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Indoor Localization Through Mobile Participatory Sensing and Magnetic Field †

Juan Pablo García Vázquez * and **Isabel Lebasi Ambriz Silva**

Facultad de Ingeniería, MyDCI, Universidad Autónoma de Baja California (UABC), Mexicali, Baja California, México

* Correspondence: pablo.garcia@uabc.edu.mx

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Abstract: Development of indoor location systems that uses smartphone sensors has been a topic of interest to industry and academia. In this paper, we describe an experiment that was performed to evaluate the feasibility of creating a mobile indoor localization model based on data from participatory sensing. To achieve it, seven smartphone users used their integrated magnetometer to collected magnetic field information on a building. The data collected are utilized to train three machine learning algorithms: k nearest neighbors (KNN), decision trees (J48) and Naïve Bayes. The performance of the algorithms was measured through the accuracy and kappa statistics. Our results indicate that is possible to create an infrastructure-less indoor localization model at room level using data from participatory sensing. The model with the most significance performance was obtained with the KNN, since it offer an accuracy of 97.12%; while the model with the most reduced performance was Naïve Bayes, since it offers an accuracy of 50.79%.

Keywords: participatory sensing; machine learning; fingerprinting

1. Introduction

The localization of a person has been of interest as context information for developers of context-aware systems and the Internet of Things [1]. This because of the diversity of applications that can be developed [2]. For instance, navigation systems that help firefighters quickly withdraw from hazardous areas, and systems that assist people to move inside a mall or an airport.

The design of indoor location systems based on the Global Positioning System (GPS) has remained a challenge because of several factors like multipath fading, distance attenuation or interference from other wireless systems that affects the accuracy of GPS to estimate the person localization. However, the development of new and sophisticated sensors has allowed proposing novel solutions for indoor location. These solutions utilize devices or sensors, like Ultrawideband, Bluetooth, Wi-Fi, RFID, accelerometer, magnetometer, to name just a few. As well as several techniques to estimate the location or positioning, for instance, triangulation, proximity and location fingerprint [3,4], the latter being the most popular.

Obtaining the location fingerprint consists of two phases: training and position calculation [5]. In training phase, the information associated with a signal of interest is measured and collected until it survey the area of interest (e.g. a building). This information is collected in a database, known as radio map. To calculate the position of a person, the signal of interest is measured and be compared with the radio map using a machine learning algorithm (e.g. k Nearest Neighbors).

The location fingerprint technique allows us to generate indoor location models [6,7]. However, we face the following problems: (i) A training phase with significant cost and time. This because of training requires an expert perform the exhaustive measurements in indoor environments and (ii) the dynamics of the environment affects the radio map; that is, any change in the infrastructure of the indoor environment requires that training phase be carried out again; which limits its implementation.

In this paper, we propose an experiment to evaluate the feasibility of using the participatory sensing as a training phase of location fingerprint technique. This to solve the problems of location fingerprint technique.

The paper is organized as follows. Section 2 presents several research works that use mobile participatory sensing at indoor location. The experiment carried out to know the viability of the participatory sensing to generate the radio map is described in Section 3. In Section 4 the results of the experiment are presented; and finally, the conclusions and future work are presented in Section 5.

2. Related Work

Participatory sensing is defined as a paradigm that empowers people to contribute to the accomplishment of a specific task [8]. In indoor location the people contribute with data detected or generated on their smartphones. Several projects demonstrate the success of this technique, such as google crowdsource, OpenStreetMap and Wikimapia.In these projects people provide information to enrich a map with notes or photos, which provide more information about the place.

Therefore, the participatory sensing has been implemented as the training phase of the systems that facilitate the automatic construction of virtual layouts for indoor environments. These systems are characterized by collecting information regarding the movement of an individual in an indoor environment (e.g. distance, direction and number of steps). As well as information from sensors or devices embedded in the environment (e.g. access points). The information collected is utilized to identify the common pathways that the people use when commuting inside indoor environments.This information allows proposing a virtual layout of the environment. Examples of such systems are: CrowdInside [9], Piloc [10], CIMLoc [11], WILL [12] and Groping [13].

Unlike previous work, in this paper, we propose to implement participatory sensing as a training phase of the location fingerprint technique. To create a radio map and a predictive model for estimating the indoor location of a person. The magnetic field was selected, because of it is available in all indoor environments and do not require additional infrastructure to generate it (e.g. access points or radio bases) [4].

3. Methods

3.1. Experiment Setting Description

The experimental setting was the Computer Systems building. It consists of the halls and five classrooms labeled with the letters A, B, C, D and E (See Figure 1). The area and dimensions of the spaces are A:64 m^2, B:32 m^2,C:55.25 m^2, D:55.25 m^2, and E:55.25 m^2.

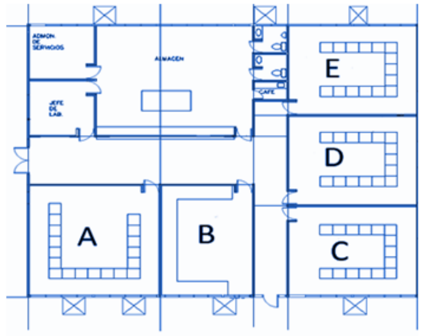

Figure 1. Building Layout

3.2. Data Collection

To collect data from the magnetic field, a mobile application was developed for Android devices 4.3 or higher. The application uses the magnetometer to measure and collect the intensity of the magnetic field, in μ Teslas (See Figure 2). Additionally the application also collects other data like time, date, name of the room where the measurement was collected (e.g. classroom B), magnetometer model and android version.The information collected is gathered in a cloud service called Firebase.

To carry out data collection persons who possessed a mobile device with magnetometer (e.g. smartphone or tablet) were invited to participate. The persons were instructed to handle our mobile application. The training consisted of three activities: (1) launch the application (2) choose the room in where they would collect the information (3) perform the measurement and collection of magnetic field information.

To perform the data collection, the person should move voluntarily in the indoor environment during 30 seconds. During the use of the mobile application, the person must handle their mobile device in the palm of her hand with the screen up. This process is replicated every time they collect information.

Figure 2. Mobile application for data collection

3.3. Data Processing

To ensure the quality of the collected data and achieve more considerable accuracy in the estimation of the location, the following activities were carried out:

- Data format. The data used in Firebase is collected in a JSON document, then it was converted to a table type format; in which the columns are separated by commas. This to facilitate its manipulation in the tools for the analysis of information (e.g. RStudio). To perform this, the Opal Convert tool was utilized.
- Normalization. To ensure that all attributes possess the same importance. The data were normalized using zero mean normalization.
- Data Partition. The data collected was randomly divided into two subsets of data: training (70%) and testing (30%).

3.4. Predictive Model for Indoor Localization

To generate the predictive model with the magnetic field intensity information collected through participatory sensing, the following machine learning algorithms were used: k nearest neighbors (KNN), Decision trees (J48) and Naive Bayesian (Naïve Bayes).

The algorithms were implemented in Rstudio. To assess the performance of learning algorithms in this paper, we considered the confusion matrix, success rate and error rate. The confusion matrix represents a tool that allows visualizing the performance of an algorithm. Each column of the matrix represents the number of predictions of the class, while each row represents the instances in the actual class. The success rate refers to the percentage of instances classified correctly, while the error rate refers to the percentage of instances classified incorrectly. These were calculated from the following equations:

$$sucess\_rate = [\frac{TP + TN}{TP + TN + FP + FN}], \tag{1}$$

$$error\_rate = [\frac{FP + FN}{TP + TN + FP + FN}]. \tag{2}$$

In the Equations 1 and 2 True Positive (TP) are examples correctly labeled as positives. False positives (FP) refer to positives samples labeled as negative. True negatives (TN) correspond to negatives correctly labeled as negative and False negatives (FN) refer to positive examples incorrectly labeled as negative.

4. Results

4.1. Training Phase

A total of 701,714 magnetic field strength measurements on three axes (x, y, z) was collected by seven subjects using five different smartphones and two tablets. The 70% of the data generated was used to train three machine learning algorithms (491,200 measurements). A total of four models were generated employing the training data.

4.2. Test Phase

A total of 201,514 measurements were employed to evaluate the performance of the models to estimate the location of an individual inside a room. The results of each algorithm are presented in Table 1. Therein it can be observed that 2 models were generated using kNN with different values of k.

The best performance models were obtained from the KNN algorithms and J48, as they offer an accuracy of 97.12% and 93.55% respectively to place an individual. The lowest performance model was obtained with the Naïve Bayesian algorithm, it offers an accuracy of 50.79% and a concordance level of 0.3834.

Table 1. Algorithms Performance

Machine Learning Algorithm	Instances Correctly Classified in %	Instances Incorrectly Classified in %	Kappa Coefficient in %
kNN (k=6)	97.03%	2.96%	96.27%
kNN (k=3)	97.12%	2.88%	96.39%
J48	93.55%	6.45%	91.89%
Naïve Bayes	50.79%	49.21%	38.34%

The algorithm with the most considerable accuracy was implemented in a mobile application. The mobile application allows a person to collect magnetic field information used to classify its location in the indoor environment. In the application's interface, it indicates in which room the person is located (See Figure 3). However, it does not provide your physical position (latitude and longitude).

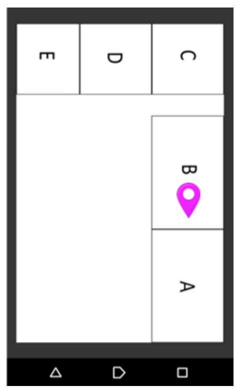

Figure 3. Application provides the user with information about his localization.

5. Discussion and Conclusions

The results show it is possible to generate a radio map and a predictive indoor localization model with data from a magnetic field collected through participatory sensing. Unlike the location fingerprint technique with participatory sensing, an exhaustive data collection of the entire interior environment is unrequired.

Four models were generated.The models of KNN offers the more considerable accuracy, since it offers an accuracy of 97.12% and 97.03% with a high level of concordance, Kappa =0.9627 and 0.9639 respectively.

The model obtained with Naïve Bayes offers the most reduced performance, since it offers an accuracy of 50.79% with a low level of concordance, Kappa =0.3834. Therefore, the generated model is unuseful to estimate the location of an individual in an interior environment.

As a future work, we consider to extract time and frequency features from magnetic field signal. This to generate a model that can be independently of the mobile device being used. In addition, the magnetic field could also be merged with information from another sensor or device to provide the position of the person.

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