Automatic Update Method of WiFi Indoor Positioning Model using Pedestrian Dead-Reckoning Technique

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Abstract

WiFi technology is very popular and has been implemented in public areas such as hospitals and train stations. So, many researchers have attempted to construct indoor positioning systems by utilizing WiFi access points (APs) with small deployment costs. WiFi based indoor positioning systems rely on a public infrastructure that is not controlled by the user or the developer of the systems. So, when one WiFi AP is removed or moved, or layout changes, recalibration of the positioning systems is required. To reduce the cost, this paper proposes a new method for maintaining the positioning system. In our proposed method, we firstly track the user, who spends a lot of time in a given environment, with pedestrian dead reckoning techniques. At the same time we obtain WiFi scan data from a mobile device possessed by the user. With the scan data and the estimated coordinates, we can automatically create a pair consisting of a scan and its corresponding indoor coordinates during the user’s daily life. Then, we periodically update signal strength fingerprints by using the information to cope with the instability of WiFi based positioning methods caused by changing environmental dynamics.

Keywords: Indoor positioning, fingerprinting, pedestrian dead reckoning

1 Introduction

Due to the recent proliferation of cheap and small sensors, many researchers in the wearable computing research field have employed body-worn sensors such as accelerometers and orientation sensors to track the movement trajectory of a person indoors by detecting steps, and estimating stride lengths and the directions of motion [1]. This methodology is called Pedestrian Dead Reckoning (PDR).

On the other hand, WiFi technology is very popular and has been implemented in public areas such as hospitals and train stations. So, many researchers have attempted to construct indoor positioning systems by utilizing WiFi access points (APs) with small deployment costs. Fingerprinting techniques based on WiFi have usually been employed to measure indoor positions [2]. However, WiFi based indoor positioning systems rely on a public infrastructure that is not controlled by the user or the developer of the systems. So, when one WiFi AP is removed, for example, recalibration of the positioning systems is required. Also, in a dynamic environment caused by layout changes, the WiFi signal strengths measured in the positioning phase may deviate significantly from those stored in the database.

To cope with the problem, we should manually re-collect fingerprints. In this paper, we propose a new approach that automatically and periodically re-collects fingerprints and uploads them to the fingerprint database. We assume that, in an indoor environment such as a hospital or office, special users, such as workers who spend a lot of time in the environment, wear various kinds of sensors such as accelerometers and orientation sensors, and we attempt to track these workers with the PDR technique. We also assume that mobile devices carried by the workers continually scan WiFi signals. So, by combining the WiFi scan data and the estimated coordinates obtained during ‘walk’ activities in their daily lives, we can automatically create a pair consisting of a WiFi scan and corresponding indoor coordinates while placing only a small burden on the workers. The WiFi fingerprints are automatically updated by using the information during the workers’ daily routine. With this approach, ordinary users (customers and other workers) who do not wear rich sensors can benefit from the continually updated WiFi fingerprints.

2 Proposed Method

2.1 Overview

Fig. 1 provides an overview of our approach. Here we assume that few Bluetooth beacons are
installed in an indoor environment as shown in the left portion of Figure 1. The input of our method consists of sensor data obtained from mobile devices of special users (e.g., workers in a particular environment). Our method has two main components: Tracking special user and Learning positioning model. We explain them briefly below.

[Tracking special user]
We track the special user by using sensor data from the user. We achieve this by integrating techniques proposed in existing wearable and mobile computing studies. With the computed trajectory and the WiFi scan data obtained with a mobile device carried by the user, we can make pairs consisting of WiFi scan data and corresponding indoor coordinates. The created pairs are stored in the WiFi scan database. So, the database is continuously updated during the user’s daily life.

[Learning positioning model]
We periodically update the WiFi positioning model by using the data stored in the database. We learn the features of the received signal strengths at each grid cell in the map of the environment. So, we aggregate scans within each grid cell. For each grid cell, we model the received signal strengths from the APs by using the scans in the cell.

We describe the procedure in detail below assuming that a device with sensors is attached to the user’s body. Note that, in the following, we explain how we compute the user’s trajectory of that after the user passed by the beacon. We can compute the trajectory before the passing or between the passings (if there are two or more beacons in the environment) in almost the same manner.

2.2 ‘Walk’ detection
We first detect ‘walk’ activities (i.e., detect start and end times of walking) in the user’s daily life by using acceleration and gyro sensor data obtained from the user (about 16 Hz). We employ the existing activity recognition methods proposed in wearable and pervasive computing studies [3; 4] that are based on supervised machine learning techniques.

2.3 Obtaining absolute coordinates
With the above procedure, we can find the start and end points (times) of a ‘walk.’ With the Bluetooth scan data obtained during the ‘walk,’ we can determine when the user passed by the Bluetooth beacon. When the user passes by the beacon, the Bluetooth signal strength gradually increases and then decreases as shown by the data in Fig. 2, which were obtained when an experimental participant passed by a beacon. So, when the value exceeds a certain threshold and becomes a local maximal value, we determine that the user passed by the beacon. Note that, when we cannot find Bluetooth signal data that exceed the threshold during walking, we discard the walking sensor data and do not use them in the following procedure.

2.4 Tracking with PDR
To track the user’s trajectory, we employ a particle filter [5] that is usually used to estimate the states of non-linear systems. We explain the procedures required for the tracking.

[Initialization]
We first set particles at the beacon’s coordinates. Since there may be small errors related to Bluetooth beacon based positioning, we randomly scatter several particles around the beacon’s coordinates generated from a bivariate Gaussian distribution. We then determine the directions in which the particles move by using orientation sensor data. Here we assume that a beacon is installed at a place where the user’s direction of movement is restricted (e.g., corridor). So, we preset the probable directions when a user passes the beacon in advance. Then, we determine in which direction the user is heading by using orientation data. We adopt this approach because the orientation sensor data obtained indoors in-
clude very large errors due to the presence of electric appliances and metals.

**Determining stride and direction**

We determine the speed and direction of the user’s movement. First, we detect steps by using acceleration sensor data. We combine the acceleration data for three axes and simply detect steps by counting the number of times the gravity acceleration value is crossed by the combined signals. For each step, we assume that the user (particle) moves the length of a stride. In the sampling process, we generate several particles from each particle by randomly changing their length of stride by using a Gaussian distribution with a predefined mean because the length of stride may change for each step. At the same time, we also determine the direction of the user (particle) by using gyro sensor data because orientation sensor data are unreliable indoors. Since we know the direction of movement when the user passed the beacon, we can compute the direction after the time of passing by using relative angular speed data (gyro sensor data). We also randomly change the direction for each particle by using a Gaussian distribution to cope with its sensor data errors.

**Clustering**

As above we move particles from the time at which the user passed the beacon to the point (time) when the walking ends. When a particle collides with obstacles in the environment, the particle is discarded. If two or more particles survive at the time at which the walking ends, we should select one of them and employ the trajectory of the selected particle as the user’s trajectory. We cluster the coordinates of the surviving particles at the end time with the X-means algorithm [6], and find the largest cluster. Then we select the particle closest to the centroid of the cluster. Also, when only one particle survives at the end of the walking, we simply determine the trajectory of the particle as the user’s trajectory. When no particle survives at the end time, we discard the walking and do not use it in the following procedure.

**2.5 Learning positioning model**

Firstly, we aggregate scans within each predefined grid cell in the environment and learn the parameters of the signal strength distribution in the cell for each AP. Previous studies support the view that the WiFi received signal strength obeys a Gaussian distribution [7; 8] when the sample size is sufficient, and so we also use a Gaussian distribution to model the signal strength from each AP at each cell and its probability density function is represented as follows.

\[
f(x_i, \mu_{i,n}, \sigma_{i,n}^2) = \frac{1}{\sqrt{2\pi\sigma_{i,n}^2}} \exp\left(\frac{-(x_i - \mu_{i,n})^2}{2\sigma_{i,n}^2}\right),
\]

where \(x_i\) is the observed signal strength from the \(i\)th AP, and \(\mu_{i,n}\) and \(\sigma_{i,n}^2\) are the mean and variance of a Gaussian corresponding to the \(i\)th AP at the \(n\)th grid cell, respectively. So, we compute \(\mu_{i,n}\) and \(\sigma_{i,n}^2\) from the scans in the cell.

As described above, we can learn the signal strength distribution from the \(i\)th AP at the \(n\)th cell. So, we can compute the likelihood with which a WiFi scan \(x\) is observed at the \(n\)th cell as follows.

\[
p(x, \lambda_n) = \sum_{i \in \mathcal{X}} f(x_i, \mu_{i,n}, \sigma_{i,n}^2),
\]

where the parameters of Gaussians related to the \(n\)th cell are collectively represented by \(\lambda_n\).

In the positioning phase, we compute the likelihood of each cell \(\lambda_n\) for an observation \(x\) obtained at unknown coordinates. As with the \(k\)NN approach, we obtain cells with the top-\(k\) likelihood values and compute the weighted average of the cell coordinates. (The weight corresponds to the likelihood value.) The average coordinates become the estimated coordinates. \((k = 3)\)

### 3 Evaluation

#### 3.1 Data set

The sensor data were obtained on one floor of our graduate school building as shown in Fig. 3. \((1m \times 1m\) cell size in our implementation) On the first day, we collected WiFi fingerprints at the training points shown in Fig. 3. Fig. 3 also shows the position of a Bluetooth beacon. We then iterated the following procedures every day for 28 days: (1) An experimental participant walked around the floor at various times with a Google Galaxy Nexus smartphone attached to his waist. He randomly selected start and end coordinates on the floor and walked according to those coordinates. He repeated the walk twenty times a day. Then, pairs consisting of a WiFi scan and its indoor coordinates were uploaded to the WiFi scan database. (2) We reconstructed the indoor positioning model with the data stored in the database. (3) We collected WiFi scans at the test points shown in Fig. 3 and computed the positioning accuracy for the test data.

#### 3.2 Evaluation methodology

We tested the \(k\)NN method \((k = 3)\) in addition to our method. To investigate the effectiveness
of our method, we virtually reduce the signal strengths from APs located outside of the floor after the 15th day on the assumption of some conversion of outer walls. We can observe stable signals in the environment from five APs located outside of the floor. We randomly reduce the signals using a Gaussian distribution with a 15 dBm mean based on our observation and existing studies [9; 10].

3.3 Results
Fig. 4 shows the transitions of accuracies related to the kNN and our methods when we reduced the signal strengths from the APs located outside the floor on and after the 15th day. Although the positioning performance of our method was not stable in the early stage, it provided good accuracy after sufficient numbers of scans were uploaded to the scan database. It greatly outperformed the kNN method. Our method created fingerprints densely placed in the environment by using the walking of the participants, and the dense fingerprints achieved good accuracies.

The mean error distance of the kNN method increased greatly (about 0.6 meters) after the reduction on the 15th day. Although the number of APs located outside the floor (five) was much smaller than that located on the floor (seventeen), the effect was significant. Immediately after the reduction, the mean distance errors with the proposed method also increased. However, the mean distance error gradually decreased because the new scans were continually uploaded by the participant.

4 Conclusion
In this paper we proposed a new approach for maintaining a WiFi indoor positioning model with respect to changing environmental dynamics with the help of body-worn sensors attached to specific users. We attempted to track the user with PDR techniques, and at the same time we obtained WiFi scan data from the user. With the scan data and the estimated coordinates, we automatically created a pair consisting of a scan and its corresponding coordinates, and updated the positioning model by using the information.

In our experimental evaluation, we confirmed that our method could cope with the sudden changes in signal strengths from APs.

References