

REDUCTION OF RSSI VARIATION AND POSITION ESTIMATION ERROR CAUSED BY HUMAN MOVEMENTS IN AN RSSI-BASED INDOOR LOCALIZATION SYSTEM

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Abstract

The experimental evaluation of a received signal strength indicator (RSSI)-based indoor localization system is studied in this paper. The major contribution of this work is that the well-known and widely used min-max and trilateration methods are tested in the case of human movement scenarios, and a new RSSI filter is designed and developed to directly reduce RSSI variation caused by human movement. Experiments have been carried out in an indoor environment using low-cost, low-power 2.4 GHz wireless nodes. The experimental results demonstrate that in human movement scenarios, the min-max method provides higher accuracy than the trilateration method. Also, by applying the proposed RSSI filter, the RSSI variation and position estimation error are more decreased. The position estimation error decreases by 71.28% in the case of the min-max method, and it decreases by 73.65% in the case of the trilateration method.

Keywords: RSSI variation, localization, human movements, filter, min-max, trilateration

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Introduction

Indoor localization is an essential subject in the context of wireless networks (Liu *et al.*, 2007; Patwari *et al.*, 2008) because position information can be used in various applications, including human tracking in buildings (Liu *et al.*, 2007; Patwari *et al.*, 2008), patient monitoring in hospitals (Redondi *et al.*, 2013), rescue robot tracking (Severino *et al.*, 2007), location detection of products stored in warehouses (Liu *et al.*, 2007; Severino *et al.*, 2007; Mautz, 2012; Redondi *et al.*, 2013), worker tracking in construction sites (Pei *et al.*, 2009; Wang *et al.*, 2010; Luo *et al.*, 2011), automated control of devices (Yeh *et al.*, 2010; Bjorkbom *et al.*, 2011; Booranawong *et al.*, 2013), and so on. Thus, one of the fundamental challenges in wireless networks is the localization problem. To determine an unknown target position, RSSI information is widely used because most wireless devices have RSSI circuits built into them. Therefore, no additional hardware is required. This can help to reduce the cost and complexity of the system (Zanca *et al.*, 2008). However, the major challenge in the use of RSSI information is that it is unreliable and time varying; it often fluctuates over time. Here, RSSI variations can be caused by several factors; the presence and movement of humans obstructing a radio signal path is among the major factors that cause RSSI variations (Pahtma *et al.*, 2009; Chapre *et al.*, 2013) and large errors in position estimates (Goldoni *et al.*, 2010; Rattanalert *et al.*, 2015).

To the best of our knowledge, assessing how RSSI variation caused by human movement enables the min-max and the trilateration methods and proposing RSSI filters to handle such a situation have not been studied in prior literature. A review of related work is summarized here. In Pahtma *et al.* (2009) and Chapre *et al.* (2013), the authors summarized factors that could cause variations in the RSSI, and also reported that the radio signal was significantly affected by a person walking in areas of wireless networks. The work in Hamida and Chaliue (2010) reported that human activities significantly affected the performance of wireless networks, both in

line-of-sight and non-line-of-sight conditions. In Turner *et al.* (2013), the human movement effects on 2.4 GHz wireless sensor networks were studied by experiments. The results showed that RSSI variation depended on the number of people and their movement speeds. In Lin *et al.* (2011), the authors showed that the signal interference by human movement caused RSSI fluctuations and increased the standard deviation of the RSSI. Although the work mentioned in Pahtma *et al.* (2009), Goldoni *et al.* (2010), Hamida and Chaliue (2010), Lin *et al.* (2011), and Turner *et al.* (2013) studied the RSSI variation caused by human movement, indoor localization systems were not included in the scope of those works. In Alshami *et al.* (2015), the authors claimed that, based on their experiments, the human presence significantly decreased the received signal strength by -2 dBm to -5 dBm, approximately. The authors then suggested that an indoor positioning system should take into account the human movement effect in order to achieve high localization accuracy. However, Alshami *et al.* (2015) did not propose any solutions to alleviate the variations in RSSI caused by humans, nor were ways to improve the localization accuracy presented. In Zanca *et al.* (2008), Goldoni *et al.* (2010), and Rattanalert *et al.* (2015), experimental comparisons of the min-max and the trilateration methods in indoor environments were studied. The authors concluded that the min-max method gave a better performance than the trilateration method in terms of estimation accuracy and computational complexity when 3 reference nodes were used. However, the performance evaluation of these methods, when using RSSI variations caused by human movement, has not been studied yet, and ways to handle such effects were not presented in those works.

In this paper, experimental evaluation of an RSSI-based indoor localization system is introduced. The major contributions of our work are twofold. First, the min-max and the trilateration methods are tested in the cases with human movement effects. Thus, how RSSI variation caused by humans affects the

estimation accuracy of both RSSI-based methods is revealed. Also, the trend of the RSSI fluctuation and position estimation error according to the human movement pattern is also shown. Secondly, we designed and developed a new RSSI filter which can automatically reduce RSSI variation caused by human movement. Here, the proposed filter is also compared with the moving maximum filter, the moving average filter, and the moving median filter to explore its performance. Experiments were carried out in a parking building as an indoor environment, and an LPC2103F microcontroller interfaced with a 2.4 GHz CC2500 RF transceiver was employed as a wireless node. Experimental results demonstrated that, for our test environment, the min-max method provides better results than the trilateration method. The results also indicate that the proposed RSSI filter can automatically detect RSSI variation caused by human movement. It also supports the min-max and the trilateration methods to estimate the unknown target position with small errors.

The structure of this paper is as follows. Section 2 explains an RSSI-based indoor localization system; the min-max and the trilateration methods are introduced. Section 3 describes the proposed RSSI filter. An experimental setup is presented in Section 4. Section 5 provides the results with discussions. Finally, we conclude the paper in Section 6.

An RSSI-based Indoor Localization System

The RSSI-based indoor localization system presented in this paper is shown in Figure 1. There is 1 base station node connected to a computer (the processing center), a target node to be the estimated position, and 3 reference nodes (stationary at the known positions). To estimate the target position, there are 3 main processes. The first process is the RSSI measurement in the wireless network. The second process is the RSSI to distance conversion using the path-loss equation. Finally, the third process is the target position

estimation by the min-max and the trilateration methods. All processes are described below.

In the first process, when the computer connected to the base station node wants to know the target position, it first commands the base station node to generate and send a command packet to each reference node sequentially. The corresponding reference node then generates a beacon packet, and sends such a packet to the target node. Upon receiving the beacon packet, the target node reads the RSSI value provided by its radio circuit and then transfers the RSSI reading as encapsulated in a data packet, to the base station node. The base station node also forwards the data packet to the computer. It should be noted that to reduce the signal interference from other radio devices which use the same radio frequency and would cause packet losses, and to study the human movement effect without that kind of interference, we intend to control the base station node to communicate with each reference node sequentially. As seen in Figure 1, the base station node is programmed to transmit the command packet to the references 1, 2, and 3, respectively. After transmitting the command packet to each reference node, the base station node also waits for a small period of time to receive the data packet and then transmits the next command packet to the next reference node. These procedures are illustrated by notations (a) to (i) in Figure 1.

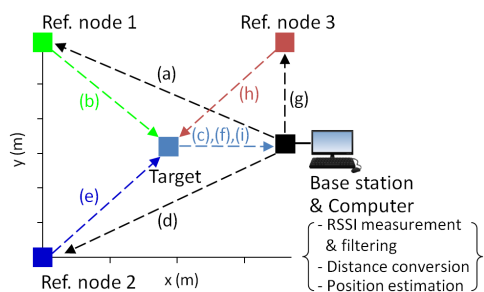


Figure 1. The RSSI-based indoor localization system presented in this work

At the computer, after the RSSI value is inserted by the base station node, the second

process then begins. The RSSI value is converted to the distance value using the path-loss equation which describes the relationship between the measured RSSI and the corresponding distance in the test field. The path-loss equation is expressed by Equations (1) and (2) (Goldoni *et al.*, 2010; Luo *et al.*, 2015), where $RSSI_d$ is the mean RSSI value (in dBm) at distance d (between the transmitter node and the receiver node), $RSSI_{d_0}$ is the mean RSSI value (in dBm) at the reference distance from the transmitter (d_0), and α is called the path-loss exponent; it is the rate at which the received signal strength decreases along with distance. The parameters $RSSI_{d_0}$ and α can be determined in the test field by collecting the RSSI data in which the distances from the transmitter to the receiver are known. They are again described in Section 4. In this work, before the RSSI value is converted to the distance value using the path-loss equation, it is applied to the RSSI filtering function to reduce its variation. This will be described in Section 3.

$$RSSI_d = RSSI_{d_0} - \left[10 \times \alpha \times \log_{10} \left(\frac{d}{d_0} \right) \right] \quad (1)$$

$$d = 10^{\frac{RSSI_{d_0} - RSSI_d}{10 \times \alpha}} \quad (2)$$

Finally, after the RSSI value is transformed to the distance value, and the computer gets all the distance values from all the reference nodes, the third process is then performed. As mentioned before, the min-max and the trilateration methods are used to determine the target position. We selected them because their algorithms are simple with low computational complexity. Thus, they are easily implemented on hardware platforms. Furthermore, they accurately give the estimated position as well (Zanca *et al.*, 2008; Goldoni *et al.*, 2010; Rattanalert *et al.*, 2015; Booranawong *et al.*, 2018b). The min-max and the trilateration methods determine the unknown target position using Equations (3) to (11), where 3 reference nodes are employed. In the min-max method (Savvides *et al.*, 2002), the target node determines an intersection area which is the

boundary within the x_{min} , x_{max} , y_{min} , and y_{max} positions, calculated from Equations (3) to (6). The intersection boundaries are given by the maximum of all coordinate minimums, and the minimum of all maximums. The center of the intersection area is assumed as the estimated target position (x_{est} and y_{est}), determined by Equations (7) and (8).

$$x_{min} = \text{Maximum of } (x_1-d_1, x_2-d_2, x_3-d_3) \quad (3)$$

$$x_{max} = \text{Minimum of } (x_1+d_1, x_2+d_2, x_3+d_3) \quad (4)$$

$$y_{min} = \text{Maximum of } (y_1-d_1, y_2-d_2, y_3-d_3) \quad (5)$$

$$y_{max} = \text{Minimum of } (y_1+d_1, y_2+d_2, y_3+d_3) \quad (6)$$

$$x_{est} = \frac{(x_{min} + x_{max})}{2} \quad (7)$$

$$y_{est} = \frac{(y_{min} + y_{max})}{2} \quad (8)$$

For the trilateration method (Langendoen and Reijers, 2003), the target node determines an intersection point of the 3 circles by solving Equations (9) to (11). The solution to these equations is the estimated target position (x_{est} and y_{est}). The trilateration method solves the intersection point from Equations (9) to (11) by using a system of linear equations: it requires more arithmetic operations than the min-max method. Thus, the min-max method is more suitable to be integrated into hardware platforms with limited resources as recommended by Zanca *et al.* (2008) and Goldoni *et al.* (2010).

$$(x_{est} - x_1)^2 + (y_{est} - y_1)^2 = d_1^2 \quad (9)$$

$$(x_{est} - x_2)^2 + (y_{est} - y_2)^2 = d_2^2 \quad (10)$$

$$(x_{est} - x_3)^2 + (y_{est} - y_3)^2 = d_3^2 \quad (11)$$

Proposed Filter

In this work, to reduce RSSI variation directly caused by human movement, only appropriate RSSI values are selected and used for position estimation. The proposed RSSI filter is developed and expressed by Equations (12) to (16). Here, to detect RSSI variation, a number of raw RSSI samples ($RSSI_i$, the RSSI

input at the sample number i) in each window size (W) are first examined. In each predefined window, the minimum RSSI value ($RSSI_min_i$) as the weakest RSSI value and the standard deviation of the RSSI values ($RSSI_sd_i$) are determined, as shown in Equations (12) and (13), respectively. If the absolute difference between the minimum RSSI value of the current window ($RSSI_min_i$) and the output RSSI value of the previous window ($RSSI_output_{i-1}$) is lower than the predefined threshold 1 ($Threshold_1$) or the standard deviation of the RSSI values of the current window ($RSSI_sd_i$) is lower than the predefined threshold 2 ($Threshold_2$), as shown in Equation (14), this estimates that no human is blocking the radio signal path in the wireless network. Thus, the mean RSSI value of the current window ($RSSI_mean_i$) is used as the RSSI output value ($RSSI_output_i$) for position estimation. Here, for the first window, $RSSI_output_i$ is equal to $RSSI_mean_i$, where $i = W$ as shown in Equations (15) and (16). On the other hand, if the absolute difference exceeds the predefined threshold 1 or the standard deviation of the RSSI values of the current window is higher than the predefined threshold 2, indicating the presence of a human, the RSSI output value of the previous window ($RSSI_output_{i-1}$) is used in estimating the position. We should make sure that there is no human presence during the calculation of the RSSI output in the first window.

$$RSSI_min_i = \text{Minimum of } (RSSI_i, RSSI_{i-1}, RSSI_{i-2}, \dots, RSSI_{i-W+1}), i \geq W \quad (12)$$

$$RSSI_sd_i = \text{Standard deviation of } (RSSI_i, RSSI_{i-1}, RSSI_{i-2}, \dots, RSSI_{i-W+1}), i \geq W \quad (13)$$

$$RSSI_output_i = \begin{cases} RSSI_mean_i, & |RSSI_min_i - RSSI_output_{i-1}| \leq Threshold_1 \text{ OR } RSSI_sd_i \leq Threshold_2, i \geq W \\ RSSI_output_{i-1}, & |RSSI_min_i - RSSI_output_{i-1}| > Threshold_1 \text{ OR } RSSI_sd_i > Threshold_2 \end{cases} \quad (14)$$

$$RSSI_mean_i = \frac{1}{W} (RSSI_i + RSSI_{i-1} + RSSI_{i-2} + \dots + RSSI_{i-W+1}), i \geq W \quad (15)$$

$$RSSI_output_i = RSSI_mean_i, i = W \quad (16)$$

The optimal values of W , $Threshold_1$, and $Threshold_2$ are manually determined by the experiments. Since W is the window size which indicates the number of RSSI input samples to be considered, the larger value of W may have a greater filtering effect but it requires more complexities (Booranawong *et al.*, 2018a, 2018b). In this work, W is varied in 5 different levels: 10, 30, 50, 70, 90, and 110, respectively. For $Threshold_1$, it represents the different level between the RSSI value during no human presence and the RSSI value during human presence. Since Alshami *et al.* (2015) reported that, according to their experiments, the human presence significantly decreased the RSSI, approximately by -2 dBm to -5 dBm, thus $Threshold_1$ is set to 2 in our test. Since in this work the target node for the estimated position is stationary at the fixed location, $Threshold_1$ it can be set to the suggested value. However, in mobile target scenarios, setting of the optimal threshold value should be reconsidered. Finally, for $Threshold_2$, it indicates the standard deviation level of the RSSI data during no human presence. As tested and reported by Solovieri and Gennarelli (2016), a human was detected in the indoor wireless network by considering the standard deviation of the RSSI values for each time window. The standard deviation in such a work was set to 0.8 after analyzing several datasets with no human moving in the test field. Solovieri and Gennarelli (2016) also suggested that the standard deviation threshold depends on the measurement configuration and the layout of the test field, and thus it needs to be recalculated when measurement conditions change. Therefore, in this work, $Threshold_2$ is set to 0.4 which is determined during no human presence in the test field.

Experimental Setup

To evaluate the min-max and the trilateration methods in the case of scenarios with human movement and to explore the performance of the proposed RSSI filter, experimental scenarios,

path-loss equations, comparative filters, and performance metrics are defined and described here.

Experimental Scenarios

The experiment was carried out in a parking building at the Faculty of Engineering, Prince of Songkla University, Thailand, as shown in Figures 2 and 3. The dimension of the field is equal to 3.60 m × 6.20 m. Three reference nodes were placed on the corners of the area at $(x_1 = 0.00 \text{ m}, y_1 = 6.20 \text{ m})$, $(x_2 = 0.00 \text{ m}, y_2 = 0.00 \text{ m})$, and $(x_3 = 3.60 \text{ m}, y_3 = 6.20 \text{ m})$, respectively. The target node was fixed at the center of the test field at the position $(x_t = 1.80 \text{ m}, y_t = 3.10 \text{ m})$. Here, the target node and the reference nodes are at the same altitude from the ground level, at a height of 1 m. To interrupt the radio signal propagation between the target node and the reference nodes, 1 human (i.e. an adult) walked in the test field along the path indicated in Figure 3. Here, the human walked past the reference nodes 2, 1, and 3, respectively. Although the human movement pattern tested in our experiment is simple, such a movement pattern can be seen in practice. For example, people walk across corridors inside buildings, people move inside their bedrooms, and people move from 1 room to another room in their houses. We intend to deploy the target node at the center of the test field because, at this point, if the actual distances between the target node and the reference nodes (i.e., d_1 , d_2 , and d_3 are 3.58 m) are directly applied to calculate the target position, both the min-max and the

trilateration methods give the same answer ($x_{est} = 1.80 \text{ m}$, $y_{est} = 3.10 \text{ m}$). This means that the min-max and the trilateration methods can correctly estimate the position at the given point. Therefore, if there is any estimated error during the experiment, it is due to the variation of the RSSI data presented in the test field. The example of the position estimation of the target node by the min-max method is illustrated below. Here, Equations (3) to (8) are applied.

$$\begin{aligned} d_1 &= \sqrt{(x_1 - x_t)^2 + (y_1 - y_t)^2} \\ &= \sqrt{(0 - 1.80)^2 + (6.20 - 3.10)^2} \\ &= \sqrt{3.24 + 9.61} = 3.58 \text{ m} \end{aligned}$$

$$\begin{aligned} d_2 &= \sqrt{(x_2 - x_t)^2 + (y_2 - y_t)^2} \\ &= \sqrt{(0 - 1.80)^2 + (0 - 3.10)^2} \\ &= \sqrt{3.24 + 9.61} = 3.58 \text{ m} \end{aligned}$$

$$\begin{aligned} d_3 &= \sqrt{(x_3 - x_t)^2 + (y_3 - y_t)^2} \\ &= \sqrt{(3.60 - 1.80)^2 + (6.20 - 3.10)^2} \\ &= \sqrt{3.24 + 9.61} = 3.58 \text{ m} \end{aligned}$$

$$X_{min} = \text{Maximum of } (0-3.58, 0-3.58, 3.60-3.58) = 0.02 \text{ m}$$

$$X_{max} = \text{Minimum of } (0+3.58, 0+3.58, 3.60+3.58) = 3.58 \text{ m}$$

$$y_{min} = \text{Maximum of } (6.20-3.58, 0-3.58, 6.20-3.58) = 2.62 \text{ m}$$

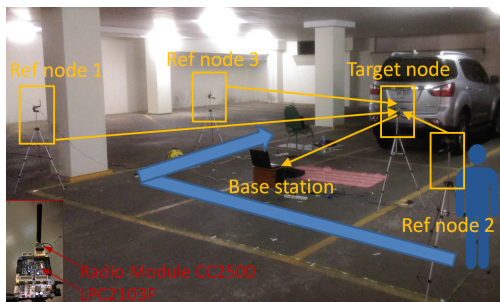


Figure 2. The test field and wireless nodes used in the experiment

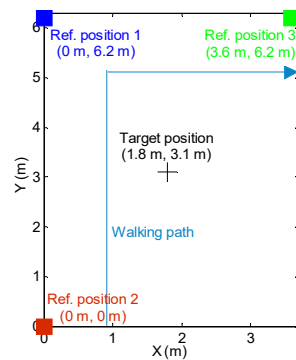


Figure 3. The target position and the walking path

$$y_{max} = \text{Minimum of } (6.20+3.58, 0+3.58, 6.20-3.58) = 3.58 \text{ m}$$

$$x_{est} = \frac{(0.02+3.58)}{2} = \frac{3.6}{2} = 1.8 \text{ m}$$

$$y_{est} = \frac{(2.62+3.58)}{2} = \frac{6.2}{2} = 3.1 \text{ m}$$

We used the LPC2103F microcontroller with the CC2500 RF transceiver as the wireless node developed by our research team (Figure 2). The CC2500 is a low-cost 2.4GHz radio module designed for very low-power wireless applications. It has a maximum data rate of 500 kbps (Texas Instruments, 2016). The CC2500 can support the use of different radio channels operating in the frequency ranges of 2.4-2.4835 GHz, and it can have up to 256 carrier frequencies based on a starting carrier frequency and channel spacing. Thus, the desired channel can be assigned by users since most of the IEEE 802.11 wireless local area network devices operate on channels 1, 6, and 11, which correspond to the channel center frequencies 2.412 GHz, 2.437 GHz, and 2.462 GHz, respectively. Thus, in this work we configured the radio channel differently from the radio channels of WLAN devices, to avoid radio signal interference. The Smart RF Studio software provided by Texas Instruments (2016) is used to automatically calculate the optimum parameters for the channel settings. Finally, the CC2500 communicated with the LPC2103F board via the serial peripheral interface (SPI), which consists of 4 pins comprising the master out slave in, the master in slave out, the slave select, and the serial clock, respectively. More implementation details of the SPI can be found in Yang (2011) and Jindamaneepon *et al.* (2016).

In this work, the target node can transfer the data packet to the base station via one-hop communications. The base station is connected to the central computer via an RS232 serial port interface, and real-time RSSI signals (Booranawong *et al.*, 2018a) and estimated positions from the min-max and the trilateration methods are displayed by the LabVIEW program.

Path-loss Equations

To find the path-loss equation for the test field in Figure. 2, we used 1 transmitter node and 1 receiver node to collect RSSI data at 5 different distances: 1 m, 2 m, 3 m, 4 m, and 5 m, respectively. At each distance, the receiver continuously collects 10,000 RSSI samples. By applying the linear curve fitting to the plot of the average RSSI value versus the distance (i.e., logarithmic scale), the path-loss equation in Equations (1) and (2) can be determined. In our experiment, the parameters $RSSI_{d_0}$ and α are equal to -42.647 and 2.715, respectively.

Comparative Filters

The moving maximum filter, the moving average filter, and the moving median filter as the widely-used filters are selected and compared with our proposed RSSI filter. The RSSI outputs by such filters are defined in Equations (17), (18), and (19) respectively, where $RSSI_output_i$ is the RSSI output value at the sample number i , $RSSI_i$ is the raw RSSI input value, and W is the window size. As in the case of the proposed RSSI filter in Section 3, in the experiment, W is also varied in 5 different levels: 10, 30, 50, 70, 90, and 110, respectively.

$$RSSI_output_i = \text{Maximum of } (RSSI_i, RSSI_{i-1}, RSSI_{i-2}, \dots, RSSI_{i-W+1}), i \geq W \quad (17)$$

$$RSSI_output_i = \frac{1}{W} (RSSI_i + RSSI_{i-1} + RSSI_{i-2} + \dots + RSSI_{i-W+1}), i \geq W \quad (18)$$

$$RSSI_output_i = \text{Median of } (RSSI_i, RSSI_{i-1}, RSSI_{i-2}, \dots, RSSI_{i-W+1}), i \geq W \quad (19)$$

Performance Metrics

An error distance is selected as the performance metric. The error distance is the distance from the actual target position to the estimated target position as given in Equation (20), where (x_t, y_t) is the actual target position, and (x_{est_i}, y_{est_i}) is the estimated position. The latter is determined by the min-max and the trilateration methods at each iteration (i).

In addition, the average error distance is also used in the evaluation, as defined in Equation (21). The 95% confidence interval (CI) is provided for the average results.

$$\text{Error Distance} = \sqrt{(x_t - x_{est_t})^2 + (y_t - y_{est_t})^2} \quad (20)$$

$$\text{Average Error Distance} = \frac{1}{N} \sum_{t=1}^N \sqrt{(x_t - x_{est_t})^2 + (y_t - y_{est_t})^2} \quad (21)$$

Experimental Results and Discussion

We first demonstrate the raw RSSI signals measured by the target node when the human is not present in the test field to see the difference in accuracy between the min-max method and the trilateration methods. They are shown in Figure 4. The error distances and the average error distances are also illustrated in Figure 5 and Table 1, respectively. Here, the average error distances are 0.16 m and 0.42 m, respectively. Without the effects of human movement, the min-max method and the trilateration method estimate the target position with small errors. We note that as mentioned in Section 4.1, if the actual

distances from the target to the reference nodes are directly used in calculating the target position, in this case the error distances by the min-max and the trilateration methods are equal to 0. However, when the distances as converted from the measured RSSI values in Figure 4 are used in calculating the target position instead, the error distances are presented as 0.16 m and 0.42 m, respectively. These errors stem from the radio signal effects of walls, floors, and nearby objects in the test field.

Figure 6 demonstrates the RSSI signals measured by the target node when the human continuously walks in the test field along the walking path of Figure 3. Here, we can observe that the trend of the RSSI fluctuation depends on the human's movement pattern. There are 3 main peaks of the RSSI signals corresponding to the human walking past the reference nodes 2, 1, and 3, respectively. Figure 7 shows the error distances of the target node, and Table 2 also shows the average error distances determined by the min-max and the trilateration methods. The results indicate that the trend of error distance directly depends on the RSSI input signal in Figure 6. The maximum error distances can reach 1.96 m and 8.35 m. Also, the average error distances increase to 0.35 m and 1.10 m, respectively (compared with Table 1). The results also indicate that, as the human moves,

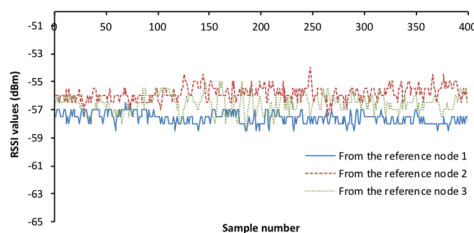


Figure 4. The RSSI signals measured by the target node without human movement

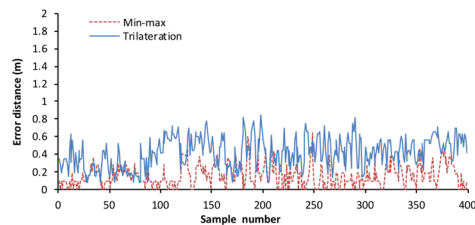


Figure 5. The error distances of the target position without human movement

Table 1. The average error distances of the target position without human movement

Localization methods	Average error distance (m)	95% CI
Min-max	0.16	0.012
Trilateration	0.42	0.017

the min-max method provides significantly smaller error distances than the trilateration method. Moreover, the min-max method better tolerates high RSSI variations than the trilateration method. It gives smaller error distances in the presence of a human.

Figures 8 and 9 show the average error distances determined by the min-max and the trilateration methods, after applying the moving maximum filter, the moving average filter, the moving median filter, and the proposed RSSI filter, when the window size (W) is set to 10, 30, 50, 70, 90, and 110. Figure 10 also shows the percent decreases of the average error distances after applying the proposed filters. We also illustrate the error distance results after applying the proposed filter with W of 10, and the moving median filter with W of 10, as shown in Figures 11 and 12. The results demonstrate that the average error distances decrease more when the proposed filter is applied. In Figure 8, the average error distances decrease from 0.35 m (from Table. 2) to 0.10 m (for the case the min-max method), and in Figure 9 the average error distances decrease from 1.10 m (from Table. 2) to 0.29 m (for the trilateration method). Here, the average error distances decrease by 71.28% and 73.65%, respectively, as shown in

Figure 10(a) and 10(b). Also, the proposed filter significantly outperforms all comparative filters. The example results in Figures 11 and 12 indicate that the error distances after applying the proposed filter with W of 10 have smaller variations than in the case of applying the moving median filter with W of 10 (i.e. the worst case), and using the raw RSSI signals as shown by the results in Figure 7.

As mentioned in Section 3, in the proposed filter the optimal values of W and $Threshold$ are manually determined by the experiments. Since W represents the number of RSSI input samples to be considered, the larger value of W requires high computational complexity, and it may not appropriately support real-time applications and mobile target scenarios. Thus, the optimal value of W should be set by considering both the accuracy and the complexity perspectives. For the threshold value, although the results above indicate that the average error distances decrease, it does not mean that the $Threshold$ of 2 can be suitably used for all test scenarios and environments. Since in this work the target node to be estimated for the position is fixed and the test environment is not complex, such a threshold can be efficiently used as proved by the results. However, in other environments

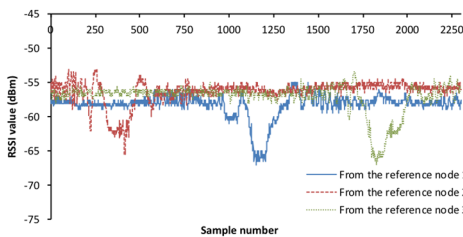


Figure 6. The RSSI signals measured by the target node when a human walks in the test field

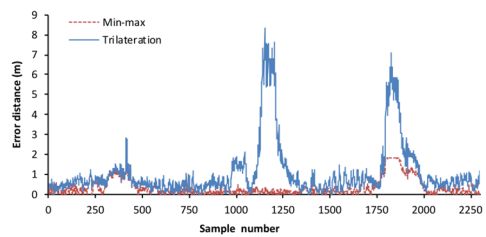


Figure 7. The error distances of the target position when a human walks in the test field

Table 2. The average error distances of the target position when a human walks in the test field

Localization methods	Average error distance (m)	95% CI
Min-max	0.35	0.017
Trilateration	1.10	0.058

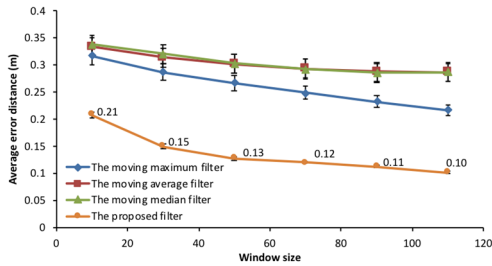


Figure 8. The average error distances of the target position after applying the filters for the min-max method

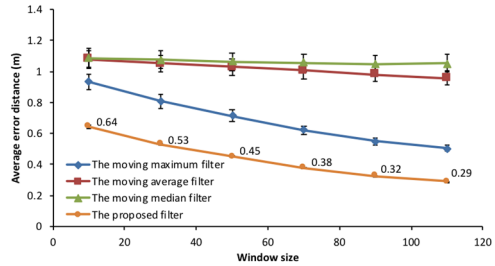


Figure 9. The average error distances of the target position after applying the filters for the trilateration method

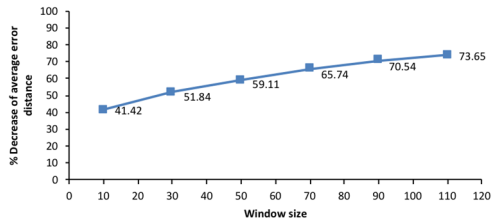
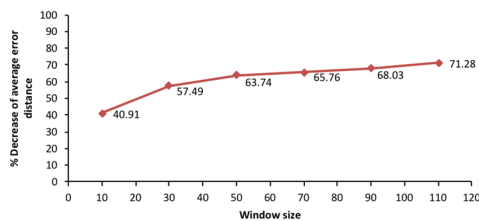


Figure 10. Percentage decreases of the average error distances of the target position after applying the proposed filters; (a) the min-max method and (b) the trilateration method

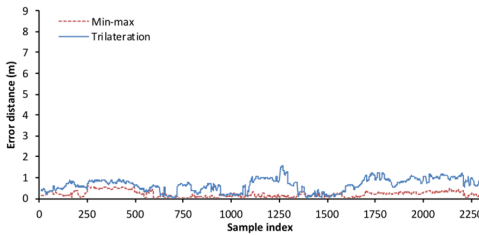


Figure 11. The error distances of the target position after applying the proposed filter with W of 10

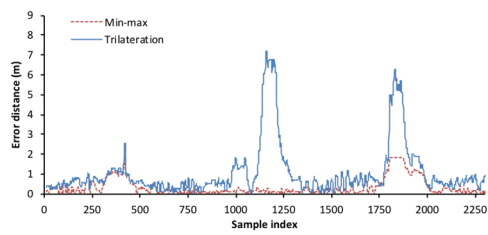


Figure 12. The error distances of the target position after applying the moving median filter with W of 10

and mobile target scenarios, an optimal *Threshold* should be redetermined. For example, in mobile target scenarios, the speed of the target node is the important factor which should be considered for the threshold setting.

Conclusions

In this work, the min-max and the trilateration methods in an RSSI-based indoor localization system are evaluated through the experiment.

Both methods are tested in the case of the effects of human movement. The proposed filter is also developed to reduce RSSI variation and the estimated position error caused by human movement. The experimental results indicate that, with human movement, the min-max method provides better estimation accuracy than the trilateration method. The results also confirm that the proposed filter can automatically reduce RSSI variation and cope with the human movement problem. It supports the localization methods to estimate

the unknown target with small errors. In future work, multiple humans with various movement patterns, speeds, and test scenarios could be experimentally assessed for their effects on RSSI variations. Also, rules for setting an appropriate threshold value should be further investigated.

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