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Performance Comparison of Several Range-based Techniques for Indoor Localization Based on Received Signal Strength Indicator

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Abstract

The classical rang-based technique for position estimation is still reliably used for indoor localization. Trilateration and multilateration, which include three or more references to locate the indoor object, are two common examples. These techniques use at least three intersection-locations of the references' distance and conclude that the intersection is the object's position. However, some challenges have appeared when using a simple power-to-distance parameter, i.e., received signal strength indicator (RSSI). RSSI is known for its fluctuated values when used as the localization parameter. Besides that, the obstacle such as furniture and the human body can increase positioning error. The improvement of classical range-based has been proposed, namely min-max and iRingLA algorithms. These algorithms or methods use the approximation in a bounding-box and rings for min-max and iRingLA, respectively. This paper discusses the comparison performance of min-max and iRingLA with multilateration as the classical method. We found that min-max gives the best performance, and in some positions, iRingLA gives the best accuracy error. Hence, the approximation method can be promising for indoor localization, especially when using a simple and straightforward parameter, i.e., RSSI.

Keywords: Indoor Localization; RSSI; Trilateration; Min-max; iRingLA

I. Introduction

IN recent years, the demands for Location-Based Service (LBS) is increasing. LBS is applied in assistive technology such as car navigation, monitoring, healthcare, a gaming [1], disaster and emergency [2], and supporting production process [3]. The most common technology used for LBS is Global Positioning System (GPS). GPS is the positioning and tracking system based on navigation satellites [4]. GPS can be used to position and track in the outdoor environment [5]. However, most of our time also spent indoors; LBS is also needed in the indoor environment [1], usually called indoor localization or indoor positioning system (IPS) [6].

The rapid development of sensor technology and micro-electrical-mechanical system (MEMS) supports wireless sensor networks (WSNs) researches. One of WSNs' real and useful applications is indoor localization [7]. By applying WSNs in an indoor environment, with specific wireless technology, i.e., Wi-Fi, ZigBee [8], Bluetooth [9] [10], Radio Frequency Identification (RFID) [11], we can build an indoor localization system. The localization parameter for the localization ranges from the economic point-of-view, easy use, less-complexity, and accuracy considerations [12]. Most of the parameters used in indoor localization are Received Signal Strength Indicator (RSSI) [13], Time of Arrival (ToA) [14], Time Difference of Arrival (TDoA) [15], and Angle of Arrival (AoA) [16].

These parameters can be used as a tool for positioning by several localization techniques. Two standard localization techniques are range-based and range-free [17]. In these terms, range-based represents the

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parameters that should be translated to distance or parameter-to-distance conversion. For instance, if we use the power to distance relationship, explicitly using the path loss model, we can directly calculate the distance based on the receiver's power based on the path loss model [18].

The range-free technique or scene analysis uses the unique radio parameters for locating the target or object. These unique radio parameters are stored as the database and then compare to the current radio parameters exhibit from the target [19]. This technique is well-known as the radio fingerprinting technique. The term fingerprint is an analogy from a human fingerprint [20][21].

The classical range-based technique, yet the algorithm's robust foundation is trilateration or multilateration (use more than three sources or references). The basic idea is to form a circle between the transmitter (TX) and receiver (RX) based on the circle radius's length based on the parameter-to-distance conversion [22]. When the localization parameters fluctuate and unreliable, some weaknesses in this technique are that the expected intersection from the three sources or references will not intersect; resulting in a high estimation error [23]. Some proposals to improve trilateration or multilateration is using bounding-box or rings concept. As previously stated, the problem in finding the correct intersection of three or more circles, the approximation of the proposed technique, is proven to reduce the estimation error. These techniques are widely applied in indoor localization techniques, namely min-max algorithm, and iRingLA. The min-max propose the bounding-box [16], while iRingLA uses the error from the empirical results to correct the resulting parameters [24].

As the author's concern, there are no publications to compare the simple-straightforward indoor localization technique in the range based on trilateration vs. min-max vs. iRingLA with the simple measurement using specific parameters, i.e., RSSI.

This paper compares indoor localization performance accuracy between the trilateration or multilateration, min-max, and iRingLA. We employ RSSI-the distance-translation from RSSI using the general path loss model in the 2D area for the parameter used. The deployed experiment area has a size of 5m × 5m and obstacles less. We set the four types of target locations, aim to obtain the most accurate positioning algorithm.

This paper's remainder is organized as follows; the introduction part has been discussed in section 1. In Section 2 and 3 we explain the research material and method. Section 4 presents the results and discussion. Finally, conclusions are given in Section 5.

II. RESEARCH MATERIAL

A. Received Signal Strength Indicator (RSSI)

RSSI is a parameter commonly used in indoor positioning. RSSI represents the signal strength from the transmitter to the receiver [24]. This parameter is straightforward to obtain because extracting the RSSI value from the transceiver does not require additional hardware [25].

$$P_r = P_t K[\frac{d_0}{d}]^n \tag{1}$$

P_r is received power, P_t is transmitted power, K is path loss value in free space, d_0 is reference distance commonly in 1 meter, d is the distance between transmitter and receiver, and n is path loss exponent value [26]. In measurements by employing the ZigBee standard, the path loss model can be described by Equation 2[16].

$$RSSI = A - 10 \cdot n \cdot log_{10}[\frac{d_0}{d}] \tag{2}$$

A is RSSI value in 1 meter. The distance between transmitter and receiver can be found by using Equation 3.

$$\mathrm{d} = 10^{\frac{\mathrm{A-RSSI(d)}}{10 \cdot \mathrm{n}}} \tag{3}$$

B. Trilateration Method

In estimating the position of the 2D plane, the trilateration method uses the distance between the target to three references based on parameter calculation or translation [27]. It takes three reference nodes that know the locations to determine the target's relative position, assuming the three circles intersect at the target point as shown in Fig. 1 [28]. The trilateration method mathematically can be described by Equation (4), (5), (6). By substituting and eliminating the three equations, the position coordinates (x, y) can be estimated.

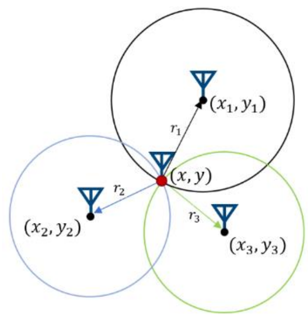

Fig. 1. The illustration of positioning target using trilateration.

$$(x - x_1)^2 + (y - y_1)^2 = {r_1}^2 \tag{4}$$

$$(x - x_2)^2 + (y - y_2)^2 = {r_2}^2 \tag{5}$$

$$(x - x_3)^2 + (y - y_3)^2 = {r_3}^2 \tag{6}$$

Where x is target position in x-axis, y is target position in y-axis, x_n is centroid of n-th circle in x-axis, y_n is centroid of n-th circle in y-axis, and r_n is radius of n-th circle.

C. Min-max Method

In the trilateration method, the three circles representing the distance between the target and each reference node are assumed to intersect at one point. However, the shadowing effect makes this assumption gives a significant error. Thus, another approach is needed. The min-max (bounding-box) method does not assume intersections between circles but an approximation by forming a box [16]. Fig. 2 illustrates the min-max method in which a box is created for each reference node.

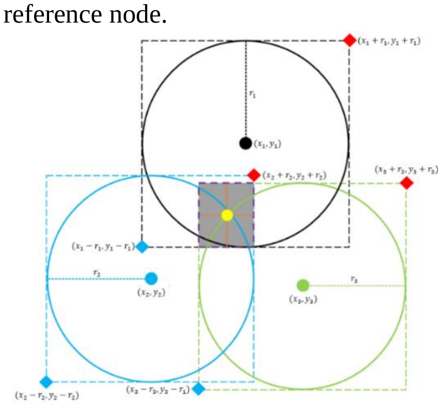

Fig. 2. The illustration of Min-max using 3 reference nodes.

From the boxes made at each reference node, we can obtain the values for $x - r$, $x + r$, $y - r$ and $y + r$.

$$\boldsymbol{x_{min}} = \begin{bmatrix} x_1 - r_1 \\ x_2 - r_2 \\ \vdots \\ x_N - r_N \end{bmatrix} \tag{7}$$

$$\boldsymbol{x_{max}} = \begin{bmatrix} x_1 + r_1 \\ x_2 + r_2 \\ \vdots \\ x_N + r_N \end{bmatrix} \tag{8}$$

$$\boldsymbol{y_{min}} = \begin{bmatrix} x_1 - r_1 \\ x_2 - r_2 \\ \vdots \\ x_N - r_N \end{bmatrix} \tag{9}$$

$$\boldsymbol{y_{max}} = \begin{bmatrix} y_1 + r_1 \\ y_2 + r_2 \\ \vdots \\ y_N + r_N \end{bmatrix} \tag{10}$$

The maximum values are chosen from Eq. (8) and (10) for the Eq. (12) and (14). The minimum values are chosen from Eq. (7) and (9) for the Eq. (11) and (13).

$$x_{minmax} = \min_{x_i + r_i} \boldsymbol{x_{max}} \tag{11}$$

$$x_{maxmin} = \max_{x_i - r_i} \boldsymbol{x_{min}} \tag{12}$$

$$y_{minmax} = \min_{y_i + r_i} \boldsymbol{y_{max}} \tag{13}$$

$$y_{maxmin} = \max_{y_i - r_i} \boldsymbol{y_{min}} \tag{14}$$

The target position is the center of this box as Equation (15)-(16),

$$x = \frac{x_{minmax} + x_{maxmin}}{2} \tag{15}$$

$$y = \frac{y_{minmax} + y_{maxmin}}{2} \tag{16}$$

D. iRingLA Method

Another improvement of trilateration-based technique in indoor localization is iRingLA method. The basic idea of this method is similar to one in min-max. However, it uses the ring instead of circle and bounding-box in trilateration and min-max, respectively. It is proposed to overcome the significant error because of the shadowing effect and multipath components (MPCs) [16]. Fig. 3 Illustrates the iRingLA method.

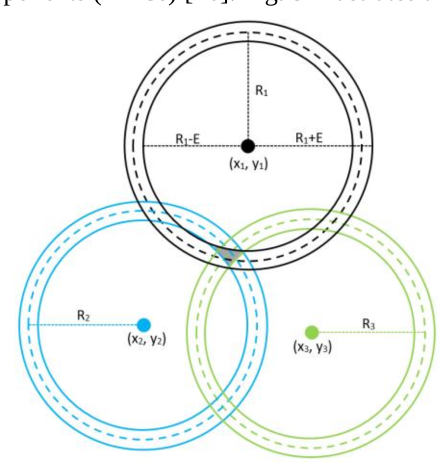

Fig. 3. The illustration of iRingLA using 3 reference nodes.

iRingLA has two state phases [24]. In the first phase, we had to find the distance between the target and each node using Equation (3). The second phase is used to estimate the position. The difference between theoretical position and actual position can be described as the estimated location error. We use the error to build imaginary rings as Equation (17)-(18).

$$R_{in} = d_{ave} - E \tag{17}$$

$$R_{out} = d_{ave} + E \tag{18}$$

where the d_{ave} is distance between target and reference node and E is an empirical error. The last step or iRingLA method is get the centroid of three closest rings.

III. RESEARCH METHOD

A. Measurement Campaign

We used the data of our previous work on indoor localization in a lobby environment. The data were taken in a lobby of Dept. of Computer Engineering, KMITL. We created a grid with 1x1 meter intervals in 5x5 meter area of interest. We measured the RSSI value at each interval's coordinates using 4 and 6 reference node sensors. Fig. 4 shows the illustration of our measurement setup and Fig. 5 depicts the actual measurement setup. The card box is used to ensure that our Zigbee system's antennas do not have an unnecessary signal reflection from the floor.

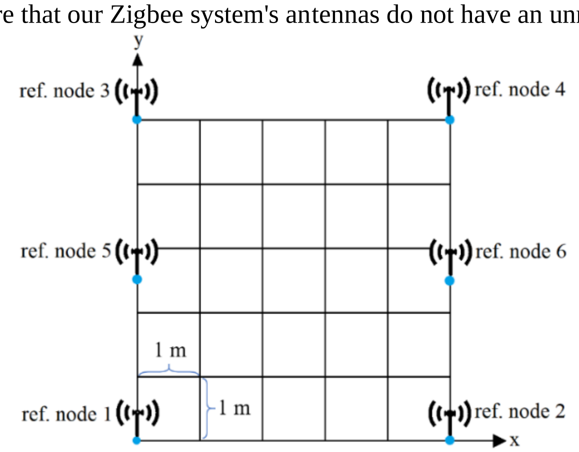

Fig. 4 The layout of the measurement setup.

Fig. 5. The actual measurement setup.

B. Wireless Sensor Networks (WSNs)

The measurement campaign followed one of the WSNs topology; the star topology. This topology consists of the one sink node or coordinator and some sensor or reference nodes as the end devices as shown in Fig. 6 [29]. We set the sink node as the target and reference nodes for the end devices. In this approach, The ZigBee standards, XBee-24ZB is used for both target and reference nodes [30].

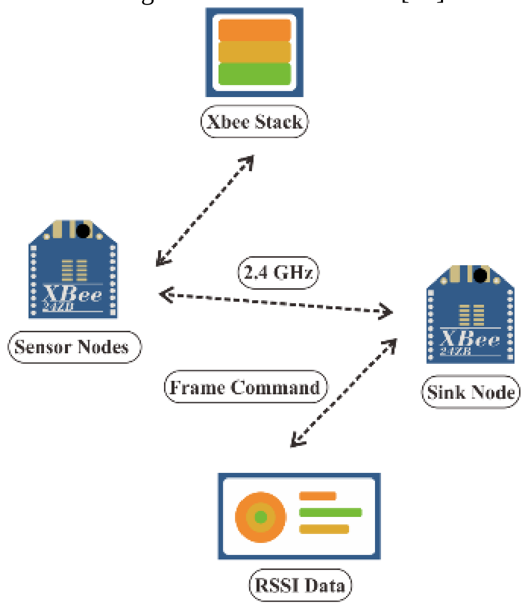

Fig. 6. The illustration of WSNs's star topology on ZigBee.

The sink node receives a command from a personal computer (PC) and sending the RSSI request. The reference nodes receive the RSSI value from the sink node and transmit it back with the RSSI data from XBee stack. Finally, the RSSI data can be accessed from the sink's or target's application programming interface (API) frame. The communication is based on the IEEE 802.15.4 standards. The RSSI process can be illustrated in Fig. 7 [31].

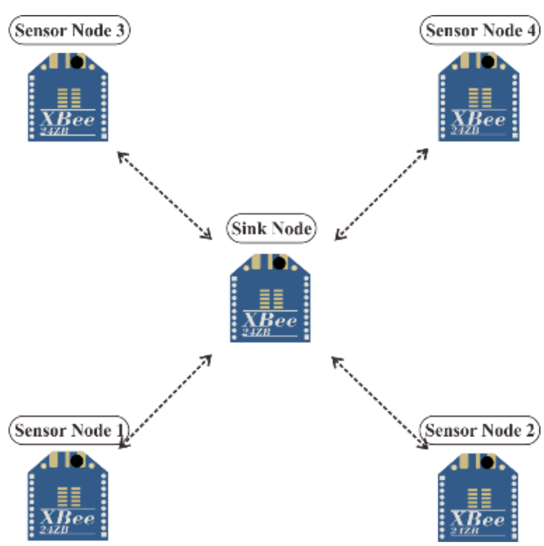

Fig. 7. RSSI obtaining process illustration.

C. Measured RSSI Values for iRingLA

TABLE I
AVERAGE RSSI (d_0) FOR 4 REFERENCE NODES

Ref. Node	RSSI (d_0) (dBm)
1	-31.9
2	-31.8
3	-32.1
4	-33.1
average	-32.225

TABLE II
AVERAGE RSSI (d_0) FOR 6 REFERENCE NODES

Ref. Node	RSSI (d_0) (dBm)
1	-31.41
2	-31.2
3	-32.04
4	-31.73
5	-32.13
6	-31.93
average	-31.74

For iRingLA, we have to know the average error to complete the RSSI equation of the formed circles. iRingLA process can be divided into two steps; the first is to calculate the distance translation from RSSI values, and the second is to find the error in meters. In the first phase, we calculate the RSSI (d0) applying Eq. (2). By using linear regression in a diagonal line, x-axis, and y-axis, we get the average value for 4 and 6 reference nodes in Table I and Table II, respectively. The n path loss and error can be found in the second phase from each reference node's error that we can see in Table III.

TABLE III
AVERAGE ERROR

Ref. Node	n path loss	Error (m)
4	1.948	0.51
6	1.986	0.483

Then we calculate the distance between target and reference node using RSSI values as below:

For 4 nodes,

$$d = 10^{\frac{-32.225 - RSSI(d)}{10 \cdot 1.948}}$$

For 6 nodes,

$$d = 10^{\frac{-31.74 - RSSI(d)}{10 \cdot 1.986}}$$

The average error of 4 nodes is 0.510 and 6 nodes are 0.483. Thus, Equation (17) and (18) becomes:

For 4 nodes,

$$R_{in} = d_{ave} - 0.510$$

$$R_{out} = d_{ave} + 0.510$$

For 6 nodes,

$$R_{in} = d_{ave} - 0.483$$

$$R_{out} = d_{ave} + 0.483$$

IV. Results And Discussion

We used measurement data to compare the accuracy of positioning performance between trilateration, min-max, and iRingLA. The estimated position was point 1 to 17, as in Fig. 8. We selected the 17 points based on the RSSI values that are not fluctuated compared to the corners' position. The sole reason is to make sure that the comparison of several range-based can be valid.

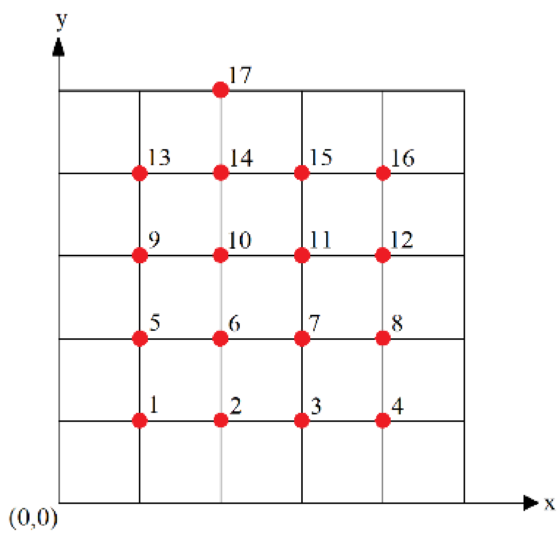

Fig. 8. Target position.

A. Four Reference Nodes

The result of the trilateration method to estimate position is shown in Fig. 9. There is a massive error for the trilateration method, about 4.809 m in the target position number 13. However, trilateration gives the smaller error in the target position number 7, about 0.148 m.

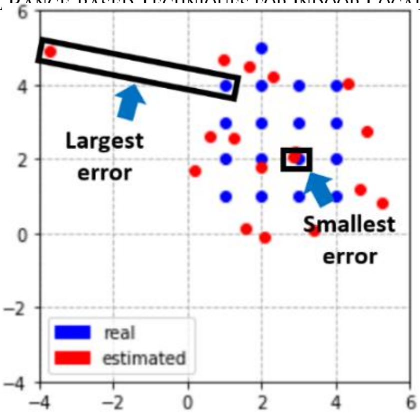

Fig. 9. Results estimation using trilateration for four nodes.

By using the min-max method, we get a better result shown in Fig. 10. The min-max method can get a better-estimated position; the largest error is still found in the target position number 13 about 1.063 m, and the smallest error is about 0.1 m in the target position number 6.

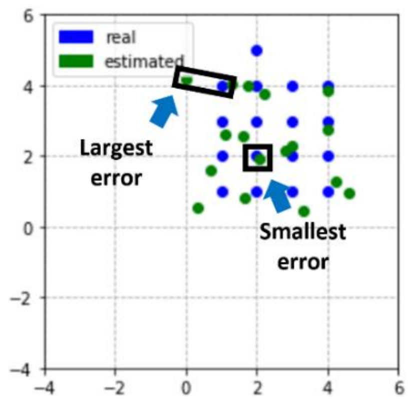

Fig. 10. Results estimation using min-max for four nodes.

Using the iRingLA method has a similar result with the trilateration method shown in Fig. 11, but there is no considerable error. We found the largest error in the target position number 4, 1.297 m, and the smallest error in the target position number 7, 0.107 m.

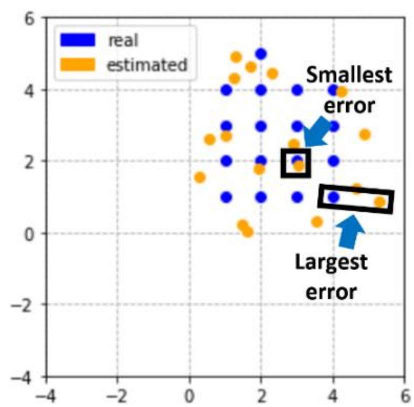

Fig. 11. Results estimation using iRingLA for four nodes.

B. Six Reference Nodes

We added the scalability of our WSN-based indoor localization system by deploying two more sensor or reference nodes. The results of the estimated position by using the trilateration method is shown in Fig. 12. The position number 16 has the smallest distance error estimated position of 0.2149 m. Similar to previous results, the target's position number 13 shows an inaccurate estimated position, and it has the largest error for the trilateration method of 1.5475 m. From all the estimated positions, the 13th position has the largest error of 1.0171 m. The sixth position becomes the most accurate estimated position by using this method of 0.1175 m error only. Fig. 13 shows how small errors resulted from the min-max.

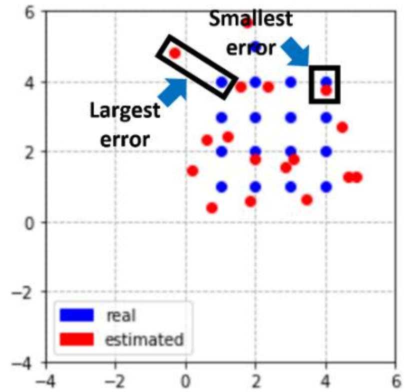

Fig. 12. Results estimation using trilateration for six nodes.

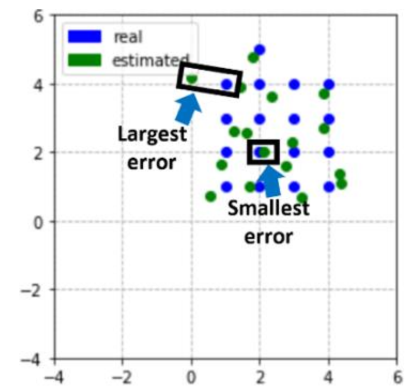

Fig. 13. Results estimation using min-max for six nodes.

The estimated position results using the iRingLA method have similar values of the largest and smallest estimated error with the trilateration method. As shown in Fig. 14, the largest and smallest error is 1.7191 m and 0.1657 m.

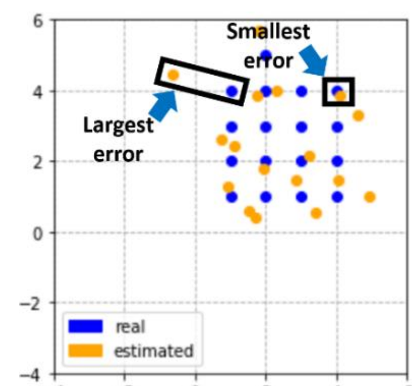

Fig. 14. Results estimation using iRingLA for six nodes.

C. Estimated Error

We use the average distance error to quantify and evaluate the performance of each positioning method. The error equation is defined as follow:

$$Error = \sqrt{(x-x')^2 + (y-y')^2} \tag{19}$$

where x is real position in x-axis, x' is predicted position in x-axis, y is real position in y-axis, y' is predicted position in y-axis. All three positioning methods have a similar largest error in the thirteenth estimated position for six reference nodes. For trilateration using four reference nodes and both trilateration and iRingLA using six reference nodes, the thirteenth estimated position has minus values on the x-axis, as shown in Fig. 9, Fig. 12, and Fig. 14. It means if we see in real-life, the estimated position is outside of the room. However, when we use the min-max method, the 13th estimated position is still inside of the room.

In this research, the min-max method becomes the most accurate positioning method with an average distance error of 0.6853 m. Almost all estimated positions using the min-max have a lower estimated error position than iRingLA or trilateration except for the 14th, 15th, and 16th positions. iRingLA has a bigger average error than the min-max method. The average accuracy is only slightly better than trilateration. The average distance error of iRingLA is 0.7276 m. Trilateration yields the biggest mean error of 0.7736 m. Overall, all of the methods used in several 2D indoor positioning have a mean positioning error of fewer than 0.8 m. As we see in Fig. 15 and Fig. 16, by employing four nodes and six for the positioning system, all three positioning methods give the smallest error in the sixth and sixteen positions.

The trilateration method gives a fluctuating estimate position and has a significant error compares to other methods, i.e., in the thirteenth position. We analyze the estimation position by assuming the ideal environment, and we do not include the other factors such as reflection and absorption of the RSSI values. There are a wall and stair near the thirteen target positions; the wall can change RSSI value due to reflection, diffraction [32]. We also found that the error increases with the object's distance to the reference nodes. For instance, the first and sixth positions can yield errors gave an out-range estimated position.

Min-max gives a solution for this trilateration problem, with trilateration error decreasing in the thirteenth position from 4.809 m to 1.0633 m. iRingLA provides better performance than trilateration but still has a slightly bigger error than min-max. An estimated position using min-max can get an error of 1.063 m in the thirteenth position, but iRingLA still has a bigger error of 1.297 m. We also compare the number of reference nodes used for the measurements. For instance, trilateration using the six nodes gives better performance, about 0.734 m average error compared to 1.048 m with four nodes. In the min-max method, we yield an average error around 0.491 m using six nodes and 0.578 m using for nodes. While in the iRingLA method, we get an average error of around 0.685 m with six nodes and 0.745 m with four nodes. Overall, six nodes have a better performance than four nodes because, in four nodes, the RSSI values have fluctuated when the distance is so far. The RSSI values are better by utilizing six nodes because the additional two reference nodes can significantly reduce the distance between target and sensor nodes. To calculate the estimated position, we need at least three nodes, so in six nodes, we can get a stronger signal to get a minimum error during estimation than using four nodes.

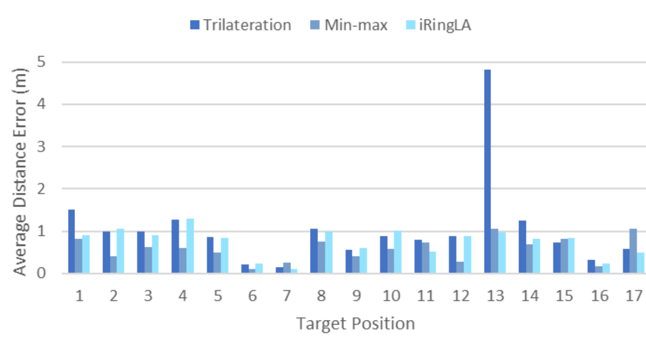

Fig. 15. Estimated location error comparison of the methods by using four reference nodes.

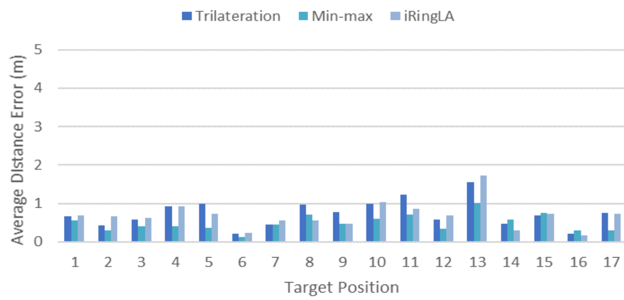

Fig. 16. Estimated location error comparisob of the methods by using six reference nodes.

V. CONCLUSION

This paper compares the three range-based positioning methods based on actual measurement campaigns for an indoor localization system. We utilized the RSSI data of the measurement in a 5x5 area of interest by employing four and six reference nodes. We found that the result of estimation by using min-max has the highest accuracy. The accuracy of estimating position by using iRingLA and trilateration was less than the min-max method. We show that trilateration gives the most significant distance error compares to min-max and iRingLA. In other words, in terms of accuracy, the iRingLA accuracy is between min-max and trilateration. Both iRingLA and min-max can reduce the maximum error yield by the trilateration by up to 400%. The six nodes were also better than the four nodes because of distance issue vs. RSSI fluctuations. We can propose our system to be installed in a less-dynamic indoor environment by observing the results achieved, with six reference nodes and indoor size not more than 5-to-7 meters in length. The min-max can fruitfully be applied in this kind of indoor environment.

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