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Reduction of RSSI variations for indoor position estimation in wireless sensor networks

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Abstract

In this paper, the reduction of RSSI (received signal strength indicator) variation for indoor position estimation in wireless sensor networks (WSNs) is studied through simulation. We demonstrate that using raw RSSI data (with high variation) to estimate a sensor position (i.e., an unknown position) is not appropriate due to a large estimation error. To cope with this problem, we propose a RSSI improvement method for reducing RSSI variation. The sum of the average RSSI value used at the previous step and the RSSI value measured at the current step are employed to determine the appropriate RSSI value (i.e., the smoothed RSSI value). The priority technique is also applied to such a function by assigning different weighted values. Simulation results show that using our proposed method with an optimal weighted value gives better estimation results than using raw RSSI data and a moving average method. With the proposed method, the position estimation by an original trilateration approach is more accurate.

Keywords: Indoor localization, RSSI, Variation, CC2500, Log-normal shadowing model, Trilateration

1. Introduction

During the last few years, WSNs have attracted a great deal of research interest. WSNs can be utilized for many applications including monitoring and control, building automation, health surveillance, military, industry, and target tracking, among others. [1-2]. Target localization is one of the essential subjects in WSNs because position information is useful for coverage, deployment, coordination, and routing. [3]. One of the fundamental challenges in WSNs is the node localization problem. Localization techniques introduced in the research literature are often performed using the time of arrival (TOA), time of difference of arrival (TDOA), RSSI, or a combination of these [3-7]. Here, the TOA and TDOA techniques including the global position system (GPS) need complicated timing and synchronization, which makes localization complex and expensive. Also, the GPS is not appropriate for indoor environments [8]. Thus, localization using the RSSI information is more widely used among these techniques. The main reason for its appeal is that most wireless devices have RSSI circuits built into them, so additional hardware is not required. This advantage can help to reduce the cost and complexity of the system.

In the RSSI-based position estimation technique, the distance between a transmitter and a receiver can be calculated from the RSSI information observed at the receiver. However, measured RSSI data is highly uncertain, and it fluctuates over time due to multipath and fading effects, especially in indoor environments. As a result, the accuracy of the position estimation certainly depends on variation in the levels of the RSSI data. According to this research problem, reducing the variation of the RSSI data should be considered.

In the research literature, [9] and [10] presented RSSI-based localization methods that used a neural network to reduce RSSI variation. Also, measured RSSI data as the inputs for the neural network were collected from various transmission powers. Consequently, the works in [9] and [10] require high processing and computation power. In [11], the fingerprinting algorithm was presented to estimate the position of mobile devices in an indoor environment. The position of an unknown target was estimated by comparing the measured RSSI values and the RSSI values stored in a radio map database. However, the method in [11] requires more time and RSSI samples to create an accurate radio map, as the author stated. In [12], the authors applied a moving average method to the measured RSSI data. Errors in RSSI-to-distance conversion were significantly reduced. In [13], an averaging method was applied to the RSSI data. The authors claimed that, by experiments conducted in indoor environments, the RSSI variation was reduced. In [14], the RSSI variation was reduced using a least mean square (LMS) algorithm. Both the simulation and experimental results demonstrated that the LMS can smoothen RSSI data. However, for the works in [12-14], how the moving average method, the average method, and the LMS method affected the accuracy of the position estimation was not included in the scope of the

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studies. The research gaps presented in the literature include how to reduce the RSSI variation for an RSSI-based position estimation and this needs further investigation.

In this paper, a reduction of RSSI variation is investigated by a simulation study. The well-known trilateration approach [15-16] is selected and used for determining an unknown target position. The sum of the average RSSI value used at the previous step and the RSSI value measured at the current step is used to determine the smoothed RSSI value, which is the input for the trilateration approach. A weighted value is also applied to the summation function. The performance of the proposed method is explored by varying the weighted value. Additionally, fading effects at various levels are included in simulated environments, where different fading levels indicate the various characteristics of indoor environments. The simulation results demonstrate that the proposed method can reduce the RSSI variation, and the estimated position by the trilateration method is close to the actual position.

The remainder of this paper is organized as follows. The RSSI-based position estimation method is introduced in Section 2. The proposed methodology (reduction of RSSI variations) is described in Section 3. Section 4 defines the simulation scenario and the performance metrics. Section 5 provides simulation results and discussion. Finally, Section 6 concludes the paper.

2. RSSI-based position estimation method

The methodology to derive raw RSSI data from a sensor node and to estimate the position of an unknown target are described as follows.

2.1 Radio propagation model

The distance between a transmitter and a receiver can be estimated based on the RSSI value obtained by a receiver. The RSSI value at a distance d can be calculated according to the log-normal shadowing model. In this model, the RSSI value at a certain distance is a random variable due to multipath propagation effects (fading effects). It includes a probabilistic term in the calculation of the received signal power. This model is widely used in RSSI-based localization techniques because of its linearity and simplicity [17-18]. It can be represented by (1).

$$\frac{RSSI(d)}{RSSI(d_0)} = -10\eta log_{10}\left(\frac{d}{d_0}\right) + X_{dB} \tag{1}$$

$$RSSI(d_0) = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 d_0^2 L} \tag{2}$$

where $RSSI(d)$ is the RSSI value at a distance, d. $RSSI(d_0)$ is the reference RSSI value at a distance, d_0. η is the path loss exponent. It is set to a value between 2 and 6 [17, 19] and is determined by field measurements. X_{dB} is a Gaussian random variable with a zero mean and a standard deviation of σ_{dB}. σ_{dB} is also called the shadowing deviation. It depends on the characteristics of the test environment. $RSSI(d_0)$ can be computed from (2). It is calculated using the free space propagation model, where P_t is the transmission power corresponding to the function of the RF transceiver. G_t and G_r are the antenna gains of the transmitter and the receiver, respectively. L is the system loss, and λ is the wavelength. It is common to select G_t = G_r = L = 1 in a simulation [20-21].

2.2 Position estimation method

The trilateration method is employed for position estimation of an unknown target. The basis of the trilateration is the calculation of the intersection point of three circles with radii, r_1, r_2 and r_3, as shown in Figure 1. The intersection point can be determined using the simple circle equations as expressed in (3) to (7).

$$r_1^2 = x^2 + y^2 \tag{3}$$

$$r_2^2 = (x-a)^2 + y^2 \tag{4}$$

$$r_3^2 = x^2 + (y-b)^2 \tag{5}$$

$$x = \frac{r_1^2 - r_2^2 + a^2}{2a} \tag{6}$$

$$y = \frac{r_1^2 - r_3^2 + b^2}{2b} \tag{7}$$

where r_1, r_2, and r_3 are the radii of the reference node IDs 1 (R1), 2 (R2), and 3 (R3), respectively. The target node (T) is located at an unknown position (x, y).

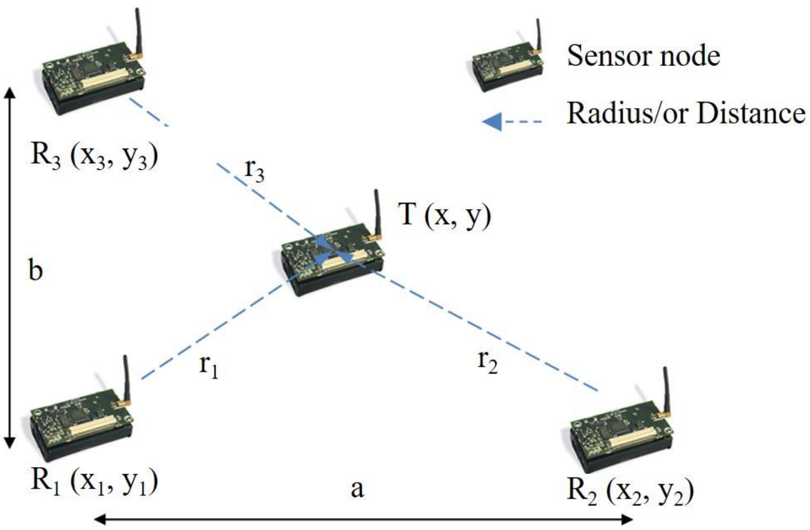

Figure 1 The position estimation of a target node by the trilateration method

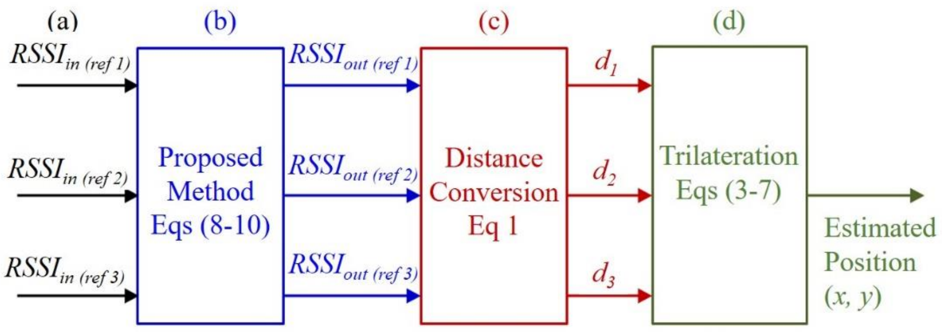

Figure 2 Position estimation processes: $RSSI_{in(ref1)}$, $RSSI_{in(ref2)}$, and $RSSI_{in(ref3)}$ are the raw RSSI values, $RSSI_{out(ref1)}$, $RSSI_{out(ref2)}$, and $RSSI_{out(ref3)}$ are the smoothed RSSI values, and d_1, d_2, and d_3 are the distances or the radii

r_1, r_2, and r_3 can be determined by solving (3) to (5). The radii of the reference nodes are used for calculating the coordinate (x, y) using (6) and (7). In our simulation, there are three stationary reference nodes at the center of three circles. The target node is at an unknown position that is also located at the position (x, y).

Each reference node broadcasts a beacon packet to the target node. Upon receiving the beacon packet, the target node reads the RSSI values using (1) and (2). Finally, the RSSI values are input into the trilateration method for determining the target position.

3. Reduction of RSSI variation

There are four steps to estimate the position of an unknown target as summarized in Figure 2. Step (a) is the RSSI measurement. The reference nodes broadcast beacon packets to the target node. Then, the raw RSSI values (i.e., $RSSI_{in(ref1)}$, $RSSI_{in(ref2)}$, and $RSSI_{in(ref3)}$) are gathered by the target node. Step (b) is the RSSI improvement method. The variation of the raw RSSI value is reduced. Step (c) is the RSSI to distance conversion. The smoothed RSSI values (i.e.,$RSSI_{out(ref1)}$, $RSSI_{out(ref2)}$, and $RSSI_{out(ref3)}$) are converted to distances using a log-normal shadowing model. Finally, step d) is the position estimation of an unknown target using the original trilateration method. Step b) is described here.

The design concept of the RSSI improvement method is that the sum of the average RSSI value used at the previous step and the RSSI value measured at the current step is employed to determine the smoothed RSSI value for position estimation. We also assign higher priority to the first function (the average RSSI value) than the second (the current measured RSSI value). This is done by setting various weighted values of those functions. We note that the optimal weight is also determined during the simulation. The average RSSI value with the smallest variation will be considered with high priority. The proposed method is shown in (8) to (10).

(I) For the RSSI sample number 1: $k = 1$,

$$RSSI_{use(k)} = RSSI_{sample(k)} \tag{8}$$

(II) For the RSSI sample number 2: $k = 2$,

$$RSSI_{use(k)} = \alpha \times \left(\frac{RSSI_{sample(k)} + RSSI_{use(k-1)}}{2}\right) + (1-\alpha) \times \left(RSSI_{sample(k)}\right) \tag{9}$$

(III) For RSSI sample number k: $k \geq 3$,

$$RSSI_{use(k)} = \alpha \times \left(\frac{RSSI_{sample(k)} + RSSI_{use(k-1)} + RSSI_{use(k-2)}}{3}\right) + (1-\alpha) \times \left(RSSI_{sample(k)}\right) \tag{10}$$

where $RSSI_{use(k)}$ is the smoothed RSSI value at sample number k which is used as the input for the position estimation. $RSSI_{use(k)}$ is equal to $RSSI_{out}$ as shown in Figure 2. $RSSI_{sample(k)}$ is the current measured RSSI value at sample number k, and α is a weighted value ranging between 0 and 1.

4. Simulation scenario and performance metrics

4.1 Simulation scenario

To evaluate the performance of the proposed method, we conducted a set of experiments using NS2 [22] version 2.34 under a Linux operating systems. The simulation scenario is the same as presented in Figure 1. Node ID 0 is the target node (T). It is located at a known position (x = 16 m, y = 16 m) in the sensor field. The target node receives beacon packets from three reference nodes in every time interval. The reference nodes are the node IDs 1 (R_1), 2 (R_2), and 3 (R_3), respectively. They are fixed at positions (x_1 = 1 m, y_1 = 1 m), (x_2 = 31 m, y_2 = 1 m), and (x_3 = 1 m, y_3 = 31 m), respectively. All nodes are located in a 31 m × 31 m sensor field. Each node has the same radio range, and the transmission range and is not farther than one communication hop. All radio parameters assigned for the sensor nodes are configured according to the CC2500 RF transceiver [23-25], which is designed for low-cost, low-power wireless applications. To set the parameters for the log-normal shadowing model as presented in (1), we use η = 2.9 [26-27] and σ_{dB} = 2.0, 3.0, and 4.0 [28], which correspond to the characteristics of indoor environments. A larger the shadowing deviation represents a higher RSSI fluctuation. Additionally, we also vary α as presented in the proposed method to find its optimal value. All simulation parameters are listed in Table 1.

4.2 Performance metrics

The performance measures are listed as follows.

The estimated position (x, y) can be calculated from (6) and (7). We also measure an average estimated position (AEP) as expressed in (11), where N is the total number of RSSI samples.

$$AEP = \left(\frac{1}{N}\sum_{i=1}^{N} x_i, \frac{1}{N}\sum_{i=1}^{N} y_i,\right) \tag{11}$$

The distance error (ED) indicates the error between the estimated position and the actual position of a target node. ED and an average distance error (AED) are defined in (12) and (13).

Table 1 Simulation parameters

Parameters and notation	Values and units
Dimension of the topology	31 m × 31 m
Number of nodes	4
Buffer size	64
Beacon packet size	20 Bytes
Radio propagation model	Shadowing (Indoor environments)
Path loss exponent (η)	2.9 [26-27]
Shadowing deviation (σ_{dB})	2.0, 3.0, 4.0 [28]
Transmitter gain (G_t)	1
Receiver gain (G_r)	1
System loss (L)	1
Reference distance (d_0)	1 m
Frequency (f)	2.4 GHz [23]
Data rate	250 Kbps [23]
Receiver sensitivity	-89 dBm [23]
RXThreshold (received threshold)	1.25892e-12 Watt
CSThreshold (carrier-sense threshold)	1.68660e-13 Watt
Transmission range without SD	48.7606 m
Transmission power at 0 dBm (P_t)	0.001 Watt [23]
Weight value (α)	0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 0.99
Actual position of the target node (x_{ap}, y_{ap})	(16 m, 16 m)

Note: In NS2, if the received signal strength of the packet is not below the received threshold (RXThreshold), the packet is correctly received. If the received signal strength is between the RXThreshold and the carrier-sense threshold (CSThreshold), the packet is received with an error. Finally, if the received signal strength is lower than the CSThreshold, the packet is not heard by the receiver [21-22, 29].

$$ED_i = \sqrt{\left(x_{ap} - x_{ep(i)}\right)^2 + \left(y_{ap} - y_{ep(i)}\right)^2} \tag{12}$$

$$AED = \frac{1}{N}\sum_{i=1}^{N} ED_i \tag{13}$$

In the simulation results using the proposed method, the raw RSSI value (without applying any RSSI improvement methods), and the moving average method [12] with the window sizes of 3, 5, and 10 are compared. We note that the moving average method is also used for RSSI improvement as presented in Step b, in Figure 2. In the moving average method, the RSSI value used at each step is calculated by averaging previous RSSI values (i.e., raw RSSI values). Moving average methods with window sizes of 3, 5, and 10 (where $k \geq 3$, $k \geq 5$, and $k \geq 10$) are illustrated in (14) to (16), respectively. In Section 5, the simulation results by the raw RSSI value, the proposed method with weighted setting, and the moving average method with window size setting are denoted by RSSI_W(weight value), raw RSSI data, and RSSI_MV(window size), respectively.

$$RSSI_{use(k)} = \frac{RSSI_{sample(k)} + RSSI_{sample(k-1)} + RSSI_{sample(k-2)}}{3} \tag{14}$$

$$\begin{aligned} RSSI_{use(k)} = \big(&RSSI_{sample(k)} + RSSI_{sample(k-1)} + RSSI_{sample(k-2)} \\ &+ RSSI_{sample(k-3)} + RSSI_{sample(k-4)}\big)/5 \end{aligned} \tag{15}$$

$$\begin{aligned} RSSI_{use(k)} = \big(&RSSI_{sample(k)} + RSSI_{sample(k-1)} + RSSI_{sample(k-2)} \\ &+ RSSI_{sample(k-3)} + RSSI_{sample(k-4)} \\ &+ RSSI_{sample(k-5)} + RSSI_{sample(k-6)} \\ &+ RSSI_{sample(k-7)} + RSSI_{sample(k-8)} \\ &+ RSSI_{sample(k-9)}\big)/10 \end{aligned} \tag{16}$$

5. Simulation results and discussion

For the average estimated position and the average distance error by using the proposed method, the raw RSSI value and the moving average method at the shadowing deviations of 2, 3, and 4 are shown in Tables 2, 3, and 4, respectively. The results are the average of 200 samples. A 95% confidence interval (CI) is also provided to indicate the range of the values. The simulation results show that using the raw RSSI data to estimate the target position gives the worst performance in all cases of the shadowing deviation settings. The proposed method (RSSI_W(weight value)) shows good estimation accuracy. The weight value of 0.99 gives the best results.

Table 2 AEP and AED; at the shadowing deviation of 2.0

Methods	***AEP* (*x*, *y*) (m)**	***AED* (m)**	**95% CI**
Raw RSSI data	(14.6246, 13.7324)	9.4994	0.9313
RSSI_W(0.1)	(14.6365, 13.7996)	8.7203	0.8227
RSSI_W(0.2)	(14.6255, 13.8266)	8.0292	0.7316
RSSI_W(0.3)	(14.6132, 13.8422)	7.4322	0.6555
RSSI_W(0.4)	(14.5983, 13.8470)	6.9001	0.5914
RSSI_W(0.5)	(14.5794, 13.8411)	6.4190	0.5368
RSSI_W(0.6)	(14.6034, 13.8724)	6.0639	0.5024
RSSI_W(0.7)	(14.5225, 13.7943)	5.5904	0.4504
RSSI_W(0.8)	(14.4796, 13.7497)	5.2576	0.4152
RSSI_W(0.9)	(14.4121, 13.6714)	5.0085	0.3876
RSSI_W(0.99)	**(14.2692, 13.4978)**	**4.9867**	**0.3838**
RSSI_MV(3)	(14.6134, 13.8886)	6.6738	0.5686
RSSI_MV(5)	(14.5323, 13.7949)	5.8782	0.4688
RSSI_MV(10)	(14.4802, 13.7359)	5.2807	0.4232
Actual position	(16.0000, 16.0000)	-	-

Table 3 AEP and AED; at the shadowing deviation of 3.0

Methods	***AEP*** **(*x*, *y*) (m)**	***AED*** **(m)**	**95% CI**
Raw RSSI data	(12.1557, 14.9501)	17.1659	2.3758
RSSI_W(0.1)	(12.1712, 14.7237)	15.0232	1.9457
RSSI_W(0.2)	(12.3301, 14.7314)	13.4168	1.6282
RSSI_W(0.3)	(12.4647, 14.7503)	12.0762	1.3826
RSSI_W(0.4)	(12.5892, 14.7817)	10.9388	1.1881
RSSI_W(0.5)	(12.7123, 14.8262)	9.9628	1.0307
RSSI_W(0.6)	(12.8404, 14.8846)	9.1166	0.9013
RSSI_W(0.7)	(12.9777, 14.9607)	8.3766	0.7946
RSSI_W(0.8)	(13.1293, 15.0697)	7.7407	0.7069
RSSI_W(0.9)	(13.3328, 15.2921)	7.2581	0.6395
RSSI_W(0.99)	**(13.8645, 16.1122)**	**7.1024**	**0.6341**
RSSI_MV(3)	(12.5620, 14.7308)	10.4405	1.1091
RSSI_MV(5)	(12.8577, 14.9158)	8.8762	0.8722
RSSI_MV(10)	(13.0856, 15.0003)	7.7955	0.7376
Actual position	(16.0000, 16.0000)	-	-

Table 4 AEP and AED; at the shadowing deviation of 4.0

Methods	***AEP*** **(*x*, *y*) (m)**	***AED*** **(m)**	**95% CI**
Raw RSSI data	(11.8475, 15.1370)	25.5427	4.0491
RSSI_W(0.1)	(11.6102, 14.7546)	21.5784	3.1091
RSSI_W(0.2)	(11.7962, 14.8173)	18.7969	2.4640
RSSI_W(0.3)	(11.9494, 14.8858)	16.5799	1.9884
RSSI_W(0.4)	(12.0885, 14.9614)	14.7742	1.6367
RSSI_W(0.5)	(12.2269, 15.0450)	13.2793	1.3737
RSSI_W(0.6)	(12.3755, 15.1379)	12.0226	1.1730
RSSI_W(0.7)	(12.5455, 15.2467)	10.9505	1.0168
RSSI_W(0.8)	(12.7650, 15.4001)	10.0502	0.8971
RSSI_W(0.9)	(13.1800, 15.7384)	9.4101	0.8353
RSSI_W(0.99)	**(15.6480, 17.7939)**	**9.2777**	**0.8023**
RSSI_MV(3)	(12.0683, 14.9218)	14.0071	1.4942
RSSI_MV(5)	(12.3314, 15.1528)	11.6190	1.0913
RSSI_MV(10)	(12.5020, 15.2762)	10.0932	0.9712
Actual position	(16.0000, 16.0000)	-	-

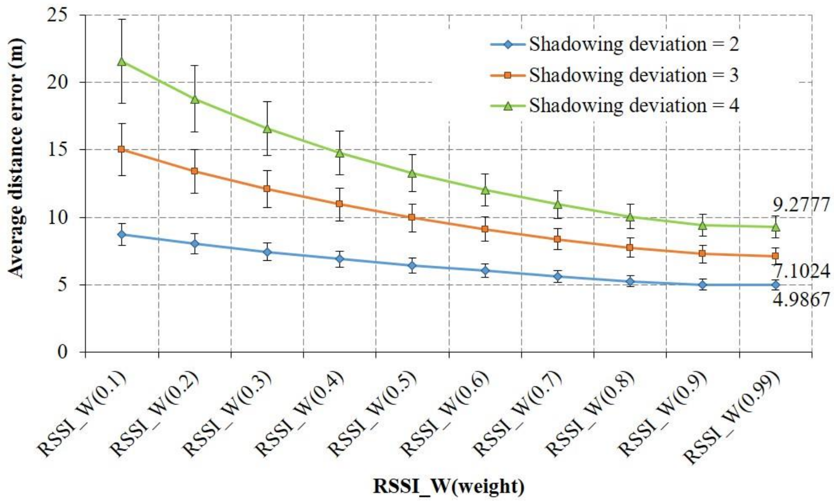

Figure 3 The average distance error by the proposed method during varying the weight values from 0.1 to 0.99; at the different shadowing deviation settings

The simulation results in Table 4 are selected for discussion. The average estimated position using the raw RSSI data is (x = 11.8475 m and y = 15.1370 m), and the average distance error is 25.5427 m. In the proposed method with a weight of 0.99, the average estimated position is (x = 15.6480 m and y = 17.7939 m), and the average distance error is 9.2777 m. Finally, for the moving average method with window sizes of 3, 5, and 10, the results are worse than the cases of the proposed method with weights of 0.8, 0.9, and 0.99. These simulation results demonstrate that the proposed method with an optimal weighted value can help to reduce RSSI variation and improve estimation accuracy. The average distance error by the proposed method while varying the weighted values is shown in Figure 3.

In Figure 4, the average distance error versus the number of samples in the case of RSSI_W(0.99) is presented. For the

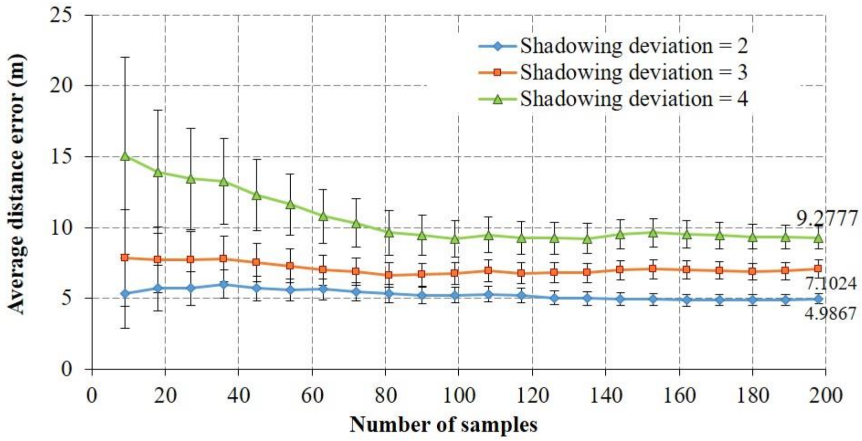

Figure 4 The average distance error versus the number of samples in the case of the proposed method with a weighted value of 0.99 at the different shadowing deviation settings

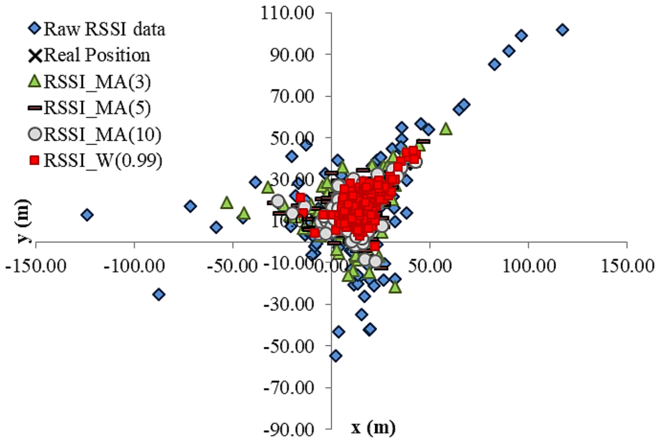

Figure 5 The estimated (x, y) positions; at a shadowing deviation of 4.0

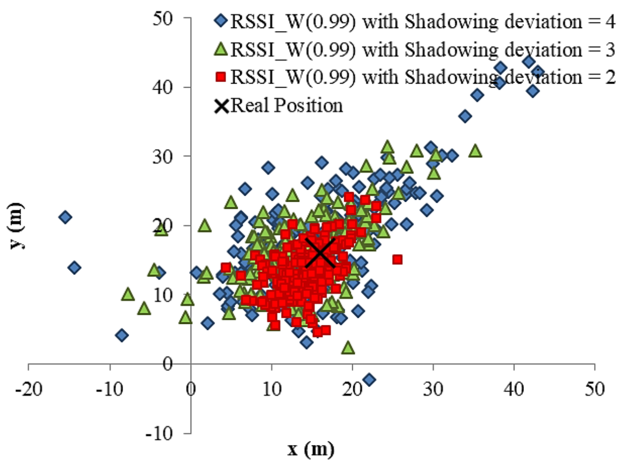

Figure 6 The estimated (x, y) positions using the RSSI_W(0.99) at the shadowing deviations of 2.0, 3.0, and 4.0

shadowing deviations of 2.0 and 3.0, the average distance error while varying the number of RSSI samples is not significantly different. For a shadowing deviation of 4.0, the trend of the average distance error is stable when the number of RSSI samples is above about 80 samples. These simulation results indicate that the proposed method requires only small numbers of RSSI samples to achieve its estimation accuracy.The number of computational steps, the processing time, and the power consumption of the system can be reduced also.

In Figure 5, the estimated (x, y) positions using the proposed method with a weighted value of 0.99, the raw RSSI value, and the moving average method with window sizes of 3, 5, and 10, at a shadowing deviation of 4.0 (as an example), are illustrated. The simulation results demonstrate that the variation of the estimated (x, y) position by the

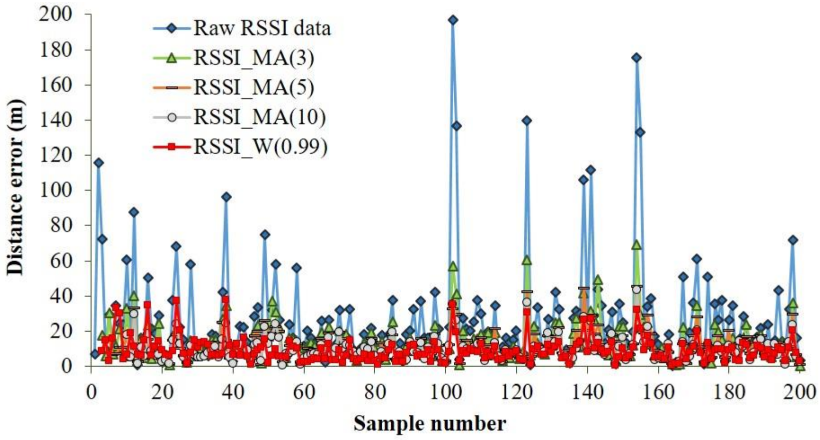

Figure 7 The distance error versus the sample number; at the shadowing deviation of 4.0

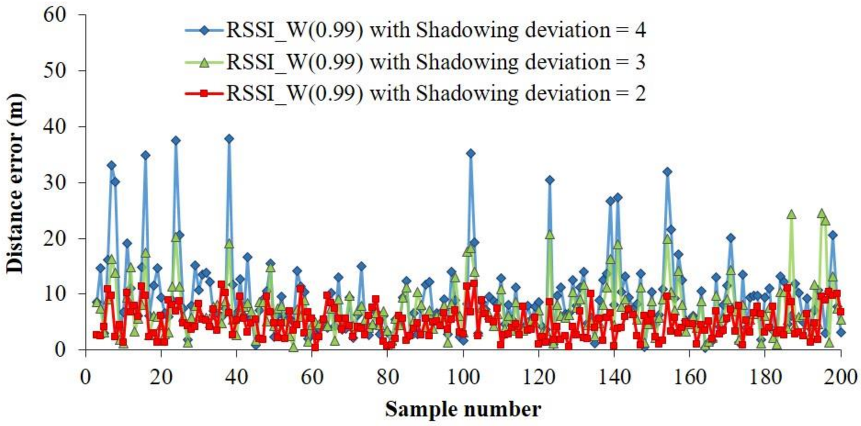

Figure 8 The distance error versus the sample number using the RSSI_W(0.99); at the shadowing deviations of 2.0, 3.0 and 4.0

Table 5 The computational cost

Methods	+	−	×	/
The proposed method	3	1	2	1
RSSI_MV(10)	9	-	-	1

RSSI_W(0.99) is smaller than the cases of the RSSI_MV(10), the RSSI_MV(5), the RSSI_MV(3), and the raw RSSI data. In Figure 6, the variation of the estimated (x, y) positions by the case of the RSSI_W(0.99) is higher when the shadowing deviation is bigger.

Figure 7 shows the distance error versus the sample number (at a shadowing deviation of 4.0) using the proposed method with a weighted value of 0.99, the raw RSSIvalue, and the moving average method with window sizes of 3, 5, and 10. Here, the proposed method shows a smaller variation of the distance error. The distance error by the proposed method with a weight of 0.99 at the various shadowing deviations is illustrated in Figure 8.

As introduced in Section 3, the proposed method uses (8) to (10) to determine the appropriate RSSI value for the position estimation. In the calculation, it assigns a higher priority to the average RSSI value used in the previous step than the raw RSSI value measured at the current step by adjusting the weighted values. Although the raw RSSI data or the current measured data have high variation, they influence the calculation with a small effect. This directly helps to reduce the RSSI variation effect and increase the estimation accuracy.

A comparison of the computational cost of the proposed and the moving average methods was done with a window size of 10. This shows better performance than window sizes of 3 and 5. The number of mathematical operations, summations $(+)$, subtractions $(-)$, multiplications $(\times)$, and divisions $(/)$ required by each method are listed in Table 5. We note that for the proposed method, (10) are considered, while (16) are for the moving average method with the window size of 10. Table 5 shows that the proposed method uses fewer $+$ operations than the case of the RSSI_MA(10), but it requires more $-$ and $\times$ operations. However, the proposed method gives higher estimation accuracy.

6. Conclusions

In this study, a reduction of RSSI variation in position estimation in wireless sensor networks is presented. The sum of the average RSSI value used in the previous step and the measured RSSI value collected at the current step are employed for determining a suitable RSSI value for position estimation. The simulation results demonstrate that our proposed method can reduce the variation of RSSI data, and the position estimation is closer to the actual position. However, this method still has imitations. In the mobile target scenario, the RSSI value used in the previous step may not be appropriately used for determining the smoothed RSSI value, which is used as an input for position estimation, and the static weighted value may not be the optimal value. Therefore, our proposed method should be redesigned and further developed to support such a scenario.

In the future work, performance evaluation of the proposed method in the case of a mobile target and comparison with other methods will be considered. Additionally, the proposed method will be implemented on embedded hardware and tested in real experiments under various scenarios.

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8. References

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