Int. J. Electron. Commun. (AEÜ) 70 (2016) 250–256

Contents lists available at ScienceDirect

International Journal of Electronics and Communications (AEÜ)

journal homepage: www.elsevier.com/locate/aeue

RSS-based indoor localization with PDR location tracking for wireless sensor networks

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ARTICLE INFO

Article history:
Received 7 April 2015
Accepted 1 December 2015

Keywords:
Indoor localization
Received signal strength
Least square
Pedestrian dead reckoning
NLOS

ABSTRACT

Traditional indoor localization techniques typically rely on a single communication source such as RF signals, ultrasound, inertial sensors, and geomagnetic fields. In wireless sensor network (WSN), received signal strength (RSS) based approach is one of the most commonly used localization techniques. It is simple to implement and costly efficient, but the estimation accuracy is significantly reduced in non-line-of-sight (NLOS) conditions. pedestrian dead reckoning (PDR) uses inertial measurement unit (IMU) for location tracking. Its tracking accuracy is not affected by the interference in NLOS conditions, but the location error is accumulated in long distance tracking. We propose the RSS-based indoor localization algorithm combined with PDR location tracking for wireless sensor networks. The objective is to compensate the NLOS localization error by using PDR, while mitigating the accumulated error of PDR by using RSS-based localization method in LOS conditions. Lab scale experiment and large scale simulation results show that the proposed algorithm significantly reduce the location estimation errors in wireless sensor networks.

1. Introduction

The interest on the indoor localization techniques has been grown rapidly as it has many practical applications in our daily life. Various information sources such as RF signals, ultrasound, inertial sensors, and geomagnetic fields have been used for indoor localization.

In wireless networks, the signal's numerical data such as received signal strength (RSS), time of arrival (TOA), time difference of arrival (TDOA), and angle of arrival (AOA) [1–3] are used for indoor localization. Among these, the RSS-based approach is one of the most commonly used localization techniques because of its simplicity for implementation in RF based networks. In the RSS-based localization techniques, the RSS values from nearby reference nodes are collected to estimate the target node location. The RSS-based localization shows fairly good estimation accuracy in line-of-sight (LOS) conditions but it has problems with estimating the location in NLOS conditions [4,5].

Pedestrian dead reckoning (PDR) is one of the inertial measurement unit (IMU) based location tracking techniques [6,7]. Gyroscope and magnetometer are used for obtaining the heading direction of the target node, and accelerometer is used in step detection and step length estimation. The location is updated by adding the step displacement to the location of prior step. PDR approach does not use wireless signals and its localization accuracy is not affected by the interference in NLOS conditions. Instead, the running duration of PDR is related to the location tracking accuracy.

To compensate the NLOS error of RSS-based localization methods and the errors of IMU-based localization techniques in long distance tracking, various hybridization techniques have been proposed recently. In [8,9], the authors combine IMU-based localization method with Wi-Fi fingerprinting method using Kalman Filter. IMUs are used for predicting the target location and Wi-Fi fingerprinting is used to compensate the predicted location. In [10], the author uses the user movement data, RSS measurements, and historical information of locations in the hidden Markov model. In [11], the authors propose a wireless assisted PDR system which involves a DR module, ad-hoc WSN, and an information center with map database. PDR is combined with wireless telemetry and map matching algorithm.

In this paper, we propose the RSS-based indoor localization algorithm combined with PDR location tracking in wireless sensor networks. In LOS condition, RSS-based geometrical least square (RSS-LS) is used for location estimation. Since the starting PDR location is resetted by RSS-LS in LOS condition, the tracking error of PDR can be reduced. The target node's location is estimated by using PDR in NLOS condition, and it compensates the NLOS estimation error of RSS-LS. This algorithm does not require the radio map

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http://dx.doi.org/10.1016/j.aeue.2015.12.004
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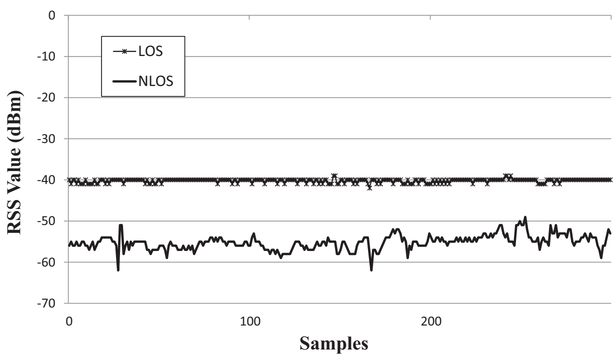

Fig. 1. RSS measurements in LOS and NLOS conditions.

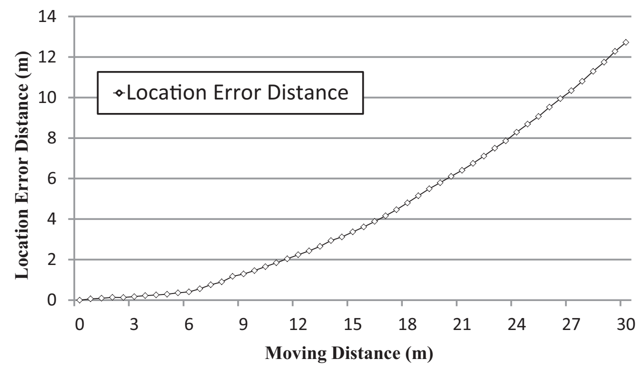

Fig. 2. PDR location error distance vs. moving distance.

collecting processes and provides the simplicity of implementation in wireless sensor networks.

The remainder of this paper is organized as follows. We begin with Section 2 by stating the characteristics and problems of RSS-LS and PDR methods. The proposed algorithm is explained in Section 3, and the experimental results and performance evaluations are presented in Section 4. We conclude the paper in Section 5.

2. Problem statement

RSS-based localization techniques can be categorized into two types. In Bayesian approach, RSS values are considered as random variables and the location of the target is estimated using the probability functions of the collected RSS vectors. Maximum likelihood (ML) method is one of the Bayesian localization approaches.

In geometric approach, which is being used throughout the paper, we deal with the geometrical relationship of the nodes. The distance d between the target and a reference node is computed from the measured RSS values and the path loss model [12].

$$P = P_0 - 10\mu\log_{10}\left(\frac{d}{d_0}\right) \quad (1)$$

where P denotes the measured RSS, μ is the path loss constant, d_0 is the reference distance which is typically 1 m, and P_o is the RSS measurement at $d = d_0$.

The location of the target is estimated from the calculated distance. In the geometrical LS approach, the coordinates of the target, $(\hat{x_0}, \hat{y_0})$, is obtained as follows:

$$(\hat{x_0}, \hat{y_0}) = \underset{(x_0, y_0)}{argmin}\left\{\sum_{i=1}^{N}|d_i - \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2}|\right\} \quad (2)$$

where N is the number of the reference nodes, d_i denotes the computed distance to the ith reference node, and (x_i, y_i) is the coordinates of ith reference node.

Interference is the biggest challenge of RSS-based indoor localization methods. Fig. 1 shows the RSS measurement results over time. Two MTM-CM3000 wireless modules [13] are placed at 1 m above the floor and 3 m apart to each other. When a person is standing between two wireless modules, RSS measurements show NLOS attenuation. The NLOS attenuation level is around 15 dBm and its standard deviation is 1.79. Geometrical LS method provides inaccurate estimation result because the RSS measurements in NLOS condition distort the distance information.

Pedestrian dead reckoning (PDR) is one of the IMU-based location tracking methods. The target node estimates its heading direction, detects each step, and estimate corresponding step length using magnetometer, gyroscope, and accelerometer. The target's current location is being updated by adding the computed displacement of each step to the estimated location of prior step [6,7].

The localization accuracy of PDR is not affected by interference because it does not depend on the wireless signals. However, the location error of each step is being accumulated as PDR is continuously being used. Angle measurement errors and poorly estimated step lengths both cause the PDR estimation error. The angle measurements from magnetometer and gyroscope are not perfect due to the limited sensing capabilities. Magnetometers are vulnerable to indoor magnetic interference and gyroscope suffers from the bias drift. The RMS noise of MPU3050 gyroscope is 0.0017 radian (0.1°) per sec and this causes bias drift error [14]. Bias drift can also be increased as the temperature of the sensor rises. Fig. 2 shows the location error of PDR along with the moving distance. A person whose step length is 0.6 m is walking straight while holding Galaxy Nexus smartphone. As shown in Fig. 2, the PDR location error keeps increasing while PDR is continuously being used.

3. Proposed algorithm

We propose a new indoor localization algorithm to improve the performance of RSS-based least square (RSS-LS) estimation method by combining with PDR location tracking. Two different estimation methods are used to complement each other. RSS-LS is mainly used for location estimation in LOS conditions, and PDR location tracking is used when the NLOS condition is detected. In this system, we consider a 2D coordinate system for simplicity.

3.1. Overview

The proposed algorithm is an iteration cycle of two phase routines: location estimation and location determination. In the location estimation phase, two methods are used independently to estimate the location of the target node. The target's trajectory is being tracked by PDR for a certain period of time, called PDR duration. The location at the end of PDR duration becomes the PDR location of the target node. Next, the target node selects four reference nodes with the highest RSS values in order and creates $\binom{4}{3}$ subsets by choosing three reference nodes at a time. Four LS results are obtained by performing RSS-LS on each subset and the center of them becomes the LS location of the target node. In the location determination phase, we check if the chosen 4 reference nodes are under the NLOS conditions and select better estimation result for target node's current location (Fig. 3).

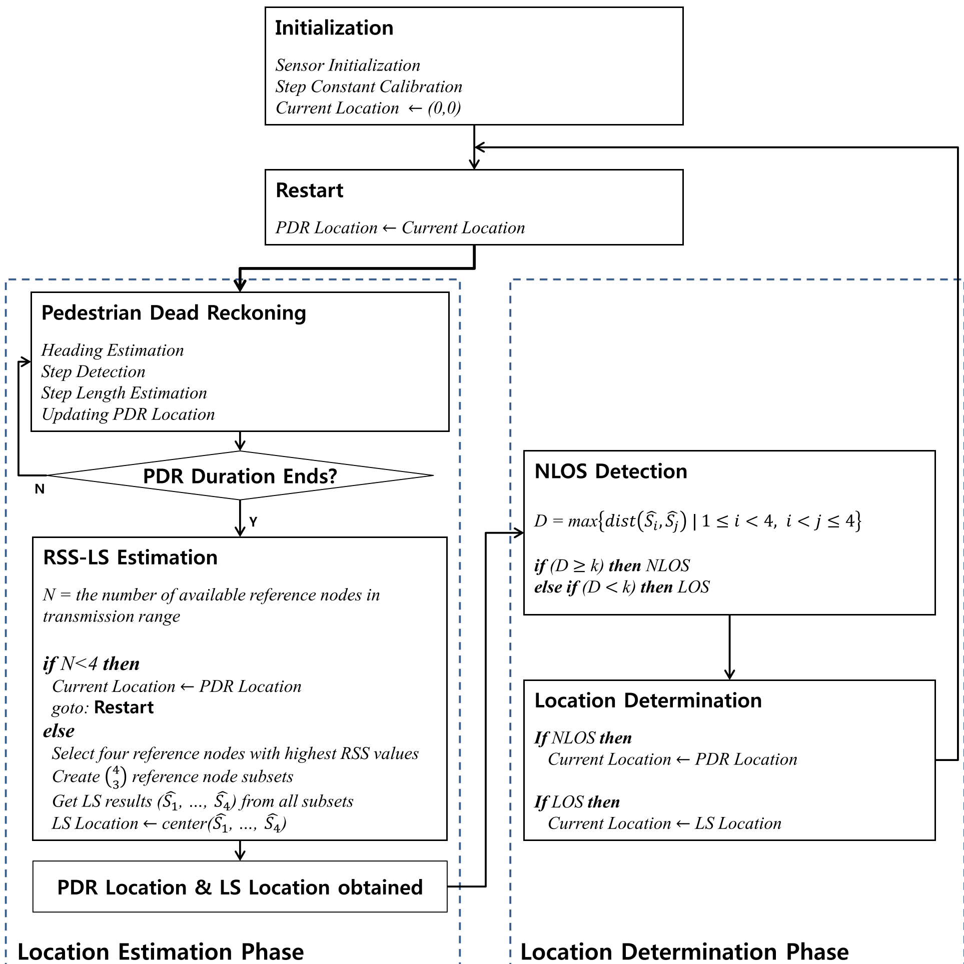

Fig. 3. Flowchart of the proposed algorithm.

3.2. Location estimation

3.2.1. Pedestrian dead reckoning (PDR)

PDR is running on relative coordinate system whose x-axis is the direction of initial heading direction of the target node, and RSS-LS is operated on global coordinate system. Global coordinate system is established when the reference nodes are placed in the area. At the very beginning of PDR, the target node measures its initial heading direction on the global coordinate system using magnetometer. During PDR procedure, gyroscope and magnetometer are being used together to get the heading direction of the target node, and the direction is obtained as the angle respect to the x-axis of global coordinate system.

In the experiments, the radian angle provided by gyroscope is rounded up to two decimal places to reduce the RMS noise effect, and 8 s of sensor warming up time is applied in the initialization stage to bypass the bias drift caused by temperature. Heading direction estimation method is used to avoid the angle measurement error caused by magnetic interference [15].

We assume the user walks while holding the smartphone in a fixed position and does no other actions like jumping or swinging arms. Under this assumption, only the step impacts can create the peaks of acceleration norm. When a person steps on the ground, the impact creates a peak of the vertical acceleration but as the smartphone is not always in right position, this impact will be distributed to all three axes. Each step is counted when the acceleration norm $a(t)$, peaks [7]:

$$a(t) = \sqrt{a_x^2(t) + a_y^2(t) + a_z^2(t)} \tag{3}$$

where a_x, a_y, and a_z denote the acceleration components. Fig. 4 shows the change of $a(t)$ of a moving person and each peak is considered as a step. Galaxy Nexus smartphone is used to measure the accelerations of a walking person whose height is 165 cm and the average step length is 60 cm. The interval between each step is set to 0.3 s to ignore the small peaks caused by natural body shaking.

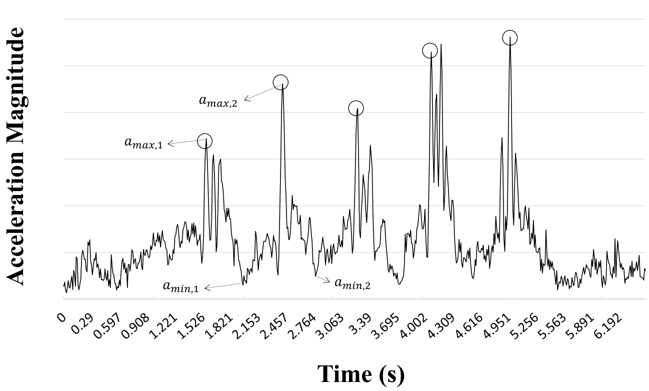

Fig. 4. Change of acceleration magnitude while moving 5 steps.

Once a step is detected, we estimate the step length of detected step. Based on the Weinberg's approach [16,17], the step length of ith step, $d_{step,i}$, is estimated as follows:

$$d_{step,i} = s * \sqrt[4]{a_{max,i} - a_{min,i}} \quad (4)$$

Note that $a_{max,i}$ and $a_{min,i}$ are the maximum and the minimum acceleration norms of ith step respectively, and s is the step constant of the user. The step constant s should be set individually in the calibration process. For example, when a person's height is 165 cm and step length is 70 cm, s is between 0.45 and 0.49. For a person whose height is 180 cm and step length is 70 cm, s is between 0.4 and 0.43. As shown in Fig. 4, the acceleration norm is changed in real time and thus the estimated step length is changed on each step.

After the direction and the step length are determined, the location of ith step $\hat{P}_i = (x'_i, y'_i)$ is updated as follows:

$$\begin{aligned} x'_i &= x'_{i-1} + d_{step,i} * \cos(\theta_i) \\ y'_i &= y'_{i-1} + d_{step,i} * \sin(\theta_i) \end{aligned} \quad (5)$$

where θ_i denotes the angle of the heading direction of ith step and $d_{step,i}$ is the estimated step length of ith step. x'_{i-1} and y'_{i-1} indicate the x and y coordinates of prior step respectively. The initial PDR location (x'_0, y'_0) is the determined location of prior iteration cycle. PDR location is repeatedly updated until the PDR duration ends, and the location at the end of PDR duration becomes the PDR location of the target node.

3.2.2. RSS-based least square estimation (RSS-LS)

After PDR duration ends, the target node checks the number of available reference nodes because it varies with time [18]. If less than four reference nodes are available, PDR location is selected as the current location of the target node, and new iteration cycle is started.

If four or more reference nodes are available, the target node chooses four reference nodes with the highest RSS values and computes the distances to the chosen reference nodes based on the log-distance path loss model [12]. The obtained distance information is used for location estimation. The placement of the reference nodes can affect the estimation accuracy of RSS-based localization [19], but in this paper, we assume that the reference nodes are placed in a square grid pattern for simplicity.

We create $\binom{4}{3}$ reference node subsets by selecting 3 reference nodes at a time. Each subset estimates the target node's location using LS estimation method. Four LS results are obtained from subsets and the center of them becomes the target node's LS location.

When kth subset R_k, contains 3 reference nodes, its LS result $\hat{S_k} = (\hat{x_k}, \hat{y_k})^T$ is obtained by LS matrix equation as follows:

$$\begin{aligned} R_k &= \{r_1, r_2, r_3\} \\ \hat{S_k} &= \begin{pmatrix} \hat{x_k} \\ \hat{y_k} \end{pmatrix} = (X_k^T X_k)^{-1} X_k^T b_k \\ X_k &= \begin{pmatrix} 2(x_3 - x_1) & 2(y_3 - y_1) \\ 2(x_3 - x_2) & 2(y_3 - y_2) \end{pmatrix} \\ b_k &= \begin{pmatrix} (d_1^2 - d_3^2) - (x_1^2 - x_3^2) - (y_1^2 - y_3^2) \\ (d_2^2 - d_3^2) - (x_2^2 - x_3^2) - (y_2^2 - y_3^2) \end{pmatrix} \end{aligned} \quad (6)$$

where r_i is the ith reference node in R_k, x_i and y_i are the coordinates of r_i, and d_i is the computed distance between the target and r_i.

The LS location of the target node, $\hat{S}$, is the center point of the LS results obtained from the reference node subsets.

$$\hat{S} = \frac{1}{4}\sum_{i=1}^{4} \hat{S}_i \quad (7)$$

3.3. Location determination

Two estimated locations are obtained from PDR and RSS-LS methods after PDR duration. Four LS results are obtained from the reference node subsets using Eq. (6), and the NLOS condition is detected by observing how far these LS results of subsets are scattered to each other. The error distance D is defined as follows:

$$D = \max\{dist(\hat{S}_i, \hat{S}_j) | 1 \le i < 4, \quad i < j \le 4\} \quad (8)$$

where $\hat{S}_i$ is the LS result of ith subset and $dist(\hat{S}_i, \hat{S}_j)$ is the Euclidean distance between $\hat{S}_i$ and $\hat{S}_j$.

NLOS condition is detected by comparing D with a threshold value k. The threshold k is empirically obtained. In the building simulation of Section 4.2, we observed the average estimation error of the proposed algorithm while increasing k from 0 m to 6.5 m, and selected k = 1.1 m because it provides the minimum average estimation error 0.4925 m.

If $D < k$, it is assumed that the area is currently in LOS condition and LS location result is chosen as the target node's location. If $D \ge k$, it is assumed that the area is in NLOS condition and PDR location result is chosen. Once the target node's location is determined, current iteration cycle is ended and next iteration cycle will be started. The determined location becomes the initial PDR location of the next iteration cycle.

Fig. 5 illustrates the concept of the algorithm. We assume that four closest reference nodes are used for RSS-LS, and PDR duration is set to 4 steps. On the first iteration cycle, the target is moving from its first real location RL1 to the second real location RL2. The target moves total four steps P1, P2, P3, and P4. PDR location is updated on every step using corresponding angle θ_i and estimated step length $d_{step,i}$. The PDR location at the end of the PDR duration, P4, becomes the target node's PDR location. Then, four closest reference nodes REF4, REF5, REF7, and REF8 are chosen and the target performs RSS-LS. Four LS results of subsets LS1, LS2, LS3, and LS4 are obtained, and the center point of them, LSR1, becomes the LS location of the target node. In this case, the target node is under the NLOS condition due to REF7, and four LS results of subsets are being scattered. The error distance α exceeds the threshold value k, and it means the target node is under the NLOS condition. PDR location will be chosen for the location of the target node.

In next iteration cycle, the target node is moving from RL2 to RL3 in four steps P5, P6, P7, and P8. Because P4 is chosen in prior iteration cycle, the initial PDR location of this iteration cycle is P4. After PDR duration ends, P8 becomes the target node's PDR location. In this case, the closest reference nodes REF5, REF6, REF8, and REF9 are in the LOS condition, and all four LS results of subsets are located near RL3. The LS location, LSR2, is selected for the current location of the target node because the error distance β does not exceeds k.

4. Performance result

4.1. Experimental result

Experiments are performed in the lab-scale testing area of 2 × 2 cells which is shown in Fig. 6. MTM-CM3000 wireless modules are used for target and reference nodes [13]. MTM-CM3000 supports IEEE 802.15.4 standard, and includes CC2420 RF transceiver and TI MSP430 microcontroller. Galaxy Nexus Android Smartphone is used to perform PDR.

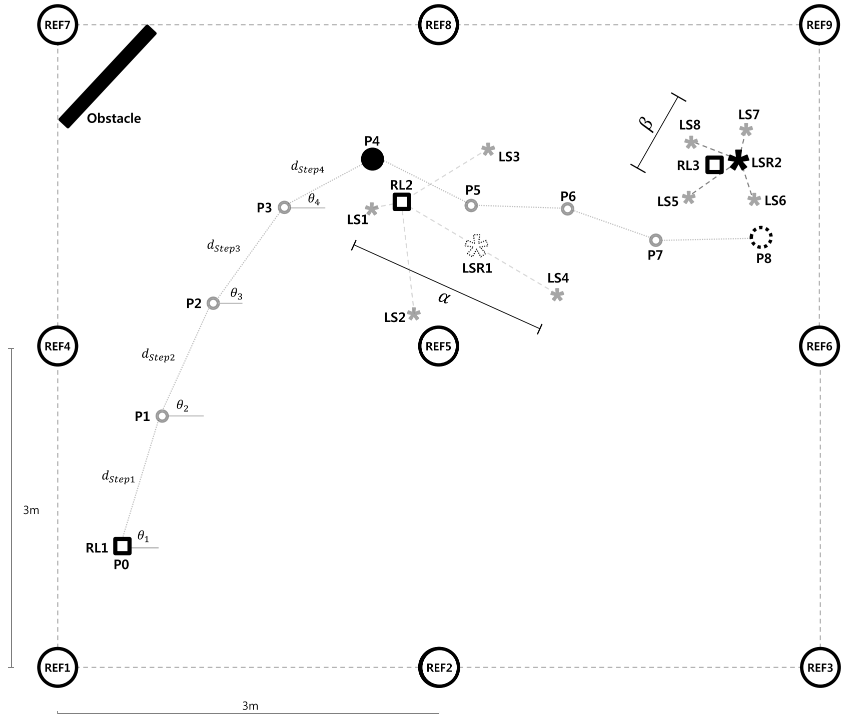

Fig. 5. Positioning based on proposed algorithm.

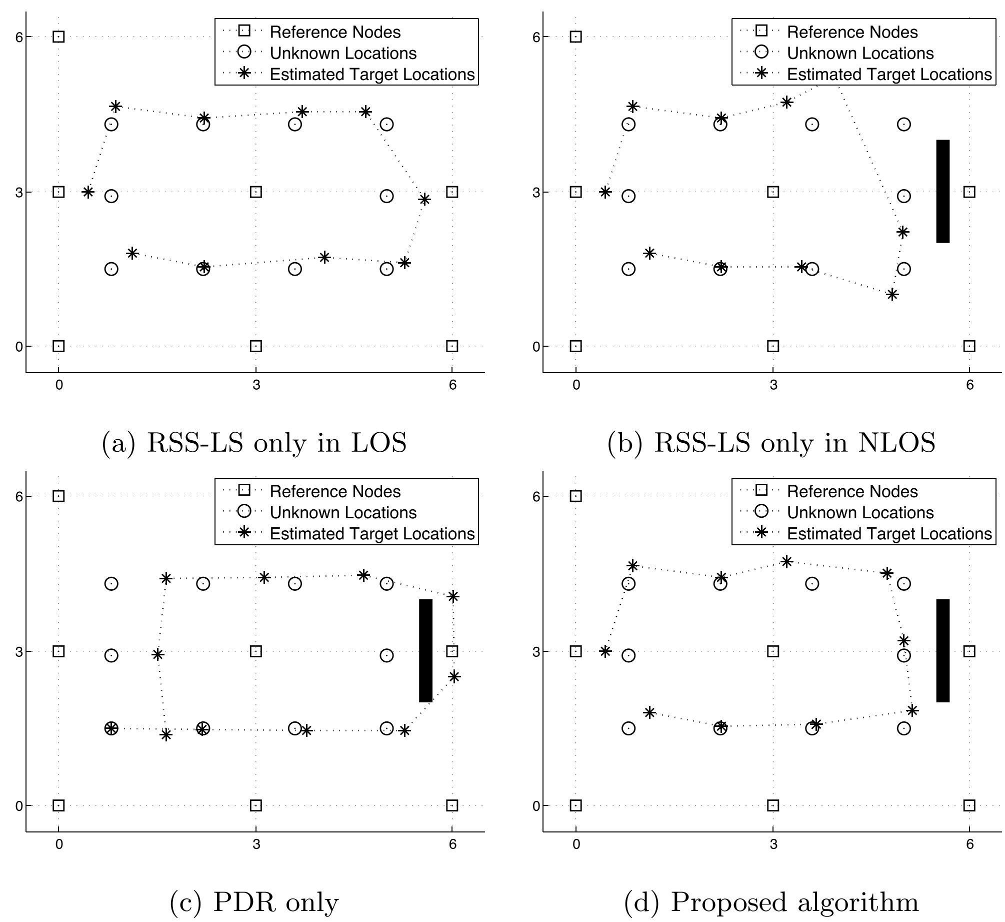

Fig. 6. Results of lab-scale experiments.

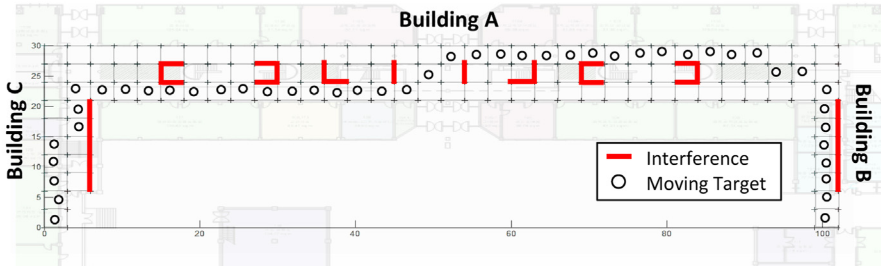

Fig. 7. Simulation area.

Table 1
Experimental results

Used method with environment	Average estimation error (m)
RSS-LS in LOS	0.27
RSS-LS in NLOS	0.50
PDR	0.62
Proposed algorithm in NLOS	0.30

Table 2
Simulation parameters

Parameters	Value
P_0 (RSS at 1 m) (dBm)	−31
μ (path loss constant)	2.4–4.6
Average step length (m)	0.5
STD of step length (m)	0.083
NLOS attenuation (dBm)	15

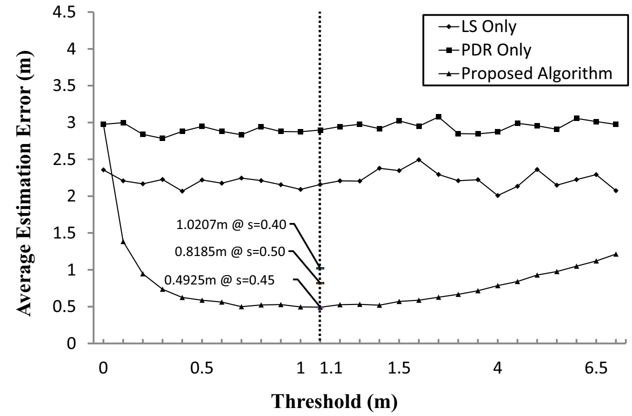

Fig. 8. Performance comparison.

Total 10 unknown locations are placed in the area and a mobile target node moves in reverse clockwise direction from the very bottom-left starting location. In Fig. 6(b)–(d), an obstacle is placed at the center-right reference node. Four closest reference nodes with the highest RSS values in order are used for RSS-LS. The average estimation errors of each case are shown in Table 1.

In Fig. 6(a), only RSS-LS is used and there is no interference in the area. The average error of 10 estimation results records 0.27 m. In case (b), an obstacle is placed at the center-right reference node and RSS-LS is used. The average location error is increased to 0.5 m. In case (c), only PDR is used to track the moving target node. The average estimation error in this case is 0.62 m. Fig. 6(d) shows the location estimation results of the target node by using the proposed algorithm. The NLOS errors are compensated by using PDR location tracking and the overall average estimation error is reduced to 0.3 m. This shows that the proposed algorithm has the NLOS error compensation capability.

4.2. Large scale simulation

We conducted the large scale simulation based on the first floor of engineering building environments, which is shown in Fig. 7. The simulation area consists of square cells with sides of 3 m, and reference nodes are placed on every corner of the cells. A target node is moving from the end of Building C to the other end of Building B, across the Building A.

The target's step lengths are Gaussian distributed random variables with the average of 0.5 m and standard deviation of 0.083 m. The PDR duration is 6 steps. The trajectory of target node and the obstacles are marked in Fig. 7. Based on Fig. 1, NLOS attenuation is set to 15 dBm with standard deviation 1.79. Simulation parameters are obtained from the experimental results in the engineering building, which are summarized in Table 2. Note that the path loss constant depends on the target's location. In this simulation, the path loss constant is 2.4 when the target is in the lobby, and is 4.6 when the target is in the hallway.

Fig. 8 shows the simulation results of the proposed algorithm for the threshold value k and the step constant s. Threshold value k controls the sensitivity of the NLOS detection. If k is set too small, the error distance D caused by natural RSS fluctuations can exceed the threshold and it can be considered as the NLOS condition. In this case, PDR location will be chosen more frequently. Especially when k is zero, LS location will never be selected in location determination phase because D is always greater than or equal to zero. The estimation error of the proposed algorithm will be increased to as high as that of PDR. If k is set too large, the error distance D caused by interference may not exceed k. LS locations can be selected even in NLOS condition and thus the estimation error of proposed algorithm is increased due to the NLOS error. Fig. 8 shows these relationship between threshold value and average location error clearly.

In the simulation, the target node moves 141 m (16 times of LOS conditions and 31 times of NLOS conditions during 47 iteration cycles). The average number of consecutively performed PDR is 4.4. The average location estimation error is 0.4925 m when s is 0.45 and k is 1.1 m. If the value of the step constant s varies within the range between 0.4 and 0.5, the average location estimation error is changed from 0.4925 m to 1.02 m. Considering the average number of consecutively performed PDR, we can see from the simulation results that the accumulated estimation error of PDR is limited, and the effect of the step constant s in the proposed algorithm is limited too.

5. Conclusion

We have presented a new indoor localization algorithm for WSN, which improves the estimation accuracy of RSS-LS by combining with PDR. PDR is used to compensate the NLOS error of RSS-LS, while the accumulated error of PDR is mitigated by using

RSS-LS in LOS condition. Two different estimation methods are used to complement each other. The NLOS condition is detected by observing the error distance of LS results obtained from reference node subsets. Lab-scale experiment and large scale simulation results proved that the proposed algorithm provides significantly reduced localization error when compared with sole PDR or RSS-LS method in LOS and NLOS mixed environments.

Future work will focus on the optimization of the reference node placement and new detection algorithm that can handle multi-interference NLOS conditions.

Acknowledgement

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science, ICT & Future Planning (NRF-2012R1A1A2007529).

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