공학석사학위논문

WiFi 및 BLE RSS 기반의 실내 측위 성능 향상

Good Indoor Localization Performance based on Wi-Fi and BLE RSS

2015년 8월

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Abstract

Good Indoor Localization Performance based on Wi-Fi and BLE RSS

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Recent years, indoor localization becomes a very hot topic. Indoor localization systems usually rely on different technologies, including distance measurement to nearby anchor nodes (nodes with known positions, e.g., Wi-Fi access points), PDR (Pedestrian-Dead-Reckoning). To improve the accuracy, various researches have been carried out. However, the precision of the current popular indoor localization systems can be poor, due to the low precision of PDR, Wi-Fi RSS fluctuation, and the difficulty in localizing a user in large-scale space.

In our framework, we locate user’s location based on PDR (Pedestrian-Dead-Reckoning) and calibrate it with Wi-Fi localization point. Aiming at improving the accuracy, we exploit BLE beacons as landmarks in our indoor localization system, to narrow the Wi-Fi Fingerprints scanning range. We put BLE landmarks at the locations with poor Wi-Fi localization accuracy. To enlarge BLE landmark's sensor field, we set each BLE beacon with a continuously changing Tx Power. We did various experiments to evaluate the performance of our proposed framework and the accuracy is improved quite a lot.

Key Words: Indoor Localization, BLE Landmarks, Wi-Fi Fingerprint

Student Number: 2013-23853

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Chapter 1

1. Introduction

Recent years, there is a popular trend in developing accurate PDR (Pedestrian-Dead-Reckoning) based and Wi-Fi Fingerprint based localization systems that enable users to navigate indoor spaces much like what GPS provides for outdoor environments.

Currently, many research works are carried out in order to improve the accuracy of indoor localization system, such as pedestrian dead reckoning (PDR) based and Wi-Fi Fingerprints based indoor localization.

However, the precision of the current popular indoor localization can be poor, for instance, Wi-Fi Fingerprints and PDR. Wi-Fi RSSs (Received Signal Strengths) of Wi-Fi access points fluctuate due to the fading of Wi-Fi signals and human body effects. Moreover, Wi-Fi scanning typically takes about 3 to 4 seconds in general smartphones, which often leads to disruptions and delays in the context of location updates. Localization based on PDR also can be poor due to errors in heading direction estimation. Besides, it is difficult to localize a user in large-scale space, such as airport, mart and so on.

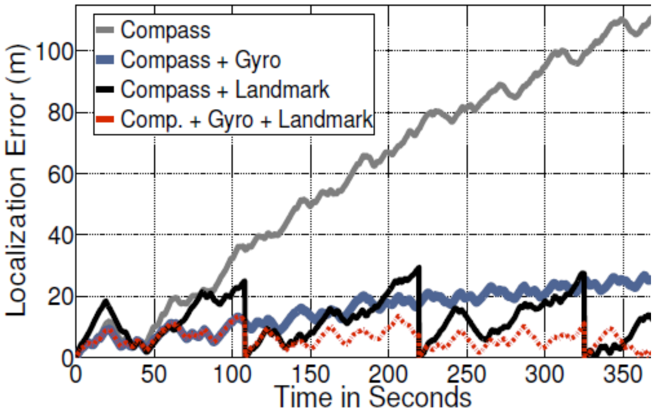

Figure 1.1 Performances with PDR only

Thus, in order to increase the accuracy, we improve the current indoor localization framework by exploiting BLE beacons. In our framework, we locate user's location based on PDR and calibrate it with Wi-Fi localization point. BLE beacons are used as landmarks to narrow the Wi-Fi Fingerprints scanning range. We put BLE landmarks at the locations with poor Wi-Fi localization accuracy. To enlarge BLE landmark's sensor field, we set each BLE beacon with a continuously changing Tx Power.

The balance of this paper is as follows. In Chapter 2, I will briefly introduce the principle of our improved framework based on BLE beacons, and some comparison among current localization algorithms. In Chapter 3, I will explain in details of our proposed framework from calibrating PDR with Wi-Fi fingerprint, the deployment of the BLE beacons, to calibrating the previous results with BLE landmarks. In Chapter 4, I will discuss how our work can be implemented and show the experiment results and the analysis of the performance of our improved framework based on Wi-Fi and BLE RSS. Finally I will conclude my paper in Chapter 5 and show our future plan.

Chapter 2

2. Background and Related Work

Before explaining proposed localization framework based on Wi-Fi and BLE RSS, I will briefly introduce pervious and current research works.

2.1 PDR based and Wi-Fi Fingerprints based Localization

Current popular Indoor localization systems are usually based on Pedestrian Dead Reckoning (PDR) and Wi-Fi Fingerprints.

The basic principle of PDR (Pedestrian Dead Reckoning) is that the current location can be found out by attaching sensor module to pedestrian and estimating movement distance toward moving direction from initial location based on information of steps obtained.

Wi-Fi based localization, leveraging the RSSs (Received Signal Strengths) of access points, has long been studied due to its wide and often dense deployment.

However, the position estimation of these popular approaches can be poor. The direction estimation of a user solely based on PDR is often inaccurate because of magnetic distortion in indoor environments. On the other hand, the fluctuation of Wi-Fi signals due to multipath fading and crowded people usually lead to poor accuracy of Wi-Fi based localization.

Motivated by these limitations, we seek to exploit other sources that are currently available in smartphones: inertial sensor, and BLE (Bluetooth Low Energy), to enhance the performance of Wi-Fi-based localization.

2.2 Improved framework with BLE beacons

Basically, we rely on PDR (Pedestrian Dead Reckoning) as a basic mechanism to track the user trajectory.

For the sake of achieving a certain level of precision, we seek to exploit landmarks, a reference location that helps a user to localize oneself. Depending on landmarks, we can calibrate the cumulative errors as PDR continues.

Thus, BLE landmarks will be used. A BLE landmark is a location where a BLE beacon node is installed for the purpose of proximity services. We put BLE landmarks at the particular locations with poor Wi-Fi localization accuracy to narrow the Wi-Fi fingerprints scanning range, as well as improve the localization accuracy.

Chapter 3

3. Improved Framework based on Wi-Fi and BLE RSS

Basically, we rely on PDR (Pedestrian Dead Reckoning) as a basic mechanism to provide smooth navigation services due to its fast refreshment intervals. However, because of the magnetic distortion in indoor spaces, the estimated direction of a user by PDR is often inaccurate. To remedy the PDR errors, we calibrate it with Wi-Fi localization point and exploiting landmarks, where a user can fix one's location with a fine-grained precision. By the Wi-Fi localization point and landmark-based calibration, we can reduce the cumulative error of PDR substantially.

The proposed localization framework is depicted in Figure 3.1

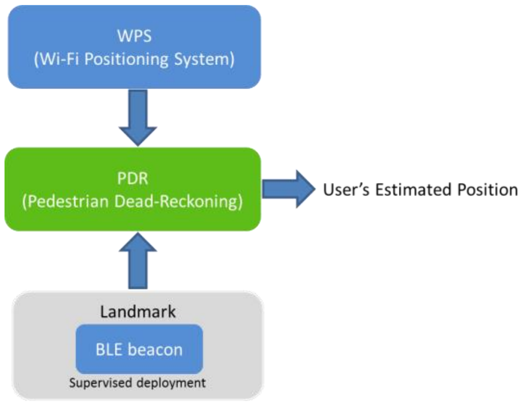

Figure 3.1 The proposed Localization framework

3.1 PDR as basic mechanism

PDR (Pedestrian Dead Reckoning) is the process of calculating one's current position by using a previously determined position, or fix, and advancing that position based upon known or estimated speeds over elapsed time and course. In our work, we infer the user's location per step, based on step detection (by using accelerometer), heading detection estimation (by using magnetic sensor), and turn detection (by using gyroscope).

PDR can provide localization results much more frequently and faster. Usually, per step detection only takes about 0.4s to 0.8s, while Wi-Fi based scheme would take nearly 3s to 4s.

However, the error of PDR can be large, due to the magnetic sensor pollution in indoor spaces. Moreover, with sufficiently frequent position updates, its linearly growing position errors can be accumulated as time goes by.

Figure 3.2 depicts a simple example of large cumulative error of indoor localization based on PDR. The error distance between the real trajectory and estimated trajectory becomes larger as time goes by.

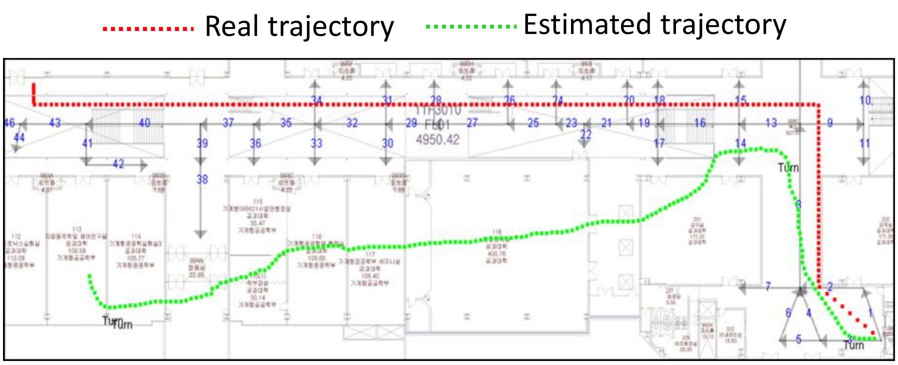

Figure 3.2 An example of large cumulative error of the PDR

3.2 Coarse-grained calibration with Wi-Fi localization point

3.2.1 Wi-Fi Fingerprint matching

In our framework, we use traditional Wi-Fi fingerprint localization matching method, consisting of two phases. The first phase involves constructing a fingerprint database in the offline. Then in the second phase, variously referred to as tracking phase, signal measurement samples collected by a user's device are used to "look up" the closest matching samples in the database to infer the user's location.

Environment

We consider the Second Engineering Building (Building 301) as a reference building and focus on the 2nd floor of this building which constitutes staff offices, common spaces and classrooms.

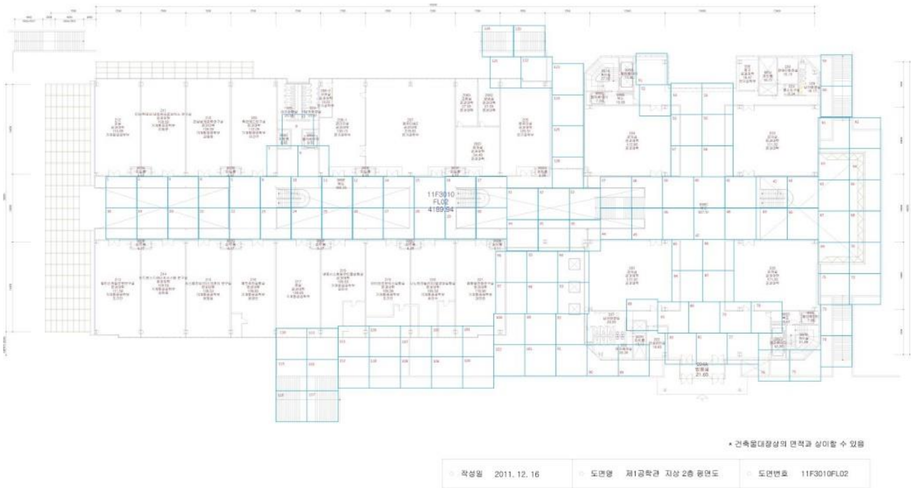

Figure 3.3 Floor plans for the 2nd floor of building 301

Data Collection

We obtain our Wi-Fi fingerprint data for the framework using Android phones and Indoor Wi-Fi fingerprint collector, a custom mobile application we developed for the specific purpose. For each measurement position, which we note as the center of each grid, Wi-Fi fingerprint collector does multiple scans, collecting 50 fingerprints. We use Samsung Galaxy S5 and Sony XPERIA phones, both Android based, to generate the various datasets. The fingerprints are collected as [{AP_1's BSSID, RSS}, {AP_2's BSSID, RSS}, …].

3.2.2 Similarity Computation between the fingerprints

We use Euclidean distance of RSSs (of APs) to compute the distance between fingerprints from the database, each with an associated location and denoted by p, with a tracking fingerprint q. In equation (1), n is the number of overlapping APs in two fingerprints in the n-dimension space. And pi is the RSS value of APi in the fingerprint from the database, whereas qi is APi’s RSS value in the tracking fingerprint.

$$d(p, q) = \sqrt{\sum_{i=1}^{n}(q_i - p_i)^2} \tag{1}$$

In our work, we use two ways to compute the Euclidean distance in signal space. One is to discard the “missing APs”, which are not shown in online phase. The other is to assume that “missing APs” have minimum RSS value (i.e. -100dBm).

3.2.3 Methods for Coarse-grained calibration

Due to the errors in heading direction estimation using only PDR, which often leads to inaccuracy localization, we calibrate it with Wi-Fi localization point. In this case, we propose the following two methods as simple and enhanced methods:

1. Always switch user's location to Wi-Fi Localization point. (simple)
2. Only switch user's location to Wi-Fi Localization when the distance between PDR and Wi-Fi localization point exceeds the thresholds. (enhanced)

We evaluate the effect of Wi-Fi calibration on PDR, and the cumulative error distance per step. As they are shown in Figure 3.4, the average location distance error is about 6.5m when we exploit the calibration following the simple method; while as described in enhanced method, calibrating only when PDR's error distance is accumulated, shows only 3.2m of the average location error distance.

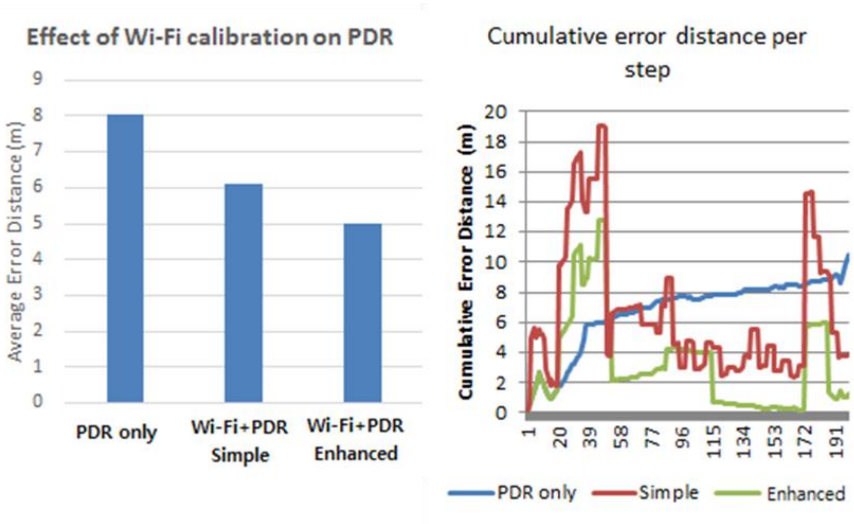

Figure 3.4 An example of large cumulative error of the PDR

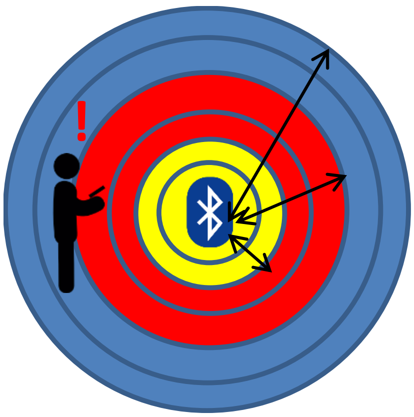

Figure 3.5 A simple use case within BLE beacon Tx Power

3.3 BLE Node Deployment

Calibrating PDR with Wi-Fi localization point improves the localization accuracy. However, Multipath fading and crowded people often make Wi-Fi RSS fluctuate. Hence, we still need to exploit other sensory data, BLE beacon, in our framework, to achieve a certain level of precision. In this case, we use the BLE beacon node as a "Proximity Sensor".

We propose a BLE-based approach, exploiting BLE bacons, with continuously changing Tx Power, in optimal locations, to further improve the localization accuracy. When the user walks close to the BLE beacons,

When the BLE beacon is detected, it indicates that the user is entering the BLE range. In that case, we search for Wi-Fi fingerprint database within this range only.

We set the BLE beacon Tx Power continuously changing as -23dBm, -12dBm and 4dBm in each period, with the range of 5m~10m, 20m, 40m respectively. Each period lasts 1 second. The interval of each BLE beacon is 20Hz, which we can easily read from its header.

The most important work is to decide the deployment location of the BLE beacons. In our framework, we put BLE beacons at the locations that show poor Wi-Fi localization performance. We divide the target space into 87 grids and give each grid a score of Wi-Fi localization performance. Then sort the entire grids by score and select 5 grids which hold the 5 highest scores. Finally, those 5 selected grids will be the locations to put the BLE beacons.

3.3.1 Wi-Fi Grid Scoring

We calculate the score of each grid based on two intuitions. The intuitions can be depicted as:

Intuition①: Areas that have similar fingerprints with their neighbors

Based on intuition①, we define the BLE suitability function 1 using P (CD) (Probability of Correct Decision). We first find the PCP (Pairwise correct probability) between target grid and neighboring grid; then compute and aggregate the PCP for all the neighbors within a certain range (20m). Supposing R_i is the fingerprint of Target Grid I, and R_k is the fingerprint of neighboring grid k, we denote the PCP between R_i and R_k using PEP (R_i, R_k) by right tail probability for a standard Gaussian random variable, where the random variable exceeds the signal distance between Grid i and Grid k.

$$PCP(\tilde{R}_i, \tilde{R}_k) = 1 - PEP(\tilde{R}_i, \tilde{R}_k) = 1 - Q(\frac{sd_{ik}}{2\sigma}) \qquad (2)$$

AS shown in Figure 3.6, same color describes grids having similar fingerprint, different color shows grids having different fingerprint. According to P (CD), grid i with four similar neighboring grids has a low P (CD) and a high error probability correspondingly, whereas, grid k with only one similar grid has a high P (CD) and a low error probability correspondingly.

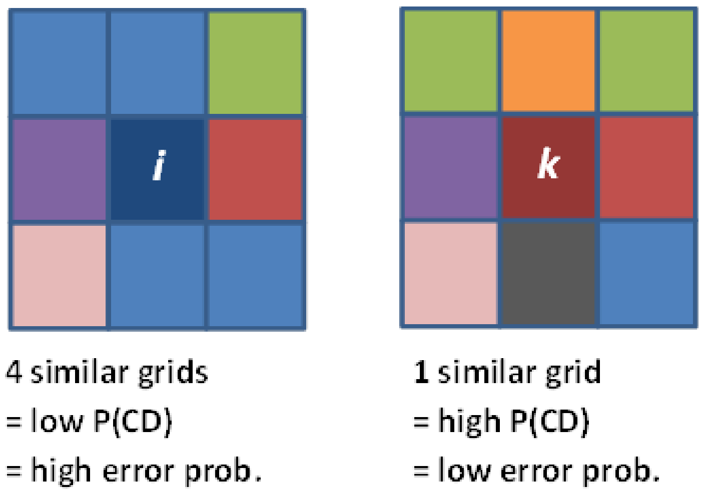

Figure 3.6 Wi-Fi Grid Scoring

Intuition②: Areas that have low stability in terms of AP scans

Based on intuition②, we calculate the number of observed RSS samples for each AP is different from the ones in the offline database and define the BLE suitability function 2 using AP appearance frequency. Count ratio, shown as follow, is used to depict AP appearance frequency in a grid, which is calculated by the number of Aps shown frequently over the threshold and the total number of Aps shown in a grid.

$$\text{"Count ratio" of a Grid} = \frac{\text{\# of APs shown frequently over the threshold}}{\text{total \# of APs shown in a Grid}} \quad (3)$$

3.3.2 Final Score

We enhanced the P (CD) by dividing the signal distance by the physical distance between the grids to normalize P (CD) score by physical distance between the target grid and the neighboring grids.

Figure 3.7 shows the similar performance between our BLE deployment function and the oracle function which is selected by the actual location error.

3.3.3 Selection of the deployment location

Based on those two intuitions, we sort the entire grids by score and select 5 grids in order. We deploy the BLE beacons in the particular areas (which hold the 5 highest scores), with bad Wi-Fi localization performance.

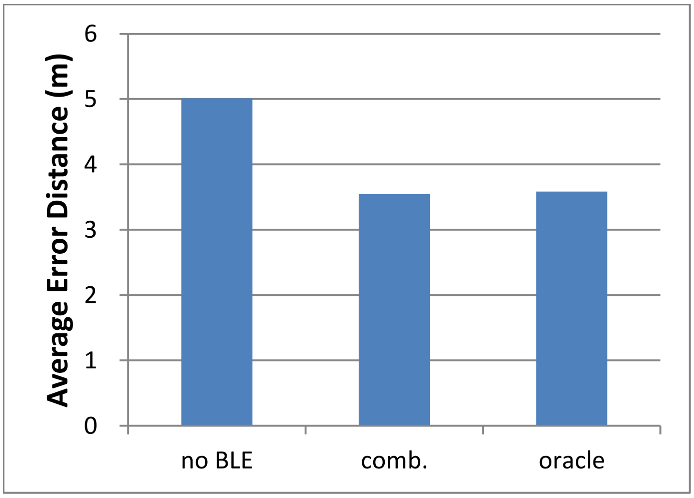

Figure 3.7 Similar performance

Chapter 4

4. Evaluation and Performance

4.1 Evaluation

We did plenty of experiment on 2nd floor in Building 301 at SNU, with width of about 50m, length of about 60m and height up to 10m, while the broad corridor is only about 10m. We divide the target space (2nd floor in Building 301) into 87 grids, with a size of 5*5 m2. In our experiment, we collect 50 Wi-Fi fingerprints at the center of each grid. In the BLE beacons deployment, we deploy BLE beacons as landmarks, based on our analysis [3.3], at 5 different positions. To evaluate our approach, we tested 7 trajectories, including walking along both middle of the corridor and closing to walls during the experiments.

Figure 3.10 presents a scenario of our evaluation process, when I was walking along the middle of the corridor, collecting data.

Figure 4.1 A scenario of experiment

4.2 Result of the Framework Performance

We test the average distance error of all trajectories, and the performance is significantly enhanced in all the data sets. Figure 3.11 and table show the results with PDR-based only, calibrating PDR and Wi-Fi, also PDR, calibrated together with Wi-Fi and BLE beacons. The performance of Wi-Fi based and BLE RSS based localization, is improved up to 56%.

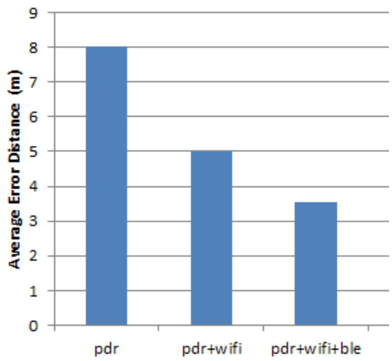

Figure 4.2 Average distance error of all trajectories

	traj 1	traj 2	traj 3	traj 4	traj 5	traj 6	traj 7	avg
pdr only	6.73	7.84	6.02	12.61	7.05	7.8	8.14	8.03
pdr+wifi	3.53	5.4	4.57	8.08	4.9	3.44	5.16	5.01
Pdr+wifi+ble	2.7	4.09	3.17	6.48	2.91	2.41	3.05	3.54

4.2.1 PDR calibrated by Wi-Fi localization only

Figure 4.3 shows a snapshot without any landmark calibration. The user walked from elevator located as right bottom corner, to room in the left end of the floor. In this case, PDR is calibrated by Wi-Fi localization only. There is still a certain average error distance between ground truth and the estimated path.

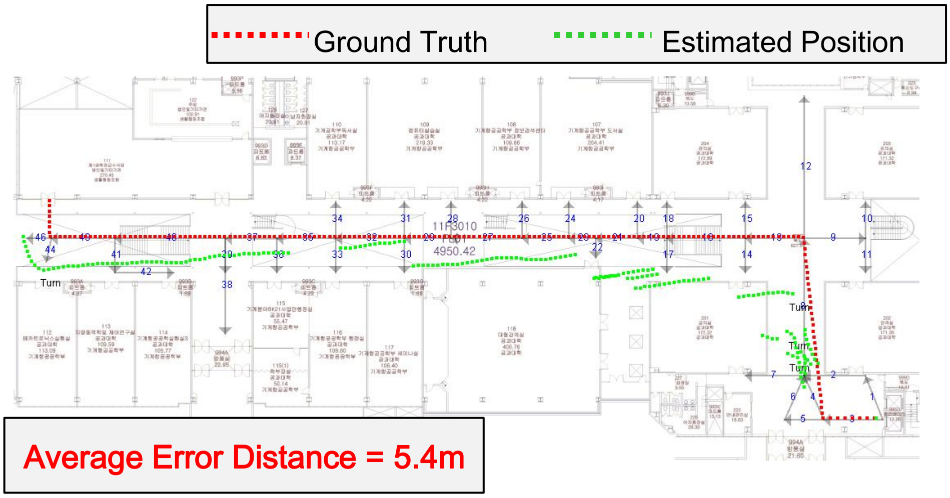

Figure 4.3 Snapshot without any Landmark Calibration

4.2.2 PDR with BLE Landmark Calibration

Figure 4.4 shows a snapshot by exploiting BLE landmark calibration. The user also walked from elevator located as right bottom corner, to room in the left end of the floor. In such a case, PDR is calibrated by both Wi-Fi localization point and BLE nodes, which is deployed on the optimal location based on our analysis. The average error distance between ground truth and the estimated path decreased about 24.3% compared with Wi-Fi localization calibration only, and about 56% compared to the PDR based only localization.

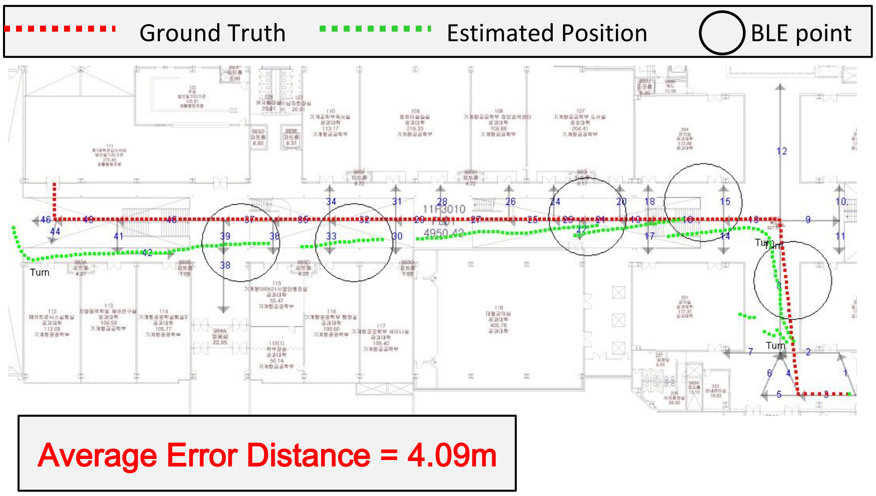

Figure 4.4 Snapshot with BLE Landmark Calibration

4.2.3 BLE Landmark Calibration with changing Tx Power

To evaluate the performance with changing Tx Power, we deploy the BLE beacons at the middle of the corridor on the wall. Figure 4.5 shows the error distance between the ground truth and the estimated user location. The two figures depict a good case (when I walked at the middle of the corridor) and a bad case (when I walked at the right side of the corridor). The average error distance in the good case is about 2.82m, which is decreased about 31% compared to fixed Tx Power BLE beacons. However, when the distance between user and BLE beacons becomes larger, in the bad case is about 10m, the average error distance accordingly increased to 6.98m

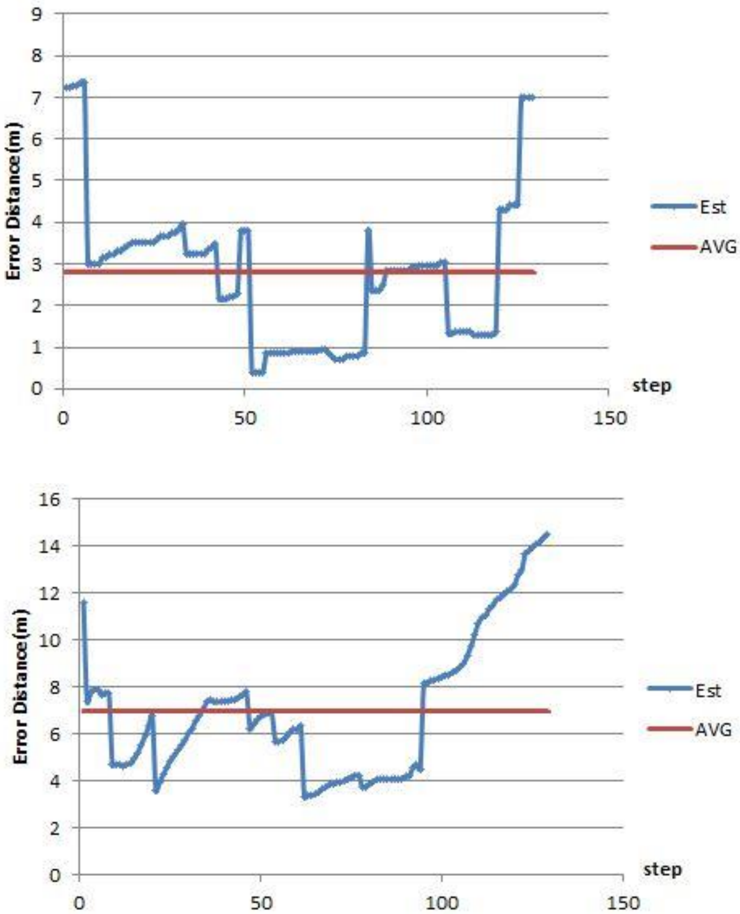

Figure 4.5 Error distance with changing Tx Power

Chapter 5

5. Conclusion

5.1 Conclusion

I have presented an improved indoor localization framework based on Wi-Fi Fingerprint and BLE RSS. To achieve a certain level of precision, we exploit BLE beacons as proximity sensors at particular locations. The deployment locations of BLE beacons are decided by the Wi-Fi scoring based on P (CD) and count ratio of a grid. With the deployment of BLE beacons, the indoor localization accuracy is improved quite a lot.

5.2 Future Works

Since we only deployed the BLE beacons at one position, the middle of the corridor, the sensor filed is not large enough. In the future, we consider deploying the BLE beacons with changing Tx Power at multiple optimal locations, to further improve the localization accuracy.

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초 록

최근 스마트폰이 많이 보급화되면서 사용자의 위치에 기반한 서비스들이 많이 각광받게 되면서 매우 흥미로운 주제가 되었다. 일반적인 실내 측위 시스템들은 주변 앵커 노드(예를 들어, Wi-Fi 액세스 포인트와 같은 이미 위치가 알려진 노드)를 활용한 핑거프린팅 기법이나 삼각측량/삼변측량을 활용하기도 한다. 다른 측위 자원으로 모바일 디바이스의 관성센서 및 지자기센서를 활용한 PDR(Pedestrian-Dead-Reckoning)을 이용하여 사용자의 위치를 지속적으로 추정하는 방식이 있다. 그러나, 실내 환경에서 일어날 수 있는 다양한 페이딩 현상으로 인한 WiFi 신호 세기의 변동이 존재하고, 대규모 공간에서는 핑거프린트 간의 차이가 크지 않아서 측위에 어려움이 있다. 또한, PDR 을 이용한 측위의 경우 센서 자체가 가지고 있는 에러나 강자성을 띈 외부적 요인으로 인해 부정확한 측위 결과를 나타낼 수 있다,

본 논문에서는, WiFi, PDR, BLE 를 융합한 효율적인 측위 시스템을 제안한다. 기본적으로 PDR 에 기반하여 사용자의 위치를 파악하고, 시간이 지남에 따라 누적되는 에러를 Wi-Fi 핑거프린팅 기법을 활용하여 보정한다. 또한, 서비스 지역에서 WiFi 측위 오차가 크게

나타날 수 있는 지점을 찾는 라디오맵 분석 알고리즘을 제안한다. 이러한 지점에 BLE 비콘(beacon)을 설치하여 랜드마크로 활용하여 측위 오차를 줄인다.

주요어 : 실내 측위, BLE 랜드마크, Wi-Fi 핑거프린트(fingerprint)

학 번 : 2013-23853