ILPS: Indoor Localization using Physical Maps and Smartphone Sensors

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***Abstract*— Indoor positioning and tracking services are garnering more attention. Recently, several state-of-the-art localization techniques have been proposed that use radio maps or the sensors readily available on smartphones. This paper presents a localization system called Indoor Localization using Physical maps and smartphone Sensors (ILPS), which is based on a building blueprint database and smartphone sensors. The blueprint database and access points (APs) provide a number of reference points that can be used to acquire the initial position and adjust the user position each time a reference point is detected. The proposed method is implemented on a smartphone and tested in real indoor environments. The experiments with ILPS demonstrate that using a static blueprint will avoid the costly database updates that are usually required in other approaches due to signal attenuation. Furthermore, ILPS performs better than existing work in term of accuracy and effectiveness for indoor localization.**

Keywords: Blueprint database, maximum average received signal strength, step counting.

I. Introduction

Indoor localization and tracking using smartphones have been widely investigated and their importance is continually increasing as a result of the numerous applications that require indoor localization, such as healthcare, advertisements in indoor environments, and so on [1].

Many techniques have been developed that provide localization and obtain user trajectories. The most popular technique is fingerprinting approaches [2, 3], which uses wireless technologies such as Wi-Fi, Bluetooth, or other radios. Other techniques provide locations based on radio signals, such as time of arrival (TOA) [4, 5], trilateration [6], and angle of arrival (AOA) [7].

In radio signal-based localization techniques, such as TOA and AOA, at least three different signals, are required in order to obtain the user's location. In addition, sensor-based techniques that rely on smartphone sensors suffer from noise. Fingerprinting-based techniques have become the most popular localization technique for several reasons. First, the Received Signal Strength (RSS) is widely used in infrastructure networks. Second, it provides accuracy up to approximately 2 m [8]. However, this technique suffers from some significant problems. One such a problem is the need for recalibration, which is where an indoor environment must be resurveyed regularly due to signal attenuation.

The pervasiveness of smartphones that are equipped with numerous sensors, such as accelerometer and compass, allows for acquiring locations and tracking users. Many techniques using smartphone sensors have been developed. For example, LifeMap uses a global positioning system (GPS), accelerometer, and digital compass to track users [1].

This paper proposes a hybrid technique called *Indoor Localization using Physical map and Smartphone sensors* (ILPS), which uses a physical map instead of a radio map and smartphone sensors to obtain a user's paths and track the user's position in an indoor environment. Also, public WiFi APs are used to adjust the user position during tracking. The significant contributions of this work include the following five points:

- A novel technique to adjust the user position according to the reference points given by the public APs;
- A more accurate distance and direction estimation using a smartphone accelerometer and orientation sensor with respect to the blueprint database;
- Representation of the inner structure of a building as database relationships;
- A technique to locate a user in an elevator based on both the acceleration and RSS level of APs; and,
- Implementation of the proposed ILPS method in an Android-based smartphone and an experimental study in a real environment in order to validate the feasibility of this work.

The rest of the paper is organized as follows: Section II discusses the related work. Section III describes the proposed system design and architecture. Section IV presents our experiments and results. Finally, Section V concludes the paper and discusses the future work.

II. Related Work

The related work on indoor localization and tracking can be categorized into two foundational techniques: location-based techniques and tracking-based techniques.

A. Location-based Techniques

Localization techniques use radio signals, smartphone sensors, and sound acoustics. In these approaches, the location is determined using a distance or angle estimation. Trilateration is a technique that requires the distances of

978-1-4799-4786-7/14/$31.00 ©2014 IEEE

three reference nodes to obtain the position as the intersection between the three circles formed [6]. In contrast, AOA requires angle estimations between the sender and receiver in order to obtain the location [7, 9]; this technique requires at least two reference points. The fingerprinting technique has two phases: an offline phase that collects a large number of radio signals to build a radio map and an online phase that measures the radio signals and then compares these with those in the radio map using several search algorithms to obtain the closest position. RADAR is one of the earliest fingerprinting techniques, and it collects Wi-Fi signal strengths during the offline phase for 70 locations in four directions [10]. The authors in [8] attempted to reduce the search process overhead in fingerprinting using a transfer function.

The significant limitations of these location-based approaches are caused by signal attenuation and scattering. For example, in fingerprinting, recalibration is required to rebuild the radio map during the offline phase. The overhead involved in the search process also poses a large challenge. In the trilateration methods, the distance estimation is the primary issue in providing good accuracy. However, the multipath and signal attenuation were obstacles in obtaining accurate distance. In AOA-based techniques, additional hardware is required in order to estimate the angles.

B. *Tracking-based Techniques*

Chon and Cha proposed LifeMap, which generates user trajectories using the accelerometer and digital compass in a smartphone [1]. They provided a technique to verify all possible movement directions of a user's smartphone to circumvent noisy sensors. However, the initial position of the user must be detected using GPS, which is ineffective in indoor environments. In UnLoc [11], a technique for correcting the user's position based on landmarks such as Wi-Fi APs, elevators, and other items was developed. It relies on a collaborative method to find a small Wi-Fi area of which all locations overhear a distinct set of APs. However, it is not easy to find much of those small areas to improve the accuracy. EZ [14] uses RSS of APs to detect the user position via genetic algorithm. It uses log-distance path loss model to detect the distance of an AP. However log-distance path loss model is not precise due to the variation of the signal over the time.

In summary, the proposed system differs from the existing methods in a number of ways. First, it uses a blueprint instead of a radio map. Second, observing the RSS of APs provides a number of reference locations in indoor environments, which can then be used to adjust the user's position in real time. Third, combining the acceleration with the RSS level to detect the elevators provides a more accurate technique for supporting multi-floor environments. Finally, the proposed approach provides a more accurate distance and direction estimation using a blueprint database as well as an accelerometer and an orientation sensor.

III. PROPOSED METHOD

The general procedure for the proposed ILPS system is described as follows.

The building is first subdivided into sections, and information about each section, such as its length and width is stored in the database. During the localization process, the Initial Position Estimator uses the MAC address of the AP with the maximum average RSS as input and verifies the *database* to determine which section of the building this AP belongs to. When the user begins moving, the data from the accelerometer and orientation sensors is monitored and collected in order to acquire the distance and the direction. During the user movement, the Wi-Fi scanning process searches for the maximum of the RSS's average, which represents the peak value. If the peak value is detected, the distance and the position are corrected based on the location of the reference point given by the physical location of the AP. The following subsections detail the database creation and system design.

A. *Creation of the Blueprint Database*

The database collection should be performed offline before the system works. The collected database represents the floor map. It contains three types of relationships: main relation, sub-relation, and reference point. The main relation is used to represent the main building sections, such as corridors and hallways. The sub-relation represents the building subsections, e.g., rooms. Finally, the reference point represents the public APs, which are usually attached to the ceiling of the building. Fig. 1 illustrates the first floor of the Computer Science (CS) Department at KAIST, while Fig. 2 presents the components of the database according to the building structure shown in Fig 1.

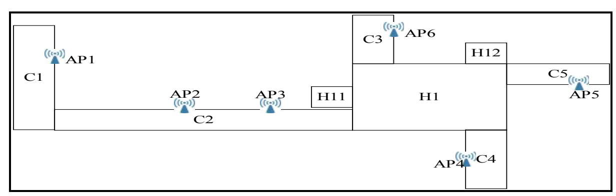

Figure 1. Structure of KAIST Computer Science Department.

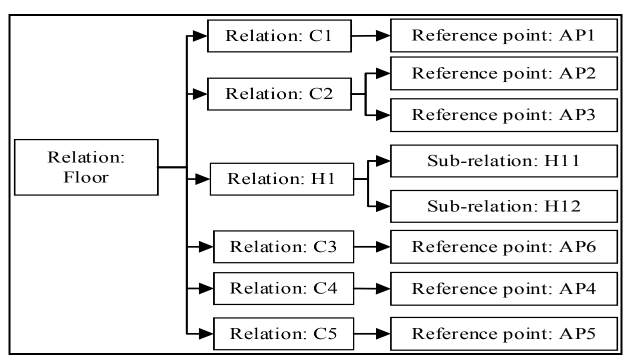

Figure 2. Database components for Fig. 1.

B. System Design and Algorithms

Fig. 3 presents the system architecture of the ILPS, which consists of the following modules: Initial Position and Reference point detector (IPR), direction estimator, step count estimator, and tracking algorithm. The following subsections describe each of these modules.

1) Initial Position and Reference point detector (IPR)

One of the significant contributions of this paper is the adjustment of the user's position in real time according to the stored reference points.

In order to overcome this problem, the ILPS system exploits the public APs that currently exist in most buildings, which are usually attached to the ceiling and placed in a specific arrangement. These APs function as reference points. The initial position of a user is estimated when the stored reference points are detected. This is undertaken by searching for the maximum of the RSS's average from these reference points. Then, the MAC address is extracted from the beacon frame, which is then used to extract the reference point's location. Several experiments were conducted in order to investigate the relationship between distance and RSS values when a user passes a reference point. Fig. 4 presents an example regression analysis, which was conducted for three different APs. Fig. 4 shows that there is a negative correlation between the distance and RSS values because the coefficient is close to –1 in all cases. The negative correlation between the distance and RSS values gives an indicator that the RSS value can be used to determine how far is a user from an AP.

In order to determine whether or not the maximum of the RSS average during a time window leads to the closest AP, several experiments were conducted in the CS Department building and IT Convergence building at KAIST. These measurements were taken as a user passed a reference point. Fig. 5 demonstrates that the closer a user is to a reference point, the higher the RSS average will be; therefore, the maximum of the RSS's average can be used to detect the closest reference point. Note that distance (0) in Fig. 5 represents the point when a user passes under a reference point.

In summary, the initial position can be estimated as follows: the RSS average is computed for a window of time.

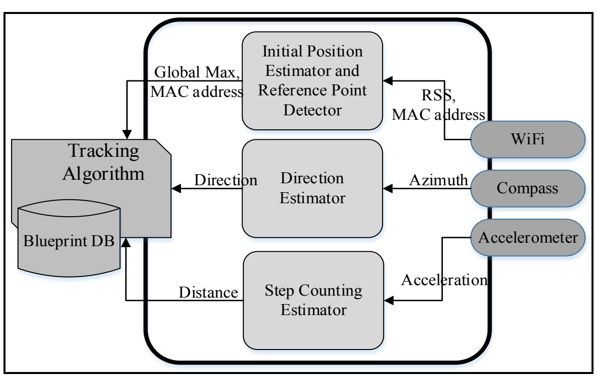

Figure 3. System architecture.

The IPR observes the RSS average until it begins to decrease, which will be the time when the user passes under a reference point. The MAC address will be extracted from the beacon and the location of the user is determined as the location of the reference point based on the database. Fig. 6 illustrates the scenario of detecting the initial position.

The maximum value of the average represents the time when a user passes under a reference point; this value is called the global maximum. However, due to the instability of the signals, the local maximum, which means that the average RSS decreases before reaching the global maximum might be obtained as shown in Fig. 6. In order to avoid adjusting the position based on the local maximum, the IPR tracks the maximum average for the last two continuous windows when the average begins to decrease. If the average increases again, then the IPR ignores the current maximum; otherwise, it stops and adjusts the user's position based on the maximum average, which is the global maximum.

The significant advantage of the proposed ILPS method over the existing methods is that a number of reference points are used to adjust user's position in real time when he/she encounters a reference point.

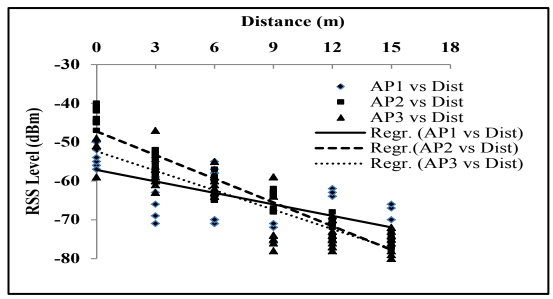

Figure 4. Regression example of an RSS with distance.

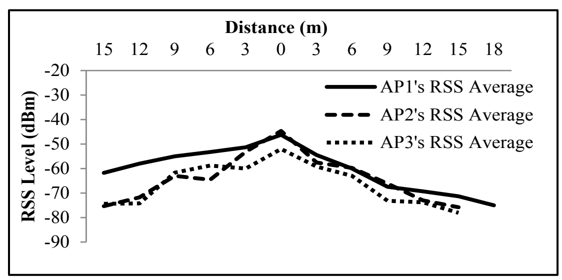

Figure 5. RSS average within ±15 m from an AP.

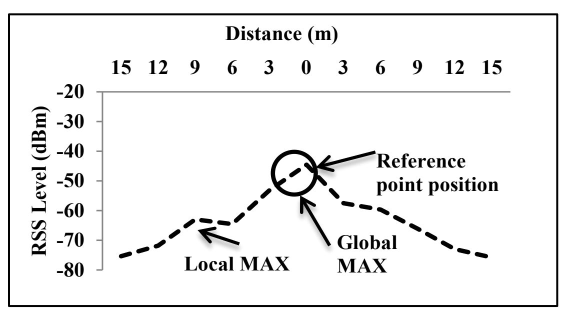

Figure 6. RSS average with local and global MAX.

2) Direction estimator

The direction of the user must be estimated after determining its initial position, and this is used as an indicator for the next building section that the user is moving toward.

Han and Kim used a smartphone orientation sensor, which provides three values that represent the azimuth (the angle measured clockwise from the magnetic north of the Earth to the y-axis of the smartphone), pitch (rotation around the x-axis), and roll (rotation around the y-axis), to perform the mobility prediction [12]. One issue with orientation sensor is that it is easily affected by user movements such as shaky hands. In order to obtain more accurate results, the sensor values must be measured over a period of time. In the proposed ILPS system, the situation where the user is holding the smartphone in their hand in order to watch advertisements, YouTube, TV program and so on is considered. Then, the sensor data collection begins when the user enters a building section. When the user reaches the end of the current building section, e.g., they reach the end of C1 in Fig. 1, the user's orientation is determined based on the average of the azimuth values and the next building section is estimated.

3) Step counting estimator

Accurate distance estimation is a critical issue in indoor positioning systems. Therefore, in order to accurately estimate the distance using smartphone sensors, e.g., an accelerometer, the most widely used technique is to count steps using the Peak Detection Algorithm (PDA), which uses the acceleration to detect the peak value during the user movements, each peak represents a step [13].

The primary drawback of this technique is miscounting steps due to shaky hands or other irrelevant smartphone movements. Another problem is that the step length can vary. Therefore, the PDA is prone to errors. In order to address these problems, the real distances are stored in the database and are used to obtain the correct distances.

The proposed ILPS system corrects the user position to be the position of the reference point when the user encounters a reference point. In order to correct the distance, suppose that (x, y) is the position of a reference point, (x_1, y_1) is the user position according to PDA, and PDA_DIS is the distance measured by the PDA; then, the difference in the distance between the user position based on the PDA and the reference point is:

$$\text{Diff\_DIS} = \sqrt{(x_1 - x)^2 + (y_1 - y)^2}. \tag{1}$$

The distance is corrected using equation (1) by adding or subtracting the Diff_DIS from the measured distance, as follows:

$$\text{Distance} = \begin{cases} \text{PDA\_DIS} + \text{Diff\_DIS}, & x1 < x \\ \text{PDA\_DIS} - \text{Diff\_DIS}, & x1 \geq x \end{cases}. \tag{2}$$

The error bound in the distance and position estimation of the proposed ILPS is very limited, because each reference point has a fixed location in the building according to the database.

4) Tracking algorithm

The tracking algorithm begins tracking the user after the user initial position is determined.

The tracking algorithm flowchart is shown in Fig. 7 and works as follows. First, the tracking algorithm fills the tracking vector by the section information. Then it detects the next section based on the blueprint database and stores the data of the next section in the candidate table. If the next section is stairs, then it uses the acceleration to determine whether the user walks up/down the stairs. If the next section is an elevator, then it uses the acceleration and RSS values together to determine whether the user enters the elevator.

Otherwise, the algorithm keeps tracking the user according to the tracking vector and candidate table. The tracking algorithm can detect whether the elevator stops on a floor or not if any changes in acceleration or RSS thresholds have occurred; then, the floor discovery process is initiated.

Existing approaches, such as [11], detects the floor level by computing the elapsed time between entering and leaving the elevator. However, in the ILPS, the floor discovery process does not use the elapsed time to detect the floor level, because the time to reach a specific floor is not fixed. Furthermore, the difficulty of distinguishing between the upper and lower floors creates a significant challenge.

The floor discovery process uses the average reference point's RSSs to detect the floor level, where each reference point has a fixed position on a specific floor. The floor discovery process accurately detects the floor level using the reference points.

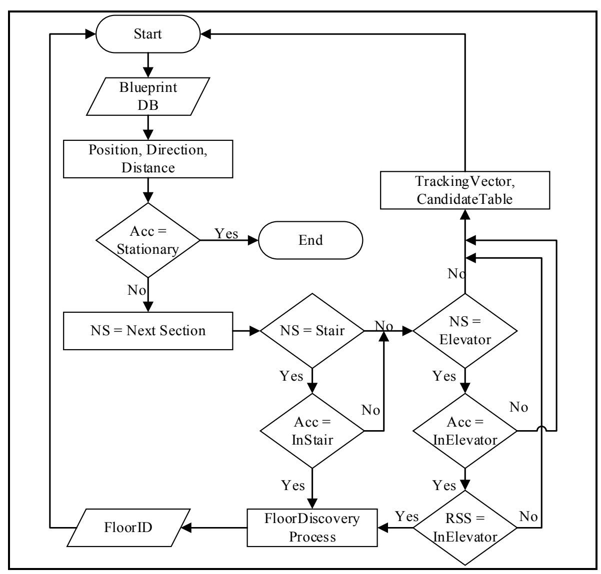

Figure 7. Flowchart of the tracking algorithm.

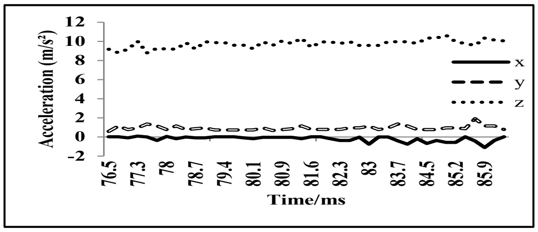

Figure 8. Acceleration in an elevator.

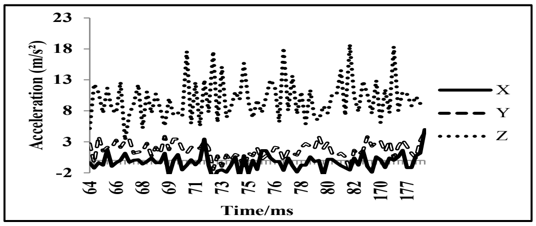

Figure 9. Acceleration in stairs.

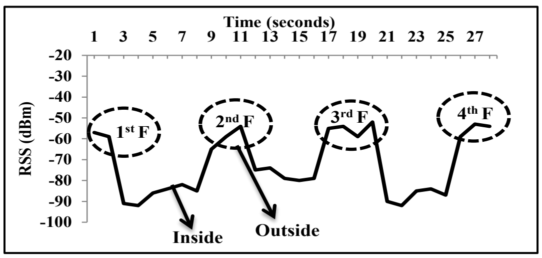

Figure 10. RSS level inside and outside an elevator.

Fig. 8 and 9 present the acceleration when the user is in an elevator, or is walking up/down stairs. Different thresholds are used by the tracking algorithm to decide if the user is in an elevator, or is walking up/down stairs.

For an elevator, both the acceleration threshold and RSS values are incorporated in order to determine whether the user enters or leaves the elevator.

Fig. 10 illustrates the reference points' RSSs inside and outside an elevator. The figure demonstrates that the RSS levels increases significantly when a user leaves an elevator to a floor; therefore, floor discovery process detects the floor level when this significant increase. Floor discovery process uses the reference points to detect the floor level where each reference point has a fixed position in a specific floor.

IV. EXPERIMENTS AND RESULTS ANALYSIS

The proposed ILPS was evaluated in two different environments: the first and second floors of the CS Department at KAIST (see Fig. 1) and the IT Convergence building at KAIST as depicted in Fig. 11.

The proposed method was implemented on an Android-based Nexus S smartphone and an Android-based LG Optimus LTE2 smartphone, which are both equipped with accelerometer sensors, orientation sensors, and Wi-Fi. The experiments were conducted during the daytime when the RSS levels may be affected by obstructions between the APs and the user's smartphone.

The real path of the user is drawn with a solid line, the ILPS path is drawn with a long dashed line, and the PDA with compass path is drawn with a small dotted line. As seen from Scenario 1 shown in Fig. 11, the ILPS path is very close to the real path, while the accuracy of the PDA decreases as the user moves. The circles in the figure represent the position adjustment when the user encounters a reference point. The existing reference points increase the accuracy of the system; therefore, as the figure demonstrates, the ILPS path will be closer to the real path if more reference points are available in the building.

Fig. 12 presents Scenario 2, which was performed on the first and second floors of the CS Department building. The letter (D) in the top right of Fig. 12 represents an example when the user encounters a reference point. As seen in the figure, the position has been adjusted directly to be the location of the reference point (circle).

The findings of this experiment indicate that there are some errors between the real and estimated locations, which originate from the uncertainty in the measurements from the distance estimation and initial position estimation.

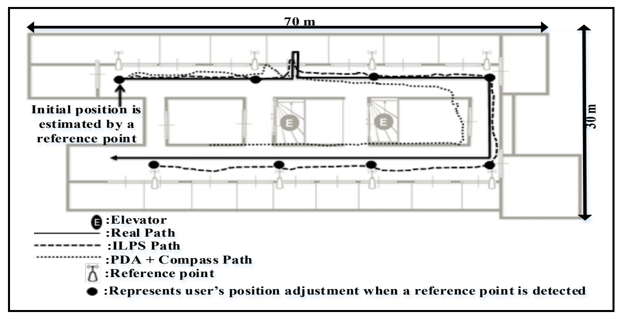

Figure 11. Scenario 1.

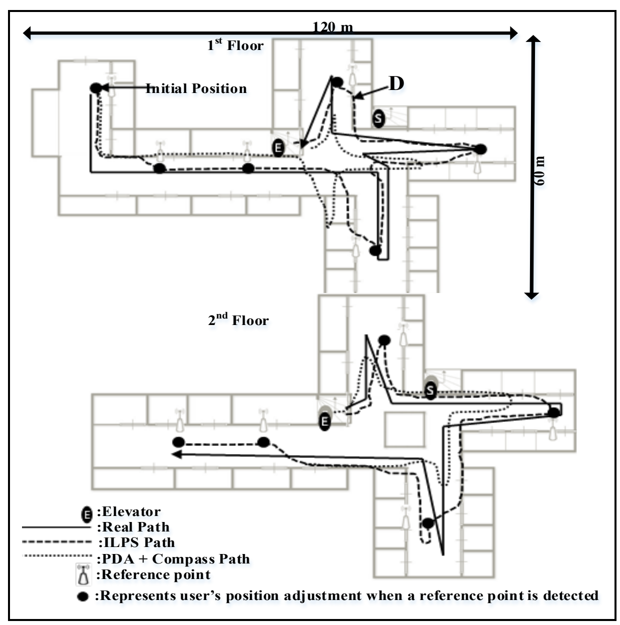

Figure 12. Scenario 2.

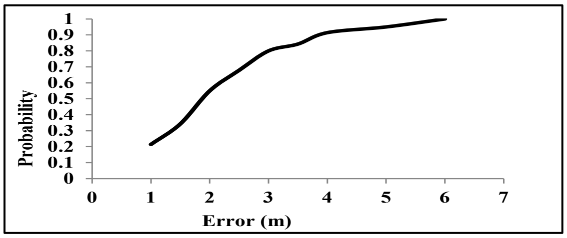

Figure 13. CDF of positioning error for ILPS.

The error bound of ILPS can be derived by calculating the distance difference between the real position and the ILPS position using Euclidean distance. Formally, let (x^t, y^t) is the real user position at time, t. and let (x^t_1, y^t_1) is the ILPS user position at time, t. Then:

$$\text{Error} = \sqrt{(x_1^t - x^t)^2 + (y_1^t - y^t)^2}. \qquad (3)$$

In Scenario 1, the mean error and standard deviation error for the ILPS were 2 m and 0.9 m, respectively. In contrast, the PDA had a mean error of 5 m and standard deviation of 2.2 m. In Scenario 2, the ILPS mean error and standard deviation were 3 m and 1.1 m, respectively. The PDA had a mean error of 6.3 m and standard deviation of 3 m. In both scenarios, the mean error of estimating the initial position for the ILPS was 3 m, while the standard deviation was 1 m for both scenarios.

Fig. 13 demonstrates the cumulative distribution function (CDF) graph, which shows that the CDF of distance error of 3.8 m is 0.9, which means ILPS has a location precision of 90% within 3.8 m.

UnLoc [11] and EZ [14] are ones of the recent papers, which are related with ILPS. UnLoc [11] has an accuracy of 2 – 3 m. However, it needs to know the location of the doors to detect the initial position. Moreover, some landmarks signatures are prone to misleading, such as acceleration on elevator and WiFi similarity. In contrast, ILPS relies on the RSS of public APs, which are available in most of the buildings; therefore, ILPS can be generalized to all buildings. EZ [14] has an accuracy of 2 – 7 m, but it needs path-loss model which has the problem of signal variation. In contrast, ILPS does not require calibration, which is needed in EZ, and has a better accuracy.

V. Conclusion and Future Work

This paper presents an indoor positioning and tracking system. The proposed approach uses a stored database for the building blueprint, which divides a building into sections and connects them using a direction table. The initial position of the user is determined using the closest AP with the strongest received signal strength average. In order to overcome the instability of the RSS, the search process is restricted to only the public APs stored in the database. The user direction is estimated using the orientation sensor after guaranteeing its accuracy by obtaining the average value. In order to obtain the user movement, the accelerometer sensor data was gathered and the PDA was used. In order to overcome the miscounting problem in this technique due to irrelevant movements of the smartphone, the public AP locations in the database were used to correct any errors in distance estimations. The user position in an elevator was estimated using both the acceleration and RSS values. The experiments with the proposed ILPS system in real environments demonstrated that the distance estimation had a mean error of 2 m and the initial position accuracy had mean error of 3 m. As future work, equipping the ILPS with dynamic map construction will create a standalone system, which can lead to other ideas, such as handling the handoff.

Acknowledgment

This work was supported by the National Research Foundation of Korea (NRF) grant founded by the Korea government (MEST) (No. 2012R1A2A2A01008244).

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