RSSI-Based Indoor Localization Using Multi-Lateration With Zone Selection and Virtual Position-Based Compensation Methods

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ABSTRACT In the well-known and widely used multi-lateration method, an unknown target position is estimated using reference node positions and received signal strength indicator (RSSI) levels which indicate the distances between the target and the reference nodes. Since the RSSI signal in physical environments is time-varying and fluctuates overtime due to multi-path effects, RSSI signal variation can significantly cause localization errors. Inaccurate results can lead to poor decisions in the overall system. In this paper, an extended multi-lateration method is proposed to increase the localization accuracy. The novelty of the proposed method is that the boundary consideration, the zone selection, and the estimated position compensation method based on virtual positions are developed and integrated with the traditional multi-lateration method. To verify the proposed method, experiments using a ZigBee, 2.4 GHz, IEEE 802.15.4 wireless sensor network deployed in a laboratory room (the area size of 4 m × 4 m) and a corridor of the building (22 m × 9.3 m) have been tested. Experimental results demonstrate that all estimated positions of targets provided by the proposed method are within the test area (or zone), while the traditional multi-lateration method very often provides estimated positions outside the test area. The results also indicate that, by the proposed method, the estimation errors of most targets are lower than the case the multi-lateration method, and only a few targets, the errors by both methods are the same. Finally, in average, the proposed method outperforms the traditional method by 57.430% and 59.194%, respectively.

INDEX TERMS RSSI, 2.4 GHz, multi-lateration, zone selection, position compensation, virtual position.

I. INTRODUCTION

In recent years, wireless sensor networks (WSNs) have been used in various applications, such as monitoring, disaster management, smart city, healthcare and biomedical health monitoring, surveillance, localization, and so on. Among several fundamental issues in WSNs, localization is deemed as one of the key technologies to determine positions of wireless sensor nodes or targets. Here, position information is very useful in many real-life applications, including human monitoring and tracking in buildings, or during emergency situations [1]–[3], patient tracking in hospitals [4], [5], mobile robot tracking [6], location detection of products stored in warehouses [1], [2], worker tracking in construction sites [7], [8], location based services, and so on.

To determine target positions, RSSI information as the power level of a received signal is widely used [9]–[12]. The RSSI-based localization technique is a good choice for low-power and low complexity of signal processing in WSNs, and this technique has been widely investigated and received vast on-going interest [13], [14]. Additionally, since most wireless devices have RSSI circuits built into them, no
additional or extra hardware is required. This helps to significantly reduce the hardware cost and power consumption of the system [7], [9], [13], [15]–[17].

However, the major problem with RSSI-based location estimation is the environmental impacts on the RSSI measurements. The measured RSSI is time-varying and unreliable in general. It often fluctuates over time, especially in indoor environments [1], [3], [9], [11], [16]–[18]. Here, the RSSI variation can be caused by different factors including a) hardware types, b) distance between the transmitter and the receiver, c) time and period of measurement, d) interference from nearby devices, e) human presence and movement, and f) environments (i.e., building types and materials) [19]. Consequently, RSSI-based localization techniques should be taken the RSSI variation problem into account, since inaccurate position estimates can lead to poor decisions of the systems.

According to the research literature, many existing RSSI-based localization methods have been presented. The well-known multi-lateration method [7], [15], [16], [20], [21] is widely used because its algorithm is simple, and it also provides good accuracy and low computational complexity. It is thus easy to implement on real hardware embedded platforms [3], [7], [9], [15], [16]. In the multi-lateration method, the target position can be estimated by using positions of reference nodes and RSSI information which refers to the distance between the target and the reference node. Due to the advantage of this method in practice, many researchers have applied and extended the multi-lateration method in their works as summarized here.

In [15], an experimental evaluation of the RSSI-based multi-lateration algorithm for indoor WSNs was presented. Experiments using IFX-Eyes sensor nodes deployed in two different indoor environments showed that localization errors were significantly reduced by increasing the number of reference nodes. Like the work in [22], the experimental results demonstrated that applying multiple access points as the reference nodes could increase the multi-lateration localization accuracy. In [23], a multi-lateration approach for 3D indoor positioning was introduced. The authors also applied the Kalman filter to the RSSI measurements in order to increase the reliability of the RSSI value. In addition, the authors suggested the method how to choose the reference nodes for multi-lateration computation. Experiments using TelosB motes and XM100 motes with CC2420 radio chips deployed in the room size of $7 \, \text{m} \times 16 \, \text{m} \times 3 \, \text{m}$ verified the performance of the system in [23]. The authors also mentioned that an increase in the numbers of reference nodes improved the localization accuracy.

In [24], an RSSI-based multi-lateration localization system in order to realize a precise localization of sensor nodes in logistic applications was presented. Such a developed system was simulated and implemented in a real sensor network for food transportation logistic. Simulation results showed that six reference nodes could provide localization error lower than 1 m. Experimental results using Tmote Sky nodes with CC2420 radio modules/IEEE 802.15.4 indicated that localization errors were smaller than 1.8 m. Also, in [25], the multi-lateration method with the RSSI filter for transport logistics was introduced. The authors summarized that the RSSI filter was able to decrease the impact of multipath reflection and reduce the localization error. The multi-lateration method with the filter concept to reduce RSSI variation caused by human movements in wireless networks was also introduced in [17] and [26]. The authors developed the RSSI filters as the statistical methods, and experimental results using 2.4 GHz CC2500 RF modules indicated that the filters could more reduce localization errors.

Adaptive distance estimation and RSSI-based multi-lateration localization in WSNs were presented in [27]. Here, two efficient methods to estimate the RSSI-to-distance; a statistical method and an artificial neural network based method, were proposed. Experimental results using seven reference nodes deployed in the test area of $3.5 \, \text{m} \times 4.5 \, \text{m}$ showed that the localization errors were between 0.48 m to 0.99 m. In [28], to improve the accuracy of the RSSI-based multi-lateration method in indoors, regression-based and correlation-based approaches were proposed. The regression-based approach used linear regression to discover a better fit of the signal propagation model between the RSSI and the distance, while the correlation-based approach utilized the correlation among the RSSI in local area to obtain more accurate signal propagation. Experiments using Tmote Sky nodes for the IEEE 802.15.4 wireless network verified that such two approaches outperformed the original RSSI-based multi-lateration methods.

In [29], a hybrid indoor positioning system that included multi-lateration and fingerprinting approaches was introduced. The Kalman filtering was also applied to the estimated positions to diminish the localization errors. The simulation study revealed that the hybrid system could improve the estimation accuracy compared to the standalone fingerprinting approach and the standalone multi-lateration. In [30], an integrated algorithm based on the round trip time (RTT) and the RSSI for multi-lateration localization was introduced. Experimental results using IEEE 802.11 networks showed that such a fusion method achieved remarkable improvement in precision. Compared with the classical fingerprinting approach, the performance of the fusion method was significantly improved, where the average positioning accuracy was 1.435 m. Finally, in [13], an RSSI-based indoor localization system was presented. Raw measured RSSI data were preprocessed by a Gaussian filter to reduce the influence of measurement noise. Also, the transmit power and the path-loss exponent were estimated by a least-squares curve fitting method. Moreover, an extended multi-lateration algorithm was proposed based on the extreme value theory, which constructed a nonlinear error function depending on distances and reference node positions. Experimental results using CC2530 wireless modules, 2.4 GHz/IEEE 802.15.4, demonstrated that, by the methodology in [13], the
The localization error obtained from the 8 m × 8 m network size was controlled within 1 m.

A summary comparison between this work and the methods introduced in prior research is also provided in Table 1. Based on the research literature described above, previous works related to the multi-lateration method increase the localization accuracy by a) applying more reference nodes and selecting appropriate

### Table 1. A summary comparison between this work and the methods introduced in prior research.

| Ref. Year | Type of study | Wireless technology | Test field | Localization method | Localization accuracy | Research issues |
|-----------|--------------|---------------------|------------|---------------------|----------------------|-----------------|
| 2008      | Experiment   | - VX-1 sensor nodes - XN5250 radio chip - 868.3 MHz | Indoor 10 m × 10 m | RSSI-based multi-lateration | About 4 m for 4 ref. nodes | • An experimental evaluation of the RSSI-based multi-lateration algorithm for indoor WSNSs was presented. • Localization errors were reduced by increasing the number of reference nodes. |
| 2018      | Experiment   | - AirTies 5341 wireless modems | Indoor 6 m × 6 m | RSSI-based multi-lateration | 2.826 m for 4 ref. nodes | Applying multiple access points as the reference nodes could increase the localization accuracy. |
| 2016      | Experiment   | - TelosB motes and XM100 motes - CC-2420 radio chips - IEEE 802.15.4 - 2.4 GHz | Indoor 7 m × 16 m × 3 m | RSSI-based multi-lateration | Indoor accuracy | The multi-lateration method for 3D indoor positioning was introduced. • The Kalman filter was applied to the RSSI in order to increase the reliability of the RSSI value. • The method of how to choose the reference nodes for multi-lateration computation was suggested. |
| 2009      | - Simulation - Experiment | - Tmote Sky nodes - CC2420 radio modules - IEEE 802.15.4 - 2.4 GHz | Indoor (Container) | RSSI-based multi-lateration | Lower than 1.8 m for 6 ref. nodes (by the experiment) | Localization system in order to realize a precise localization of sensor nodes in logistic applications was presented. |
| 2011      | Experiment   | - | Indoor (Container) 6.06 m × 2.44 m × 2.59 m | RSSI-based multi-lateration | Lower than 1.18 m for 4 ref. nodes, with max. error of 2.14 m (by the experiment) | The multi-lateration method with the RSSI filter for transport logistics was introduced. • The RSSI filter was able to decrease the impact of multipath reflection and reduce the localization error. |
| 2019      | Experiment   | - CC2500 transceivers - 2.4 GHz | Indoor 4 m × 2.8 m | RSSI-based multi-lateration | 1.887 m for 3 ref. nodes | The multi-lateration localization method with the filter concept to reduce RSSI variation caused by human movements in wireless networks was introduced. |
| 2020      | Experiment   | - CC2500 transceivers - 2.4 GHz | Indoor 3.60 m × 6.20 m | RSSI-based multi-lateration | 0.30 m to 0.51 m for 3 ref. nodes | The multi-lateration localization method with the filter concept to reduce RSSI variation caused by human movements in wireless networks was introduced. |
| 2007      | Experiment   | - BTnode sensor nodes - Chipcon CC1000 - 868 MHz | Indoor 5 m × 8 m | RSSI-based multi-lateration | 0.48 m to 0.99 m for 7 ref. nodes | Adaptive distance estimation and RSSI-based multi-lateration localization in WSNSs were presented; a statistical method and an artificial neural network based method. |
| 2009      | Experiment   | - Tmote Sky nodes - CC2420 radio modules - IEEE 802.15.4 - 2.4 GHz | Indoor 66.75 m × 51.51 m (overall floor size) | RSSI-based multi-lateration | 4.572 m to 5.7912 m for 5 ref. nodes | Regression-based and correlation-based approaches were proposed to improve the accuracy of the RSSI-based multi-lateration method. |
| 2020      | Simulation   | - | Indoor | RSSI-based multi-lateration (Extended version) | 1.60 m for 4 ref. nodes | A hybrid indoor positioning system that included multi-lateration and fingerprinting was introduced. • The Kalman filtering was applied to the estimated positions to diminish the localization errors. |
| 2019      | Experiment   | - IEEE 802.11 networks | Indoor 12.14 m × 16.71 m | RSSI-based multi-lateration (Extended version) | 1.435 m for 4 ref. nodes | An integrated algorithm based on the round-trip time (RTT) and the RSSI for multi-lateration localization was introduced. |
| 2020      | Experiment   | - CC2530 wireless modules - IEEE 802.15.4 - 2.4 GHz | Indoor 8 m × 8 m | RSSI-based multi-lateration (Extended version) | Within 1.00 m for 4 ref. nodes | Raw RSSI data were preprocessed by a Gaussian filter to reduce the influence of measurement noise. • The transmit power and the path-loss exponent were estimated by a least-squares curve fitting method. An extended multi-lateration algorithm was proposed based on the extreme value theory. |
| **This work** | Experiment | - Z1 node - CC2420 RF transceivers - IEEE 802.15.4 - 2.4 GHz | Indoor 4 m × 4 m (Laboratory) 22 m × 9.3 m (Building) | RSSI-based multi-lateration (Extended version) | 0.682 m for 4 ref. nodes (Laboratory) 1.776 m for 4 ref. nodes (Building) | The extended multi-lateration method is proposed to increase the localization accuracy. • The boundary consideration, the zone selection, and the estimated position compensation with virtual position concept integrated with the traditional multi-lateration method are developed. |
The system implemented in this work is shown in Fig. 1. It is also corresponding to the real system to be tested in Section 4. We note that list of notations and symbols used in this paper is provided in Table 2. We have one base station node (BSN) connected to a computer as the processing center. Four reference nodes are located at predefined positions \((x_1, y_1)\) to \((x_4, y_4)\), and an unknown target node to be estimated its position is placed at the position \((x_t, y_t)\).

There are three steps to determine the target position. The first step is the RSSI measurement and collection by our designed communication protocol. The second step is the RSSI to distance conversion using the path-loss equation, and the last step is the applying of the multi-lateration localization method and the zone selection and the estimated position compensation techniques. They are explained here.

### TABLE 1. RSSI-based indoor localization system implemented in this work.

| Notation | Description |
|----------|-------------|
| BSN      | Base station node |
| RN       | Reference node |
| CP       | Command packet |
| BC       | Beacon packet |
| RP       | Report packet |
| CSMA/CA  | Carrier-sense multiple-access/collision-avoidance |
| T1, T2, T3, T4, T5, T6, T7, T8, T9 | Target nodes 1 to 9 |
| CI       | Confidence interval |
| \(x_i, y_i\) | Reference node position |
| \(n\)   | Number of reference nodes |
| \(d_{ij}\) | Distance between the target and the reference node number \(i\) |
| \(Z_{min}, Z_{max}\) | The minimum and the maximum \(x\) and \(y\) positions of all reference nodes |
| \(d_{min}\) | The minimum value of distances among \(d_1\) to \(d_4\) |
| \(P_{i1}, P_{i2}, ..., P_{IN}\) | Virtual positions defined in each zone |
| \(N\)   | Number of virtual positions |
| \(X_{i1}, X_{i2}\) | Virtual positions, where \(i = 1\) to \(4\) (zone) |

### II. RSSI-BASED INDOOR LOCALIZATION SYSTEM WITH THE MULTI-LATERATION METHOD

The localization system implemented in this work is shown in Fig. 1. It is also corresponding to the real system to be tested in Section 4. We note that list of notations and symbols used in this paper is provided in Table 2. We have one base station node (BSN) connected to a computer as the processing center. Four reference nodes are located at predefined positions \((x_1, y_1)\) to \((x_4, y_4)\), and an unknown target node to be estimated its position is placed at the position \((x_t, y_t)\).

There are three steps to determine the target position. The first step is the RSSI measurement and collection by our designed communication protocol. The second step is the RSSI to distance conversion using the path-loss equation, and the last step is the applying of the multi-lateration localization method and the zone selection and the estimated position compensation techniques. They are explained here.
A. RSSI MEASUREMENT AND COLLECTION

The communication among nodes in the network is shown in Algorithm 1. When the computer wants to know the target position, it first instructs the base station node to send a command packet to each reference node (dashed black arrow in Fig. 2). The reference node then generates and transmits a beacon packet to the target node (dashed red arrow in Fig. 2) using the sampling rate for packet transmission which is ordered by the base station. Upon receiving the beacon packet, the target node reads the reference node ID, the reference node position, and the packet number from the beacon packet and also gathers the RSSI value from its radio circuit. Then, the target node sends such an information encapsulated in a report packet, to the base station node (dashed blue arrow in Fig. 2). At the base station, the report packet is forwarded to the computer. The RSSI value, the reference node ID, the reference node position, and the packet number are then used for position estimation.

B. RSSI TO DISTANCE CONVERSION

At the computer, after RSSI data from all reference nodes are received, the second process then begins. The RSSI is converted to the distance value by applying the path-loss equation, which describes the measured RSSI versus the corresponding distance in the test field \cite{Ref1}, \cite{Ref2}. The path-loss equation is expressed by (1) and (2), where $\text{RSSI}_d$ is the mean RSSI (in dBm) at distance $d$ and $\text{RSSI}_{d_0}$ is the mean RSSI (in dBm) at the reference distance from the transmitter ($d_0$), and $\alpha$ refers to the path-loss exponent indicating the rate at which the received signal decreases along with distance. Both $\text{RSSI}_{d_0}$ and $\alpha$ are determined by collecting the RSSI data from the test field in which the distance between the transmitter and the receiver is known. The path-loss equations for the experiments in this work will be again explained in Section 4.

\begin{equation}
\text{RSSI}_d (\text{dBm}) = \text{RSSI}_{d_0} (\text{dBm}) - 10 \times \alpha \times \log_{10} \left( \frac{d}{d_0} \right)
\end{equation}

\begin{equation}
d = 10^{\frac{\text{RSSI}_{d_0} (\text{dBm}) - \text{RSSI}_d (\text{dBm})}{10 \times \alpha}}, \quad \text{for } d_0 = 1
\end{equation}

C. POSITION ESTIMATION

After distance values from all references are provided (i.e., $d_1$, $d_2$, $d_3$, and $d_4$ in Fig. 1), the third process immediately performs. As mentioned before, the multi-lateration method is employed to estimate the unknown target position. We choose this well-known method because the final form of its algorithm is simple as indicated by its mathematical operation. Therefore, this method is easy to implement on hardware platforms. Also, it can provide good position estimation.
estimation, as reported in [3], [7], [9], [15], [16], [21]. In the multi-lateration method, the basis is to solve the intersection point of circles with radius $d_1$, $d_2$, $d_3$, and $d_4$. The intersection point as the estimated target position $(x_{est}, y_{est})$ can be determined by solving (3) to (6).

\[
\begin{align*}
(x_{est} - x_1)^2 + (y_{est} - y_1)^2 &= d_1^2 \\
(x_{est} - x_2)^2 + (y_{est} - y_2)^2 &= d_2^2 \\
(x_{est} - x_3)^2 + (y_{est} - y_3)^2 &= d_3^2 \\
(x_{est} - x_4)^2 + (y_{est} - y_4)^2 &= d_4^2
\end{align*}
\] (3)

Note that equations (7) to (12) are used to solve (3) to (6), where $(A^T A)^{-1}$ is the inverse matrix of $(A^T A)$.

\[
\begin{align*}
(x_{est} - x_1)^2 + (y_{est} - y_1)^2 &= (x_{est} - x_4)^2 - (y_{est} - y_4)^2 \\
(x_{est} - x_2)^2 + (y_{est} - y_2)^2 &= (x_{est} - x_4)^2 - (y_{est} - y_4)^2 \\
(x_{est} - x_3)^2 + (y_{est} - y_3)^2 &= (x_{est} - x_4)^2 - (y_{est} - y_4)^2 \\
= d_2^2 - d_4^2
\end{align*}
\] (7)

\[
\begin{align*}
(x_{est} - x_1)^2 + (y_{est} - y_1)^2 &= (x_{est} - x_2)^2 - (y_{est} - y_2)^2 \\
(x_{est} - x_2)^2 + (y_{est} - y_2)^2 &= (x_{est} - x_3)^2 - (y_{est} - y_3)^2 \\
(x_{est} - x_3)^2 + (y_{est} - y_3)^2 &= (x_{est} - x_4)^2 - (y_{est} - y_4)^2 \\
= d_3^2 - d_4^2
\end{align*}
\] (8)

\[
\begin{align*}
(x_{est} - x_1)^2 + (y_{est} - y_1)^2 &= (x_{est} - x_2)^2 - (y_{est} - y_2)^2 \\
(x_{est} - x_2)^2 + (y_{est} - y_2)^2 &= (x_{est} - x_3)^2 - (y_{est} - y_3)^2 \\
(x_{est} - x_3)^2 + (y_{est} - y_3)^2 &= (x_{est} - x_4)^2 - (y_{est} - y_4)^2 \\
= d_1^2 - d_4^2
\end{align*}
\] (9)

\[
\begin{align*}
\begin{bmatrix}
(x_{est} - x_1) & (y_{est} - y_1) \\
(x_{est} - x_2) & (y_{est} - y_2) \\
(x_{est} - x_3) & (y_{est} - y_3)
\end{bmatrix}
\begin{bmatrix}
x_{est} \\
y_{est}
\end{bmatrix}
\begin{bmatrix}
x_{1} & y_{1} \\
x_{2} & y_{2} \\
x_{3} & y_{3}
\end{bmatrix}
\begin{bmatrix}
(x_{est} - x_1) & (y_{est} - y_1) \\
(x_{est} - x_2) & (y_{est} - y_2) \\
(x_{est} - x_3) & (y_{est} - y_3)
\end{bmatrix}
\begin{bmatrix}
x_{est} \\
y_{est}
\end{bmatrix}
\begin{bmatrix}
x_{1} & y_{1} \\
x_{2} & y_{2} \\
x_{3} & y_{3}
\end{bmatrix}
\begin{bmatrix}
x_{est} \\
y_{est}
\end{bmatrix}
\begin{bmatrix}
x_{1} & y_{1} \\
x_{2} & y_{2} \\
x_{3} & y_{3}
\end{bmatrix}
\end{align*}
\] (10)

\[
X = \begin{bmatrix}
x_{est} \\
y_{est}
\end{bmatrix}
\]

\[
B = \begin{bmatrix}
d_1^2 - d_4^2 & -x_1^2 - y_1^2 + x_2^2 + y_2^2 \\
d_2^2 - d_4^2 & -x_2^2 - y_2^2 + x_3^2 + y_3^2 \\
d_3^2 - d_4^2 & -x_3^2 - y_3^2 + x_4^2 + y_4^2
\end{bmatrix}
\]

\[
X = \begin{bmatrix}
A^T
\end{bmatrix}^{-1} A^T B
\] (12)

III. PROPOSED METHOD

As investigated in [3], [9], [16], [17], [33], [34], the RSSI signal is time-varying and unreliable in general. RSSI signals fluctuate overtime, where causes of RSSI variations including hardware types, distance among transmitters and receivers, time of measurement, interference from nearby devices, human presence and movement, and environments (i.e., building types, obstacles, and materials) [19]. Here, RSSI signal variations in RSSI-based localization systems can cause high position estimation errors. Inaccurate results can lead to poor decisions in the system, and cannot support some applications at all.

Due to the RSSI variation problem, the traditional multi-lateration method often provides estimated positions outside the test area, as experimented and tested by the works in [17], [26]. To address this problem, in this work, the boundary consideration, the zone selection, and the estimated position compensation technique based on virtual positions are developed and integrated with the traditional multi-lateration. Our proposed system is presented in Fig. 3.

From Fig. 3, the proposed system consists of four steps including a) position estimation by the multi-lateration method, b) boundary consideration, c) zone selection, and d) estimated position compensation, respectively. They are explained as follows.

A. POSITION ESTIMATION BY THE MULTI-LATERATION METHOD

As described in Section 2, the RSSI values are measured and $d_1$ to $d_4$ calculated from the path-loss equation are determined. Also, the estimated position ($E$) of the unknown target position $(x_{est}, y_{est})$ is estimated (i.e., $E = (x_{est}, y_{est})$). In this step, $E$ provided by the traditional method is first considered and $d_1$ to $d_4$ are collected in the database which will be used in the next step.

B. BOUNDARY CONSIDERATION

In this step, the estimated position $E = (x_{est}, y_{est})$ from the previous step is checked to ensure that it locates in the considered test area or not, where the test area is the area within the reference node position (i.e., $(x_1, y_1)$ to $(x_4, y_4)$). Here, the base station and the computer can know the reference node positions by checking the report packet as presented in Section 2 before. As shown in (13) to (17) and Fig. 4, if $(x_{min} \leq x_{est} \leq x_{max})$ and $(y_{min} \leq y_{est} \leq y_{max})$ where $x_{min}$, $x_{max}$, $y_{min}$, and $y_{max}$ are the minimum and the maximum $x$ and $y$ positions of all reference nodes, the estimated position is in the considered area and $E = (x_{est}, y_{est})$ is the final result $(x_{final}, y_{final})$, as expressed in (18). Else, $(x_{est}, y_{est})$ will be compensated to the compensated position. We note that, in this work, $n = 4$, since we have four reference nodes.

\[
\begin{align*}
\text{Considered area} &= \{(x_{min} \leq x_{est} \leq x_{max}), (y_{min} \leq y_{est} \leq y_{max})\} \quad (13) \\
x_{min} &= \min (x_1, x_2, \ldots, x_n) \quad (14) \\
x_{max} &= \max (x_1, x_2, \ldots, x_n) \quad (15) \\
y_{min} &= \min (y_1, y_2, \ldots, y_n) \quad (16) \\
y_{max} &= \max (y_1, y_2, \ldots, y_n) \quad (17) \\
(x_{est}, y_{est}) &= \begin{cases} 
(x_{final}, y_{final}), & \text{if } \{(x_{min} \leq x_{est} \leq x_{max}) \text{ and } (y_{min} \leq y_{est} \leq y_{max}) \} \\
\text{Compensate, else}
\end{cases} \quad (18)
\end{align*}
\]
stored in the database is determined using (19). If \( d_1 \) is the minimum value as in (20), we define that the unknown target may locate in the zone 1 with the high possibility, since the minimum distance refers to the strongest RSSI level. We note that as in Fig. 4, the area is separated into four zones (i.e., Zone 1 to Zone 4), and each zone is defined by (20). Thus, by (21), the possible zones for the unknown target can be selected.

\[
d_{\text{min}} = \min (d_1, d_2, \ldots, d_n)
\]

(19)

\[
\text{Zone consideration} =
\begin{cases}
\text{Zone} 1, & \text{if } d_{\text{min}} = d_1 \\
\text{Zone} 2, & \text{if } d_{\text{min}} = d_2 \\
\text{Zone} 3, & \text{if } d_{\text{min}} = d_3 \\
\text{Zone} 4, & \text{if } d_{\text{min}} = d_4
\end{cases}
\]

(20)

\[
\text{Selected Zone} =
\begin{cases}
\text{Zone} 1, & \text{if } d_{\text{min}} = d_1 \\
\text{Zone} 2, & \text{if } d_{\text{min}} = d_2 \\
\text{Zone} 3, & \text{if } d_{\text{min}} = d_3 \\
\text{Zone} 4, & \text{if } d_{\text{min}} = d_4
\end{cases}
\]

(21)

D. ESTIMATED POSITION COMPENSATION BASED ON VIRTUAL POSITIONS

When the possible zone is selected, then we will estimate a possible position in such a corresponding zone that the unknown target should be located. In this process, the estimated position by the traditional multi-lateration method and virtual positions defined in each zone are mapped, and the
minimum distance among them is determined to find an appropriate estimated position (i.e., position compensation).

Here, virtual positions defined in each zone \( (P_{i,1}, P_{i,2}, \ldots P_{i,N}) \) are shown in (22) to (23) and Fig. 5, where in each zone, there are three virtual positions (\( N = 3 \)) to be considered (as an example). Note that we can add more virtual positions to increase the estimation accuracy. However, this depends on the network size, and this also requires more computational complexity for calculation. Thus, the optimal number of virtual positions should be further taken into consideration that it is the open research issue.

\[
\begin{align*}
\{ & P_{1,1}, P_{1,2}, P_{1,3} \} \in \text{Zone}_1 \\
\{ & P_{2,1}, P_{2,2}, P_{2,3} \} \in \text{Zone}_2 \\
\{ & P_{3,1}, P_{3,2}, P_{3,3} \} \in \text{Zone}_3 \\
\{ & P_{4,1}, P_{4,2}, P_{4,3} \} \in \text{Zone}_4 \\
or & \{ & P_{i,1}, P_{i,2}, \ldots P_{i,N} \} \in \text{Zone}_i, \quad \text{where } i = 1 \text{ to } 4
\end{align*}
\]

where \( x_{est} \) and \( y_{est} \) are determined using (22) as provided in the next step A, and the minimum distance of the virtual positions of the selected zone and \( (x_{est}, y_{est}) \) is determined using (24). We note that the distance can be calculated based on the Euclidean distance as illustrated as an example in (25).

\[
\begin{align*}
\text{min} \quad \{ d(E, P_{i,1}), \\ d(E, P_{i,2}), \\ d(E, P_{i,3}) \} & , \quad \text{for Zone}_1 \\
\text{min} \quad \{ d(E, P_{i,1}), \\ d(E, P_{i,2}), \\ d(E, P_{i,3}) \} & , \quad \text{for Zone}_2 \\
\text{min} \quad \{ d(E, P_{i,1}), \\ d(E, P_{i,2}), \\ d(E, P_{i,3}) \} & , \quad \text{for Zone}_3 \\
\text{min} \quad \{ d(E, P_{i,1}), \\ d(E, P_{i,2}), \\ d(E, P_{i,3}) \} & , \quad \text{for Zone}_4 \\
\end{align*}
\]

Finally, after determining the minimum distance, the new estimated position (after compensation) is also obtained, and it is set to the final result \((x_{final}, y_{final})\). It is expressed by (26).

For Zone1:
\[
\text{If } \begin{cases} 
\text{d}(E, P_{1,1}) = \text{min} & \Rightarrow (x_{final}, y_{final}) = P_{1,1} \\
\text{d}(E, P_{1,2}) = \text{min} & \Rightarrow (x_{final}, y_{final}) = P_{1,2} \\
\end{cases}
\]

Else \((x_{final}, y_{final}) = P_{1,3}\).

For Zone2:
\[
\text{If } \begin{cases} 
\text{d}(E, P_{2,1}) = \text{min} & \Rightarrow (x_{final}, y_{final}) = P_{2,1} \\
\text{d}(E, P_{2,2}) = \text{min} & \Rightarrow (x_{final}, y_{final}) = P_{2,2} \\
\end{cases}
\]

Else \((x_{final}, y_{final}) = P_{2,3}\).

For Zone3:
\[
\text{If } \begin{cases} 
\text{d}(E, P_{3,1}) = \text{min} & \Rightarrow (x_{final}, y_{final}) = P_{3,1} \\
\text{d}(E, P_{3,2}) = \text{min} & \Rightarrow (x_{final}, y_{final}) = P_{3,2} \\
\end{cases}
\]

Else \((x_{final}, y_{final}) = P_{3,3}\).
For Zone4:

\[ If \ d(E,P_{4,1}) = \min \rightarrow (x_{\text{final}}, y_{\text{final}}) = P_{4,1} \]
\[ If \ d(E,P_{4,2}) = \min \rightarrow (x_{\text{final}}, y_{\text{final}}) = P_{4,2} \]
\[ Else \ (x_{\text{final}}, y_{\text{final}}) = P_{4,3} \]

(26)

For better understanding, three different examples of the estimated position compensation are illustrated in Fig. 6. Here, the examples show that the estimated positions by the traditional multi-lateration method (i.e., \((x_\text{est1}, y_\text{est1})\), \((x_\text{est2}, y_\text{est2})\), and \((x_\text{est3}, y_\text{est3})\)) located outside the considered area, are compensated to the optimal positions (i.e., \((x_\text{final1}, y_\text{final1})\), \((x_\text{final2}, y_\text{final2})\), and \((x_\text{final3}, y_\text{final3})\)), as the virtual positions in the considered area.

IV. EXPERIMENTS

Experiments have been conducted in the laboratory room at the Department of Electrical Engineering, Prince of Songkla University, Thailand, and the indoor corridor of the building, the 10th floor, Hatyai, Thailand.

In the laboratory room, in a half zone of the room, our RSSI-based localization system is set, where the network dimension is 4.0 m \times 4.0 m, as shown in Fig. 7 (a). We note that, in this room, the wireless network is in the right side, while the left side is the working area with some obstacles and furniture. The network layout is also illustrated in Fig. 8 (a). Here, there are four reference nodes fixed at the four corners of the area; \((x_1 = 0.00 \text{ m}, y_1 = 0.00 \text{ m}), (x_2 = 4.00 \text{ m}, y_2 = 0.00 \text{ m}), (x_3 = 4.00 \text{ m}, y_3 = 4.00 \text{ m}), \) and \((x_4 = 0.00 \text{ m}, y_4 = 4.00 \text{ m}), \) respectively. We place nine target nodes at the target position 1 \((x_{1,t} = 0.00 \text{ m}, y_{1,t} = 2.00 \text{ m}), \) target position 2 \((x_{2,t} = 1.00 \text{ m}, y_{2,t} = 3.00 \text{ m}), \) target position 3 \((x_{3,t} = 1.00 \text{ m}, y_{3,t} = 1.00 \text{ m}), \) target position 4 \((x_{4,t} = 2.00 \text{ m}, y_{4,t} = 4.00 \text{ m}), \) target position 5 \((x_{5,t} = 2.00 \text{ m}, y_{5,t} = 2.00 \text{ m}), \) target position 6 \((x_{6,t} = 2.00 \text{ m}, y_{6,t} = 0.00 \text{ m}), \) target position 7 \((x_{7,t} = 3.00 \text{ m}, y_{7,t} = 3.00 \text{ m}), \) target position 8 \((x_{8,t} = 3.00 \text{ m}, y_{8,t} = 1.00 \text{ m}), \) and target position 9 \((x_{9,t} = 4.00 \text{ m}, y_{9,t} = 2.00 \text{ m}), \) respectively. We note that all nodes are at the altitude of 1 m height from the ground level.

As mentioned in the introduction section, the proposed system can be applied for medical and healthcare services, like equipment, patient, elderly, and robot tracking in hospitals or buildings. Thus, experiments have also been performed in the corridor of the building, where the network dimension is 22.0 m \times 9.3 m, as shown in Fig. 7 (b) and Fig. 8 (b). In this test field, four reference nodes are placed at \((x_1 = 0.00 \text{ m}, y_1 = 0.00 \text{ m}), (x_2 = 22.00 \text{ m}, y_2 = 0.00 \text{ m}), (x_3 = 22.00 \text{ m}, y_3 = 9.30 \text{ m}), \) and \((x_4 = 0.00 \text{ m}, y_4 = 9.30 \text{ m}), \) respectively. We place eight target nodes along the corridor at the target position 1 \((x_{1,t} = 5.00 \text{ m}, y_{1,t} = 9.30 \text{ m}), \) target position 2 \((x_{2,t} = 11.00 \text{ m}, y_{2,t} = 3.00 \text{ m}), \) target position 3 \((x_{3,t} = 16.50 \text{ m}, y_{3,t} = 9.30 \text{ m}), \) target position 4 \((x_{4,t} = 22.00 \text{ m}, y_{4,t} = 4.65 \text{ m}), \) target position 5 \((x_{5,t} = 16.50 \text{ m}, y_{5,t} = 0.00 \text{ m}), \) target position 6 \((x_{6,t} = 11.00 \text{ m}, y_{6,t} = 0.00 \text{ m}), \) target position 7 \((x_{7,t} = 5.50 \text{ m}, y_{7,t} = 0.00 \text{ m}), \) and target position 8 \((x_{8,t} = 0.00 \text{ m}, y_{8,t} = 4.60 \text{ m}), \) respectively.
For virtual positions defined in each zone of both test fields as introduced in Section 3, they are provided in Tables 3 and 4, respectively. We note that, as mentioned before, more virtual positions can be applied to increase the estimation accuracy. However, this depends on the network size, and requires more computational complexity for calculation. Therefore, the issue of obtaining the optimal number of virtual positions is very challenge and should be further studied.

In the experiments, we use Z1 module [35] as a low-power wireless sensor network module, as demonstrated in Fig. 9. The Z1 is equipped with a second generation MSP430F2617 low-power microcontroller, and it includes the CC2420 RF transceiver [36], the ZigBee/IEEE 802.15.4 standard, which operates at 2.4 GHz with an effective data rate of 250 Kbps. Z1 hardware guarantees maximum efficiency and robustness with low energy cost. The Z1 is attached with the tripod and connected to the power...
source via the serial port. Each sensor node has a sampling rate of 200 ms for packet transmission. Also, a carrier-sense multiple-access/collision-avoidance (CSMA/CA) protocol is used for medium access control, and channel 16 is operated.

We make sure that there is no signal interference from Wi-Fi channels in the laboratory and the building environments, since we first monitor them by using the Wi-Fi analyzer software. For all RSSI signals received at the base station node,
they will be forwarded to the computer as the processing center, and the RSSI signals and the RSSI data stream are displayed, as illustrated in Fig. 9.

As introduced in Section 2, the measured RSSI is converted to distance values used for the localization by using the path-loss equation. To determine the path-loss equations for the test fields in Fig. 7 (a) and Fig. 7 (b), in the beginning, one transmitter node and one receiver node are used to measure the RSSI data at different distances which cover the test fields. Here, at each distance, the receiver collects 10,000 RSSI data samples. Fig. 10 is a plot of the average RSSI in dBm units versus the distance in meters (i.e., a logarithmic scale).

By applying linear curve fitting, the path-loss equations of the laboratory and the building can be obtained.

V. RESULTS AND DISCUSSION

First, we illustrate the calculation results which demonstrate the theoretical accuracy of the traditional multi-lateration method for the nine target nodes of the test field in Fig. 7(a) and Fig. 8 (a). Here, the effect of radio signals or the RSSI factor is not considered, while the actual distance (without any errors from the RSSI-to-distance conversion) is directed...
TABLE 5. Calculation results of the multi-lateration method; The laboratory room.

| Target | Target position \((x_t, y_t)\) | Distance from reference nodes | Calculated position | Error Distance |
|--------|-------------------------------|-----------------------------|-------------------|--------------|
|        | \(d_1\) | \(d_2\) | \(d_3\) | \(d_4\) | \((x_{est}, y_{est})\) |             |
| T1     | (0.00, 2.00) | 2.000 | 4.472 | 4.472 | 2.000 | (0.00, 2.00) | 0.000 |
| T2     | (1.00, 3.00) | 3.162 | 4.242 | 4.414 | 1.414 | (1.00, 1.00) | 0.000 |
| T3     | (1.00, 1.00) | 1.414 | 3.162 | 4.242 | 3.162 | (1.00, 1.00) | 0.000 |
| T4     | (2.00, 4.00) | 4.472 | 4.472 | 2.000 | 2.000 | (2.00, 4.00) | 0.000 |
| T5     | (2.00, 2.00) | 2.828 | 2.828 | 2.828 | 2.828 | (2.00, 2.00) | 0.000 |
| T6     | (2.00, 0.00) | 2.000 | 2.000 | 4.472 | 4.472 | (2.00, 0.00) | 0.000 |
| T7     | (3.00, 3.00) | 4.242 | 3.162 | 1.414 | 3.162 | (3.00, 3.00) | 0.000 |
| T8     | (3.00, 1.00) | 3.162 | 1.414 | 3.162 | 4.242 | (3.00, 1.00) | 0.000 |
| T9     | (4.00, 2.00) | 4.472 | 2.000 | 2.000 | 4.472 | (4.00, 2.00) | 0.000 |

Average error distance | 0.000 |

SD | 0.000 |

FIGURE 11. Raw RSSI signals of the target node 4 (T4).

TABLE 6. Average distances calculated from RSSI signals in the experimental case; The laboratory room.

| Target | Target position \((x_t, y_t)\) | Average distance from reference nodes (calculated from the measured RSSI signal) | Error distance |
|--------|-------------------------------|------------------------------------------------|--------------|
|        | \(d_1\) | \(d_2\) | \(d_3\) | \(d_4\) | \((x_{est}, y_{est})\) |             |
| T1     | (0.00, 2.00) | 1.933 | 5.970 | 5.327 | 1.335 |
| T2     | (1.00, 3.00) | 2.612 | 8.151 | 2.771 | 1.089 |
| T3     | (1.00, 1.00) | 1.194 | 3.161 | 5.369 | 3.094 |
| T4     | (2.00, 4.00) | 5.232 | 7.911 | 1.306 | 1.642 |
| T5     | (2.00, 2.00) | 2.697 | 2.802 | 2.471 | 2.360 |
| T6     | (2.00, 0.00) | 1.552 | 1.482 | 4.751 | 5.772 |
| T7     | (3.00, 3.00) | 4.290 | 3.236 | 1.603 | 2.309 |
| T8     | (3.00, 1.00) | 3.223 | 1.253 | 2.993 | 6.037 |
| T9     | (4.00, 2.00) | 5.168 | 1.437 | 1.653 | 5.422 |

used for calculation. We note that we provide only the calculation results for the case of the laboratory as an illustration, since there is the same result and conclusion for the case of the building.

Based on the calculation using equation (12), the estimated positions are shown in Table 5. Note that, in Table 5, the actual distances (between the references and the targets: \(d_1, d_2, d_3, \text{ and } d_4\)) are calculated using \(d_i = \sqrt{(x_t - x_i)^2 + (y_t - y_i)^2}\). For the error distance in the last Column of the tables, it is the difference between the actual target position and the calculated position; \(\text{Error distance} = \sqrt{(x_t - x_{est})^2 + (y_t - y_{est})^2}\). Table 5 demonstrates that, without the effect of radio signals, the multi-lateration method can estimates the unknown target position without any error.

For the experimental results (using the distances calculated from the measured RSSI signals), the average error distances estimated by the proposed method and the traditional multi-lateration method are shown in Fig. 12. The 95% CI
FIGURE 13. The positions estimated by the proposed method and the traditional multi-lateration method.
is also indicated for the average results. We note that the average distances calculated from the measured RSSI signals in the experimental case are also provided in Table 6. Here, we can see the distance variation as the difference of the distances between the calculated case and the experimental case. For example, for T4, $d_1$ to $d_4$ in the calculated case are 4.472 m, 4.472 m, 2.000 m and 2.000 m, respectively, while in the experimental case, they are 5.232 m, 7.911 m, 1.306 m, and 1.642 m, respectively, where the measured RSSIs corresponding to this case are illustrated in Fig. 11.

For Fig. 12, it indicates that, by the real experiment, the multi-lateration method provides more estimation errors than the calculation case. The results also indicate that our proposed method has error distances smaller than the traditional method for both test fields. In the laboratory environment, the average errors are 0.682 m with SD of 0.201 (the proposed method) and 1.603 m with SD of 0.873 (the multi-lateration), respectively. Here, the proposed method outperforms the multi-lateration method by 57.430%. In the corridor environment of the building as a big scale network, the average errors are 1.776 m with SD of 1.360, and 4.353 m with SD of 2.484 respectively. Here, the proposed method outperforms the traditional method by 59.194%.

Fig. 13 also shows the estimated positions of all target nodes for both test fields to illustrate the variation of the estimated results performed by both methods. The experimental results indicate that the positions estimated by the proposed method are closer to the actual target positions than the multi-lateration method. Here, in the laboratory scenario, all estimated positions by the proposed method are fallen within the test room, while six estimated target positions (i.e., T1, T2, T4, T6, T8, and T9) determined by the traditional multi-lateration method are outside the room. Likewise, in the building scenario, the proposed method provides all estimated positions within the corridor, while six estimated target positions (i.e., T2, T3, T4, T5, T7, and T8) by the traditional method strays outside. The results here indicate that the traditional multi-lateration method frequently provides the estimation results outside the test area. On the other hand, the proposed method including the boundary consideration, the zone selection, and the estimated position compensation based on the virtual position concept can significantly address such a mentioned problem.

Finally, in Fig. 14, the error distances of all target positions are also illustrated. In Fig. 14 (a), the results demonstrate that, for six target positions (i.e., the target positions 1, 2, 4, 6, 8, and 9), the error distances estimated by the proposed method are significantly lower than the multi-lateration method. For the target positions 3, 5, and 7, the error distances by both methods are the same. The results here confirm the performance efficiency of our design methodology and the proposed method.
VI. CONCLUSION
In this paper, we develop the RSSI-based indoor localization system and extend the traditional multi-lateration method to improve the localization accuracy. The novelty of the proposed method is that the localization errors are more reduced by the multi-lateration method integrated with the boundary consideration, the zone selection, and the estimated position compensation method based on the virtual position concept. Experiments using the ZigBee, 2.4 GHz, IEEE 802.15.4 wireless sensor network in the laboratory and the indoor corridor of the building have been tested to verify the proposed method. The experimental results indicate that the proposed method provides all estimated positions of targets within the test area (or zone), and the localization errors of most targets are lower than the case the multi-lateration method. In average, the localization errors by the proposed method is lower than the traditional method: 0.682 m and 1.603 m, respectively, for the laboratory scenario, and 1.776 m and 4.353 m, respectively, for the building scenario. Here, the proposed method outperforms the traditional method by 57.430% and 59.194%, respectively.

In the future work, the proposed method will be tested and evaluated in the case of the mobile target with different movement speeds, movement patterns, and environments. Additionally, as mentioned in Section 3 (i.e., proposed system), more virtual positions can be added in the proposed algorithm to increase the localization accuracy. However, the optimal number of virtual positions related to the network size and the computational complexity should be taken into consideration.

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