Locating using Prior Information: Wireless Indoor Localization Algorithm

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ABSTRACT

Most indoor localization algorithms are based on Received Signal Strength (RSS), in which RSS signatures of an interested area are annotated with their real recorded locations. However, according to our experiments, RSS signatures are not suitable as the unique annotations (like Fingerprints) of recorded locations. In this study, we investigate the characteristics of RSS (e.g., how the RSS values change as time goes on and between consecutive positions?). On this basis, we design LuPI (Locating using Prior Information) that exploits the characteristics of RSS: with user motion, LuPI uses novel sensors integrated in smartphones to construct the RSS variation space (like radio map) of a floor plan as prior information. The deployment of LuPI is easy and rapid since little human intervention is needed. In LuPI, the calibration of "radio map" is crowd-sourced, automatic and scheduled. Experimental results show that LuPI achieves comparable location accuracy to previous approaches, even without the statistical information of site survey.

Categories and Subject Descriptors

C.2.4 [**Computer-Communication Networks**]: Miscellaneous

Keywords

Indoor Localization; Floor Plan; Smart Devices; Wireless Networks

1. INTRODUCTION

The popularity of smart-device-based mobile and pervasive computing stimulates extensive research on wireless indoor localization. Based on the potential functionality of these sensor-embedded mobile devices, many solutions are introduced to provide room-level location-based services, for example, locating a person or a printer in an office building. Even, data collection from mobile phones can be used to uncover regular rules and structures in the behavior of both individuals and crowds.

Received Signal Strength (RSS) is easily obtained from most off-the-shelf wireless equipment (such as WiFi- or ZigBee-compatible devices). However, considering RSS as a database to support indoor localization (e.g., RSS fingerprint space) is time-consuming and labor-intensive. Especially, from extensive experiments, we observe that the RSS database is vulnerable due to environmental dynamics (an example is shown in Figure 1). These weaknesses are inevitable for RSS-based approaches. For mitigating the influence of environmental changes on RSS absolute values, we exploit the relative change of RSS between different positions.
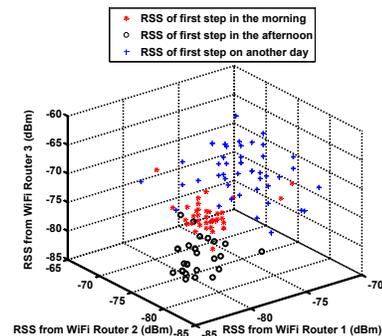

Figure 1: Instability of RSS values

In this study, we propose LuPI (Locating using Prior Information). The key idea of LuPI is that human motion can be distinguished and recorded by radio information (e.g., RSS deviation between different positions) and a pedometer (it is based on accelerometer embedded in a smartphone). LuPI utilizes the RSS and the sensor-based pedometer to build a RSS variation space as prior information. Then, based on this prior information, LuPI estimates the location of a mobile node. LuPI requires no prior knowledge of router locations which are often unavailable in commercial or office buildings where routers are installed by different organizations. In addition, accessing these routers by password is also unnecessary for LuPI.

To estimate the performance of LuPI, we deployed a prototype system and conducted extensive experiments on the third floor of a middle-size building.

2. OUR APPROACH AND KEY CONTRIBU-TIONS

The steps of LuPI are shown as follows. **Input:** One hundred RSS sets from three different WiFi routers at each step, $[RSS_1 = (rss_1, rss_2, rss_3), RSS_2, ..., RSS_{100}]$. **Step 1:** Build the RSS variation space: (1) Partition all RSS sets into k clusters in which each set belongs to the cluster with the nearest mean, using the k-means clustering, where k is the number of steps. Moreover the cluster center can be obtained for each step. (2) Calculate the distance matrix $D = [d_{ij}]_{k \times k}$. The elements of matrix D represent the Euclidean distances between cluster centers, e.g., d_{12} is the Euclidean distance between RSS sets of steps 1 and 2. (3) Calculate the relative coordinate matrix Y concerning all steps, using MultiDimensional Scaling (MDS) algorithm, based on the distance matrix D. (4) Accumulate coordinates and construct the RSS variation space. The elements of matrices D and Y form the RSS variation space. **Step 2:** Locate a mobile node using the RSS variation space. (1) Add the current RSS set of mobile node to the RSS variation space as a new element, and update the distance matrix D. (2) According to the new distance matrix, the new relative coordinate matrix Y can be calculated. The mobile node can be located with a relative coordinate in the RSS variation space. **Output:** The relative coordinate of a mobile node.

The key contributions of LuPI are: (1) It is a room-level localization algorithm. Experimental results show that LuPI achieves comparable location accuracy to previous approaches in the rooms. (2) It is a dynamic adaptive localization algorithm. The calibration of "radio map" is crowd-sourced and automatic. (3) It mitigates the impact of environmental change on localization. LuPI is based on the RSS variation space, and avoids the use of RSS absolute values. (4) The deployment of LuPI is easy and rapid, and LuPI only needs slight human intervention.

3. PRELIMINARY RESULTS

We develop the prototype of LuPI on the increasingly popular Android OS which supports WiFi and accelerometer. We conducted the experiments in two laboratories of $84m^2$ and $63m^2$, where three WiFi routers without location information were installed in each laboratory.

We sample the experiment area every two grids as a step ($0.6m \times 0.6m$ for one grid). Only three volunteers are needed in the experiment. LuPI records the pedometer readings (how many steps) to count the walking distance, and at the same time LuPI picks up RSS values along the walking path. We implement LiFS [3], and compare its performance with LuPI on the same experiment data. The average localization errors of LuIP are 1.39356 meters and 1.88574 meters for two laboratories, respectively, which are smaller than LiFS's average localization error (about 5.88 meters). Even in the corridor the performance of LuPI is comparable to the state-of-the-art model-based approaches (larger than 5 meters) reported in [2], and outperforms EZ (larger than 7 meters) [1].

We estimate 248 localization queries on LuPI. For the corridor and two rooms we integrate all the localization results (the Cumulative Distribution Function (CDF) of localization error (Figure 2)).

As shown in Figure 2, for the big room, the localization

(a) CDF of localization error in the corridor (b) CDF of localization error in the big room

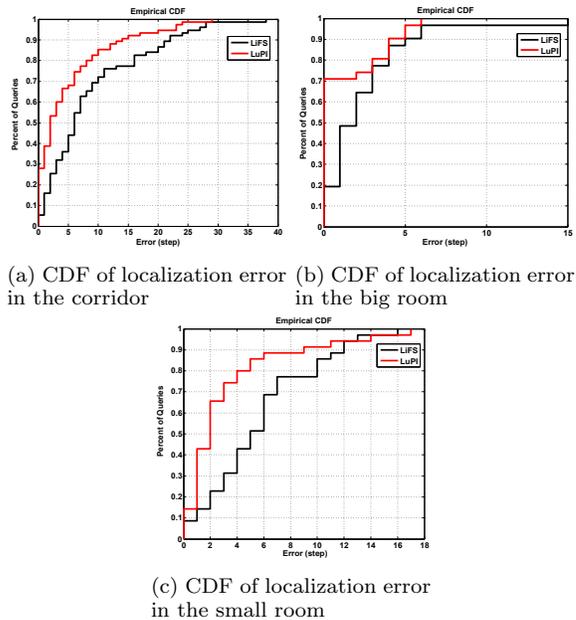(c) CDF of localization error in the small room

Figure 2: CDF of localization error

error of 100% queries is under 7.2 meters while about 90% is under 4.8 meters. For the corridor, the localization error: 69% queries is under 6 meters. The accuracy of LuIP is impressive, as it needs no site survey and no specific infrastructure.

4. CONCLUSION

The average localization error is 5.91996 meters in the corridor, the average localization error is 1.39356 meters in the big room, and the average localization error is 1.88574 meters in the small room. So the localization accuracy of LuPI is room-level. Moreover, the localization errors of 50% localization queries are less than 2.4 meters in the corridor, and the localization errors of 90% localization queries are less than 4.8 meters in the big room, and the localization errors of 50% localization queries are less than 1.2 meters in the small room.

5. ACKNOWLEDGEMENT

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