WIP: Daily Life Oriented Indoor Localization by Fusion of Smartphone Sensors and Wi-Fi

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***Abstract*—Smartphones are the best personal assistants in our lives on several counts. However, their services can still be improved for a better quality of life. In this paper, we aim to determine the exact location of a smartphone in a room, i.e, on a study desk, a television table, etc. By this way, our daily settings may be automatically activated from the smartphone itself. For example, if a user puts his/her phone on the bed commode, then the phone would be able to switch itself to the night mode on its own. A successful localization in a room should be able to distinguish different corners from each other so that it can be used in various applications as a supported technology. Hence, in this work, we are proposing an indoor localization system that can distinguish different indoor places by using the smartphones' sensors and Wi-Fi services. Unlike the common location-based services, our solution is not a server-client based system. In order to enhance feasibility and availability, we only use the mobile device but no additional infrastructure. We developed two applications on Android platform. The first one allows the user to easily collect sensor data from his/her living places, such as home and office settings. The second one is a data mining application sourced by Weka. The tests were performed in different rooms of a house and office environment. We achieved 86% accuracy for room level localization.**

Keywords—indoor localization, smartphone sensors, magnetic field, Wi-Fi, ID3, decision tree, classification

I. Introduction

Indoor localization is a system to locate objects or people inside a building. The existence of the huge and complicated buildings in modern life has created a need for distinguishing indoor locations and navigating people who spend most of their time inside. The acquisition of physical location is the fundamental basis for Location-Based Systems (LBS). To acquire high-accuracy localization in indoor environments, many techniques have been developed [2].

Generally, applications have focused on distinguishing different rooms, corridors and such places that are obviously separated from each other. On the other hand, they are tracking the phone[1]. In this study, we construct our localization system based on where smartphones are placed during the day. We neither attempt to navigate the user nor track the phone. Our main target is to make it possible to determine whether a smartphone is on a study desk versus a nightstand, or whether it is in front of a window or on top of a dinner table, in the same room. Thereby, our daily settings can be automated by the smartphone itself. Thus, we have done our experiments in certain locations in home and office environments. This is beyond the usual approach of indoor localization, giving an advantage to analyze the ambient specifications of the environment. A successful localization in a room to distinguish different corners can be used in many smartphone applications. Mobile devices can take automatic actions according to their current positions. It can also be used for improving the precision of tracking systems in indoor environments.

In order to enhance feasibility and availability of our indoor positioning system, we did not use any additional infrastructure. Furthermore, we have developed all computation processes on smartphone. Unlike the common location-based services, this is not a server-client-based system. Our proposed system is working with ambient light sensor, proximity sensor, magnetometer, and Wi-Fi fingerprint technology to identify the exact location of smartphones in indoor environments. All sensor and Wi-Fi data have been used to create a fingerprint database. The produced database becomes an input for data classification processes.

This paper is organized as follows: In section II, we mention about our data collection process. In section III, data analysis for collected sensor data is discussed and in the last section classification process and results of classification tests are given.

II. Data Collection

In accordance with our motivation, we have developed a data collection system that allows us to gather data from the daily life locations of users. Since we aim to distinguish pre-determined places in a room or in an office from each other, and focus on making this study a part of a daily routine of a user, a simple, handy Android application has been developed to collect ambient sensors' data and Wi-Fi signals, and record them in the memory of smartphone. The user places the smartphone in a fixed position of his choice. For demonstrative purposes, we have determined five locations in each selected room. Two different experiemnts were undergone in two different house enviornments: the first one was in the living room and the second one was in the lounge. In addition, we have done experiments in an open office environment where there are divided rooms at different floors. We have determined five tables at locations that differ within but not between floors to collect data. For each determined location, the smartphone was approximately placed at the same place with the same position and direction during the data collection process. To make our tests under stable environmental conditions, we have paid attention to keep objects, especially electronics and metal items, in the places they have always been.

III. Data Analysis For Collected Sensor Data

We have labelled chosen places for each room as Place1, Place2, Place3, Place4 and Place5.

Place1 in the lounge is located in front of the window, on the floor. There is a flowerpot right next to it. Place2 is located on a radiator that is on the right side. Place3 is on a coffee table, the furthest spot from the window. Place4 is on the sofa's side furthest from the window, to the right next to the Wi-Fi modem. Place5 is on the console opposite to the wall near the window.

To visualize the characteristics of the sensor data for different locations, radarcharts have been created. These charts provide a chance to make comparisons between the data which were collected at the same times of different days.

To visualize our dataset on radarcharts, we scaled all variables by using z-score. Z-scores of variables are calculated by subtracting the mean of all data points from each individual data point, then dividing those points by the standard deviation of all points. Thus, z-scores can expressed as the number of standard deviations from their means. As we explained in the data collection part, we have datasets from different times of different days. Each sample of each place took approximately 1 minute long. We have created radarcharts for these 1-minute samples separately. To locate a dot on the radarchart of each variable, we have calculated median values for each variable. In the radarcharts, variables are reprsented as: L; Lux, P; Proximity, X; Magnetic field on X-axis of smartphone, Y; Magnetic field on Y-axis of smartphone, Z; Magnetic field on Z-axis of smartphone, R1; RSSI of Wi-Fi AP1, R2; RSSI of Wi-Fi AP2, R3: RSSI of Wi-Fi AP3, R4; RSSI of Wi-Fi AP4.

In the lounge, when we look at Fig. 1, we can observe that for Place1 the lux value almost reaches maximum at any time but evening times without florescence. For this setting nearest to the window, the lux value is always the highest in the room. Magnetic field is a stable component for each axis. The Wi-Fi RSSI values do not show similar characteristics during the day for all places. It is noteworthy to emphasize that, while the values of proximity sensor are almost zero in all places, in Place1, it shows an increase in certain hours of the day. The reason behind this increase is stemmed from the changing position of curtain which tend to be brought down during evening hours.

As it is seen in Fig. 2, in Place2 at the lounge, it can be said that the polygons of close times look very similar, yet they have been collected on different days. For example, the polygon at 19:10 and the polygon at 19:16 are almost the same, with a slight difference in the R1 and Z. Another notable point for Place2 is that the magnetic field on the X-axis mostly reaches to maximum value at different hours. And the average values of R2 component throughout the whole day is remarkably higher than the average values of R2 component of other places.

When we look at Fig. 10 in Place4, the magnetic field values on X, Y, and Z-axes do not change much at different times of the day. Apart from this, it can be seen that R1 value is relatively higher due to the proximity of Place4 to Wi-Fi Ap in the same room.

For each environment where data was collected from, radarcharts for different times have been created. Given radarcharts are chosen to show that, ambient features of indoor locations deeply affect sensor data and demontrate various characteristics in different places at different times. Hence, it could be said that all of the sensor variables could be used as an attribute to distinguish places from one another. Time is also a distinctive parameter for the sensor data classification.

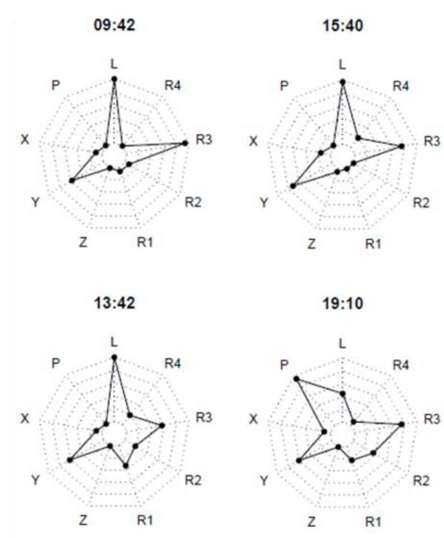

Fig. 1. Radarchart for Place1 in the lounge

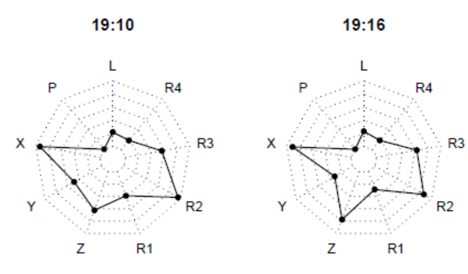

Fig. 2. Radarchart for Place2 in the lounge

IV. Data Classification

In this study, a Weka library is deployed on an Android application to classify collected sensor data. In order to eliminate outliers in raw sensor data, we applied a sliding window median function to raw data. This function provides equal-length sensor data for all sensors. If we take *w* as the window size, the median of the first *w* values of raw data records is calculated and added to the new array. Then, if we take *s* as shift size, the median value of the next *w* records is calculated by beginning from the (*s*+1)th record. This calculation needs to be maintained until the end of the raw data records. We divided raw data records in 1-second-length windows, and applied a 0.5-second length segments as shift size.

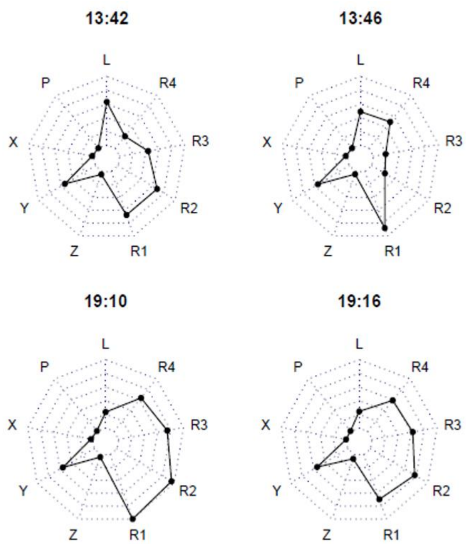

Fig. 3. Radarchart for Place1 in the lounge

Wi-Fi data is processed differently due to its different characteristics. In the home environment, we create Wi-Fi fingerprint by the following methodology: During a data collection period, each received Wi-Fi signal is recorded in cache memory with their BSSID, SSID and RSSI information for each location. At the end of the collection phase, received signals are sorted according to their power in descending order. Then, BSSID's of Wi-Fi access points that have the strongest signals are appended on each other. Obtained strings are assigned to places as Wi-Fi labels.

A. Iterative Test

When the training set includes the test set, the error rate of the prediction decreases defectively. Not using the entire data set during training is a way out to handle this problem. Some data can be excluded to use as test data. In this manner, the real performance of the trained model on new data sets can be assessed.

TABLE I. AVERAGE RESULT OF ITERATIVE TEST

Location	Correctly Classified	Incorrectly Classified
Lounge	80,4088	19,5912
Living room	87,9654	12,0346
Office	88,8712	11,1288
Average	**85,7485**	**14,2515**

This is the basic concept of the cross-validation. To improve the reliability of cross-validation, we applied an iterative test. We distinguished the learning set from the data of the test set. We used (n-1) data sets to build a training model and applied it on remaining data set for classification. This process was iterated n times until all data sets were once in the testing and computed the overall confusion matrix. All computations have been made on a smartphone. Results for all three rooms are given in Table 1.

B. Reliability Test

To assess effect of enhancing training set on classification accuracy, the reliability test is applied. In this test, training data set has been collected from five chosen places in a room at the evening times of different days. Our data set enhanced cumulatively with the collected data sets and the classification application run for classifying test data iteratively. With this method, we aimed to demonstrate how much we have to train to reach the maximum accuracy for classification. We reached almost 100% accuracy at the end of the 8th iteration.

CONCLUSION

In this study, we first offered a sensor data collection application that can be used in everyday life. With this application running on the Android platform, we aimed to be able to locate devices in closed and physically small spaces, like our homes and business locations. We used light, proximity and magnetic field sensors, and the surrounding Wi-Fi signals to reveal the characteristics of the locations. We have marked five different points for three different locations (two houses, one office). We developed an application to create a decision tree model by using Weka library on Android. By using this application, a decision tree model was created for each location. As a result of iterative test, we achieved an average accuracy of 85%. In addition to that, with the reliability test, we have demonstrated that, when the training set is enhanced by data collection we can reach almost 100% classification accuracy. The prominent feature of this work is that data collection, preprocessing, building the decision-tree model, and making classification according to the created model are all done on the mobile device. In this way, we provide a basis for smartphones to support users in their daily lives by taking automatic actions. For future work, we aim to enable smartphones to automatically perform certain operations at certain times and at certain locations according to the habits of their users.

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