An Integrated Approach for Position Estimation using RSSI in Wireless Sensor Network

Chuan-Chin Pu and Wan-Young Chung

Abstract—Received signal strength indicator (RSSI) is used as one of the ranging techniques to locate dynamic sensor nodes in wireless sensor network. Before it can be used for position estimation, RSSI values must be converted to distances using path loss model. These distances among sensor nodes are combined using trilateration method to find position. This paper presents an idea which attempts to integrate both path loss model and trilateration as one algorithm without going through RSSI-distance conversion. This means it is not simply formulas combination but a whole new model was developed. Several advantages were found after integration: it is able to reduce processing load, and ensure that all values do not exceed the maximum range of 16-bit signed or unsigned numbers due to antilog operation in path loss model. The results also show that this method is able to reduce estimation error while inaccurate environmental parameters are used for RSSI-distance conversion.

Index Terms—Location Estimation, Ranging, Received Signal Strength, Wireless Sensor Network.

1 INTRODUCTION

To estimate the position of a mobile target within specified area of wireless sensor network (WSN) coverage, sensor nodes first measures the distances between stationary nodes and the mobile node. Distance between two sensor nodes can be measured through one of the ranging techniques such as time-different-of-arrival (TDOA) [1] and received signal strength indicator (RSSI) [2].

Among them, RSSI is the most convenient ranging method for distance measurement which simply records the received power level during signal reception. In addition, the power consumption is lower than other techniques since it does not need additional components dedicated for ranging. Therefore, RSSI ranging is widely used in various applications.

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Generally, the RSSI values represent received power in decibel form in IEEE 802.11 and IEEE 802.15.4 wireless interfaces. These RSSI values are first converted to normal scale using antilog function, and the distances between sensor nodes can be obtained using path loss model [3]. With these distances, trilateration [4] can be used to calculate the position of the mobile node.

Since antilog function is used to convert RSSI values to distance values, small RSSI variation in decibel form leads to large variation in estimated distance. Hence, the position error becomes sensitive to input variation. In addition, path loss model is based on attenuation exponent as the major environmental parameter for RSSI-distance conversion. If the calibrated attenuation exponent is not accurate due to uncertainty of RSSI, it leads to permanent large position estimation error. In other words, the output performance of the estimation result becomes too environmental dependant and unreliable.

The intention of this study is to evaluate whether the two main processes (distance conversion and trilateration) of position estimation can be integrated as one, thus ignoring the antilog operation required in the distance conversion process. The rest of the paper is organized as follows: Section 2 gives the related works done previously that describes range-based estimation algorithms and the relevant ranging techniques. Section 3 states the practical problems that may be faced in implementation and the proposal of solution. Section 4 describes the proposed integrated position estimation algorithm. Section 5 gives the details of experiment and settings. Section 6 illustrates the experimental results and discussion. Section 7 gives conclusions about the work.

2 RELATED WORKS

Localization problems have been widely researched that result in broad categories of position estimation techniques [5]. The related works that mainly affect the result of estimation are the modeling of radio propagation manner and characterization of environment. If the studies of radio signal propagation can be modeled optimally, the ranging results can be more accurate and stable, leading to more accurate and precise position estimation. For this reason, various experiments have been conducted for RSSI characterization.

One of the previous works characterized empirically the radio signal strength variability in 3-D area based on IEEE 802.15.4 using monopole antennas [6]. From the experiments, several sources of RSSI variability were studied including radio transmitter and receiver variability, the antenna orientation, and the multipath effect of radio propagation in indoor environment. This research indicates an important fact that characterizing indoor environment for distance measurement is difficult using the existing radio propagation models because of multipath reflection and shadowing.

Another work was done for comparing the RSSI and link quality indicator (LQI), which studies the detail profile of RSSI and LQI performance in [7]. In this work, the packet yield, RSSI, and LQI values were measured as a function of distance, angle, and transmit power, with the consideration of environmental conditions. The most significant result found in this research is that transmitting and receiving node heights have a major impact on link performance.

For the research works on path loss model, [3] provides an empirical path loss model for indoor wireless channels in laboratory building. The most significant contribution is the characterization of multi-wall or multi-floor attenuation using path loss model. [8] and [9] studies the path loss model with additional considerations including the distance-dependent path loss, the attenuation due to reflections of walls, and the attenuation due to transmitting through the walls. A dynamic indoor signal map construction and localization algorithms was also developed based on the model.

To use path loss model effectively and accurately for position estimation, environmental characterization strategies [10] was studied to find accurate parameters in the calibration phase. This research discovered that the environmental parameters in path loss model can be divided into temporal and spatial nature. The results in this study show that all sensor nodes which are located at different places share the same characterization value for the temporal parameter whereas different values for the spatial parameters.

3 PROBLEMS STATEMENT

Theoretically, position finding based on range-based techniques requires the true distances among sensor nodes for trilateration. However, the RSSI values are normally expressed in dBm [11] using IEEE 802.15.4 radio interface. This is a compressed version of received power. The problem is that when these values are measured and stored in the RSSI register, some least-significant digits after the decimal point are ignored. This leads to good distance resolution at near distance and worse resolution at far distance after RSSI-distance conversion using path loss model. If the distance is very far, small increment of RSSI value causes a large leap of distance estimation. On the other hand, increasing RSSI from one quantized level to another level requires long distance movement. This gives difficulty to obtain accurate and high resolution position estimation.

In the typical path loss model [3], the main characterization factors are based on attenuation exponent n and the path loss $P_{PL(d0)}$ at reference distance d_0:

$$P_d = P_t - P_{PL(d0)} - 10 \times n \times \log 10 \left(\frac{d}{d_0} \right) \quad (1)$$

where P_t is the transmission power and P_d is the received power at distance d to the transmitter. All powers are expressed in dBm. During the field measurement and calibration phase, attenuation exponent n and $P_{PL(d0)}$ are obtained for each transmitter. During location estimation phase, the received power P_d is converted into distance d using the following expression:

$$d = d_0 \times 10^{\frac{P_t - P_{PL(d0)} - P_d}{10n}} \quad (2)$$

In (2), all determinate parameters and input are elements of the exponent with base 10. It is clear that a small error of n or $P_{PL(d0)}$ produces large distance estimation error at output. For indoor environment, the value of n can be measured differently at different locations during calibration phase. Therefore, the resulting estimation is not absolutely accurate in practical. If the received power has slight fluctuation, the estimated distance can be large fluctuation and unstable.

Another practical problem is the size of data during computation process. For most of the low-power mobile devices such as wireless sensor motes, the processors or microcontrollers are limited in processing capability and power supply. All algorithms and methods used in these devices for in-network processing are expected to be simple and fast in computation. Therefore, the numbers involved in the computation must be small and confined in small variation. Inevitably, path loss model using antilog operation to directly convert RSSI to distance produces extremely large values at output that may exceed the limit of bit storage support when measurement is unstable and fluctuating.

To solve the practical problems stated above, it is necessary to review and develop new estimation algorithm, which are suitable for lightweight implementation in sensor nodes. Taylor series is able to avoid antilog operation in the RSSI-distance conversion, hence reducing processing difficulty. However, the resultant values from Taylor series are close to or equivalent to the values found using antilog operation, thus still cannot avoid large number produced at output. The only way to solve this problem is to skip RSSI-to-distance conversion step.

The proposed idea of solution is to estimate position without going through the RSSI-to-distance conversion process, and directly estimate location using the raw RSSI values. However, it is not that simple as the RSSI value is not able to represent distance exactly. With this, in-depth study was carried out to match the unconverted RSSI values to position values. The proposed algorithm is shown in the next section.

4 Proposed Position Estimation Method

The RSSI value provided from CC2420 radio transceiver using IEEE 802.15.4 is not exactly received power. Therefore, it is necessary to convert RSSI into the actual power P received at the RF pins of the radio transceiver as shown in the following expression:

$$P = RSSI + offset \quad (3)$$

where $RSSI$ is the value recorded in the register of the radio transceiver. $offset$ was found empirically from the front end gain and it is approximately equal to 45 dBm. This is to make sure that the received power P has dynamic range from 100 to 0 dBm. Here, 100 dBm indicates the minimum and 0 dBm indicates the maximum power.

For position estimation, it is assumed that three sensor nodes are used as beacon nodes or stationary nodes and one as mobile node. The beacon nodes are located at the three corners of the estimation area (0,0), (L,0), and (0,W) respectively, where L represent the length and W represent the width as illustrated in Fig. 1.

The mobile node measures RSSI of signals from beacon node 1 to 3 and calculates received powers P_0 to P_3 respectively. These values are

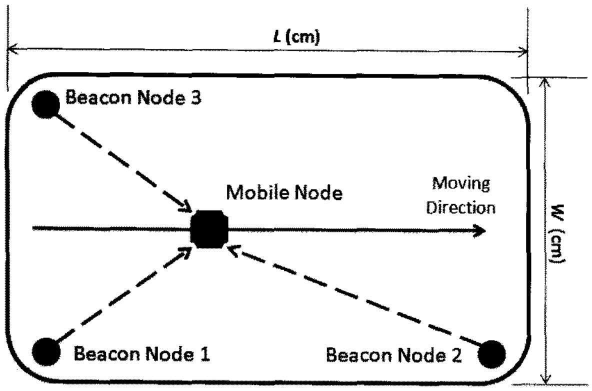


Fig. 1. The scenario of position estimation using three beacon nodes and one mobile node

then directly fed into trilateration process without going through conversion as shown in the following expressions:

$$H = \frac{P_L^2 + (P_1^2 - P_2^2)}{L} \tag{4}$$

$$V = \frac{P_W^2 + (P_1^2 - P_3^2)}{W} \tag{5}$$

where H and V are the horizontal and vertical estimates and used to represent the input for x and y respectively. P_L and P_W are the received powers obtained when two sensor nodes are placed apart with a distance L and W respectively.

In this approach, a linear approximation model is developed to map the H and V values to true x and y values as shown in the following expressions:

$$H = a_x M + b_x \tag{6}$$

$$V = a_y N + b_y \tag{7}$$

where a_x and b_x are the coefficients of the model for x, while a_y and b_y are the coefficients of the model for y. During calibration phase, these coefficients are used to characterize environment. These coefficients are relevant to each other and they are derived from the typical path loss prediction model as shown in the following expressions:

$$a_x = \frac{10n(1 - P_{d0})}{L} \tag{8}$$

$$a_y = \frac{10n(1 - P_{d0})}{W} \tag{9}$$

$$b_x = \frac{P_{d0}^2 + 20n(1 - P_{d0}) \log L}{L} \tag{10}$$

$$b_y = \frac{P_{d0}^2 + 20n(1 - P_{d0}) \log W}{W} \tag{11}$$

From (8) to (11), n and P_{d0} are the attenuation exponent and the received power measured at reference distance d_0. In this case, all attenuation exponents n_i are assumed the same for every beacon nodes. In (6) and (7), M and N can be expressed in terms of x and y:

$$M = \log\left(\frac{d_1^2}{d_2^2}\right) = \log\left(\frac{x^2 + y^2}{(u - x)^2 + y^2}\right) \tag{12}$$

$$N = \log\left(\frac{d_1^2}{d_3^2}\right) = \log\left(\frac{x^2 + y^2}{x^2 + (v - y)^2}\right) \tag{13}$$

where x and y are the true location coordinate of the mobile node. d_1, d_2 and d_3 represent the true distances between the mobile node and the three beacon nodes. Using the true location coordinate x and y, M and N in (12) and (13) can be found for calibration purpose in (6) and (7).

By applying the expressions mentioned above, the proposed estimation algorithm consists of two phase operation. In the initial phase, field measurements are performed to find the parameters a_x, b_x, a_y and b_y that appropriately characterize the environment. In the second phase, position estimation is performed to find location coordinate x and y.

During the field measurement phase, several parameters are required to obtain. At first, P_L and P_W can be obtained by finding the values between beacon node 1 and 2 for P_L and beacon node 1 and 3 for P_W. The coefficients b_x and b_y can be obtained by placing the mobile sensor node at the center location $(L/2, W/2)$ of the room. This causes M and N become zero in (12) and (13). With this, the coefficients b_x and b_y are exactly equal to the values of H and V respectively. This can be obtained by referring (6) and (7). The H and V values are found from (4) and (5).

After the coefficients b_x and b_y are obtained, the next step is to find the coefficients a_x and a_y. This can be achieved by placing the mobile node on the horizontal center line $(x,W/2)$ for a_x and the vertical center line $(L/2,y)$ for a_y. When the mobile sensor node is placed at any point except center of the horizontal line, the value of M can be calculated by providing x and y values into (12). This M is put into the (6) to calculate the coefficient a_x. Since b_x was obtained previously, and H value is from (4), the coefficient a_x can be easily computed. The finding of a_y is similar to a_x but the mobile sensor node is put at any point except center of the vertical line, and using (13) to find N and both (5), (7) to find a_y.

For the procedure of finding a_x and a_y, it is recommended to choose several locations on the horizontal line and vertical line, and use the average value of a_x and a_y to improve accuracy. Another recommendation is to keep the measuring points on the horizontal and vertical line close to center but not at the center. For example, $(L/4) < x < (3L/4)$ and $(W/4) < y < (3W/4)$.

Once all of the coefficients are obtained, field measurement phase is completed. The next phase is the online location estimation phase. In this phase, the following expressions are used to estimate x and y:

$$x = \frac{H - b_x}{a_x}\left(\beta \times \alpha^{S_x}\right) + \frac{L}{2} \tag{14}$$

$$y = \frac{V - b_y}{a_y}\left(\beta \times \alpha^{S_y}\right) + \frac{W}{2} \tag{15}$$

where S_x and S_y are called "linear selector", which choose the most fitting linear approximations to x and y. Depends on the input conditions, the values of S_x and S_y have to be selected appropriately. The linear selectors S_x and S_y have values ranging from -5 to +5, and β = 300, α = 1.25. The selection of S_x and S_y are based on the displacement between mobile node and beacon nodes 1 and 2 for S_x, and the displacement between mobile node and beacon nodes 1 and 3 for S_y. Thus, the currently estimated y can be used to find S_x, and the currently estimated x can be used to find S_y.

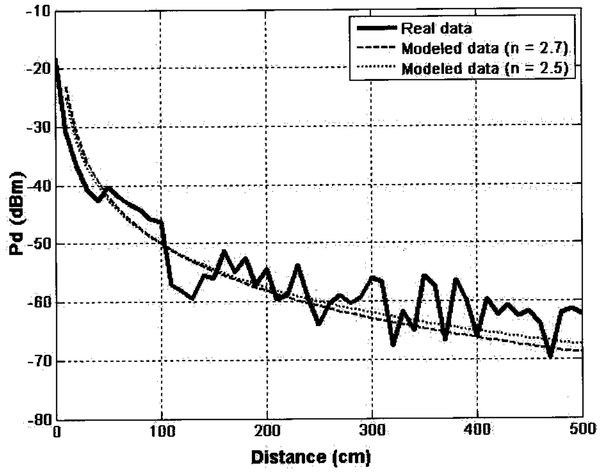


Fig. 2. Characterization of the radio channel

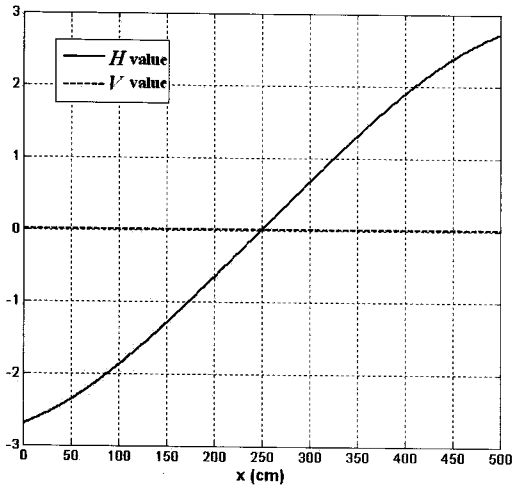
5 EXPERIMENTAL SETUP

For comparison between the proposed method and path loss model, the characterization of environment was also done to find reference environmental parameters. This is to provide a result that can be used to evaluate the performance of the proposed new approach. During the characterization process, RSSI values are slightly different each time and each node due to different directions and locations. Therefore, several times of measurement were done to find the average values as shown in Fig. 2. Note that the measurement results are expressed in power (dBm).

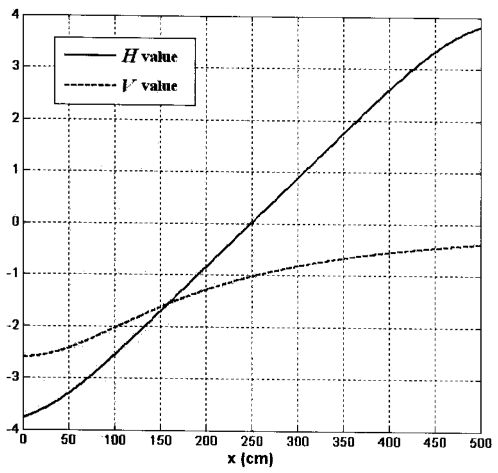
In Fig. 2, besides the real data, two modeled data lines were obtained using path loss model with the attenuation exponent n = 2.7 and n = 2.5. Both of the modeled data are using d_0 = 100 cm reference distance, and P_{d0} = 50 dBm as the power received at reference distance.

6 EXPERIMENTAL RESULTS

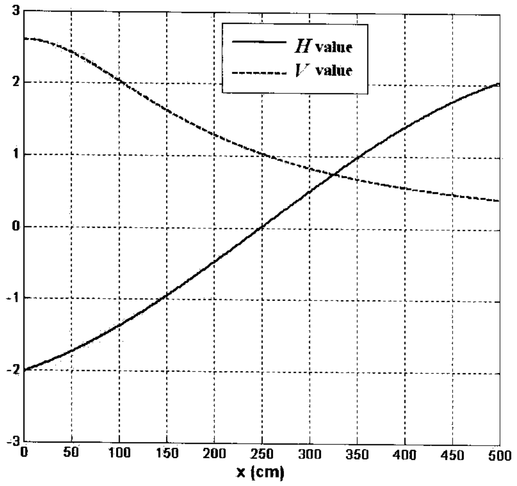
In the experiment, the mobile sensor node was first located at the center $(L/2,W/2)$. Two coefficient values were obtained: b_x = 9.09 and b_y = 10.58. The following steps were performed by fixing y values and observing H and V values when x is varying from 0 to L. Three y values were chosen, which are 120, 200, and 280. The results are shown in Fig. 3. Note that the values illustrated are $(H - b_x)$ and $(V - b_y)$.



(a) y setting: Fixing y to $W/2$ (200 cm)



(b) y setting: Fixing y to 120 cm



(c) y setting: Fixing y to 280 cm

Fig. 3. Relationship of H and V in three different conditions of y setting

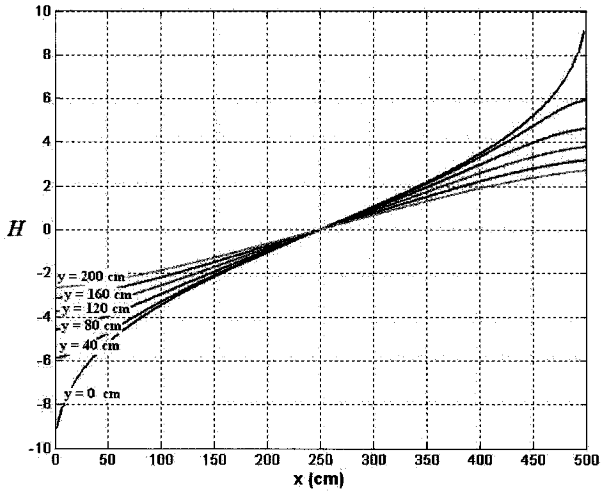
Fig. 3 explains the relationship of H and V values with different y settings. The crossing point of H and V is moving when the y is changing. When fixing y to $W/2$, the crossing point is exactly at center $(L/2)$ in Fig. 3(a). From analyzing the three figures, it shows a truth that the H values are always crossing the origin when the x value is exactly $L/2$. The only difference among Fig. 3(a), 3(b) and 3(c) for H values is the slop. For V values, it is always kept at zero when y is exactly $W/2$. From the experimental observation, the crossing point of H and V curves happen when $x \equiv y$. The values before crossing point happen in the condition $x < y$, and after crossing point in the condition $x > y$.

In order to use the H and V values effectively for the finding of x and y, analysis on the variation of H and V values is necessary. In the following results, all H values with fixing y at several equal-distance points are plotted as shown in Fig. 4.

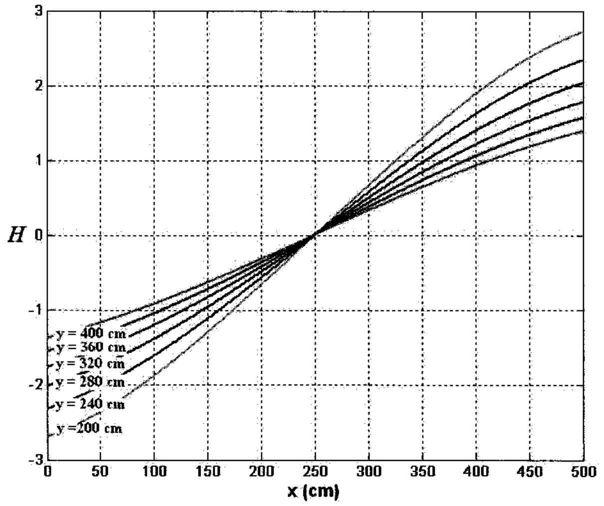
For better illustration, Fig. 4(a) shows the H values when y is fixed from 0 to $W/2$ (200 cm), and Fig. 4(b) shows the H values when y is fixed from $W/2$ (200 cm) to W (400 cm) with 40 cm apart. Both Fig. 4(a) and 4(b) produce a total of 10 characteristic curves for H. At $y = W/2$ (200 cm), the H values are treated as the standard for the reference to others. The difference among these curves is the slop. For $y < W/2$, the slops are larger, and for $y > W/2$, the slops are smaller. By observation, all slops follow a certain pattern. This gives a systematic modeling scheme to be established. The models described in (14) and (15) are derived from Fig. 4.

For better modeling of the H values, (12) and (13) are used instead of (4) and (5). One of the purposes is to make the modeling available to all possible environment settings. The comparison of the real and modeled H values with fixing y at several equal-distance points is shown in Fig. 5(a) and 5(b).

All H values in Fig. 5(a) are the real data for (12) and the values in Fig. 5(b) are the modeled data for $(\beta \times \alpha^S)$ in (14). Comparing Fig. 5(a) and 5(b), we can prove that (14) is able to model (12) with slight difference only. For the x and y closer to the center of room such as $(L/4) < x <$

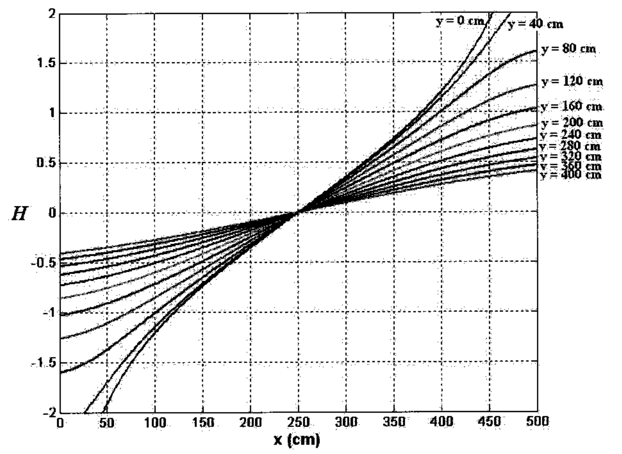


(a) y = 0 to 200 cm

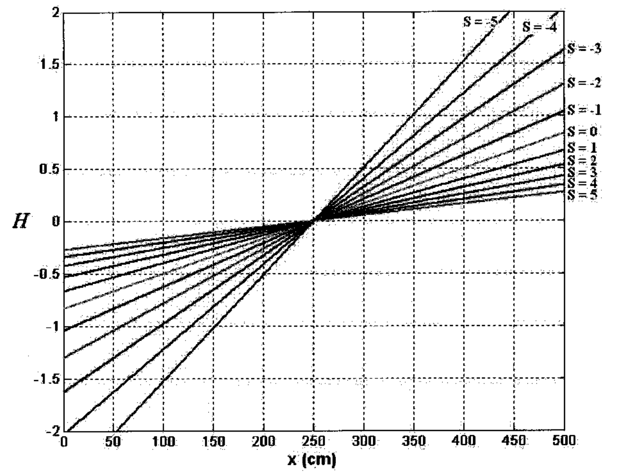


(b) y = 200 to 400 cm

Fig. 4. H with fixing y at several equal-distance points



(a) Real H values



(b) Modeled H values

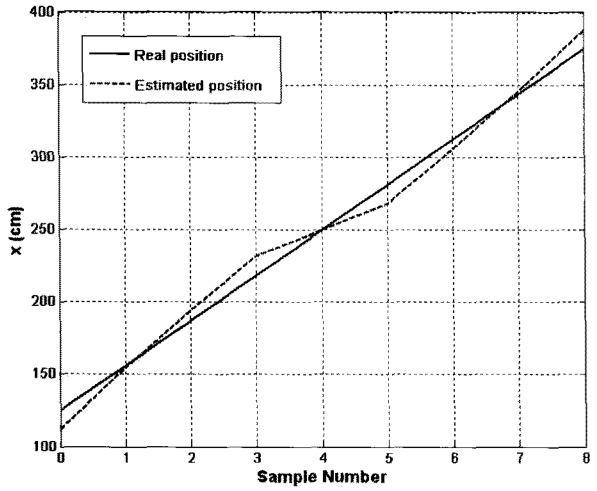
Fig. 5. Comparison of the real and modeled H values

$(3L/4)$ and $(W/4) < y < (3W/4)$, the modeling result is more accurate.

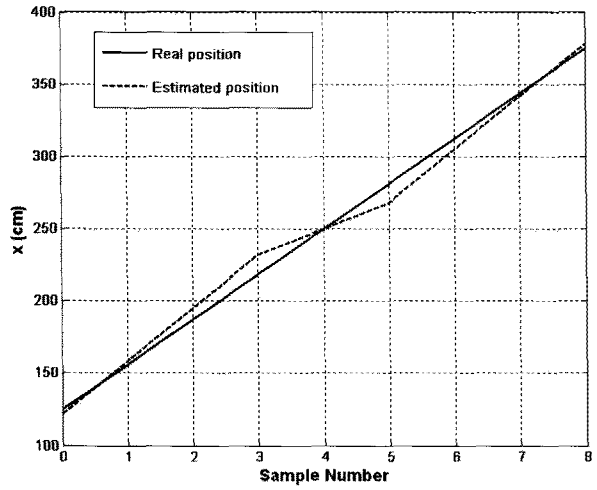
In the following experiments, the proposed algorithm is used to estimate position to find x. The experiment was done by moving the mobile sensor node from location (125cm, 200cm) to location (375cm, 200cm). In between, a total of 9 samples were taken for location estimation. The sampling locations are 31 cm apart. The same data was provided to both the proposed method and pass loss method for comparison as shown in Fig. 6.

Fig. 6(a) is the estimation result obtained using path loss model and Fig. 6(b) is using the proposed method. In this case, the estimation is assumed to be the best scenario as the most accurate parameters or coefficients are used for estimation (n = 2.5, a_x = 2.8). The root mean square error for typical path loss model in Fig. 6(a) is 9.29 cm, and for the proposed method in Fig. 6(b) is 7.38 cm. This result proves that the proposed method is able to estimate position as good as path loss model in the best scenario, and the result is even slightly better since the root mean square error between the real and estimated position values is reduced 1.9 cm.

Fig. 7 shows the location estimation results for x when the environmental parameters are not accurate. This means the parameters obtained during the field measurement phase are

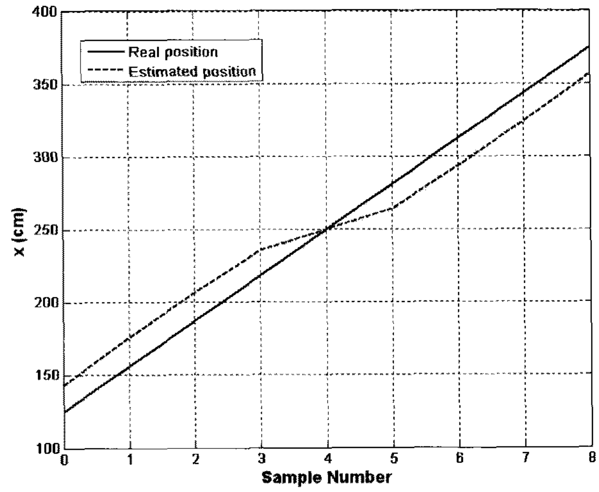


(a) Using path loss model

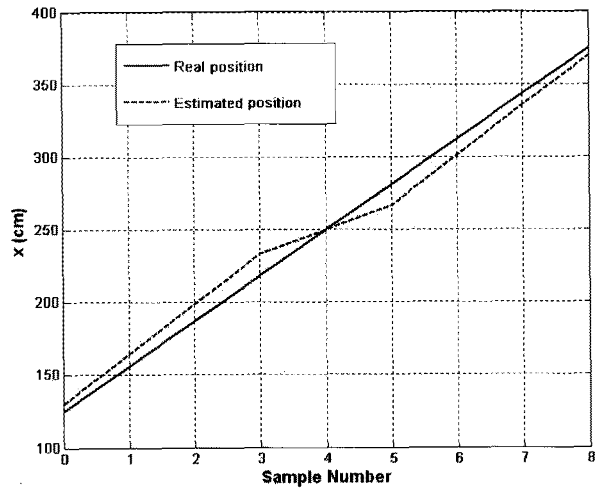


(b) Using the proposed method

Fig. 6. Position estimation for x in the best scenario



(a) Using path loss model



(b) Using the proposed method

Fig. 7. Location estimation for x when the parameters are not accurate

not optimal. In Fig. 6(a), the best scenario was obtained using the attenuation exponent n = 2.5 for estimation. In Fig. 7(a), the attenuation exponent n = 2.7 was used for estimation. It is clear that n = 2.5 and 2.7 are only small difference as observed in Fig. 2. However, the estimation error can be very large due to amplification of antilog operation. To the large variation of RSSI values, this problem could happen frequently. For the estimation result using path loss model in Fig. 7(a), the root mean square error between real and estimated position is large (17.38 cm).

In Fig. 6(b), the best scenario was obtained using the coefficient a_x = 2.8 for estimation. In Fig. 7(b), the coefficient a_x = 3.0 was used for estimation. The difference is 0.2, same as the case of attenuation exponent n in the previous example. For the estimation result using the proposed method in Fig. 7(b), the root mean square error between real and estimated position is still small (9.65 cm). Compared to path loss model, this proves that the proposed method reduces root mean square error by 7.7 cm.

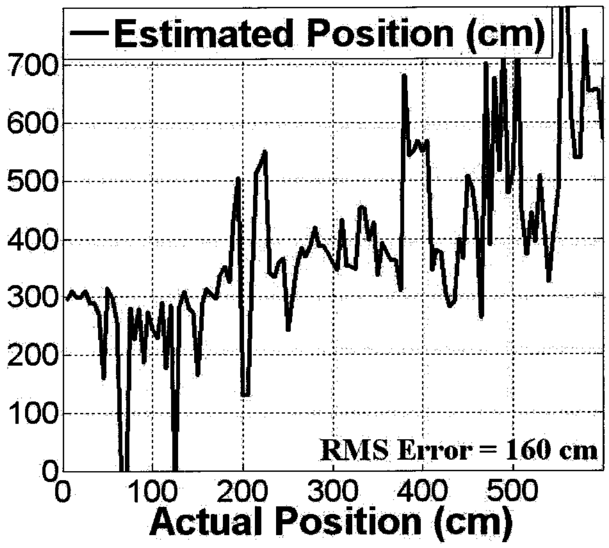
Compare the root mean square error between the best scenario and the inaccurate parameters condition, the typical path loss model increases

8.1 cm (17.38 cm - 9.29 cm), and the proposed method only increases 2.3 cm (9.65 cm - 7.38 cm) when the parameters have 0.2 error. This proves that the proposed method has smaller change at output as the input or parameters are changed.

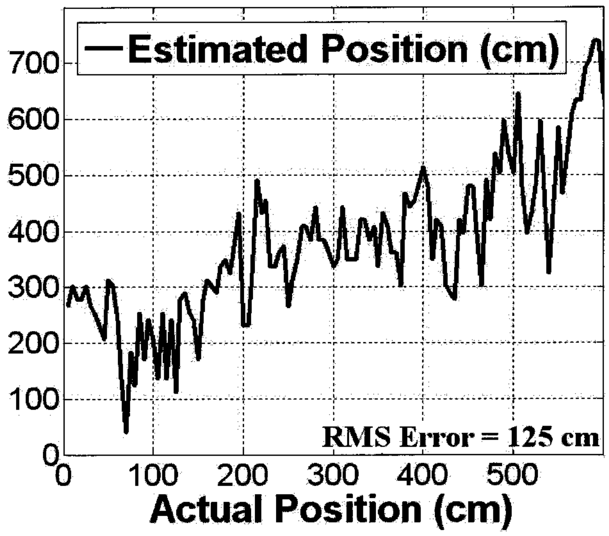
In practical condition, real and raw RSSI values are unstable and fluctuating against time and space because of multipath fading and shadowing effects in indoor environment. Fig. 8 shows the performance of estimation using both path loss model and proposed integrated method by feeding the input with real and raw RSSI values. Raw RSSI values means the values are obtain directly from measurement without going through any signal processing.

In Fig. 8(a), the estimation of position was obtained by providing raw RSSI values to path loss model for RSSI-distance conversion, and pass to trilateration for position x. From the illustration, the estimated values are also fluctuating largely with a root-mean-square error of 160 cm. In Fig. 8(b), the estimation of position was obtained by providing raw RSSI values to our proposed integrated algorithm for position x. From the diagram, the estimated values are more stable and smaller fluctuation amplitude. The overall root-mean-square from this estimation is only 125 cm. By comparing Fig. 8(a) and 8(b), it is very clear that the proposed method reduces fluctuation and overall root-mean-square error.

Fig. 9 illustrates the performance comparison of estimation using both path loss and proposed integrated algorithms by feeding the input with real and smoothed RSSI values. Dash line indicates the estimation using path loss model, bold line indicates the estimation using proposed integrated method, and the narrow line indicates the actual position. From this comparison, it is clear by observation that proposed integrated estimation is closer to the actual position. This proves that our proposed method is more accurate than path loss method.



(a) Using path loss model



(b) Using the proposed method

Fig. 8. Location estimation for x using real and raw RSSI signals

7 Conclusions

A new approach to RSSI position estimation algorithm is presented. The proposed algorithm estimates location without converting the RSSI values to distance directly, thus the required processing is lower, and the data range is small that it does not exceed the data size provided.

The experimental results show that this method reduces estimation error 1.9 cm in the best scenario, and 7.7 cm when 0.2 inaccurate parameters obtained during field measurement. This proves that the algorithm is able to provide stable location estimation. When the input values are fluctuating, the output of

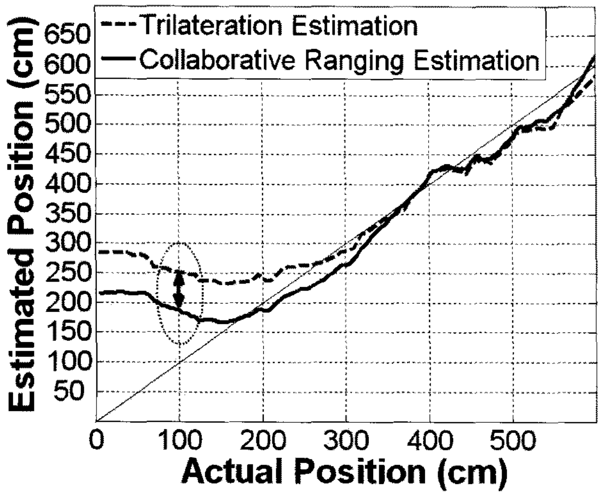


Fig. 9. Location estimation for x using real RSSI signal after curve smoothing algorithm for refinement

the estimation does not amplify the variation. When the parameters obtained during the field measurement phase are not optimal, the influence can be small. From the estimation of position using real and raw RSSI values, we are able to prove that the overall root-mean-square error can be reduced 35 cm.

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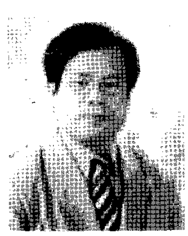

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