# Effects of Partial Infrastructure on Indoor Positioning for Emergency Rescue Evacuation Support System

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## ABSTRACT

Indoor positioning is a key component of an Emergency Rescue Evacuation Support System (ERESS). However, there has been limited works on evaluating indoor positioning schemes in consideration of emergency situations such as fire and earthquakes. Especially, some or all of the indoor infrastructures (e.g. WiFi APs) could be unavailable due to the disasters, which are reference points of the schemes. We design and implement a realistic simulation to evaluate the schemes with ignition of fire, spread of smoke, and malfunction of infrastructure. In the simulation, positioning accuracy of two representative bases of indoor localization schemes is evaluated, which are Pedestrian Dead Reckoning (PDR) and Wi-Fi fingerprinting based on Received Signal Strength (RSS). In both techniques, we use the Particle Filter algorithm to improve the accuracy of localization. For realistic simulations, we model a WiFi infrastructure and its breakdown process using the Anylogic software with smoke propagation data with the Fire Dynamics Simulator (FDS). We also compare the real time pedestrian trace with the estimated locations obtained by the schemes.

## CCS CONCEPTS

• **Computing methodologies** → *Simulation tools*; • **Information systems** → *Location based services*;

## KEYWORDS

Indoor Positioning, Partial Infrastructure, Emergency Rescue Evacuation Support System, Simulation, Particle Filter


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## 1 INTRODUCTION

Locating the position of an evacuee is crucial for emergency rescue and evacuation. Due to the rapid growth of mobile positioning schemes, mobile devices can be found with high accuracy (within few meters of radius) both outdoors and even indoors. In emergency situations, this location data is viable for taking adequate and timely actions.

If disasters such as fire and earthquakes occur in indoor environments like libraries, shopping malls and subway stations, it can lead to the loss of lives and serious injuries. In order to prevent such tragic consequences, the indoor positioning would play an important role in Emergency Rescue Evacuation Support System (ERESS) by locating individuals inside the building and guiding them to a safer place.

There are already many solutions for indoor positioning based on IrDA (Infrared Data Association), Ultrasound, Bluetooth and Radio Frequency technologies; however, none of which may be suitable for the disaster situations [10]. Considering the breakdown of an infrastructure due to the disaster, the above solutions are not expected to achieve the accuracy as they do in normal situations.

Therefore, we propose a novel indoor positioning scheme with a partial infrastructure, which refers to the case where only a part of the infrastructure provides its functionality like electricity. Especially the proposed scheme focuses on the high error distribution of Pedestrian Dead Reckoning (PDR) [2], and the high variation of Wi-Fi Received Signal Strength Indication (RSSI) [1, 4, 11] as the infrastructure becomes collapsed gradually. Depending on an partial availability of infrastructure, the two elements can play complementary roles.

After that, we develop a simulation tool that visually displays the pedestrian movement on the map, which enables the calculation of the estimated pedestrian position depending on the selected indoor

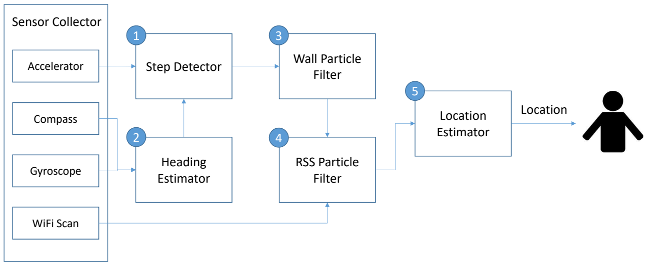


**Figure 1: Components of The Localization System**

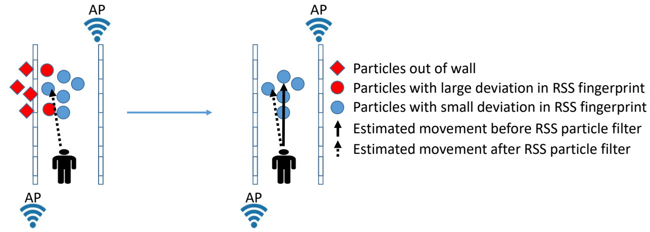


**Figure 2: The particle filtering algorithm is compensated by the fingerprinting data**

positioning schemes. Our tool uses the Anylogic software to design a map of a building on fire with walls, and Wi-Fi APs with their RSSI fingerprint information. We expect that this simulation tool will be helpful for indoor localization researchers who might have a problem to build the indoor fire testbeds in real because it may cost huge and they may also be in danger. For the evaluation purposes, we implement and evaluate the performance of two indoor positioning schemes: one is based on the PDR only, and the other is based on the PDR with Wi-Fi RSSI fingerprints. Both implementations employ the Particle Filtering algorithm to probabilistically track the pedestrian position on the map. We will describe the implementation of the tool and the two indoor positioning schemes and their results in this paper later on.

## 2 BACKGROUND

In recent years, the rapid advances in wireless communications technologies and the wide availability of various sensors in smartphones have made indoor localization techniques proliferate. One of the important components in indoor localization is the PDR that relies on inertial and magnetic sensors in smartphones to detect the movement and heading direction of the pedestrian [7]. Another popular approach is based on Wi-Fi, which leverages the RSSI of Wi-Fi APs. Since the RSSI measurements are sensitive to multipath propagation in indoor environments, numerous studies have been devoted to deal with the issue.

In Wi-Fi based approaches, there are two typical approaches to localizing a mobile from indoor RSSI measurements: modeling RF propagation losses and fingerprinting. The former uses multilateration to compute the distance between a user's mobile, based on the RSSI, and the Wi-Fi APs, while the latter uses a RSSI fingerprint database where the RSSI data of each location measured from multiple APs are stored.

In this paper, we implement a simple PDR-based localization scheme and another scheme based on the PDR and RSSI-fingerprinting that can give a more promising result even if one or more APs break down in disaster situations [6].

## 3 SYSTEM DESIGN

To cope with disaster situations, an indoor positioning system should be able to operate properly even though some part of the infrastructure malfunctions or becomes out of service. We assume that the disaster never changes the building structure in our scenario. PDR-based localization can be the first priority considering the unavailability of the infrastructure because it does not require any reference infrastructure to estimate user's position. However, the PDR has an intrinsic limitation of error-propagation (e.g., the estimation error keeps accumulated by the error of direction or stride length). On the other hand, Wi-Fi fingerprint approach may be free from the limitation while the reference infrastructure is positively necessary to this approach. We believe that the PDR based estimation of the position can be enhanced by leveraging Wi-Fi RSSI measurements especially when only some part of the infrastructure (e.g., Wi-Fi APs) can serve as reference points. The proposed system can operate in two modes: PDR-only and PDR + RSSI. The former mode is for the worst case—all the Wi-Fi APs in the infrastructure are down. The latter mode is for the case when the partial infrastructure is available (some APs are operating). The system automatically takes one of the two modes according to the number of available APs.

Figure 1 introduces the functional blocks of the proposed system. First, the sensory data is collected from the sensors—accelerator, compass, gyroscope, and Wi-Fi module. We need the above sensors because the proposed system combines PDR approach with Wi-Fi based approach. For the PDR scheme, the step-wise movement of a person should be detected for accurate estimation because a human movement consists of repeated steps (in the 1$^{st}$ block in Figure 1). The heading direction could be estimated from the compass and gyroscope data with the previous direction (in the 2$^{nd}$ block). Then two types of particle filters are applied to estimate the location of a user. The wall particle filter is used for estimating the probable locations by excluding physically-blocked locations (in the 3$^{rd}$ block). The RSS particle filter adjusts probable locations by calculating the proximity of given particles with the RSSI fingerprints (in the 4$^{th}$ block). Finally the location is estimated using the filtered data from the other blocks (in the 5$^{th}$ block). The details about the method of handling the data will be discussed in Section 4.1.

## 4 IMPLEMENTATION

### 4.1 Indoor Localization

We used Anylogic to model a building with walls and a person moving towards a destination. Unfortunately, the Anylogic does not provide the models of smartphone-related sensors such as Wi-Fi RSSI and compass. In order to model APs and their signal, we implement the model of the RSSI signal associated with an AP, at any point in the map, following the ITU path loss model at 2.4GHz [5], which calculates the signal loss in terms of the distance and the number of walls between two points. Once the starting point and destination of the person are set, the path of the person is determined automatically by the pedestrian model of Anylogic software.

For both of the PDR-only and PDR + RSSI fingerprint approaches, we assume that the user provides the starting position of himself/herself on the map. We also assume that the user holds her smartphone pointing towards his/her walking direction during the evacuation process. Then the direction of the user can be easily obtained using the magnetic sensor. In the simulation, we implement and obtain the current direction $d(1+n)$ of the user for compass sensor by measuring his/her movement for a short time, with measured direction $d$ and noise $n$ of uniform distribution $U(-0.1, 0.1)$, and calculating the heading direction every second.

In the PDR-only approach, we estimate the next position of a user by using the heading direction and uniformly-distributed speed of $U(0.9, 1.1)$ on the average of $1m/s$. To get a more accurate result, we scatter particles around the estimated position, and get rid of the particles if there is a wall between the location of each particle and the previous estimated position. The estimated position is then updated by averaging the positions of remaining particles after the filtering.

In the PDR + RSSI fingerprint approach, we first divide the map into rectangular grids. Each grid's size is 1m X 1m. We pre-measure the RSSI fingerprint—the vector of the RSSI data from nearby APs—for each grid, which is stored in a fingerprint database. When the simulation starts, the particles are scattered around the user's position within about 2.5m. At every second, the particles are moved by a certain distance toward the walking direction of the user, and are assigned certain weights based on the RSSI fingerprint for resampling. The RSSI fingerprint of a particle is that of the grid where the particle is located. A particle gets more weight if its RSSI fingerprint in the database is closer to the RSSI measured by the user's smartphone as shown in Equation 1. If the particles are beyond the wall, we'd rather giving low weight to the particles than just removing the particle because it may cause the problem that the removal makes our approach to judge that the estimated location keeps being inside the room although the user already escapes from the room.

$$weight f_{p_i} = w \prod_j \left(1 - \frac{|R_{m,AP_j} - R_{p_i,AP_j}|}{|R_{m,AP_j}| + |R_{p_i,AP_j}|}\right)^2 \tag{1}$$

where $p_i$ is the $i^{th}$ particle, $AP_j$ is the $j^{th}$ AP, $R_{m,AP_j}$ is measured RSSI at the current position from $AP_j$, $R_{p_i,AP_j}$ is the pre-measured RSSI fingerprint at $p_i$ from $AP_j$, and $w$ is the weight coefficient. By varying $w$, we can avoid a trajectory that goes through physically-blocked walls and adapt the proposed scheme to the partially available infrastructure.

Re-sampling re-selects the group of particles, and those with more weights have higher chance of getting picked. In this way, we can implicitly get rid of the particles which are far from the real location of the user as shown in Figure 2. We choose the particle with the heaviest weight as the estimated position for the user. If there are the particles with the same weight, we calculate the average coordinate of them.

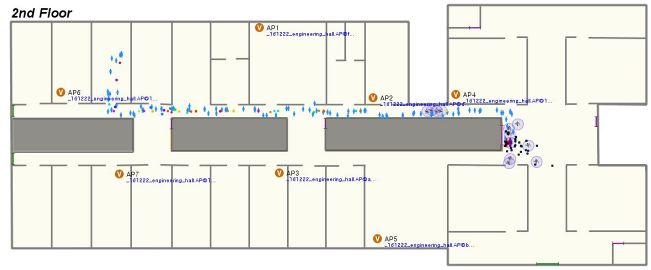


**Figure 3: Capture of the Anylogic simulator is shown for evaluating localization in the case of an indoor fire.**

## 4.2 Fire/Smoke Propagation

In order to incorporate the effect of smoke propagation from the fire, the Fire Dynamics Simulator (FDS) is linked with the developed model. FDS is developed by the National Institute of Standards and Technology (NIST) in the US aiming to analyze the smoke and heat transport in case of fires in buildings [8]. The software uses a computational fluid dynamics (CFD) model to numerically solve fire-driven fluid flow [8]. By changing the input parameter, the properties of the building such as geometry, obstacles, and materials can be reflected in the model. Once the parameters for the building information and initial ignition information (e.g., ignition location, heat release rate per unit area) are configured, FDS simulates the fire situation, and generates output data on the changing environment including temperature, toxicity, and visibility values inside the building. Considering the purpose of this study, the proposed model utilizes the visibility data, which represents the estimation of visibility through smoke in a certain area [8]. That is, it is assumed in the model that the smoke layer becomes thicker due to the smoke propagation and the area is considered hazardous to evacuees.

## 4.3 Details of Simulation

As shown in Figure 3, we develop the simulation tool, based on the Anylogic simulator, which can visualize the evacuee and provide the well-organized pedestrian model. It is also possible to visualize the estimated locations of evacuees and particles which are candidates where they might be located. In order to evaluate the localization scheme in the indoor fire, we need to put the additional layer of context information such as the sensor's value and fire/smoke dispersion because the Anylogic simulator does not provide such data.

The context layer needs the information of the heading direction, step detection, signal strength and fire dispersion for evaluation of indoor localization. In order to estimate the heading direction of an evacuee, we calculate the angle by comparing the previous position to the current position at every step. However, there exists the error of heading direction in real environments since the soft-iron or hard-iron effect causes the distortion of magnetic sensors[3]. To reflect

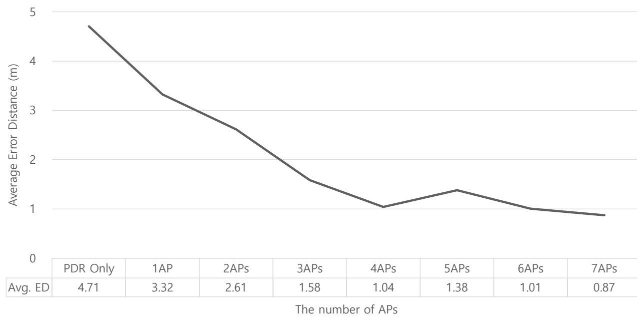


**Figure 4: We plot the localization performance with the partially available infrastructure. The localization error is decreased as the number of available APs increases in the simulation.**

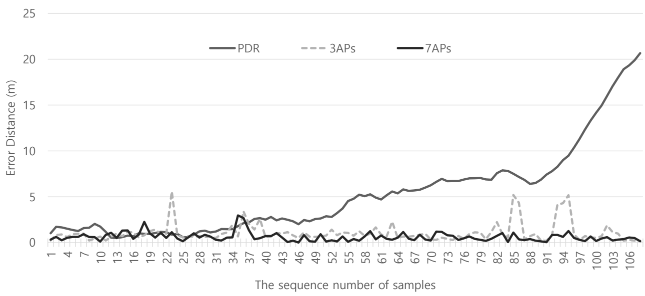


**Figure 5: How localization error is propagated is shown depending on the number of available APs.**

the distortion, it is possible to set the distribution of directions (We use the uniform distribution for our simulation). In addition, we assume that an evacuee walks down at one step per one second and the average of his/her stride is 1m long(the uniform distribution over the length from 0.9m to 1.1m). The RSSI is already described in Section 4.1. Moreover, we can make the Anylogic simulator to co-work with FDS by inserting the time-series events of fire/smoke dispersion into the context layer because FDS can generate their results in the form of a database. Anylogic can handle the events in real-time by reading the database.

## 5 EVALUATION RESULTS

### 5.1 Effects of Partial Infrastructure

Figure 4 shows the simulation results with the partially available infrastructure. The total number of Wi-Fi APs are 7, thus the RSSI fingerprints are collected from the 7 APs. The number of unavailable APs is varied for evaluation purposes.

Obviously, the RSSI fingerprint with WiFi APs can enhance the overall localization performance, even with the aid of only a few APs. In the PDR + RSSI approach, we measured the localization error distance for different numbers of APs since APs may become out of service in disaster situations. The localization performance tends to become better as the more APs are available. Note that

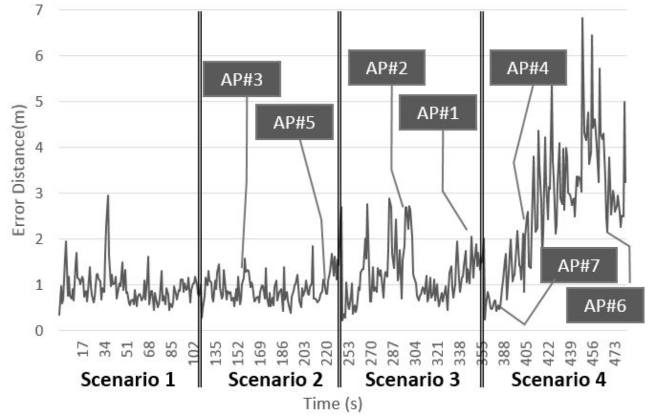


**Figure 6: Localization errors are plotted for each different scenario. Each AP number is to indicate when it is broken down.**

the localization error becomes stabilized when more than 3 APs are available in our simulation. The PDR-only approach has some limitations since the PDR error is accumulated as the time goes on as shown in Figure 5. In Figure 5, the cases of 3 and 7 APs show low localization errors relatively. Notice that we can observe some spikes in error distances in case of 3 available APs.

### 5.2 Effects of Infrastructure Breakdown as Spread of Fire/Smoke

For more realistic simulation results, we model the smoke propagation and diffusion due to the fire ignition using the FDS. Incorporating the modeled data with our simulator, the smoke layer indicates the hazardous area by its thickness. In our simulator, we assume that the indoor environment is windless. Therefore, the thick area may be very close to the fire. Considering the thick area as toxic to evacuees and as prone to break down the infrastructure, WiFi APs in the simulation are gradually turned off as time goes by.

Figure 6 shows the simulation results with the partially available infrastructure with the smoke spread data. For every scenario, an evacuee tries to exit the building with the same starting point. However the starting time is different for each scenario, which means the next scenario starts right after the previous one. In addition, each scenario has a different number of available WiFi APs as we note the turn-off moments of APs in the Figure 6.

As shown in Table 1, the average error distance for each scenario increases as the available WiFi APs are decreased. These results are in line with Section 5.1. Also, the increase of the standard deviation for each scenario means that both the fluctuation of the error distance and the instability of the estimated location are getting higher as the number of available APs decreases.

### 5.3 Weight Coefficient and Partial Infrastructure

As introduced in Section 4.1, the weight function can play an important role for avoiding walls and adapting to the partially

**Table 1: Average error distance and standard deviation per each scenario.**

| Scenario # | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Average Error Distance (m) | 0.94 | 1.01 | 1.28 | 2.81 |
| Standard Deviation | 6.76 | 9.73 | 11.17 | 28.79 |

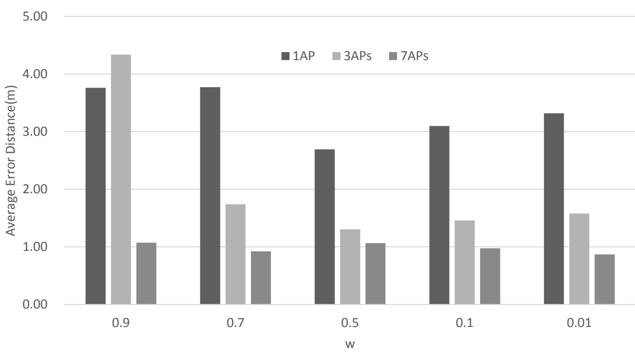


**Figure 7: Average error distance by varying $w$ and number of APs, respectively.**

available infrastructure. As the weight function is controlled via the weight coefficient $w$, the effects of $w$ are investigated by varying the $w$ value. Note that $w$ is set to 1.0 by default when the last estimated position and the given particle are separated by a wall. Otherwise we vary $w$ value in range of 0.0 to 1.0 in order to give less probability of choosing the particle over the wall.

Figure 7 shows the average error distance by varying $w$ and number of APs. The $w$ value of minimum error distance is different as we vary the number of available APs, which means that there are no universal optimal value for choosing $w$. However, with our simulation settings, there are trends for the best $w$ with different number of APs. For the cases of 1 AP and 3 APs, the best $w$ is about 0.5. However, for the 7 APs case, the worst $w$ is around 0.5. Overall, the error distances of $w \leq 0.5$ is lower than the ones of $w > 0.5$. Therefore adjusting $w$ value depending on the observed number of APs would result in the lower error distance.

## 6 CONCLUSION

In this paper, we have developed and evaluated an indoor positioning scheme for a partially available infrastructure in disaster situations. We have implemented a tool to evaluate indoor positioning schemes with modeled data of smoke propagation. We have implemented and evaluated the PDR-only and PDR + RSSI based indoor positioning schemes using the tool, so that it can be used as a reference for ERESS evaluations. Even if few APs are available, we proved that it can achieve the better performance than PDR, being robust against the damage from fire dispersion.

We plan to perform more accurate simulations with the measured data from real-world fire/smoke situations and smartphone sensor, and also more practical evaluations with multiple sources of data such as spread of heat and/or with alternative positioning schemes such as the one using FM radio stations [9]. In addition, we will investigate the relation between the accuracy of indoor localization and the time taken to escape from the disaster. After that, we are also scheduled to research on the smart direction guidance which can consider the visibility and fire dispersion for the efficient emergency escape.

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