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A Practical Indoor Localization Scheme for Disaster Relief

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Abstract

A Practical Indoor Localization Scheme for Disaster Relief

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Indoor localization technique is very helpful for rescuing people in disaster relief. However, since the existing communication facilities may shut down and the indoor environment can be changed (damaged) under disaster conditions, the traditional localization scheme is likely to cause a large estimation error and even may not work. In this paper, we propose a new indoor localization scheme for disaster relief. The proposed localization scheme is composed of two phases: in the first (off-line) phase, the target area is divided into several subareas; in the second (online) phase, the scheme finds out the subarea where the target node locates. Because the proposed scheme does not require any pre-measurement of radio characteristics between points in the target building, it is very useful from the practical point of view. The simulation results show that the proposed scheme provides a higher localization accuracy compared with the existing approach.

In addition, the experimental results verify the feasibility of the proposed scheme in practice.

Keywords : Indoor localization, Disaster relief, Radio, Floor plan, Subarea

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Chapter 1
Introduction

When a disaster such as a fire and earthquake occurs, an indoor localization technique can be very helpful for rescuing people in the building. Since a disaster is highly likely to be accompanied with blackout, communication facilities which are installed in the building may not work. In this case, the indoor localization techniques utilizing infrastructures [1]-[3] cannot be used. Instead, the received signal strength (RSS) between the rescuer's device and the victim's one can be used for indoor localization.

Many indoor localization techniques based on RSS have been developed recently. Lateration and fingerprinting are two major techniques in this category. The lateration-based method [4] uses a path loss model and triangulation to estimate the location of a node. In triangulation, distances from three or more different points are needed to estimate the location of certain point. Thus, the location of a target can be estimated by using distances from three or more different signal sources. Also, the distance between a signal source and a target can be calculated from RSS by utilizing a path loss model. However, in complex indoor environment, path loss model may not be accurate. Accordingly, the distance estimated by path loss model may not also be accurate. When one or several distances from signal sources are not accurate, the localization accuracy drops significantly. Therefore, lateration-based method is not likely to be suitable for a disaster relief situation.

The fingerprinting-based method [1] utilizes the pre-surveyed RSS

data between a signal source and certain points of a building. In fingerprinting-based localization method, the localization process consists of two phases which are the off-line phase and the online phase. In the off-line phase, RSSs are measured from some predetermined reference points (RPs) with known coordinates. These measured RSSs are called fingerprints and stored in a database. In the online phase, the location of a target device is determined by comparing fingerprints with the RSS measured at the target device. The accuracy of fingerprinting-based method is highly affected by the number of RPs. Note that it is very time consuming and labor intensive task to measure the RSS from a lot of RPs. Furthermore, as the number of the RPs increases, the computational cost for localization in the online phase increases geometrically. In addition, the fingerprinting-based localization is so sensitive to a change of the environment. For example, if indoor environment in the online phase becomes different with that in the off-line phase, the accuracy of a fingerprinting-based localization can be highly degraded. Since the indoor environment of a certain building may become different during a disaster, fingerprinting-based method may not also be suitable in a disaster relief situation.

To reduce the computational cost of fingerprinting-based method, the indoor localization using a subarea division method [5] was proposed. In the subarea division method, the indoor area is divided into several subareas based on the indoor layout. For example, since RSS is highly affected by walls in the indoor environment, each room enclosed with the walls can be a candidate for the subarea of the environment. Then, the room where a target device locates can be found in relatively short

time. In a disaster relief situation, it is more useful to find a room where the victims are located in short time than to find an exact position of victims in relatively long time. Therefore, the subarea division technique is useful in the disaster relief situation. However, since [5] uses fingerprinting-based method to find out which subarea the target device locates, the scheme still has the weakness of fingerprint technique as mentioned above.

We, in this paper, design a new indoor localization scheme based on the subarea division method, which can work effectively in the disaster relief situation. Since the fingerprinting-based method requires a high cost of building fingerprints database in the off-line phase, our scheme uses a probability based on a path loss model to estimate the subarea where the node locates. In the proposed scheme, the localization process consists of two phases which are the off-line phase and the online phase. In the off-line phase, we divide a target building into several subareas based on the floor plan of the building. Since the proposed scheme does not measure RSS in the off-line phase, it can reduce the cost of the off-line phase compared with fingerprinting-based method.

In the online phase, mobile nodes corresponding to rescuers go around the building to find stationary nodes such as victims which are not moving. Mobile nodes can track their respective locations through, for example, the pedestrian dead reckoning (PDR) technique [6]. The PDR technique utilizes sensing values from accelerometer and magnetometer in a mobile device to track the location of the device. In the proposed scheme, each mobile node estimates the moving distance from accelerometer and the moving direction from magnetometer and gyroscope. Then, each mobile node can estimate its location by using the moving distance and

the moving direction during certain time period. While each mobile node tracks its location, the node sends a signal to stationary nodes (victims) near the mobile node. When stationary nodes receive a signal from mobile nodes, they report RSS to mobile nodes. Then, mobile nodes estimate the location of the stationary node based on a path loss model and a subarea database constructed in the off-line phase. Instead of directly calculating a distance between nodes, a localization server estimates the probabilities that each stationary node locates on each subarea based on path loss model. Finally, the location (subarea) of the stationary node is determined by these probabilities.

The goal of this paper is to design a practical indoor localization scheme which can be used even in the harsh environment like the disaster situation. First, we propose the subarea division method by using the floor plan of the building to eliminate the cost of measuring RSS which is needed in the fingerprinting-based technique. Since the database is constructed automatically by using only the floor plan, the proposed subarea division method is simply applicable to the various buildings. In addition, we propose the RSS-based localization scheme using communication between devices instead of pre-installed facilities. Finally, the simulation results show that the proposed method is more tolerant to the environmental changes, compared with the traditional fingerprinting-based method. Therefore, our scheme can be a practical solution for the disaster relief application like rescuing people in the building.

The remainder of this paper is organized as follows. We describe the system model in the next section. In Section III, we present the proposed scheme in details. Simulation results and experimental

results for evaluating the performance of proposed scheme are presented in section IV and V, respectively. Finally, the paper is concluded with Section VI.

Chapter 2
System Model

We assume that there are two types of nodes in the building which are stationary nodes and mobile nodes. Stationary nodes which represent victims in the building do not know their own locations. On the contrary, mobile nodes which represent rescuers in the building know their respective locations. Since rescuer may get in a floor by the entrance of the building or by stairs, we assume that all mobile nodes know their initial locations in the floor. In addition, similar to [7], we group several mobile nodes and select one of these nodes as a group leader for accurate localization of mobile nodes. Then, we use RSS between a group leader and the other group members to correct an estimation error.

We consider a system with M mobile nodes and N stationary nodes in a single-floor area. In the proposed scheme, path loss model is utilized to estimate the probability that each stationary node locates on each subarea from reported RSS. We consider not only the distance between two nodes but also the wall attenuation factor (WAF) by walls between two nodes. According to COST231 Multi Wall Model [8], the path loss model with WAF can be represented as

$$PL(d) = PL(d_0) + 10\gamma\log(d/d_0) + WAF, \tag{1}$$

where $WAF = \sum_{w=1}^{N_w} \mathrm{waf_w}$ and $\mathrm{waf_w}$ is the signal attenuation due to wall w. And, γ is a path loss exponent and d_0 is a reference distance which is typically assumed as 1 m.

Let d_{ij} be the distance between the mobile node i and the

stationary node j. When the mobile node i transmits a signal with transmit power T_i (dB), RSS at the stationary node j, R_{ij}, is given by

$$R_{ij} = R_0 - 10\gamma\log(d_{ij}) - WAF + \eta_i, \tag{2}$$

where $R_0 = T_i - PL(d_0) + 10\gamma\log(d_0)$ is RSS at distance d_0 and η_i is a zero-mean Gaussian noise with standard deviation σ. Since $\eta_i \sim N(0,\sigma^2)$, $R_{ij} \sim N(C,\sigma^2)$ is met for certain γ and d_{ij} where $C = R_0 - 10\gamma\log(d_{ij}) - WAF$. Therefore, we can calculate the accuracy of given distance d compared to real distance d_{ij} when measured RSS is r_{ij} by using the following accuracy function.

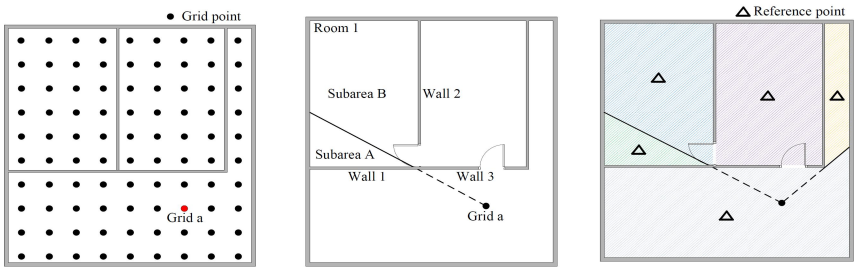
$$A(d,r_{ij}) = \Pr\left\{\frac{r_{ij} - \hat{C} - \epsilon}{\sigma} \le Z \le \frac{r_{ij} - \hat{C} + \epsilon}{\sigma}\right\}, \tag{3}$$

where $\hat{C} = R_0 - 10\gamma\log(d) - WAF$ and ϵ is a constant value which controls the accuracy of this function.

Chapter 3
Proposed Localization Scheme

In the proposed scheme, the localization process consists of two phases which are the off-line phase and the online phase. In the off-line phase, we create a subarea database by using a floor plan of the building. In the online phase, the locations of stationary nodes are estimated as following steps. First, each mobile node calculates its current position (for example, based on PDR technique). To enhance the accuracy of mobile node localization, each mobile node determines whether the estimated position needs a correction by checking a certain condition. If a mobile node meets the condition, the mobile node requests the correction to the group leader. Then, a group leader performs the correction process for the position of the mobile node that needs correction and notifies the corrected position to the mobile node. Next, each mobile node calculates the position of each stationary node based on its estimated position, the RSS from the stationary node and the subarea database constructed in the off-line phase. Since the positions of a stationary node estimated at different mobile nodes may be different from each other, each mobile node reports the estimated position of each stationary node to the localization server for finding the best-fit position of the stationary node. Finally, the localization server determines the position of a stationary node with the highest accuracy among the positions reported from all mobile nodes as the final position of the stationary node. We give further details about each part of the proposed scheme.

A. Subarea Division



(a) (b) (c)

Fig. 1. A process of a subarea division.
(a) Grid points in the area. (b) Subarea of room 1 at grid point a.
(c) Reference points at grid point a for the whole area.

To build a subarea database, we divide a target area into grids with equal size like Fig. 1(a). Then, the target area is partitioned into several subareas for each grid point. Since RSS is mainly affected by walls in indoor environment, we divide the target area into subareas according to the number and the kind of the walls between the area and each grid
point. Fig. 1(b) describes the subarea division for room 1 at grid point a. For example, if a signal is transmitted from the grid point a, the signal is attenuated by wall 1 when the signal is received from any points in subarea A. Similarly, the signal from the grid point a is attenuated by wall 2 and 3 when the signal is received from any points in subarea B. Therefore, we divide the room 1 into two parts which are subarea A and subarea B in this case. After dividing subareas for the entire target area in a similar way, we select the center of each subarea as an RP. Fig. 1(c) describes the RPs at grid point a for the whole target area. In this way, we create a set of the RPs separately for each grid point.

Let WAF_{ij} denote the attenuation factor by the walls between

the grid point i and RP j. WAF_{ij} is given by $\sum_{k=1}^{n} \mathrm{waf_k}$ where n is the number of walls between the grid point i and RP j. For each grid point i and each RP j, we store the position of RP and WAF_{ij} in a database. This database will be used for localization of the stationary node in the online phase. When a mobile node locates on a certain grid point in the online phase, the location of stationary node is determined as one of the RPs corresponding to the grid point. Each RP indicates the possible position of stationary node and WAF_{ij} indicates the signal attenuation due to walls between two nodes. Then, the proposed algorithm calculates the probability that a stationary node locates on each possible position.

B. Mobile Node Localization

The proposed scheme can be used with a variety of methods to track the location of a device moving in the building. Among them, we consider the PDR technique [6] as an example, since PDR can be simply applicable to track a mobile node. The PDR uses the measured values from sensors to estimate the moving distance and the moving direction. Moving distance is estimated by counting the number of step events. The step event is the event representing whether the mobile node moves. In the proposed scheme, when a measured value of accelerometer becomes a peak value, it is considered that a step event happens. We assume that every step event has the same step length l. Thus, the moving distance can be calculated by $D = l \times N_s$ where N_s denotes the number of step events during certain time period. Also, we estimate a moving direction by averaging the measured values of gyroscope during

certain time period. It is noted that the error of the moving direction is not large because an averaged value of gyroscope is used for estimating the moving direction.

Since the initial location of a mobile node is known, the location of the mobile node can be estimated by the moving distance and moving direction. However, this simple PDR technique may have a large estimation error due to the errors in the sensing values accumulated over time. In [7], the mobile nodes are grouped and the locations of them are corrected by using RSS between the nodes in the group. In the proposed scheme, a similar correction technique by grouping is used.

Let us describe this correction process in more detail. At every localization time t, a group leader sends a localization request message to the other mobile nodes in the group. When receiving the localization request message, each mobile node i measures the RSS of this message, r_{il}, and computes its estimated position, $\widehat{M_i^t}$, using the moving distance D_i^t, the moving direction θ_i^t, and its location at time $t-1$, M_i^{t-1}. After that, the mobile node i checks whether $\left|\theta_i^t - \theta_i^{t-1}\right|$ is larger than a certain threshold value τ_θ. If $\left|\theta_i^t - \theta_i^{t-1} > \tau_\theta\right|$, the moving direction of the mobile node is changing. Otherwise, this difference may come from the error of sensing values and cause an estimation error. In this case, the estimated location of each mobile node needs correction. Let S_u denote the set of mobile nodes such that the difference between moving directions of the node at time $t-1$ and time t is smaller than τ_θ. Each mobile node i in S_u requests the correction by reporting its final estimated position at time $t-1$ (M_i^{t-1}), the computed position at time t ($\widehat{M_i^t}$), D_i^t, θ_i^t, and r_{il} to the leader.

Then, the group leader l corrects the locations of mobile nodes in S_u.

The correction process is as follows. For each mobile node i in S_u, two candidate positions are considered in correction process. One is the position $\widehat{M_i^t}$, calculated and reported by the mobile node i at time t. The other is the position m_i^t, calculated by the group leader l. The leader computes m_i^t under the assumption that the mobile node i located at M_i^{t-1} at the time $t-1$ moves the distance of D_i^t (reported by the mobile node i) in the direction of θ_i^{t-1}. Note that $\widehat{M_i^t}$ is calculated by using the direction θ_i^t whereas m_i^t is obtained by using the direction θ_i^{t-1}.

On the other hand, the group leader also can be in S_u. In this case, the position of leader should be corrected. The group leader l selects one having higher average accuracy among m_l^t and $\widehat{M_l^t}$, as its final corrected position M_l^t. That is, when $dis(a,b)$ denotes the distance between points a and b,

$$M_l^t = \mathrm{argmax}_{v \in \mathrm{m}_l^t, \widehat{\mathrm{M}}_l^t} \frac{1}{2n} \left\{ \sum_{i \in S_u, i \neq l} A\left(dis(v, \widehat{M_i^t}), r_{il}\right) + A\left(dis(v, \overline{M_i^t}), r_{il}\right) \right\}, \quad (4)$$

where n is the number of mobile nodes in S_u, except the leader. Similarly, the position of mobile node i in S_u is corrected by using the final estimated position of the leader, M_l^t, as follows,

$$M_i^t = \mathrm{argmax}_{v \in \mathrm{m}_i^t, \widehat{\mathrm{M}}_i^t} A\left(dis(M_l^t, v), r_{il}\right), \quad (5)$$

After correcting the positions of all mobile nodes in S_u, the leader notifies these corrected positions to the mobile nodes.

C. Stationary Node Localization

After mobile node localization finishes, all mobile nodes estimate the location of each stationary node. The mobile node i estimates the location of the stationary node j as follows. First, mobile node i gets the RPs and the wall attenuation factor WAF_{ir} corresponding to each RP r from the database constructed in the off-line phase. Since the estimated location of mobile node i is any position in the area, we assume that each mobile node locates on the nearest grid point from the estimated location of the mobile node.

Next, the mobile node i measures the RSS, r_{ij}, from the stationary node j. Let d_{ij}^{r} denote the distance between the mobile node i and the stationary node j under the condition that the stationary node j locates on the RP r. Then, we can calculate the accuracy of d_{ij}^{r} by accuracy function in (3). If the real position of the stationary node j is close to the RP r, the accuracy of d_{ij}^{r} becomes higher. Therefore, the accuracy of d_{ij}^{r} can be referred to as the probability that the stationary node j locates on the RP r in terms of the mobile node i.

However, since the mobile node usually locates at any position (not at a grid point), selecting the RP with the highest probability may not be accurate. Therefore, localization result at time $t-1$ is used additionally in the proposed scheme. We define S_{ij}^{t} as the set of RPs of which the calculated probability is higher than a certain threshold value τ_a at time t,

$$S_{ij}^{t} = \left\{ X_r \mid X_r \in S,\ A\left(dis(M_i^{t}, X_r), r_{ij}\right) > \tau_a \right\}, \tag{6}$$

where S is a set of all RPs. If $|S_{ij}^t| = 0$, the mobile node i lowers the τ_a by δa and calculates again until $|S_{ij}^t| > 0$. Then, mobile node i estimates the location of a stationary node j as an RP with the highest probability from S_{ij}^{int} which is the set of RPs that is made by considering a previous result,

$$S_{ij}^{\text{int}} = \{X_r \mid X_r \in S_{ij}^t,\ X^{t-1} \in S_{ij}^{t-1},\ dis(X_r, X^{t-1}) \le \tau_d\}. \tag{7}$$

This is based on the following reasoning. When a mobile node (i.e., rescuer) is a pedestrian, its moving speed is not high and its moving distance during location update interval is expected to be small. For this reason, the estimated position of a stationary node at time t is not greatly different from that at time $t-1$. Accordingly, the position of stationary node j can be selected from set S_{ij}^{int}. However, if $|S_{ij}^{\text{int}}| = 0$, a mobile node estimates the location of a stationary node as an RP with highest probability from S_{ij}^t. The steps of localization of stationary node j at mobile node i are given in the Algorithm 1.

To enhance the accuracy of localization further, the localization server collects the localization results of all mobile nodes and chooses one of the results as the final location of stationary node. If there are two or more mobile nodes in a group, each mobile node sends its position M_i^t, the estimated position of the stationary nodes j, X_{ij}^t, and the RSS from each stationary node r_{ij} to the localization server. Let P_j^t denote a set of estimated positions of the stationary node j from all mobile nodes.

$$P_j^t = \{X_{1j}^t, X_{2j}^t, \cdots, X_{Mj}^t\}. \tag{8}$$

Then, the localization server selects an RP having the highest

Algorithm 1 Stationary Node j Localization by mobile node i

$S_{ij}^{t} \leftarrow \phi$
while $|S_{ij}^{t}| = 0$ **do**
    Compute the S_{ij}^{t} by using M_i^t and S.
    $\tau_a \leftarrow \tau_a - \delta_a$
end while
Compute the S_{ij}^{int} by using S_{ij}^{t} and S_{ij}^{t-1}.
if $|S_{ij}^{int} = 0|$ **then**
    $X_{ij}^{t} \leftarrow \underset{X_r \in S_{ij}^{t}}{\operatorname{argmax}} A\left(dis(M_i^t, X_r), r_{ij}\right)$
else
    $X_{ij}^{t} \leftarrow \underset{X_r \in S_{ij}^{int}}{\operatorname{argmax}} A\left(dis(M_i^t, X_r), r_{ij}\right)$
end if
return X_{ij}^{t}

average accuracy from P_j^t as the final estimated location of stationary node j, by using (9) similarly to (4).

$$X_j^t = \operatorname{argmax}_{X \in P_j^t} \frac{1}{M} \sum_{i=1}^{M} A\left(dis(M_i^t, X), r_{ij}\right). \tag{9}$$

Chapter 4
Simulation

A. Simulation Setup

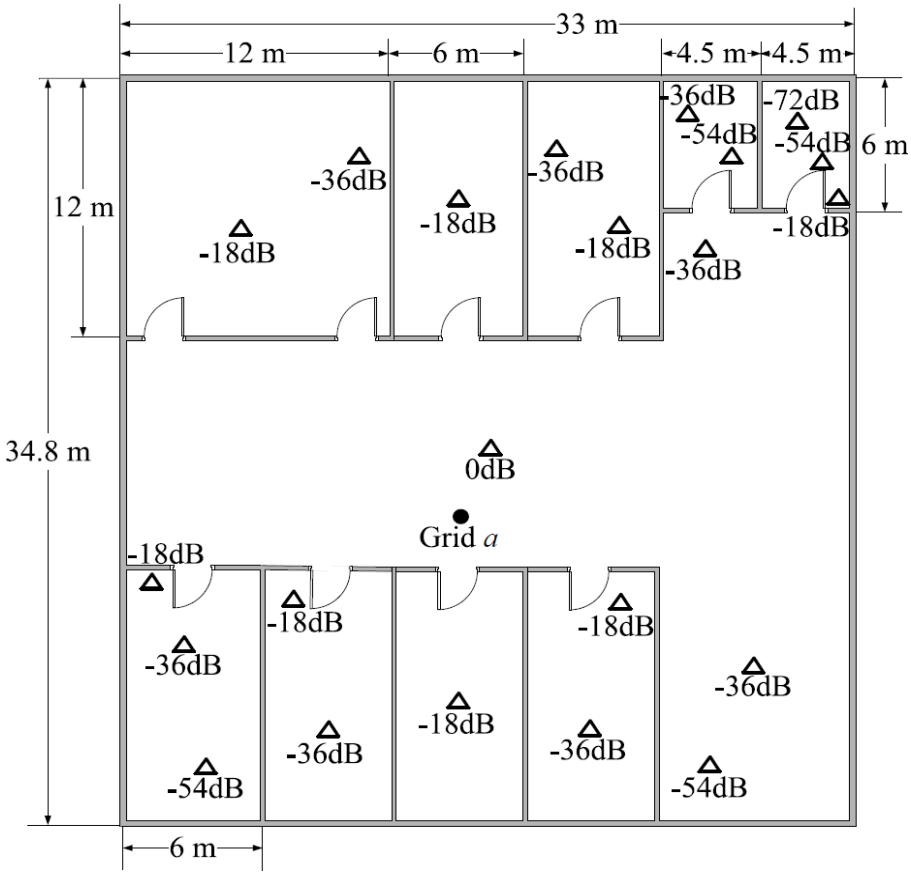


Fig. 2. Floor plan of the testing environments and an example of subarea database at grid point a (△: reference points).

In this section, we evaluate the performance of proposed localization scheme through simulation. The total floor plan is 33.0

m $\times$ 34.8 m size. Fig. 2 shows the floor layout which models third floor of the Engineering Building 302 of Seoul National University. We use $R_0 = -23$ dB and the standard deviation of shadowing effect $\sigma = 6$ dB. Also, we assume that all walls respectively have the same wall attenuation factor of 18 dB. These parameters are obtained through empirical ways. As an example, the set of RPs and wall attenuation factor at grid point a are shown in Fig. 2. Other parameters are accuracy threshold $\tau_a = 0.85$, $\tau_\theta = \frac{\pi}{18}$ rad, $\epsilon = 18$, and $\tau_d = 2$ m. The localization update interval is set to 1 second. We randomly distribute 10 stationary nodes in the area. In simulation, each mobile node moves with speed of 1 m/s and its position is assumed to be exactly known for concentrating on showing the accuracy of stationary node localization which is a final goal of the proposed scheme.

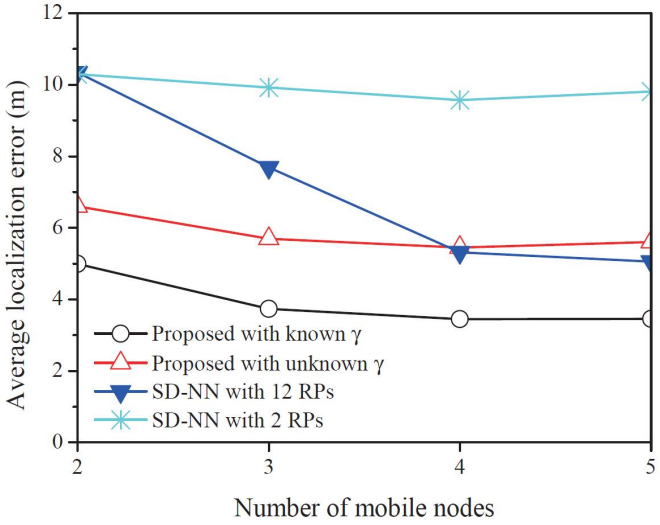
For the performance evaluation, we compare the proposed scheme with the existing fingerprinting-based nearest neighbor algorithm coupled with the subarea determination algorithm in [5] (shortly, SD-NN). In SD-NN algorithm, the number of RPs in each subarea affects not only the cost in the off-line phase but also the performance of an algorithm. So, we evaluate the performance of SD-NN algorithm for two cases which are 12 RPs in each subarea and 2 RPs in each subarea. As shown in (3), the accuracy in the proposed algorithm is based on the path loss model and, as a result, it is influenced by the path loss exponent γ. Thus, we assess the performance of the proposed scheme for two cases which are an ideal case that γ is known and a realistic case that γ is unknown. In each simulation run, the path loss exponent γ is set to the value distributed uniformly in between [2.0, 6.0]. For the

ideal case (known γ), we use the same value of γ for the computation in (3). On the contrary, for the realistic case, since we do not know the value of γ, we assume that $\gamma = 4.0$ for the computation in (3).

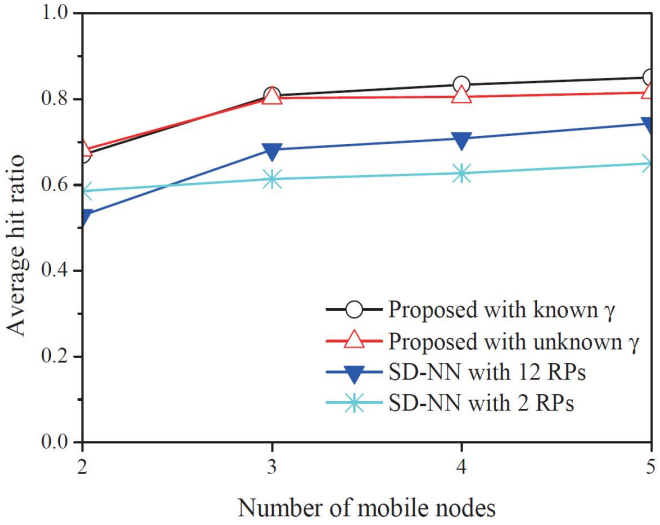
We compare the average localization error of stationary nodes and the average hit ratio. We define the hit ratio as the ratio of the number of stationary nodes of which a subarea is correctly determined to the number of all stationary nodes under test. In addition, since one of goals of the proposed scheme is the robustness to the environmental changes for a disaster relief situation, we compare algorithms in two different scenarios which are a normal scenario and a wall-damaged scenario. In a normal scenario, there are no environmental changes between the off-line phase and the online phase. In a wall-damaged scenario, some of walls in the area are damaged in the online phase. For each scheme in both scenarios, 200 runs of simulation are conducted.

B. Results of Normal Scenraio

In a normal scenario, we compare the average localization error and the average hit ratio versus the number of mobile nodes used for localization. Since the number of rescuers in the disaster relief situation may not be large for a single floor, we set the number of mobile nodes from 2 to 5. SD-NN algorithm uses AP which locates on a fixed and known position for localization. So, we give a fixed and known position for each mobile node that can be regarded as AP in SD-NN algorithm.



(a) Average localization error of stationary nodes



(b) Average hit ratio

Fig. 3. Simulation results of a normal scenario.

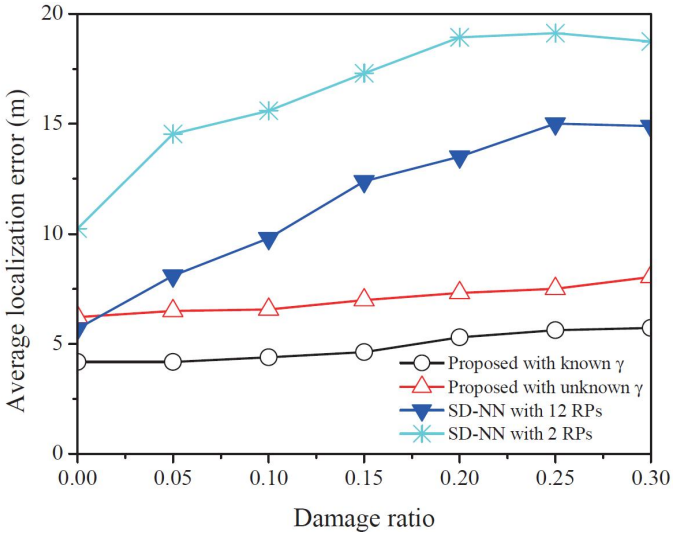
Fig. 3(a) and Fig. 3(b) illustrate the average localization error of stationary nodes and the average hit ratio in a normal scenario, respectively. Both the proposed scheme and the SD-NN algorithm show that as the number of mobile nodes increases, the average

localization error of stationary nodes decreases. This is because available RSS measurements increase as the mobile node gets more. Accordingly, since the effect of measurement noises becomes lower, the average localization error decreases. In case that the number of mobile nodes is small, even though the SD-NN algorithm uses many RPs per subarea, our scheme accomplishes more accurate localization. Even with 5 mobile nodes, the proposed scheme gives similar performance compared to the SD-NN algorithm with many RPs per subarea. However, if the existing algorithm uses many RPs per subarea, it requires a large cost of building fingerprints for RPs in the off-line phase. Since the proposed scheme requires much less cost in the off-line phase, it is more efficient in terms of the localization accuracy per the building cost. On the contrary, if the SD-NN algorithm uses less RPs to lower a training cost of the off-line phase, the proposed scheme gives more accurate localization results. In other words, our scheme can achieve higher localization accuracy with less cost than the existing approach.

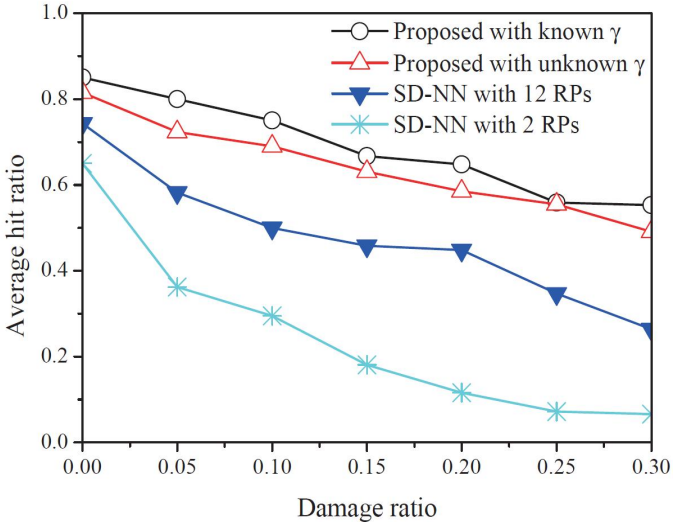
C. Results of Wall-damaged Scenario

In a wall-damaged scenario, we use 5 mobile nodes for each setting. Instead, we compare the average localization error and the average hit ratio versus the damage ratio of the area. Damage ratio is defined as the ratio of the number of walls which are damaged by a disaster to the number of all walls in the area.

Fig. 4(a) and Fig. 4(b) depict the average localization error of stationary nodes and the average hit ratio in a wall-damaged scenario, respectively. Both the proposed scheme and the SD-NN



(a) Average localization error of stationary nodes



(b) Average hit ratio.

Fig. 4. Simulation results of a wall-damaged scenario.

algorithm show that the average localization error of stationary nodes increases and the average hit ratio decreases as the damage ratio of the area gets larger. This is because the pre-surveyed data in the off-line phase becomes less reliable as the damage

ratio of the area increases. However, if environment is changed in the online phase, a change of RSS is much larger than the change of the wall attenuation. Also, since the proposed scheme checks the probability that RSS is within certain range, it is more tolerant than the SD-NN algorithm which uses fingerprint directly for localization. Therefore, our scheme suffers from less performance degradation than the SD-NN algorithm in a wall-damaged scenario.

Chapter 5
Experiments

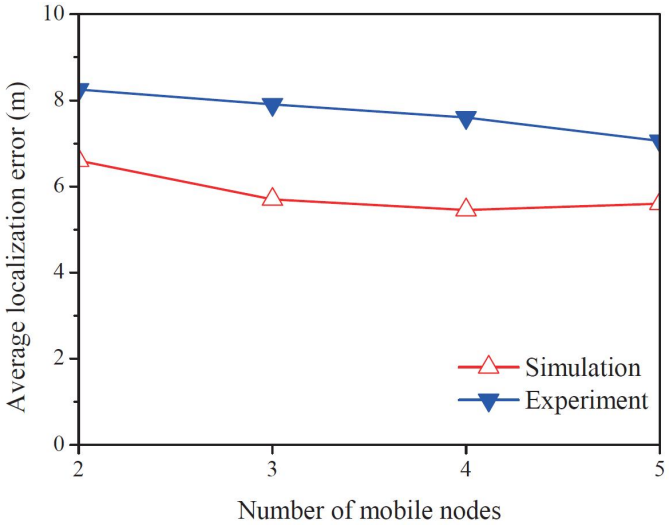
A. Experiment Setup

In this section, we evaluate the performance of proposed localization scheme through experiments. To verify the proposed scheme in practice, we compare experimental results with simulation results of it in Section IV. Experiments are conducted at third floor of the engineering building 302 of Seoul National University. We distribute 4 stationary nodes in our laboratory. The mobile nodes go around the corridor of the floor. Since signal from a mobile node cannot be detected at a stationary node if the mobile node is too far from the stationary node, experiment is conducted at one part of the floor. Testing environment is 33.0 m × 34.8 m size and Fig. 2 shows the layout. We use the same parameters as those used in simulation for the experiment. Also, we use the same database which was constructed by using only the layout of the building and the wall attenuation factor of 18 dB for each wall in the simulation. We implement the proposed scheme as the android application and conduct the experiment using commercial smart phones, Samsung Galaxy S4 and Samsung Galaxy Note 10.1. In our implementation, the mobile nodes use Bluetooth for communication between a group leader and the other group members. Since the distance between the group leader and the other group members may be small, it is enough to use Bluetooth for communication despite of the short communication range of Bluetooth. Also, the mobile nodes use Wi-Fi hotspot for

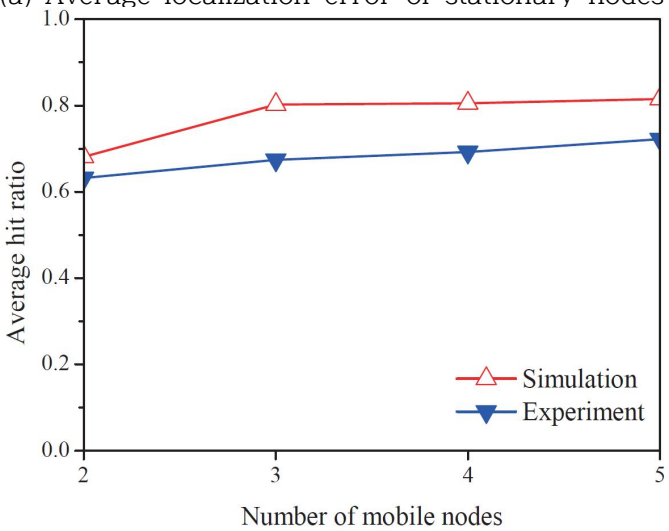
communication between mobile nodes and stationary nodes. Because almost every smart phone are equipped with Bluetooth and Wi-Fi hotspot, our implementation can be feasible even in the disaster relief situation.

We compare the average localization error of stationary nodes and the average hit ratio versus the number of mobile nodes used for localization. Like in a simulation setting, the number of mobile nodes changes from 2 to 5. For each case, experiment is conducted for 2 minutes.

B. Experiment Results



(a) Average localization error of stationary nodes



(b) Average hit ratio

Fig. 5. Experiment results compared with simulation results.

Fig. 5(a) and Fig. 5(b) illustrate the average localization error of

stationary nodes and the average hit ratio, respectively. Experimental results show that the accuracy is degraded about 10% compared with simulation results. Biased positions of the transmitters mainly cause the performance degradation. In simulation, we assume that the exact location of each mobile node is known to assess the localization performance of stationary nodes. On the contrary, since the locations of mobile nodes in experiments may have some estimation error, the localization accuracy of stationary nodes decreases. In addition, an inaccuracy of the path loss model may cause the performance degradation. Although the performance is degraded a little in experiments, it is enough to demonstrate the feasibility of proposed scheme in practice. Furthermore, since the proposed scheme needs only the floor plan of the building and a simple path loss model in the off-line phase, it can be simply applicable to the various buildings, compared to the fingerprinting-based approach which needs a high cost to actually measure the RSS for building a fingerprint database. Even if the average localization error may seem large, the proposed method can find the room where stationary node locates with high probability in short time. Therefore, our scheme is a very practical localization method with low cost especially in the urgent situation like a disaster relief. We expect that the localization accuracy can be improved if the rescuers use the mobile devices specialized for disaster relief usage.

Chapter 6
Conclusion

In this paper, we propose a new indoor localization scheme based on a floor plan.

Our scheme has two main advantages compared to the existing indoor localization method. By conducting subarea division according to the number of walls between nodes, our algorithm has more tolerance to the environmental changes in the online phase. In addition, the proposed scheme does not measure any RSS in advance to reduce the cost of building a database. The simulation results show that the localization accuracy is slightly improved compared with the existing fingerprinting method in a normal situation. Furthermore, the proposed scheme provides considerable performance improvements in a disaster situation. In addition to simulation, the experimental results verify that our scheme is feasible in practice.

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요 약

화재와 같은 실내 재난 상황이 발생한 경우, 실내 위치 추정 기술은 인명 구조에 크게 도움이 된다. 하지만 그러한 재난 상황에서는 건물 내의 기존 통신 시설들을 사용할 수 없게 되거나 실내 환경이 손상되어 변형이 발생하게 된다. 이러한 이유로 인하여 기존의 전통적인 실내 위치 추정 방식들은 재난 상황에서 큰 위치 추정 오류를 발생시키거나 동작하지 않을 수 있다. 이 논문에서는 기존의 실내 위치 추정 방식의 문제를 개선하여 재난 상황에서도 사용될 수 있는 새로운 실내 위치 추정 방식을 제안한다.

제안하는 방식은 오프라인 단계와 온라인 단계의 두 단계로 구성된다. 오프라인 단계에서는 건물의 설계도를 이용해서 해당 구역을 몇 개의 소구역으로 분리하는 작업을 수행한다. 온라인 단계에서는 피해자와 구조자 단말 간의 통신을 이용하여 피해자 단말이 위치하고 있는 소구역을 찾아낸다. 제안하는 방식은 대상 건물의 각 지점 간의 무선 특성에 대한 사전 측정을 필요로 하지 않기 때문에 실제 재난 상황에서 적용하기에 유용한 방식이다.

제안 방법에 대한 시뮬레이션 결과, 기존 방식에 비해 일반적인 상황과 재난으로 인해 건물의 구조가 변화한 상황 모두에 대하여 더 높은 위치 추정 정확도를 보여주었다. 또한 실제 실험 결과를 통해 제안하는 방식의 실제 상황에 대한 적용 가능성을 보여주었다.

주요어 : 실내 위치 추정, 재난 구조, 무선 통신, 실내 도면,
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