Error Estimation for Magnetic Field based Localization

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Abstract— The geomagnetic field is highly distorted due to the existence of concrete or metal objects in indoor environments. Such significant changes in the magnetic field are useful for achieving indoor localization. This paper presents an indoor localization system in which several tests were performed in order to determine the position of the user using a magnetic sensor in a handheld smartphone. One of the major advantages of this technology is that there is no need for any external infrastructure unlike other localization technologies based on UWB, Wi-Fi, RFID, and Beacon. This advantage makes magnetic field based indoor positioning cost beneficial and offers easy maintenance. This research is based on two phases: an online phase (training phase) and an offline phase (testing phase). In the training phase, location dependent magnetic signatures were recorded at different reference points and then stored in a local database. This data is then used to generate the magnetic map. In the testing phase, the mobile unit fingerprint i.e., the current position of the mobile is compared with the previously stored values in the database.

Keywords— Magnetic localization, magnetometer, reference points, fingerprinting

1. INTRODUCTION

Global navigation satellite system (GNSS) using GPS is used for positioning applications in outdoor areas. But, GNSS cannot be properly functioned in indoor environments due to variety of reasons such as multipath effect which can degrade the applications' accuracy and signal interference which are result of the buildings' structure in an indoor area. Thus, indoor positioning is majorly achieved by using different technologies [1-3]. Bluetooth [4] is one of the technologies used for localization. Radio frequency identity [5] is also used to locate people/objects. However, there are drawbacks of these approaches like installing special hardware externally and maintaining them time to time. Doing so in large buildings will not be cost beneficial, also it will be time consuming. The system's overall performance cannot to be up to the mark as signal strength is also highly affected due to interference in wireless channel.

Variation is caused in magnetic field intensity [6] due to different reasons. Iron, steel and concrete structure [7] are major reasons of such disturbance. The magnetic field based location information can be uniquely recognized since the location information is inferred according to the components and materials inside the building.

For these obvious reasons, the omnipresent Magnetic Field has gained huge popularity in academics as well as practical work environments. These non-human generated signals based systems are cost beneficial since there is no installation of external hardware thus, no maintenance is required. Sensors such as (Gyroscope, Magnetometer, Proximity Sensors, Accelerometer) are necessarily packed in modern smartphones. In particular, magnetometer, sensors for measuring earth magnetic field, have become essential part of smartphones. These magnetometers are actually responsible for functioning of mobile phones' compass. Thus, helping us in achieving positioning in indoor environments.

Many works have been presented previously which show success ratio in indoor positioning based on magnetic field using motion sensors [8-10]. In this paper, we present a similar systematic approach to reproduce the results using magnetometer in smartphone. Since the magnetic signals are not always noticeable [11], the overall system's performance might be affected by using only magnetometer embedded in smartphone to find the location.

Even after these facts, the system is still cost-effective, scalable and predict the current location of user or object in a building without installations of any external hardware.

The organization for the rest of the paper is as follows. Section 2 describes the literature review i.e., work done in the field of indoor positioning and localization. Section 3 describes the overall system architecture. The results are shown in section 4 where the conclusion and future work are included in section 5.

2. RELATED WORK

There is a vast literature about indoor positioning and localization. Many surveys for IPS have been published [12-16] which classify different IPS technologies organized in some conceptual model. Numerous approaches have been used to test the best for indoor positioning. Some of those are special infrastructure based while some are widely available infrastructure based [17]. Special infrastructure based are Bluetooth [18], infrared [19] and acoustic [20] while FM, GSM and Wi-Fi based IPS are found to be dependent on widely available infrastructure. Out of these, Wi-Fi based indoor Wi-Fi based indoor positioning is preferred due to its easy availability. Prior Wi-Fi based approaches were based on inseminating model which receive signal strength (RSS) from mounted Wi-Fi access points (APs) to predict the location of the receiver [21]. However, preceding knowledge of access points is required to build such a model and the overall accuracy of the system is much depended on the multi-path fading effect. The Wi-Fi fingerprinting based approaches have become popular in recent times as they do not require any preceding knowledge about access points, also they do not depend on any specific propagation model.

By using Wi-Fi based fingerprinting, RADAR [22] and Horus [23] have achieved 3-5m and 2m localization accuracy. However, the Wi-Fi received signal strength is affected by human presence, and it varies time to time consequently limiting the overall localization accuracy. PinLoc [24] has improved the accuracy by 1m by taking advantage of some physical layer. However, extensive profiling is needed. FM fingerprinting is also achievable in indoor positioning.

Chen et al. [25] used FM signals. These signals are energy efficient as compared to Wi-Fi fingerprinting, but localization is limited, like on some room level only. Work on GSM based indoor localization method [26] has also been proposed.

MaLoc [30], is an indoor localization system build using magnetic fingerprint data. This work presented that magnetometer's sensitivity varies with different smartphones. Therefore, difference in magnetic magnitude was used in order to compare the real-time testing data with previously collected i.e., trained data.

3. MAGNETIC FIELD-BASED POSITIONING SYSTEM

In this section we give brief background on characteristics of magnetic signatures, our proposed system architecture and implemented algorithm for positioning.

A. *Site Selection for experiment*

We start by analyzing the magnetic field at an empty and an equipped room located on the ground floor of Telecommunication department of Mehran university of Engineering and technology Jamshoro (Sindh Pakistan). Different equipment such as computers and printers are considered as the magnetic field landmarks. The resultant magnetic field intensities significantly vary from one another thus can be used as unique signatures in a magnetic map. Moreover, magnetic field was measured on the same places at different days to determine the variation in magnetic field, but the magnetic field was found to be almost mathematically similar. Fig. 1 and Fig. 2 show the distribution of magnetic field in an empty and an equipped room respectively in the building on two different days.

B. *The testbed Anatomy*

Two test areas were set to collect the real-time magnetic fingerprints i.e., an empty and an equipped room. The magnetic fingerprints were collected using magnetometer, embedded on smartphone. Samsung galaxy a51 was the phone used to conduct this experiment. The testbeds were of size 25'0" x60'0". Each test area was divided in 5X5 square grids hence leading to 25 RPs (reference points) in each experimental area. Each reference point is considered to be in the center of the gird. Our system aims

Recent studies have showed that magnetic field distribution is used over RSSI in order to create georeferenced map. Many researchers have thoroughly investigated (MFD) magnetic field data for indoor localization.

Locate me [27] identified the stable nature of magnetic signatures over time and can be used to create georeferenced map with the help of smartphone. Haverinen et al. [28] have used a particle filter in an indoor localization system. They have targeted a corridor and determined the user's location with the help of available magnetic field. Different experiments were performed Having both robot and pedestrians. Final results were demonstrated that the error during pedestrian's localization is greater due to user's inconsistent heading.

Other researchers [29] used 2D magnetic map in order to estimate the direction and movement of the robot. To find out the magnetic field data at reference points, bilinear interpolation was utilized where the magnetic field was considered to be a continuous function. In the end, the training set (magnetic map) was compared to the magnetic data collected from robot

This phenomenon is achieved using a magnetic sensor (magnetometer) already embedded in today's smartphones. Also, the implemented algorithm lessens the overall computational cost of the system.

to leverage earth's magnetic field as a main characteristic of a location for positioning and localization.

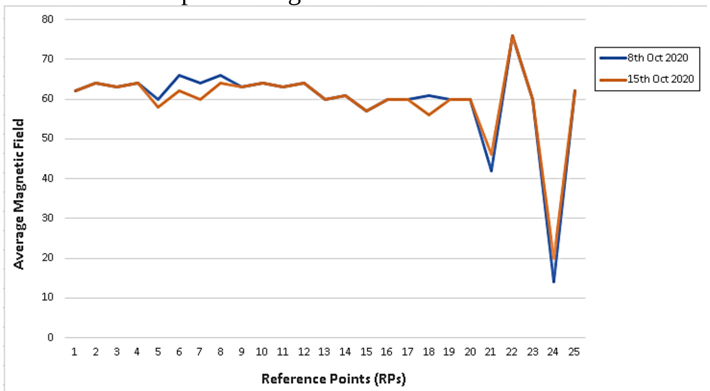

Fig. 1. Distribution of magnetic field inan empty room in the building on two differentdays.

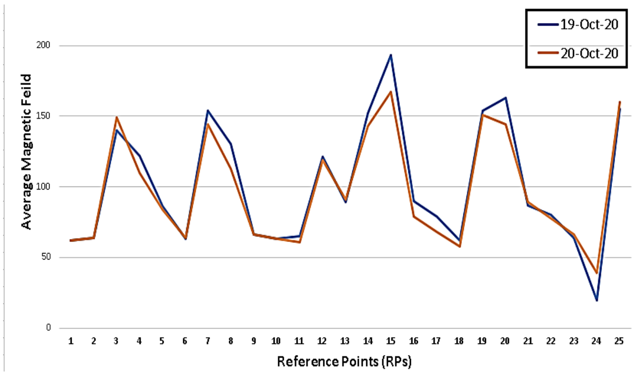

Fig. 2. Distribution of magnetic field inan equipped room in the building on two differentdays.

C. *Functionality of the system*

The whole system is majorly consisted on two phases: model training phase (offline phase) and fingerprinting localization phase (online phase or testing phase). In offline phase, the magnetic fingerprints are collected at different selected reference points using magnetometer, embedded in smartphone. The magnetic data at each reference point is collected followed by the coordinates of RPs and stored locallyin our smartphone, in the fingerprinting database. This is how localization model is generated and later used in localization phase also called as online phase or testing phase.

In online phase (testing phase), the user's real-time fingerprint is recorded using the magnetic sensor present in smartphone and then estimate the user's current location by comparing it with localization model. Fig. 2 illustrates the architecture of magnetic field-based positioning.

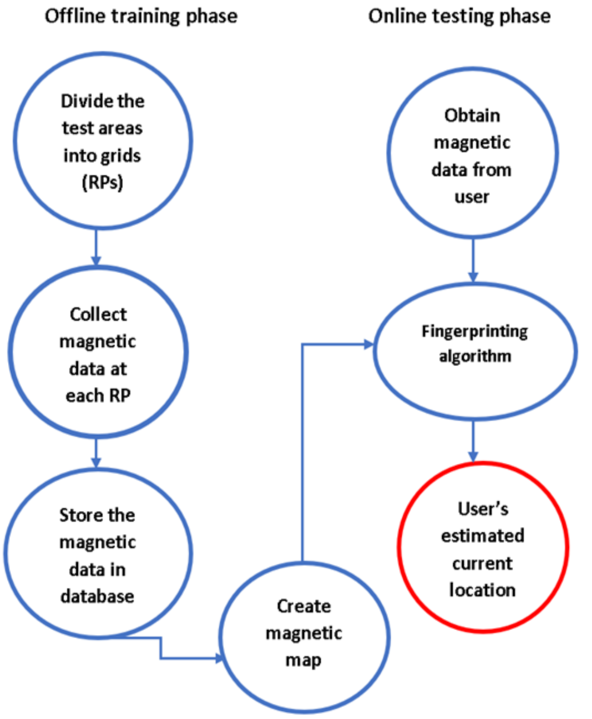

Fig.2. System Flow chart

D. *Mathematical Description*

The algorithm performed here to determine the average magnetic field Ave(MF) between the training phase and testing phase is nearest neighbor search based on root mean square deviation/error.

$$\textbf{Ave (MF)=} \quad (mf_x^2 + mf_y^2 + mf_z^2) \quad \textbf{(1)}$$

Here mf_x, mf_y and mf_z represent the magnetic axis for x-axis, y-axis and z-axis respectively.

The root mean square error (RMSE) implemented in this work is represent as:

$$E_j = \left(\sum_{k=1}^{P} (Ave(MF)\ 1st - Ave(MF)\ 2^{2}) \right) / P \qquad (2)$$

$$j=1,2,3,..,n$$

Here Ej is the total error at jth reference point, Ave(MF) 1st is the average magnetic field from smartphone database (1st phase) where Ave(MF) 2ndis the average magnetic field from magnetic sensor(2nd phase), n is the total number of reference points, P is the total number of average magnetic field Ave(MF) taken at every reference point.

Different values are attained at Ej which are then sorted in an ascending order. The value of E*j* which is lowest,gives the possible approximate about the current position of the user.

4. RESULT ANALYSIS

To analyze and demonstrate the methods discussed in the paper, we carried out experiments in the equipped and empty room using smartphone which is commercially available. A positioning application was installed to test the positioning method. Experiments were performed which evaluated the positioning error in each test area. Each testbed was divided in 5x5 square grids hence leading to 25 reference points.The magnetic field at each reference point was recorded for 10 seconds and having 10 samples per second leading to 100 samples which were later averaged out in order to get the closest possible value.

When experiments were performed at a point in empty room, the accuracy was not 100%. There was positioning error at every point during the experiment.The estimation error for empty room was less than 1.7 meters for 70% times during the experiments. The estimation error in equipped room wasless than1.5 meters for 85% of the whole experiment.Fig. 3 shows the estimation error. The errors plotted in Fig.3 were measured on different positions randomly around the reference points.

$$\textbf{Estimation error (e)=} \quad ((x_1 - x_2)^2 + (y_1 - y_2)^2) \qquad \textbf{(3)}$$

Here (x1, y1) represents the coordinate of a reference point where (x2, y2) represents the estimated position of the user. During the testing phase (online phase), the errors were calculated. 10 different location points were targeted for error calculation with each point having 20 sets of data. Maximum estimation error, standard deviation and mean localization error were also calculated for both experiments. The standard deviation and maximum estimation error from average value in empty room is comparatively higher than equipped room. The reason for lesser error in equipped room could be due to presence of different equipment like printers, computers, laptops etc which exhibit magnetic signatures having different nature. TABLE 1 and TABLE 2 show the results for empty and equipped room respectively.

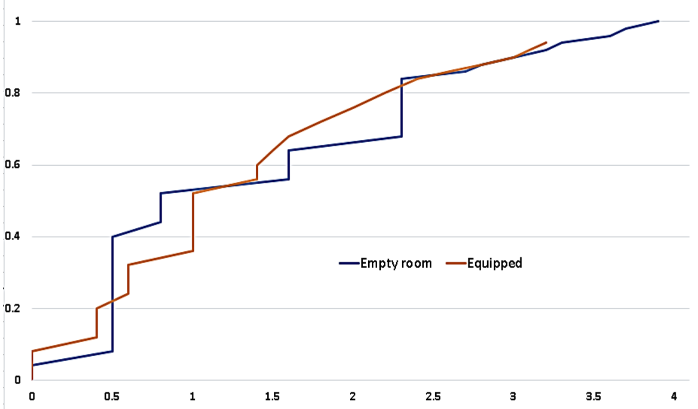

Fig.3. Distribution of estimation error in empty and equipped room

Name (error)	Value (meter)

Maximum estimation	3.9462
Standard deviation	1.2134
Mean localization	1.3624

TABLE 1. Positioning accuracy results for empty room

Name (error)	**Value (meter)**
Maximum estimation	3.2742
Standard deviation	1.0128
Mean localization	1.1420

TABLE 2. Positioning accuracy results for equipped room

5. CONCLUSION

This work presents a productive indoor localization system using magnetic field in order to estimate user's current location. A pre-existing algorithm is used for this work. In the experiments, only magnitude is used hence limiting the system to a fixed height where smartphone is placed throughout experimenting. However, this work can be extended in future by adding other factors like working at different heights or at different speeds. This work presents a cost-effective system with less computational overhead.

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