nodes. The output of initial estimated position is weighted using a quadratic algorithm. The estimated results that were produced by the multi-lateration and quadratic algorithms will be corrected using EKF and Different Estimated Distance algorithm which is called as DDC after combining with EKF algorithm.

The contribution of this paper is provided a new approach for enabling indoor to outdoor positioning system using one parameter as indicator for calculating estimated position which will be improved with DDC and EKF algorithm. The testing process was carried out in real implementation environment at University of Surabaya laboratory as indoor area, around lab corridor as outdoor area and using BLE transmission from ESP32 as the reference's node.

In order to ensure the effectiveness of this proposed system, this paper is organized as follows: the related works are discussed in Section II, which are involved the adopted algorithm as well as conventional multi-lateration as the initial estimated position and quadratic algorithm in the form of multi-quadratic calculation. The proposed system for indoor to outdoor positioning utilizing the Extended Kalman Filter-Different Distance Correction (EKF-DDC) algorithm is detailed in Section III. The experimental results according to the real implementation system will be presented to verify the proposed system in Section IV. Finally, we draw the conclusion in Section V.

II. Adopted Algorithm

In this section, we describe the adopted algorithms which are used for indoor to outdoor positioning system. Those are multi-lateration as an initial estimated position and multi-quadratic as a comparative algorithm intended for utilization as a calculation parameter for the EKF-DDC algorithm in the proposed system.

A. Multi-Lateration Algorithm

Multi-lateration as the derivative algorithm from tri-lateration was used more than three reference distances. The reference distance is established from the difference in coordinate positions between the reference nodes and target node by euclidean distance calculation as in this following equation:

$$d_{n\rightarrow 1,2,3,4} = \sqrt{\left(x_{R_{n\rightarrow 1,2,3,4}} - x_{T_n}\right)^2 + \left(y_{R_{n\rightarrow 1,2,3,4}} - y_{T_n}\right)^2} \quad (1)$$

There are four reference nodes (R_n) which located at specific coordinates as (X_{R1}, Y_{R1}), (X_{R2}, Y_{r2}), (X_{R3}, Y_{r3}), (X_{r3}, Y_{R3}). The location of reference nodes will be used for calculating the target node position *(X_{TN}, Y_{TN})* as the central circle formed by four circle reference nodes intersection at Fig. 1.

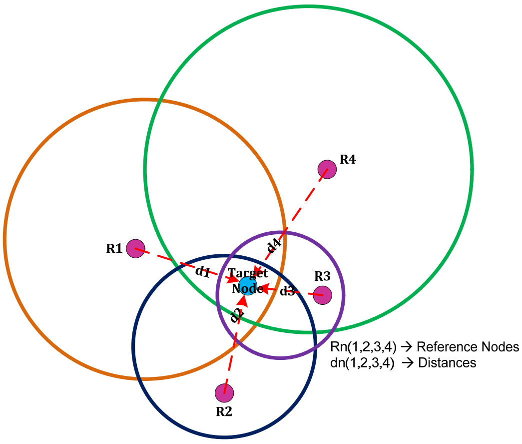

Fig. 1. Multi-lateration algorithm illustration.

Therefore, according to the distances, coordinate position of each reference nodes and target node can be used to formulate multi-lateration algorithm in estimating position as follows:

$$A = \begin{bmatrix} 2(x_{R_1} - x_{R_4}) \times 2(y_{R_1} - y_{R_4}) \\ 2(x_{R_2} - x_{R_4}) \times 2(y_{R_2} - y_{R_4}) \\ 2(x_{R_3} - x_{R_4}) \times 2(y_{R_3} - y_{R_4}) \end{bmatrix} \quad (2)$$

$$X = \begin{bmatrix} x_{multi-lateration} \\ y_{multi-lateration} \end{bmatrix} \quad (3)$$

$$B = \begin{bmatrix} {x_{R_1}}^2 + {y_{R_1}}^2 - {x_{R_4}}^2 - {y_{R_4}}^2 - {d_1}^2 + {d_4}^2 \\ {x_{R_2}}^2 + {y_{R_2}}^2 - {x_{R_4}}^2 - {y_{R_4}}^2 - {d_2}^2 + {d_4}^2 \\ {x_{R_3}}^2 + {y_{R_3}}^2 - {x_{R_4}}^2 - {y_{R_4}}^2 - {d_3}^2 + {d_4}^2 \end{bmatrix} \quad (4)$$

Matrix X as the output of estimated position from multi-lateration algorithm can be obtained using this following formula as follows:

$$A \times X = B \rightarrow X = (A^T \times A)^{-1} \times A^T \times B \quad (5)$$

B. Multi-Quadratic

Basically, multi-quadratic algorithm is formed by quadratic weighted algorithm with multi references node that adjusted to the multi-lateration algorithm. The primary idea behind quadratic weighted involves incorporating a multiplier factor into the references node. Similar to the multi-lateration algorithm, the quadratic weighted factors are applied to the four reference nodes. According to the number of reference nodes, there are five weighted value calculation, as follows:

$$W_1 = \frac{1}{d_1 + d_2 + d_4} \quad (6)$$

$$W_2 = \frac{1}{d_1 + d_3 + d_4} \quad (7)$$

$$W_3 = \frac{1}{d_2 + d_3 + d_4} \quad (8)$$

$$W_4 = \frac{1}{d_1 + d_2 + d_3} \quad (9)$$

$$W_5 = k \times \left(\frac{1}{d_1} + \frac{1}{d_2} + \frac{1}{d_3} + \frac{1}{d_4}\right) \rightarrow k = 0.328 \quad (10)$$

Weighted values calculation at Eqs. (6–10) are obtained from combination distances value *(d_1, d_2, d_3, d_4)* between the reference node and target node and also adding weights that are appropriate to the existing environmental conditions *($k \rightarrow 0.328$)*. So that result of estimated position coordinates calculation from multi-quadratic can be determined using this following equation:

$$(x, y)_{multi-quadratic} = \left(\frac{((x,y)_{R_1} \times W_1) + ((x,y)_{R_2} \times W_2) + ((x,y)_{R_3} \times W_3) + ((x,y)_{R_4} \times W_4)}{W_5} \right) \quad (11)$$

Each references node coordinate (x_{Rn}, y_{Rn}) will be multiplied with the weighted values that have been calculated before using Eqs. (6–10).

III. Proposed System

In this section, we explain in detail the method used to obtain optimal estimated position result in indoor and outdoor environment. This process begins with the accurate measurement of RSSI and its subsequent processing to determine estimated distance data. These distances are then optimized for estimated position calculations, based on the difference in distances derived from multi-lateration and multi-quadratic methods, using EKF-DDC algorithm.

A. Measurement Scenario

In this paper, estimated positions are obtained from RSSI measurement which is transmitted from HM-10 module as target node through BLE protocol. RSSI level will be received by the reference nodes using ESP32 module via BLE protocol also. There are 15 reference nodes placed on 2.5 m height, and target node move to the specified points at 1.5 m height. All measurement processes are implemented on indoor laboratory of Surabaya University with several obstacles such as: chair, table, cupboard, wall and some laboratory tools, and also outdoor environment around outside of the laboratory hall way. First phase of measurement scenario as the pre-processing system is determining Path Loss Exponent (PLE) value as the parameter for calculating estimated distance from RSSI. The Target Node (TN) serves as the transmitter, moving while transmitting RSSI to reference node (RN) in increment of 0.5 meters to adjust the size of the environmental dimensions under Line-of-Sight (LOS) conditions. In this phase, RN is only stay in one position by receiving the RSSI from the TN. Therefore, the PLE value can be calculated using log-normal propagation loss model which is derivative equation from RSSI equation given as:

$$RSSI_i = \left(10\ PLE\ log_{10}\left(\frac{d_i}{d_0}\right) + RSSI_0\right) \tag{12}$$

$$PLE = \frac{RSSI_i - RSSI_0}{10\ Log_{10}\frac{d_i}{d_0}} \tag{13}$$

Apart from the real objects around the lab, Wi-Fi signals also affected to the RSSI measurement result. The disturbance of RSSI is also determining in the form of deviation standard value (σ) as the noise variance. Then, the standard deviation determination is achieved from RSSI measurement between RN and TN in 0.5 m fixed distance but different position.

The result of PLE and deviation standard (σ) value for each room which have been obtained from measurement process are listed at Table I. According the result show that PLE value and deviation standard value at outdoor area is achieved larger than indoor area due to the placement of RN can be attenuated by the concrete wall to the TN outdoor location. These values are also influenced to the estimated distance calculation directly as derived at this following equation:

TABLE I. PLE AND DEVIATION STANDARD VALUE OF EACH ROOM

Rooms Name	PLE Value	Deviation Standard Value (σ)
Robotics Lab	2.85	0.84
Final Project Lab	2.79	0.71
Biomedical Lab	2.87	0.32
Network Lab	2.84	0.73
Hallway	2.84	0.67
Outdoor 1	3.97	1.7
Outdoor 2	4.68	0.7
Outdoor 3	4.52	0.55
Outdoor 4	4.16	1

$$d_i = d_0\left(10^{\left(\frac{RSSI_i - RSSI_0 - \sigma}{10\ PLE}\right)}\right) \tag{14}$$

d_0 and *$RSSI_0$* are references value that should be measured at the initial process from positioning system. These values can be derived from 1 meter, 0.5 meters or maybe larger than 1-meter references between TN locations to the RN location depend on the room size. The deployment distribution each node of this system is shown at Fig. 2.

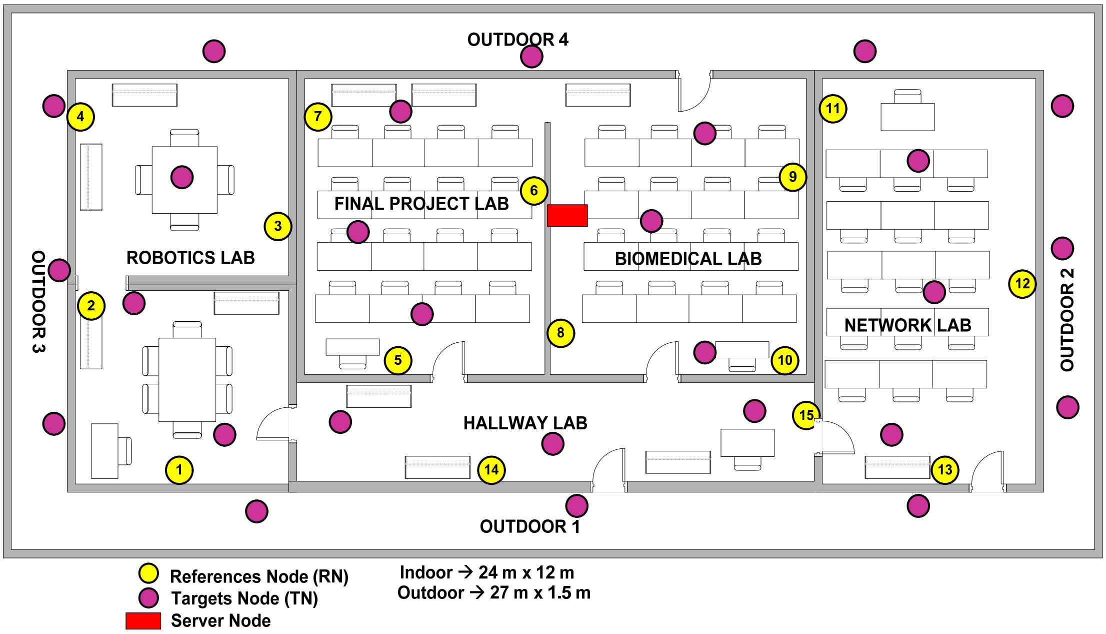

Fig. 2. Deployment distribution each node of indoor to outdoor positioning system.

There are 27 positions of TN consist of 12 outdoor locations and 15 indoor locations. Each TN sends RSSI To the all RNs, then all RSSI measured data will be forwarded to the server included also with RNs coordinate. Server will be filtered the four strongest measured RSSI and processed with multi-lateration, multi-quadratic, different estimated distance and EKF-DDC algorithm for determining estimated position, as shown at Fig. 3.

B. *EKF-DDC Algorithm*

According to the Fig. 3, there are four algorithms of indoor to outdoor positioning system. Multi-lateration as the initial estimated position will be weighted using multi-quadratic as the second estimated position. Then, the difference estimated results between multi-lateration and multi-quadratic will be calculated using different estimated distance algorithm which called as multi-DED and also as the third estimated position. The estimated output from multi-DED will be corrected and improved using EKF which is called as EKF-DDC (different distance correction) algorithm. The main concept of multi-DED is still using weighted approach as well as multi-quadratic algorithm. However, the weight values of multi-DED are based on the results of calculating the difference in distance estimation produced between multi-lateration and multi-quadratic algorithm.

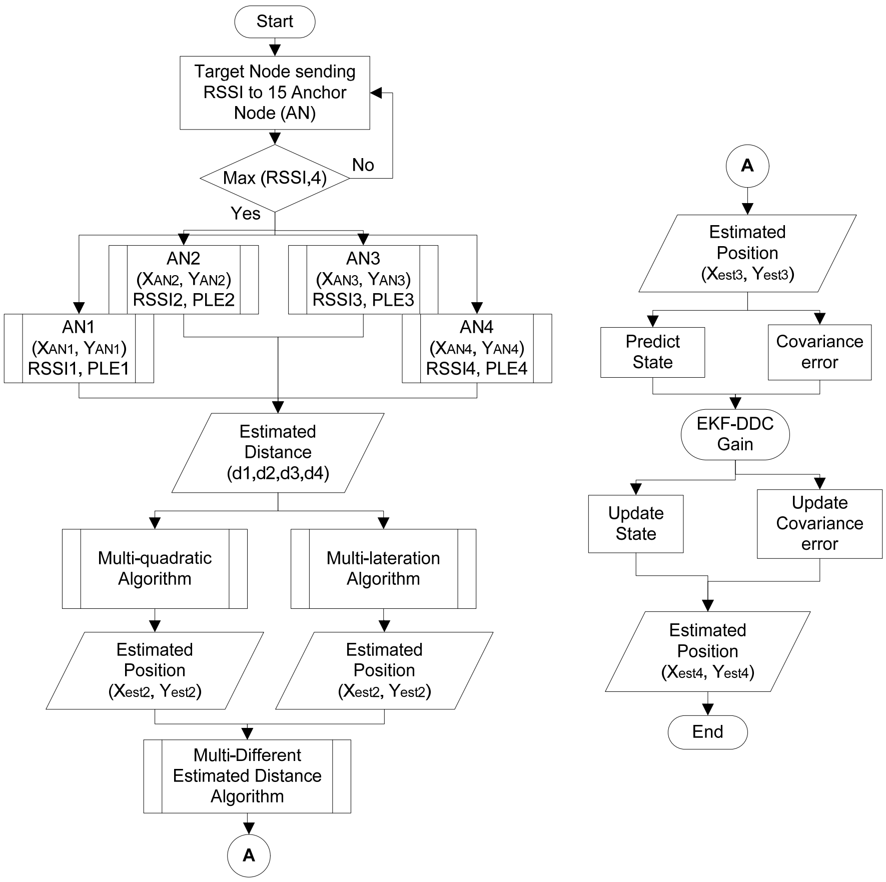

Fig. 3. Proposed scheme of indoor to outdoor positioning system.

Multi-DED algorithm is adopted from previous work in [28] that used difference in estimated distance on trilateration algorithm. Whereas in this paper, proposed another approach using difference estimated distance between two kind of different algorithms that can be applied for multi references of positioning system which is not also limited with three references. Therefore, the weight value calculation of multi-DED algorithm is derived as:

$$w_{x_i} = X_{RN_i}\times\begin{pmatrix}\left(2\times\left(d_{multi-lateration_i}-d_{multi-quadratic_i}\right)^{\alpha}\right)+\\ \frac{1}{d_{multi-lateration_i}}+\frac{1}{d_{multi-quadratic_i}}\end{pmatrix} \tag{15}$$

$$w_{y_i} = Y_{RN_i}\times\begin{pmatrix}\left(2\times\left(d_{multi-lateration_i}-d_{multi-quadratic_i}\right)^{\alpha}\right)+\\ \frac{1}{d_{multi-lateration_i}}+\frac{1}{d_{multi-quadratic_i}}\end{pmatrix} \tag{16}$$

$$w_{DED} = \beta\times\begin{pmatrix}\begin{pmatrix}\left(d_{multi-lateration_i}-d_{multi-quadratic_i}\right)^{\alpha}+\cdots+\\ \left(d_{multi-lateration_4}-d_{multi-quadratic_4}\right)^{\alpha}\end{pmatrix}+\\ \frac{1}{d_{multi-lateration_i}}+\cdots+\frac{1}{d_{multi-lateration_4}}+\\ \frac{1}{d_{multi-quadratic_i}}+\cdots+\frac{1}{d_{multi-quadratic_4}}\end{pmatrix} \tag{17}$$

According to the Eqs. (15–17), the value of estimated position from multi-DED can be calculated using this following equation:

$$x_{multi-DED} = \frac{w_{x_i}+\cdots+w_{x_4}}{w_{DED}} \tag{18}$$

$$y_{multi-DED} = \frac{w_{y_i}+\cdots+w_{y_4}}{w_{DED}} \tag{19}$$

$i\rightarrow 1, 2, 3, 4$, as the four strongest references node

The reference calculation process of multi-DED algorithm is dependent on the calculation process from multi-lateration and multi-quadratic algorithm. Apart from estimated distance, the four strongest reference nodes (RN_i) are also used at this multi-DED. The value of α and β is variable which is utilized for multiplying factor adjusted to the environment condition. The value of α can be used at less than 1, while the value of β can be used at range of $1 > \beta \leq 2$.

Some estimated position results from multi-DED are still not optimal; especially at outdoor environment still reach up to 5 meters. Therefore, EKF is proposed for improving and correcting the error estimation from multi-DED, which will produce a new approach in the form of EKF-DDC algorithm. EKF is one of an algorithm that can be implemented for non-linear system especially in RSSI based positioning system. Due to losses propagation effect of indoor to outdoor environment of this system, EKF algorithm will be utilized the estimation position result from multi-DED algorithm *($X_{multi-DED}$, $Y_{multi-DED}$)* as initialization state, then it will be predicted and processed to the EKF gain based on its different distance measurement, and last the output will be updated with minimized error result of position estimation as *($X_{EKF-DDC}$, $Y_{EKF-DDC}$)*. Here, the main step of EKF-DDC is derived as:

1) Initialization state

In this phase, there are three main variables as the initialization state from EKF-DDC algorithm; those are state vector (x_k) that obtained from DED algorithm estimated result, observation matrix (z_k) as the measurement data of estimated distance and equipped with P_0 as the noise matrix covariance. The initialization state which is formed by multi-DED algorithm result can be derived as follows:

$$x_k = [x_{multi-DED} \quad y_{multi-DED}] \tag{20}$$

The value of z_k is utilized estimated distance from four nearest references node as follows:

$$z_k = [d_{est1} \quad d_{est2} \quad d_{est3} \quad d_{est4}] \tag{21}$$

$d_{est\,(1,2,3,4)}$ is the estimated distance of target node to the references node that was obtained from estimated result of multi-DED using Eq. (1) calculation. Then, the covariance matrix of P_0 is determined using variance calculation of multi-DED coordinate estimation result which is described to this following matrix:

$$P_0 = \begin{bmatrix} \sigma_{x_{multi-DED}} & 0 & 0 & 0 \\ 0 & \sigma_{y_{multi-DED}} & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \tag{22}$$

The size dimension of matrix is adjusted the estimated distance state which is formed by four distances; therefore, the noise matrix is arranged to 4□4 size dimension.

2) Predict state

The purpose of prediction state is to predict the patterns of initialization state between one set of data and another, in order to understand the data distribution pattern. This is represented as x_k for the predicted state data and P_k for the predicted state noise. In this system is assumed that the changes in the data are caused by noise measurement factors rather than self-generated multiplier factors. Therefore, the F value is set as an identity matrix, ensuring that its value remains unchanged. The prediction state can be described as follows:

$$x_k = [x_{multi-DED} \quad y_{multi-DED}]^T \times F$$
$$Where \rightarrow F = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{23}$$

$$P_k = F \times P_0 \times F^T + Q \rightarrow Q = P_0 \tag{24}$$

3) Update state

The refinement and correction process are performed at update state by multiplying each state with Kalman gain (K_k). This update state is influenced by several variables such as: jacobian matrix H_k, updated state noise P_k and its covariance matrix S_k. Jacobian matrix H_k is expected result of estimation data to the real data. In this paper, the jacobian matrix is arranged based on the difference estimated distance between multi-lateration and multi-quadratic algorithm to the each coordinate reference node, as follows:

$$H_k = \begin{bmatrix} x_{j1} & y_{j1} & 0 & 0 \\ x_{j2} & y_{j2} & 0 & 0 \\ x_{j3} & y_{j3} & 0 & 0 \\ x_{j4} & y_{j4} & 0 & 0 \end{bmatrix} \tag{25}$$

$$(x_{j_i}, y_{j_i}) = \frac{(x,y)_{ReferenceNode_i} - (x,y)_{multi-lateration_i}}{d_{multi-quadratic_i}} \tag{26}$$

where, ➞ $i = 1, \dots, 4$

Covariance matrix value S_k is calculated by combination of updated state covariance matrix P_k, jacobian matrix H_k and also added with noise variance of estimated distance R_k from DED algorithm result, derived as:

$$S_k = H_k \times P_k \times {H_k}^T + R_k \tag{27}$$

$$R_k = diag\,(\sigma^2 d_{DED_1}\, \sigma^2 d_{DED_2}\, \sigma^2 d_{DED_3}\, \sigma^2 d_{DED_4}) \tag{28}$$

While, the value of Kalman gain K_k can be derived as:

$$K_k = P_k \times {H_k}^T \times {S_k}^{-1} \tag{29}$$

The value of noise P_0 will be updated by measurement state from jacobian matrix H_k and Kalman gain K_k, as follows:

$$P_0 = (P_k - K_k \times H_k) \times P_k \tag{30}$$

Then, the observation matrix as the measurement state Y_k from two difference algorithm between multi-lateration and multi-quadratic can be calculated using this following equation:

$$Y_k = z_k - h_k \tag{31}$$

$$z_k = [d_{multi-lat1} \quad d_{multi-lat2} \quad d_{multi-lat3} \quad d_{multi-lat4}] \tag{32}$$

$$h_k = [d_{multi-quad1} \quad d_{multi-quad2} \quad d_{multi-quad3} \quad d_{multi-quad4}] \tag{33}$$

Therefore, the posterior state as the estimation result from EKF-DDC algorithm is produced coordinate output ($X_{EKF-DDC}$, $Y_{EKF-DDC}$) as follows:

$$x_k = x_k + K_k \times Y_k \tag{34}$$

Each estimated position result from each algorithm at this paper will be compared to the real position Based Mean Square Value (MSE) calculation, which uses Euclidean distance calculation approach, as shown in the following equation:

$$MSE = \sqrt{(x_{Real} - x_{estimation})^2 + (y_{Real} - y_{estimation})^2} \tag{35}$$

IV. Experimental Results and Discussion

Multiple experiments were conducted to assess the performance of each algorithm within this implementation system. Here, we assess the error estimation result MSE of our proposed indoor to outdoor positioning system employing EKF-DDC, while also contrasting it with the results obtained solely through multi-DED, multi-lateration and also multi-quadratic.

A. Experimental Parameters and Estimated Position

In this paper, we established the system within the laboratory premises of Surabaya University. The communication between the target node and reference nodes operated through the BLE protocol, employing a broadcast and distributed scheme. Meanwhile, the communication between each reference node and server node utilized the UDP Wi-Fi protocol with a centralized approach. Detailed specifications and parameters of this experimental setup are outline in Table II.

TABLE II. Experimental Parameters and Specifications

Parameters	Value	Remarks
Operating Frequency	2.4 GHz ISM Band	BLE HM-10 (27 Target Nodes)
RF Power	23 dBm	
Device Specification	ESP32 (BLE & Wi-Fi) BLE ⟶ Reference Node to Target Node Wi-Fi ⟶ Reference Node to Server	15 Reference Nodes
	Raspberry Pi 3B (Wi-Fi)	1 Server Node
	Mikrotik Hap lite RB941-2nD (Wi-Fi)	1 Server Node Extension Device

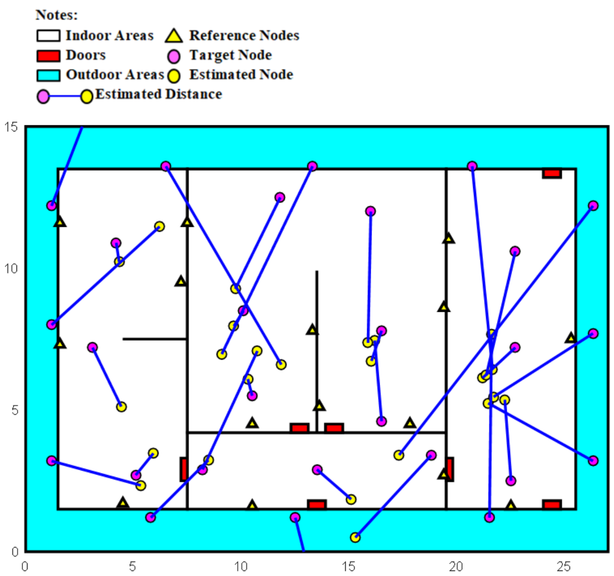

Fig. 4. Estimated position result using multi-lateration algorithm.

The target node will be sending RSSI to all reference nodes. The reference nodes will be forwarded the data to the server via Wi-Fi. The server will be directly sorted four strongest RSSI and processed for estimating distance using PLE and standard deviation value. The estimated distance will be used for calculating estimation using multi-lateration algorithm. The estimated positions result show that using multi-lateration algorithm are still out from coverage area. As shown at Fig. 4, outdoor estimated position has estimation at indoor area. This proves that only using multi-lateration algorithm is not compatible for indoor to outdoor positioning system.

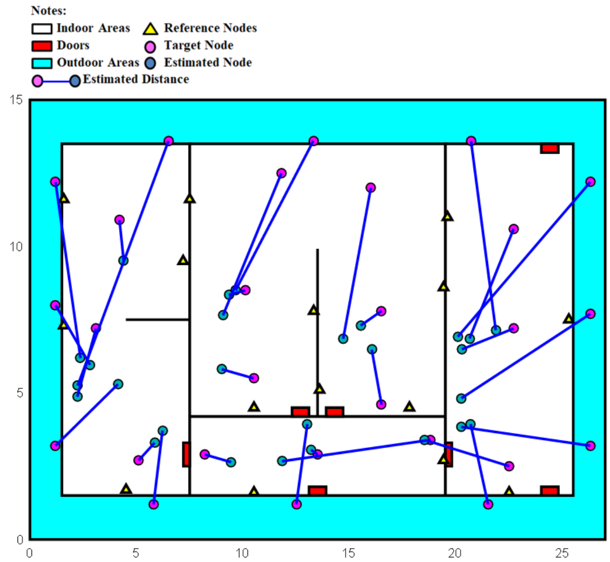

Fig. 5. Estimated position result using multi-quadratic algorithm.

Then, the result estimated position resulting from multi-lateration will be calculated using multi-quadratic algorithm, which involves multiplying weighted values. The results at Fig. 5 show that using multi-quadratic algorithm still does not efficiently improve the estimated position. Several estimated positions have errors larger than 5 meters, especially in outdoor areas.

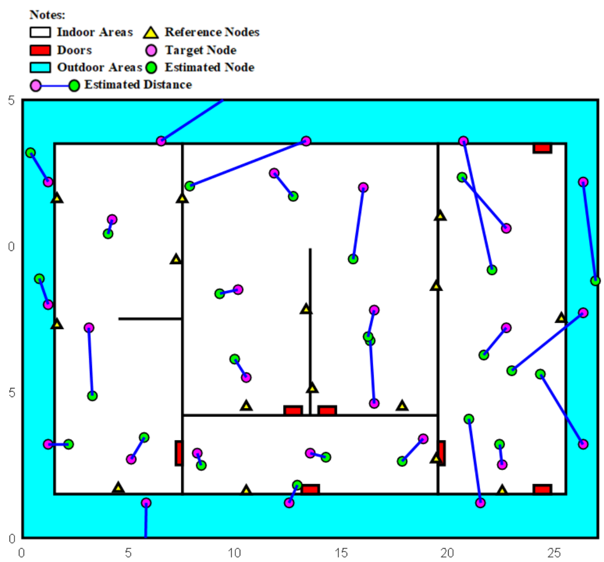

Fig. 6. Estimated position result using multi-DED algorithm.

Utilizing the Directed Energy Deposition (DED) algorithm, which is derived from differential estimated distance calculation between multi-lateration and multi-quadratic, significantly reduces the estimated error, as shown in Fig. 6. In indoor environments, the average estimated results have reached less than 4 meters. However, for outdoor environments, the average still exceeds 5 meters and remains beyond the expected range for outdoor accuracy.

The implementation of the EKF with different distance correction scheme has effectively reduced the error in estimation results, as depicted in Fig. 7. Nearly 90 percent of the estimated errors closely approximate the real position in both indoor and outdoor environments. However, there remain several points where the estimated results exceed 1 meter.

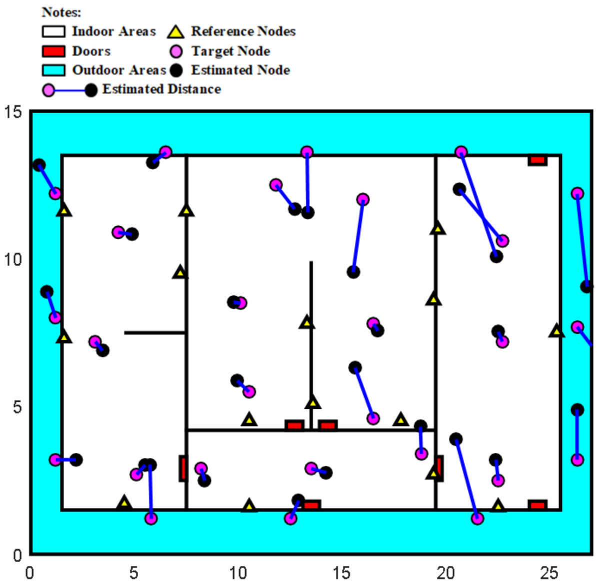

Fig. 7. Estimated position result using EKF-DDC algorithm.

Then, the analysis dan explanasion regarding the estimated error values generated from each algorithm in both indoor and outdoor environments will be discussed at the next session.

B. Discussion

This paper MSE in an indoor to outdoor positioning system using four algorithms: multi-lateration, multi-quadratic, multi-DED and EKF-DDC. These algorithms will be compared based on results from indoor and outdoor environmentes. The resulting position estimation outcomes will be analyzed using a CDF-based data distribution, as depicted in Fig. 8.

This Cumulative Distribution Function (CDF) graph is utilized to identify the worst performance of MSE values based on cumulative probability distribution for each algorithm. According to result show that, the best performance with smallest MSE value is EKF-DDC algorithm, which combines correction schemes from multi-DED algorithm and also calculate different distance between multi-lateration and multi-quadratic as jacobian matrix in EKF algorithm. It estimated error ranges are from 0.34 to 2.72 meters at indoor area, while outdoor area from 0.73 to 3.67 meters.

Using EKF-DDC algorithm, 20% estimated position are achieved smaller than 4 meter, 60% smaller than 1 meter’s error, and 20% smaller than 2 meters error. On other hand, using multi-DED algorithm in error estimation performance ranging from 0.44 m up to 5.65 m, 8% estimated error is larger than 4 meters. It proves that using EKF-DDC have been successful for reducing losses effect of RSSI transmission from indoor to outdoor environment. Therefore, the estimated errors from EKF-DDC are significantly decreased than using only multi-lateration and multi-quadratic algorithm. Using multi-lateration has high estimated errors up to 13.3 meters, while using multi-quadratic up to 7.01 meters. Although using multi-quadratic is better than using multi-lateration, it is still not appropriate for indoor to outdoor positioning system.

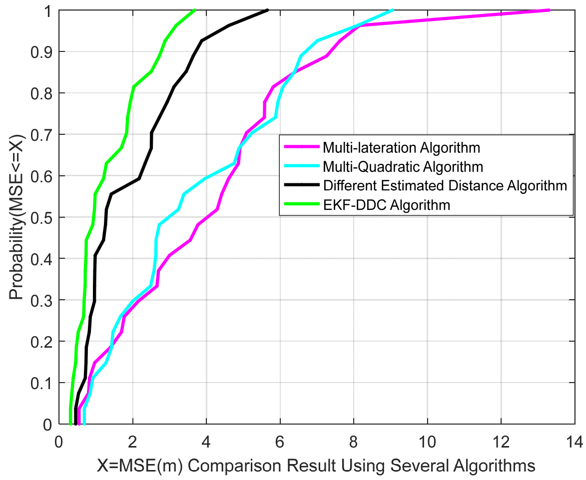

Fig. 8. CDF graph comparison of each indoor to outdoor positioning algorithm.

TABLE III. MSE RESULT OF EACH ALGORITHM

Algorithm	MSE (in meters)	Environment
Multi-lateration	2.52 m	Indoor
Multi-quadratic	2.71 m	
DED	1.3 m	
EKF-DDC	0.96 m	
Multi-lateration	6.31 m	Outdoor
Multi-quadratic	5.24 m	
DED	2.81 m	
EKF-DDC	1.81 m	

Presented in a Pareto chart (Fig. 9), the average MSE value and its average accuracy percentage relative to each algorithm based its environment can be observed. When utilizing EKF-DDC algorithm, both accuracy percentage at indoor and outdoor area are larger than 90%. Then, using multi-DED algorithm is smaller than 90% for outdoor environment. It is also followed by multi-lateration and multi-quadratic algorithm which have accuracy smaller than 90 % for both indoor and outdoor environment. While for the estimated error average as shown at Table III, except from EKF-DDC is still has average larger than 2 meters. Therefore, according to the estimated error and accuracy percentage analysis, EKF-DDC is suitable for RSSI based indoor to outdoor positioning system, which have average estimated error less than 2 meter and accuracy percentage larger than 90%.

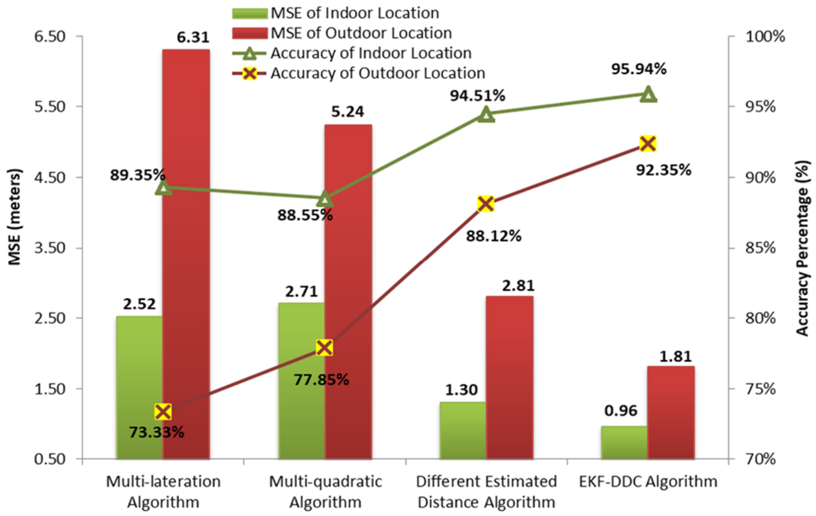

Fig. 9. Pareto chart comparison of each indoor to outdoor positioning algorithm.

Based on the experimental result of this paper, it is important to note some remaining limitations, particularly regarding the use of RSSI technique. Despite its easy and inexpensive for implementing this indoor to outdoor positioning system, RSSI measurements are influenced by environmental factors like signal attenuation and multipath propagation, requiring accurate propagation modeling. However, existing models may not fully capture real environment complexities, leading to discrepancies in RSSI values. Therefore, while our paper highlights the potential of EKF-DDC algorithm for RSSI-based positioning system at indoor to outdoor environment, further this paper still needed to develop more robust algorithms that can address these environmental challenges and improve system reliability. Even though, this paper has been succeeded in providing a new approach of RSSI based indoor to outdoor positioning system using EKF-DDC algorithm which have low estimation results below 2 meters.

V. Conclusion

In this paper, we propose RSSI based indoor to outdoor positioning system based on EKF-DDC algorithm, which is formed by different distance calculation between multi-lateration and multi-quadratic algorithm, then it is corrected using EKF algorithm. The estimated position is determined using four strongest RSSI transmission of BLE module. Indoor to outdoor communication links are represented as transmission between reference nodes placed at indoor area, while the target node placed both at indoor and outdoor area. The comparative analysis show that using EKF-DDC algorithm could improve MSE of estimated position up to 6 times better for indoor environment and 3 times better for outdoor environment than using multi-lateration algorithm as the conventional algorithm of positioning system. According to the 95 % accuracy percentage results, using EKF-DDC algorithm are compatible for RSSI based indoor to outdoor positioning system.

In the future work, we will utilize RSSI based LoRA protocol for expanding the coverage area of indoor to outdoor positioning system, moreover it can be implemented to the wide area location, and also reduce the propagation losses effect by the other derivatives of Kalman Filter algorithm followed by adaptive schemes for all environment without determining propagation environment characteristics. We also recognize several opportunities in implementing the RSSI based LoRA protocol, including enhanced coverage, improved battery efficiency and the potential for seamless integration with existing IoT infrastructure.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Ronal Tandiawan had programmed the system, data collection, data validation; Rafina Destiarti Ainul had modeling the system, analyzed the data, wrote the paper; Susilo Wibowo had conceptualization, hardware selection, PIC research grant, proofread and error correction; All authors had approved the final version.

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