Indoor Localization Using Ambient Magnetic Fields

by

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Declaration

I hereby declare that

i) the thesis comprises of my original work towards the degree of Master of Technology in Information and Communication Technology at Dhirubhai Ambani Institute of Information and Communication Technology and has not been submitted elsewhere for a degree,

ii) due acknowledgment has been made in the text to all the reference material used.

Siddhant Gupta

Certificate

This is to certify that the thesis work entitled "Indoor Localization Using Ambient Magnetic Field" has been carried out by SIDDHANT GUPTA for the degree of Master of Technology in Information and Communication Technology at *Dhirubhai Ambani Institute of Information and Communication Technology* under my/our supervision.

Prof. P. S. Kalyan Sasidhar
Thesis Supervisor

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Contents

Abstract

For over a decade, Indoor Localization has been a crucial topic among researchers. A multitude of localization solutions has been provided so far, including radio frequency based solutions like WiFi, Bluetooth and RFID based localizing and positioning systems. These infrastructure-based solutions require a set of additional devices to be installed, which comes with challenges like huge installation costs. These solutions are device-dependent. Also, attenuation in signal strength throughout the day leads to a major error in localization. A recent addition to this system is magnetic field-based localization techniques. The solution lies in exploiting the ambient magnetic fields present inside buildings and their unique variations caused by the presence of ferromagnetic objects such as pillars, doors, and elevators.

Smartphone-based built-in magnetometers have been the default data sensing platforms. The data collected from smartphones are used by deterministic or probabilistic algorithms for estimating locations. However, the performance of these algorithms depends on the diversity in the sensor models built- in the smartphones, diversity in the users using the phones, and diversity across space and time. There is a dearth of analyses of how these diverse factors affect the performance of magnetic field-based solutions. We assess the impact of the four diversity parameters on the dynamic time warping algorithm in estimating the users' location. We discuss our findings from experiments conducted across three different buildings and eight different sensor models with five users.

List of Principal Symbols and Acronyms

A_H	Accuracy of predicting hallway signatures
DTW	Dynamic Time Warping
GPS	Global Positioning System
ILS	Indoor Localisation systems
LBS	Location Based Services
MF	Magnetic Field
PNC	Psuedorandom Number Code
RF	Radio Frequencies
RFID	Radio Frequency Identification
WiFi	Wireless Fidelity

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Chapter 1
Introduction

1.1 Location Based Services(LBS)

Numerous systems have been developed for locating a person on a map, as there is an immense growth in the usage of smartphones and ubiquitous inertial sensors embedded into them. Such systems present over the internet are collectively called location-based services (LBS). These location-based services could be anything from the well known Global Positioning System(GPS) to the recent topic of discussion, including Signal based or Infrastructure based Indoor Localisation systems (ILS). GPS has a limitation of not being able to work indoor due to its shortest range being around 10 meters. There was a need for a system that could locate an entity (had it be a room, hall or any person) on an indoor map as buildings like hospitals, airports and malls have a complex structure and a person may find it difficult to locate any of the mentioned entity. Researchers have been working on creating such systems and making them available readily to users on their smartphones or any handheld devices. This led to the creation of various Indoor Localization Systems.

1.2 Variety of Indoor Localization System

There are a plethora of Indoor Localization Systems available, which could be broadly classified into two categories Infrastructure based or Infrastructure less indoor localization system.

1.2.1 Infrastructure based Indoor Localization System:

The system that makes use of WiFi[46], Bluetooth[49] or RFID[23, 14] based system is termed an infrastructure-based system as it would require an extra set of equipment like WiFi routers, access points, Bluetooth beacons or RFID sensors to be installed inside the building for localization. These systems make use of various characteristics of signals for positioning and localization. The characteristics, including the Angle of Arrival, Time of Arrival, received signal strength etc, plays a vital role in positioning.

1.2.2 Infrastructure-less Indoor Localization System:

The system that makes use of the unique structure of a building and senses the ambience of the building like light[36], sound[11] and radio frequencies[35], A recent addition to which is a magnetic field based localization system. This system doesn't require the installation of any extra infrastructure. Still, to make use of such a system in practice, the ambience of building is supposed to be maintained consistently throughout the day, like the intensity of light inside a room, which is the major source of reference, is supposedly be maintained consistently and no abrupt changes could be tolerated.

1.3 Drawback Of infrastructure based system

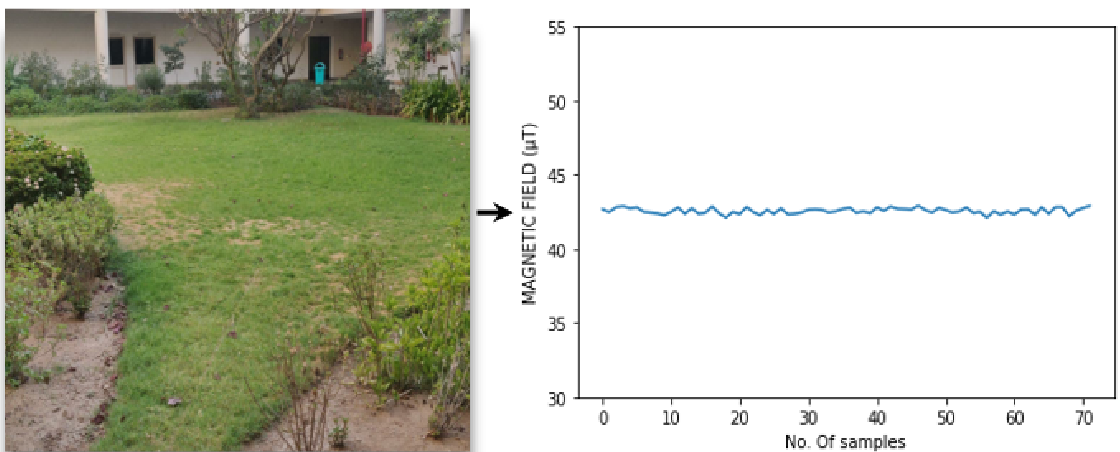
Adding an extra set of equipment or additional infrastructure to a building is a costlier procedure, i.e., it may require a huge cost of installing such infrastructure inside already developed buildings like public buildings and monuments. Various properties may get concerned about the privacy of data flowing across their routers and access points, and authorities may bother sharing it for testing. Also, many research has proven that the signals produced by WiFi are less stable across time and throughout the day. Which raised a requirement for Ambient sensing based approach.

1.4 Ambient sensing and inclusion of magnetic field in localization

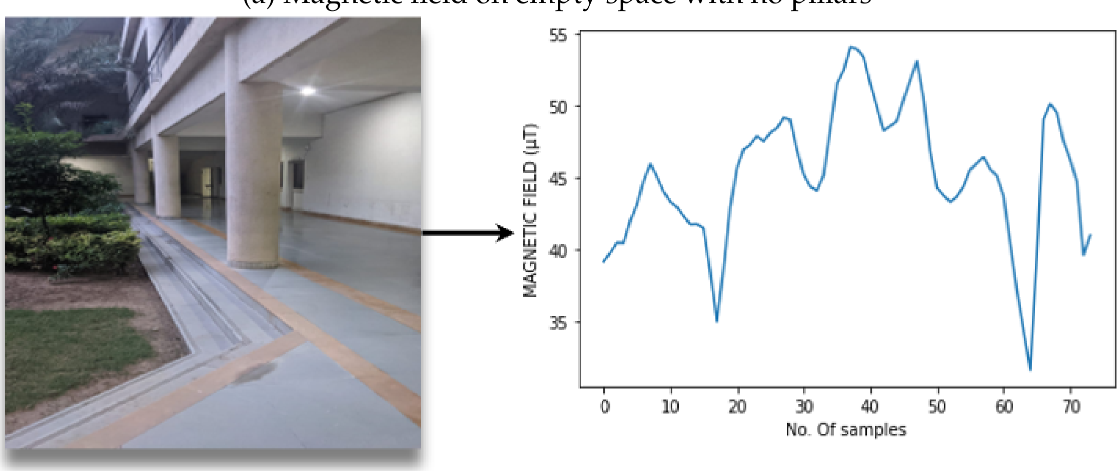
Ambient Sensing is a procedure of sensing the ambience of a building for localization. The ambience of building can be anything like a consistent light[36] where a room inside a building is established in a way to maintain the stable intensity of light. Another method a set range of sound[11] where sensing a continuous sound could be used for positioning. A similar approach is sensing specific radio frequencies inside the room or building to locate the entity. As mentioned earlier, the recent addition to ambient sensing method is using magnetic field intensity captured by embedded magnetometer inside the smartphones.

1.4.1 Magnetic Field For localization

Early Works showcased the potential of magnetic fields as sources for estimating the location of any entity like room, hallway, or any user inside building[34][45]. Earth's magnetic field is omnipresent. Adding to this, is the presence of ferromagnetic structures such as pillars doors and elevators which influence the Earth's magnetic field by causing disturbances or anomalies in Geo-magnetic field intensities captured by smart-phones. Fig. 1.1b shows how the difference in the intensities is noticed within an indoor environment that has pillars compared to the case where the environments is not enclosed with any ferromagnetic materials.



(a) Magnetic field on empty space with no pillars



(b) Magnetic Field in Hallway with pillars

Figure 1.1: Comparison of Magnetic signatures inside hallway vs in an empty environment

Observations in existing work shows a sense of uniqueness in these disturbance, leading to create a stable pattern while captured by walking past the ferromagnetic entities. These patterns could be termed as a Magnetic Signatures(MS) and could be used as a reference for our localization system this arises due to the unique structure and organization of building. This theory has paved its way for applying these signatures for indoor location estimation. For instance, Fig.1.2 illustrates how the presence of ferromagnetic entity perturb the Earth's magnetic field.

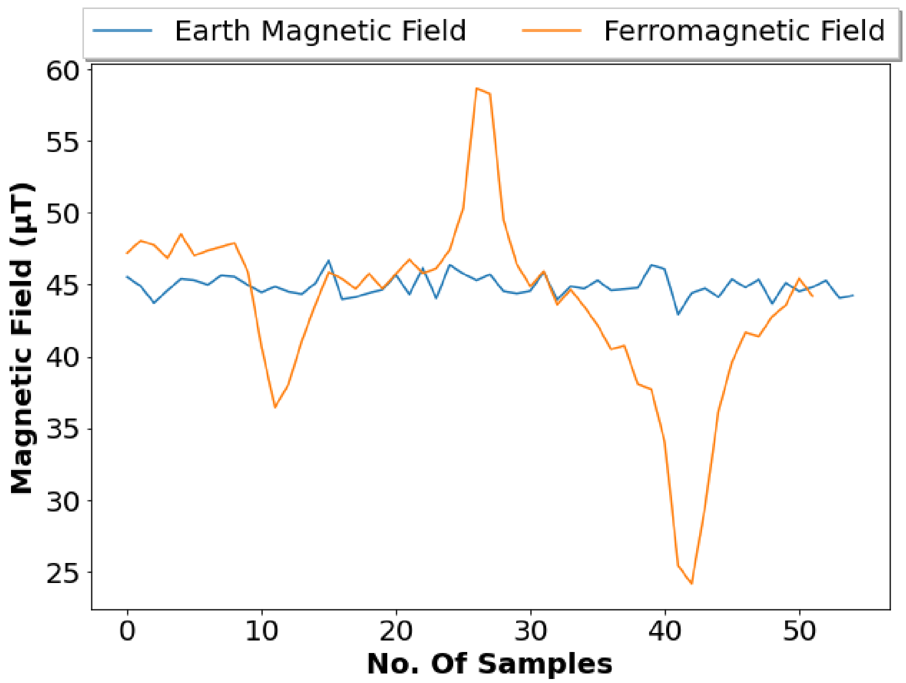


Figure 1.2: The earth's magnetic field as can be seen is fairly consistent around magnitudes of 45 to 65. However, the presence of ferromagnetic structures like pillars cause perturbations in the field, causing variations in the magnitude.

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1.5 Advantage of using magnetic field for localization

the biggest advantage of magnetic fields is their natural occurrence, i.e, they are provided to us for free and also its omnipresence needs no installation of extra infrastructure unlike RF based techniques. Moreover, MF signatures are stable compared to RF signals. Work in [15] proved the stability and consistency of magnetic signals over a long time. Also, authors in [48] empirically prove that Wi-Fi signals collected across five days are less stable than magnetic signals.

1.6 Challenges of Magnetic field based approach

Despite its advantageous property of stability and consistency, the system faces challenges that require attention.

First, the diversity of smartphone brands poses a big challenge for magnetic field-based indoor positioning. Specifically, these phones are built-in with magnetic field sensor models that vary in their specifications, such as resolution, sensitivity, specificity, and accuracy. Second, variations (if any) of magnetic fields across time and space(location) may impact the location estimation. Lastly, users with different walking speeds could contribute to the changes in the magnetic field intensity, in turn affecting the estimation.

We will talk about these challenges in detail in later chapters. We'll also learn the performance variation of our system based on these challenges.

1.7 Motivation and Problem Statement

1.7.1 Motivation

Infrastructure less and ambient sensing based localization systems has been in high demand. This combination makes it easier for the owner to get the detailed information required for localization, and also, it does not bother users while navigating them on a map. Just like GPS, which requires no set of infrastructure to be installed, we planned to create one such platform in an indoor environment, which could be created at a minimal cost. Also, one motive of this project is to utilize the pervasiveness of smart devices around the globe. Apart from all these we are also validating the existing work on localization based on geo-magnetic field in our work.

1.7.2 Problem Statement

This thesis revolves around an issue of providing information about the location to an individual in an indoor environment using just a smartphone. Embedded sensors inside the smartphones are capable enough to generate data which could help in identifying a person's location when he walks a certain distance in that location or a hallway. The procedure involves collecting of information from ambient sensors, and classify those information. Hence leading to a problem statement as follows.

"Locate a person on a map in an indoor environment using just a smart phone based application and embedded sensors inside them."

1.8 Organization of Thesis

The thesis talks about the methods for sensing the ambience of indoor environment and utilizing it for localization and positioning application. The content in this thesis is organised and discribed into 7 chapters.

- Chapter 1 (Introduction): This chapter provides a brief description about Location Based services, indoor localizationi system, drawback of some existing indoor localization systems and then I have provided a motivation of this thesis and the problem statement

- Chapter 2 (Literature Survey): This chapter gives a gist of almost all the location based services, especially the variety of indoor localization systems, including WiFi, Bluetooth, Light and other radio frequency based localization systems. Later in the chapter, various methodology of indoor localization using a magnetic field is described.

- Chapter 3 (Empirical Setup): This chapter describes the setup we required throughout this work, introducing an in-house Andriod application for data collection and a robot that we employed for the same purpose. Later in this chapter, I've described the data collection methodology that we followed to generate and process the sensor data.

- Chapter 4(Magnetic Fingerprints): In this chapter, I have briefly described the magnetic field signatures and how these signatures are used for fingerprinting. In this chapter, I have also described one of the crucial parts of this project, a distance matrix used throughout the classification and estimation part of this thesis.

- Chapter 5 (Classification System): This chapter discusses the steps we followed to develop our system and classify and generate results. Later in this chapter, we discussed an approach we picked for classification and then an entire system architecture for our system. I have also introduced an error estimation mechanism with an example used in a further chapter.

- Chapter 6 (Performance Evaluation): I have described all the challenges that we faced while designing the classification system and how would they affect our classifier. This chapter gives an overview of a study that we devised as a part of experimentation and results for this thesis.

- Chapter 7 (Conclusion And Future work):This chapter concludes my work and discusses the future possibilities of work that could be done to improve the system.

CHAPTER 2

Literature Survey

Several work has already been done on various aspects required for positioning and localization system. As we have discussed earlier about the infrastructure-based vs infrastructure-less localization systems, in this chapter, we will see about all the mentioned techniques we saw earlier.

2.1 Global Positioning System (GPS)

GPS is a satellite-based positioning system that is said to be working upon three different interfaces satellites [2], control and user(receivers). The system has employed 24 satellites, orbiting in six orbits at the inclination of 55 degrees relative to the Equator; The angle is selected in such a way that at least six satellites are available at every point on the earth. These satellites send navigation messages continuously at a rate of 50 bits per second. This message contains Ephemeris parameters, which is the information about coordinates of satellites (orbital information), the time parameter to calculate clock offsets (contains the exact time the message was sent), service parameters with satellite health information, and rough orbits of all satellites called the almanac parameter. The control portion consists of a number of satellites; they monitor the health of satellites and do necessary corrections when needed. Users have two variety of positioning systems, the Precise Positioning Service used by the military and the Standard Positioning System used by civilians.

GPS receiver utilizes trilateration [3] of satellites to combine the information and predict the correct location. The receiver computes the distance of the satellite using the transfer time of each message, and with trilateration, the distances to the satellites together with the locations of the satellites are used to calculate the position of the receiver. GPS estimates how long it takes a satellite signal to reach a receiver, which creates its own signal in order to get an exact lock on a moving item or person. GPS compares the satellite signal's pseudorandom number code, a digital signature unique to each satellite, with the receiver's PNC to compute the signal's journey time, assuming the signals are synchronous. And to calculate the satellite's distance from the receiver, the system multiplies this figure by the speed of light.

The speed of radio signals is constant only in vacuum, but there are various factors that affect the speed of radio signals resulting in propagation delay. These factors could be water vapours or any other particles inside the earth's atmosphere. Errors due to signals bouncing off a building due to multipath fading lead to reduced accuracy.

GPS Receivers are accurate from 60 to 300 feet which could not be used for indoor positioning as it requires a much lesser distance of accuracy. Also, due to blockage from concrete walls and floor, we could notice attenuation in signal

2.2 Indoor Positioning using WiFi

Wireless Local Area Network(WLAN), Using the 802.11b or WiFi provide local wireless access to network devices [7]. With the need for wireless technology, there has been a noticeable increase in the availability of such networking throughout the building. Researchers have been using this for estimating the location of a person inside the building. This technology requires a set of routers and access points to be installed inside the building as a point of interaction.

WiFi-based Positioning makes use of RSSI values where the signals are RF signals sent from access points or Bluetooth beacons, similar to radio frequency in GPS, RF signals in WiFi also face attenuation, But this attenuation is the thing which is used for positioning indoors. This attenuation leads to increment and decreament in RSSI values. There are two types of location-sensing techniques

- Propagation Based
- Location Fingerprinting Based

Propagation Based Techniques for localization techniques use the measured Received Signal Strength(RSS), Angle Of Arrival(AOA), and Time difference of arrival of received signals and determine location using applied mathematical models based on Euclidean distance. This technique that uses the Euclidean model is one of the most widely used approaches as it gives better results with a low computational load. Whereas The procedure of location fingerprinting (LF) is twofold. During an offline calibration phase, a radio map of observed signal strength values from various locations is first recorded. Then, using proximity-matching algorithms, the signal strength values detected at the user's mobile device are matched to the radio map data in real time to infer current user locations.

Commercial companies such as Ekahau [4] and Skyhook [5] have subsequently begun providing Wi-Fi positioning solutions for dedicated applications like business buildings, hospitals and schools. Google Maps has also enabled Wi-Fi sensors to locate mobile devices when GPS is not available.

2.3 Bluetooth based localization

Bluetooth uses the 2.4 GHz band and has a lower range than Wi-Fi (usually 10–15 m). Most mobile phones, Personal Digital Assistants (PDAs), laptops, and other devices contain it. Bluetooth is an efficient technology for creating indoor localization systems since it is low-cost and low-power. [21] implements a Bluetooth Local Positioning Application (BLPA). Bluetooth uses the 2.4-GHz band and has a shorter range (typically 10–15 m) than Wi-Fi. It is found in most mobile phones, Personal Digital Assistants (PDAs), laptop computers, and other electronic devices. Bluetooth is an efficient technology for designing indoor localization systems because it is low-cost and low-power.[21] includes a Bluetooth Local Positioning Application (BLPA). The Bluetooth RSS levels are converted into distance estimates using a simple propagation model first. Based on these distance estimates, the Extended Kalman Filter (EKF) is used to compute a 3-D position estimate. The location accuracy of this system is 3.76 metres. Similar work has been done in [16]. The majority of Bluetooth-based positioning systems employ fingerprinting and/or trilateration techniques [39], [44].

Tadley created a commercial location and tracking system that employs Bluetooth technology for indoor positioning [33]. There are three sorts of pieces in this modular positioning solution: positioning server(s), wireless access points, and wireless tags. It has a placement precision of up to 2-3 metres on average and can locate tens of tags at once, spanning thousands of square metres. Due to the device discovery mechanism that runs in each location finding, this system, like other Bluetooth positioning systems, has various limitations, including a significant localization delay (15-30 s). Furthermore, in complex and changeable indoor environments, these systems suffer from the disadvantages of the RF localization technique. Recent studies have started integrating IoT using Bluetooth beacons for positioning[40] based on the RSS and work by dividing the indoor environment into an equal area called hives.

2.4 RFID Based Positioning

The RFID based system contains a reader having an antenna in it and an active or passive transceiver called 'tags'. Active tags are low-power transceivers equipped with a battery and keep transmitting signals autonomously, Whereas passive tags hold no battery and require interaction with an external source for transmitting signals. Each tag has a set of information stored in a memory embedded, and this information includes the position data. RFID based localization is categorized based on what is need to be localized, i.e., a person or a tag. WhereNet positioning system [1] is well known system that is a tag localization technique, WhereNet provides tags with absolute location information that can be used by a variety of location-based applications.This system has an error range of about 2-3 metres, which is insufficient for indoor use. [29] creates an active RFID system to create an indoor/outdoor localization system for vehicle and pedestrian navigation. In addition, active RFID tags are used in [41] to develop a 3D indoor localization algorithm and improve positioning accuracy. [24] uses the passive RFID solution to create a hybrid method for tracking mobile objects with high accuracy and low computational costs. The passive Ultra High Frequency (UHF) RFID Indoor and Outdoor Localization systems technology is used in [13] as supplementary support for robot navigation and localization. RFID technology is frequently combined with other enabling technologies to improve system accuracy [43].

2.5 Sound Based Localization

Sound based localization techniques mostly make use of two types of schemes. Ultrasonic localization and Audible sound based localization

2.5.1 Ultrasonic localization

Ultrasonic localization makes use of ultrasonic signals that works at a frequency of 40kHz with a low propagation speed of sound. Due to this low propagation speed, it becomes easy to produce accurate positioning by using slow clock rates. The Active Bat System [6], [17] turned out to be one of the most successful implementations of ultrasonic localization, where multiple ultrasonic receivers are placed at the ceiling of the building. These receivers are synchronized using an RF signal of higher speed than that of sound. The transmitters are provided to humans or are placed on the entity to be localized, and it transmits both the RF signal as well as the ultrasonic signal. RF signal reaches early to the receivers, and it synchronizes them up by sending a synchronization signal. Each receiver measures the receiving time of the synchronization signal and the ultrasonic signal and then calculates the distance between itself and the transmitter. Now using the trilateration technique, the position of the transmitter is derived. Cricket localization[32] technique is yet another commercial ultrasonic technique that calculates the position inside the mobile application.

2.5.2 Audible Sound based Localization

Indoor positioning can be accomplished using audible sound technology [26]. Mobile devices with the capability of emitting audible signals can be used to achieve indoor positioning. The Beep [27], [25] is one of the most affordable audible sound-based positioning systems. It consists of several acoustic sensors installed at fixed locations in the area of interest and wirelessly connected to a central server. A roaming device that needs to be located emits an audible sound. The sensors receive the audible sound and send it to the central server via Wireless Local Area Networks.

The TOA measurement and triangulation technique are used to calculate the device's position, which is then transmitted to the roaming device via WLAN. The audible sound positioning systems have some limitations due to sound interference and the very limited ability of sound to penetrate walls. Transmitting audible sound is a type of noise in indoor environments that causes annoyance to people.

2.6 Light Based Localization

Epsilon is a visible light-based localization system that takes advantage of visible Light-Emitting Diode (LED) sources [22]. The Epsilon system consists of several LED bulbs installed on the ceiling and a light sensor mounted on a mobile phone, which serves as a tracked target (Figure 2.15). Each bulb emits light that contains location information, such as the bulb's position and duty cycle.

The sensor measures the RSSs from multiple bulbs and uses the optical channel model to calculate the distances to each bulb.

Light Fidelity (Li-Fi) technology has recently piqued the interest of navigation researchers who attempted to apply it to indoor positioning [20]. The authors of [19] use Li-Fi technology in conjunction with Wi-Fi technology to improve location accuracy in smart buildings. This hybrid Li-Fi and Wi-Fi positioning system can improve existing Wi-Fi-based positioning systems' location precision by up to 80The main disadvantage of light-based systems is the requirement for a direct line of sight between transmitter and receiver.

2.7 Work Done on Magnetic Field Based Localization

Researchers have been working on creating an indoor localization system that is easy to use, requires minimal infrastructure, and makes it available to everyone. Authors in [34] observed the fluctuation on magnetometer readings when it was taken near a ferromagnetic material, where he showed fusion of magnetometer with gyroscope and accelerometer could be used to check the orientation of human body segments. Authors in [38] used this as a potential of magnetic field and used these magnetic anomalies as a signature, and showed how these signatures could be used for indoor localization. Not just indoors, this approach is also used for localizing a building, espacially in GPS Denied Environments[9]. Authors in [18] showed how robot localization could be performed using the naturally present Earth's magnetic fields and ferromagnetic fields from structures like pillars, elevators, or other metallic objects which remain static. Work by [15] conceptualized the idea of indoor navigation through smartphones using ambient magnetic fields as landmarks. The work presented detailed magnetic maps and statistically verified the stability of magnetic fields across various locations. Work in [38] evaluated the performance of magnetic fields based localization on four different phones.

Author in [28] compared the noise levels while measuring magnetic field using an iPhone and a Samsung phone. Results show that the Samsung phone reported large glitches (sudden changes in magnitudes) when compared with iPhone. Author in [8] conducted a performance evaluation of an indoor positioning algorithm using only two smartphones and four users. Their results show that the performance is affected by the diversity in phone models and users. Author in [12] made use of magnetic field data and making use of a deep learning based approach or using recurrent neural network(RNN), showed how these data could be used in indoor localization in large-scale buildings like malls, metro stations and airports. [10] proposed a mechanism for floor identification based on the pervasive magnetic field data without need of. We'll see a detailed description of the working of Magnetic field-based localization in the later chapters. We'll also see how the performance is affected by various factors like distance from a ferromagnetic entity, speed of user and time.

2.8 Chapter Summary

Summarizing this chapter, we learnt about various location Based services. We showed the working of the Global Positioning System and the working of the trilateration method used in other localization systems. I've mentioned some of the well-known positioning systems developed for indoor and are in production. This chapter has a reference to many works done on magnetic field based localization systems proposed so far. In the forthcoming chapters, we'll see the actual working of our system for localization.

CHAPTER 3

Empirical Setup

This chapter will briefly discuss the entire setup required for data collection, whether hardware, software, infrastructure or number of volunteers. This chapter will also provide a gist of the whole data collection procedure we followed for our project.

3.1 Measurement Platform

3.1.1 Software Platform

We developed an in-house android based application to collect sensor data called usage tracker, which is compatible with almost all the Android-based smartphones having Android version 4.0 and above. The best part of this application is that it could be tuned to work on a varying range of sampling rates so that we could experiment with a variety of dataset properties. Fig. 3.1 shows an interface of the application.

3.1.2 Smartphone Platform

We employed around ten different smartphones for data collection, all of which had varying specifications in terms of android generation and sensor models. Varying sensor models lead to experimenting with a diverse range of accuracies. All of them had built-in three-axis monolithic geomagnetic sensors or magnetometers. The sensors were capable of providing and recording data a dynamic sampling rates, which can be changed using APIs offered by the Android applications.

Table 3.1 displays the detailed description of smartphones used and their varying magnetometer for data collection.

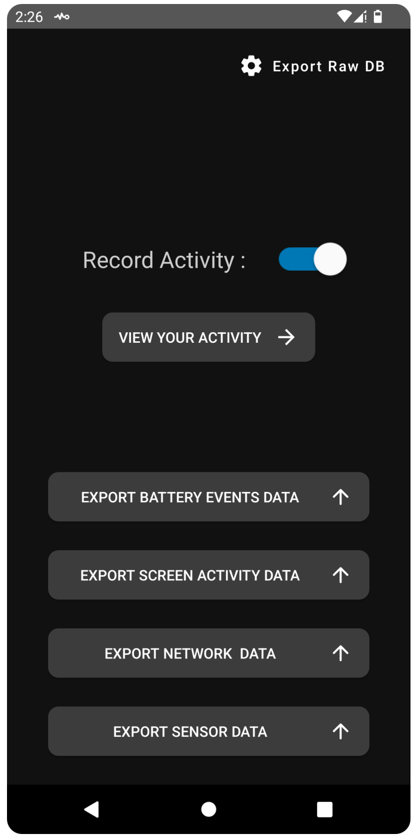


Figure 3.1: User Interface of Usage Tracker

Phone Model	Sensor Model	Maximum Range	Resolution
OnePlus 6T	AK-0991x	4911.994	0.15
OnePlus Nord	mmc-5603x	3000.0044	0.0976
OnePlus Nord 2	mmc5603	4911.994	0.15
Realme 3 pro	Ak0991x	4911.994	0.15
Redmi Y3	AK09918	4911.9995	0.149
Oppo F19 pro	mmc5603	4911.994	0.15
Nexus 5	AK8963	4911.9995	0.149
Pixel 4a	LIS2MDL	4915.2	0.01
Lenovo A6020a40	st480	3200.0	0.1
Xiaomi Redmi 5	AK09918	4911.995	0.149

Table 3.1: List of all the phones used for the project and their sensors

3.2 Miscellaneous: Robot

We employed a robot to capture data across the building; this robot was used for experimenting across one factor and keeping other factors constant. Factors like

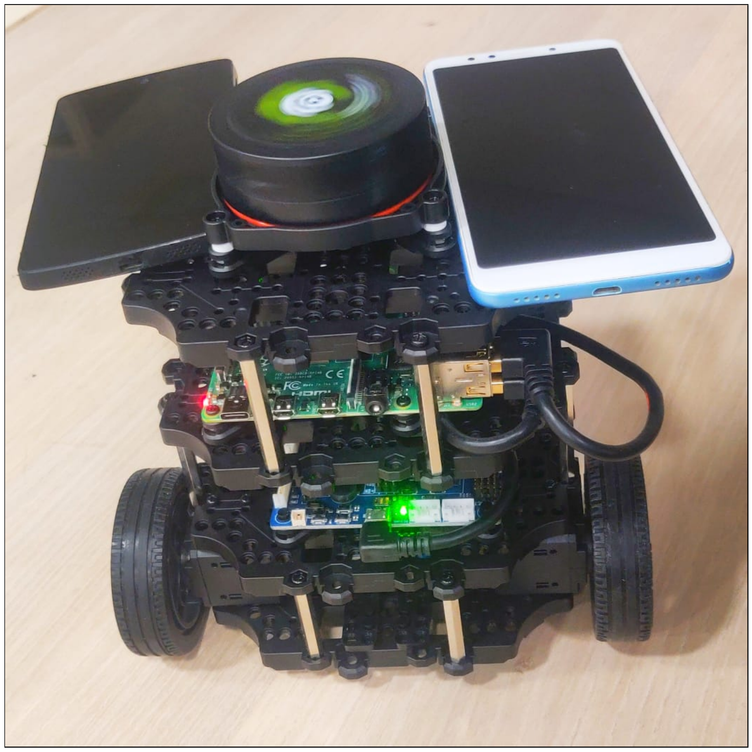


Figure 3.2: Turtlebot burger we employeed for data collection

speed, time, distance and height were to be tested using datasets collected using this robot. Fig. 3.2 shows the robot could hold two phones at a time and could capture the data in them simultaneously.

Due to the variation in sensors, we can capture a variety of data for the same factor, like in the section

3.3 Infrastructure and Volunteers

The magnetic field data were collected in all hallways of three buildings of the college, the Continuation of Education Program (CEP), the Laboratory Building(CEP) and the new Hall of Residence(HoR, men), and two public buildings, The Nexus Ahmedabad One Mall and Gandhinagar Railway Station. Fig.3.3 shows the structural appearance of the hallways of all three buildings. Fig. 3.3a shows how the Lab building is supported by pillars that are closer to each other.

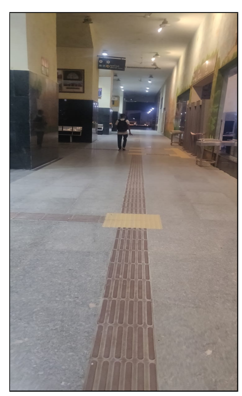
(a)

(b)

(c)

Figure 3.3: (a)Corridor of Laboratory Building and (b) Corridor of CEP Building. The pillars are indicated on each corridor. Although the pillars look exactly the same across all hallways, the underlying property of ferromagnetism is the major reason for the uniqueness. In (c), there are no visible pillars, yet the walls and doors present create a magnetic field.

(a)



(b)

Figure 3.4: (a) Corridor of Nexus Ahmedabad One mall (b) Corridor of Gandhinagar Railway station

They are separated by 6-8m away from each other, Fig 3.3b shows the structure of the CEP building where it is also supported by pillars, but the gap is in the range of 6-10m, whereas the HoR building in Fig. 3.3c have entirely different structure which is not enclosed with any pillars the hallways have rooms on both the sides. Details about No. of hallways and No. of floors in all the buildings are provided in table 3.2. To collect the data in these three buildings we employed in total of 8 different volunteers, combining me and dheerja, the total number was ten; the volunteers were selected to have varying heights and walking speeds, which led us to show the influence of different factors in the performance of our system.

3.4 Geomagnetic field Components

Geomagnetic field intensity is a vector consisting of elements in three directions namely X(North), Y(East) and Z(Downward) in units of μT (micro tesla). In this work, we use multiple smartphones embedded with a magnetic field sensor alias magnetometer.

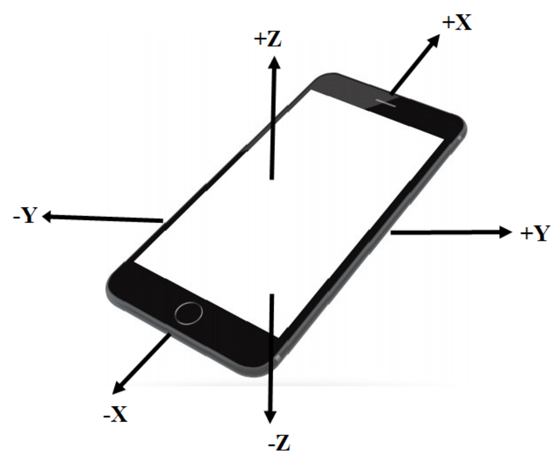


Figure 3.5: Orientation of magnetometer embedded in smartphone

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The three-axis magnetometer is a miniature (millimeter-sized internal chip) which measures the geomagnetic field intensity. The coordinate system of the magnetometer is as follows: The positive x- direction is defined as pointing directly left to right in the plane of the phone screen. The y-direction also lies in this plane and is pointing directly upwards along the screen. The z-direction is perpendicular to the x- y-plane and is pointing directly out of the screen.

The principle of the sensor is that it creates an output voltage that changes when a magnetic field passes through them. The change in voltage is directly pro-

	Lab Building	CEP Building	Hostel Building	Railway Station	Ahmedabad One Mall
No. of Floors	3	3	4	1	4
No. of Corridors	4	4	4	2	4
Average No. of Iterations Per Corridor	15	11	10	10	10
No. of Fingerprints Collected Per Corridor	1800	1500	1760	800	2500

Table 3.2: Data Collection Statistics

portional to the change in field strength. The sensor has three axes corresponding to the three directional elements of the magnetic field. The magnitude of the field is calculated by $\sqrt{x^2 + y^2 + z^2}$. Fig. 3.5 depicts the orientation of the axes of the sensor in the phone.

3.5 Data Collection Methodology

As mentioned above, we employed ten volunteers to collect data across all the corridors of 3 buildings. The technique or walking style used for data collection followed three different regimens. First, where volunteers were asked to walk across the hallways walking closer to the pillars in the case of CEP and Lab, this way, we could get better-intensified data. Second, walking almost 1.5m away from the pillars so to capture data at various distances. And the third routine was to walk in both directions of hallways,i.e., in forward and reverse directions.

These routines were followed by keeping the mobile phones closer to the chest so as to mimic the walking style of a normal human; they were all allowed to walk at their usual walking speed, which ranged from 0.98m/s to 1.5m/s to cover up all possible range of walking and also to check the performance of our classification procedure on varying speed.

All the volunteers were provided with the number of mobile phones as per the requirements of the experiments that we followed.

Table 3.2 shows the detailed statistics of data collected

In order to check the variation of magnetic field intensities across the locations, we took data standing at the location for a few minutes across different days and time, and checked whether intensities dropped in the same location or it stays constant. The Box plot in fig 3.6 represents the varying intensities of magnetic field values across the four locations we experimented upon. The plot shows there's a minor drop in intensities across the location over the time we took data for. This shows how the magnetic field values stay almost constant for a spot across the hallway.

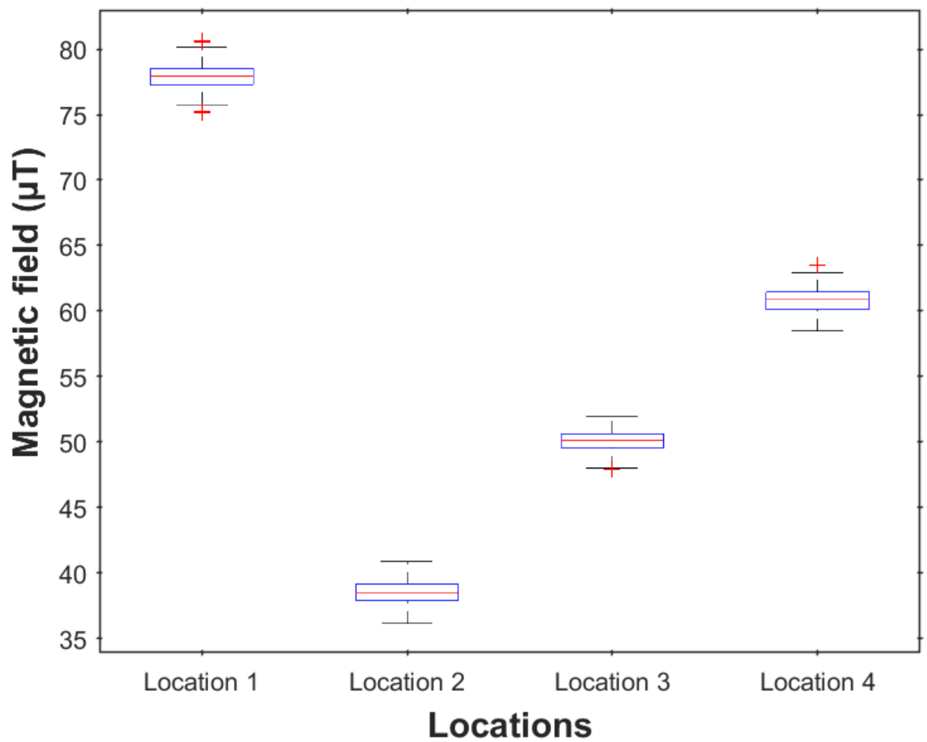

Figure 3.6: Box plot of variation in magnetic field data taken for multiple locations

3.6 Chapter Summary

In this chapter, we discussed the entire data collection procedure and the setup we required throughout the process of data collection. I mentioned the walking procedure our volunteers followed and how we collected datasets for various experiments we were planning to work upon. I also discussed what part of geomagnetic field components is helpful to us in developing signatures.

The next chapter will discuss how these signatures are created and how these are used for fingerprinting procedure of localization.

CHAPTER 4

Magnetic Fingerprints

4.1 Uniqueness and Stability of signatures

As mentioned earlier in the data collection methodology, the way we captured the dataset involved walking across the hallway and keeping the phone at an idle chest height. Apart from the data collected for the entire hallway, we also collected some experimental datasets standing across the pillars and walking past them to capture the variation in their signatures. These experimental datasets were collected in order to check whether the magnetic field measurements along a certain location form a unique pattern across that location and also whether these patterns are stable around the distance and time,i.e., do the measured magnetic field pattern show stability throughout the distance and time or not.

4.1.1 Stability of a location:

Among the collected data, we tested the data for stability where we saw whether they were unique when they were collected at a distance closer (1 meter away) to a referencing ferromagnetic entity (pillars in our case) and 2 meters away from the same referencing entity. And we found the patterns formed were the same for the same location; just minor changes in intensity were noticed as we moved away from the pillars. Fig. 4.1 shows how the signature across the same location over multiple iterations remained stable. Fig. 4.2 shows that even though the distance is increased, the pattern remains ideal around the same location. This proves the uniqueness of the pattern.

4.1.2 Uniqueness of a location:

Apart from testing for stability, we were to prove the uniqueness of the signature in order to map that signature for a particular location. To do so, we captured a dataset for another similar referencing entity, i.e., around another pillar present

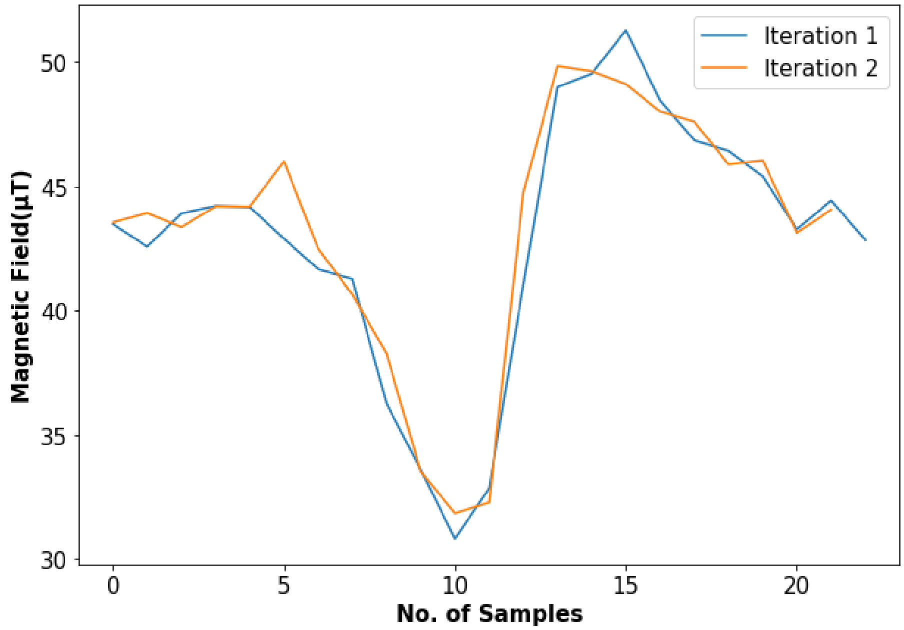

Figure 4.1: Signatures of a single location over multiple iterations of reading

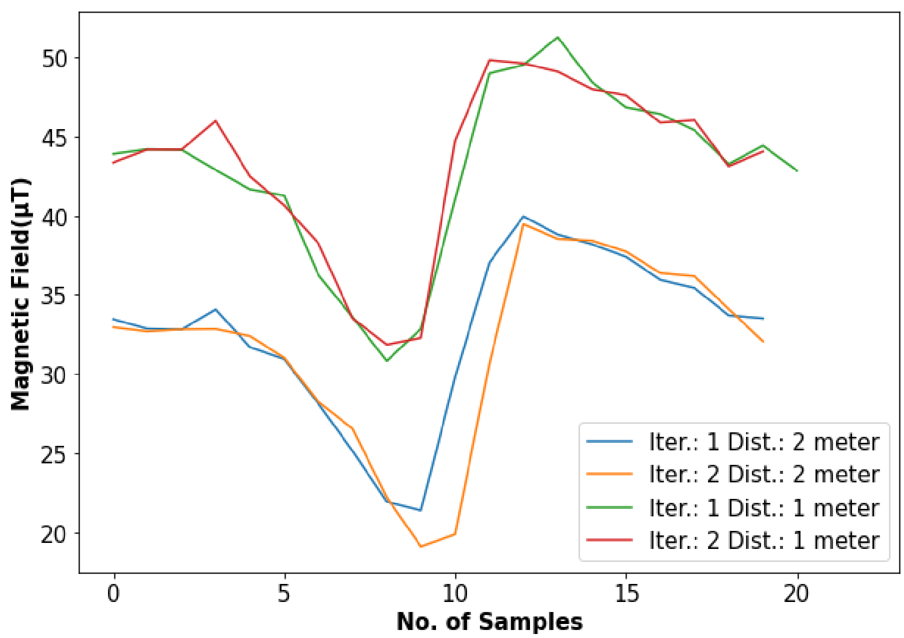

Figure 4.2: Signatures of a single location over multiple iterations of reading taken 1m and 2m away from pillar

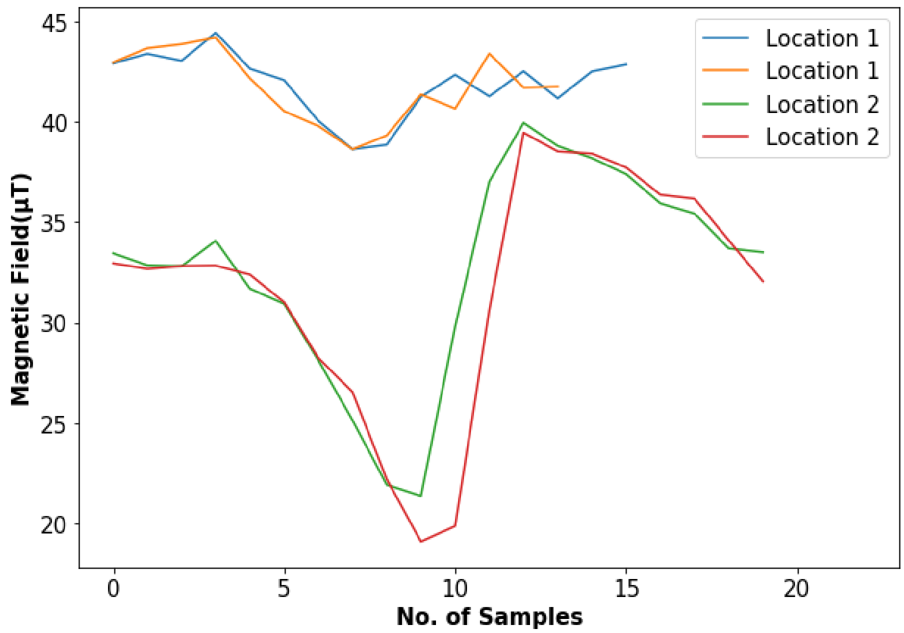

Figure 4.3: Signatures of a multiple location over multiple iterations of reading

in that building. Fig. 4.3 shows that the pattern from one location remains stable for that location, whereas the pattern in the magnetic field reading for another location stays unique for that particular location.

4.2 Fingerprinting

Developing fingerprints of different hallways is required to classify an unknown signature to a set of stored signatures and thus infer the location. A 1D magnetic map was created by averaging the magnetic field data obtained from the two subjects along a specific hallway. Another type of magnetic map is the spatial distribution of magnetic signatures along hallways, which can be obtained by collecting data at evenly spaced points on both sides of the hallway as well as the centre to obtain a grid-like data collection formation. This data was then interpolated to produce the 2D magnetic map depicted in Fig. 4.4, the figure shows the magnetic field values across the pillars, and the spikes on the other side are due to the presence of doors to the room in a hallway of the laboratory building. Because this method of map creation takes a long time and processing such a signature for the closest match also consumes a lot of computational resources, we will stick to the 1D map as the reference signature in the entire literature.

Although the fingerprints look visually similar and have a noticeable pattern in them, the classifier is supposed to be designed to prove the existence of sim-

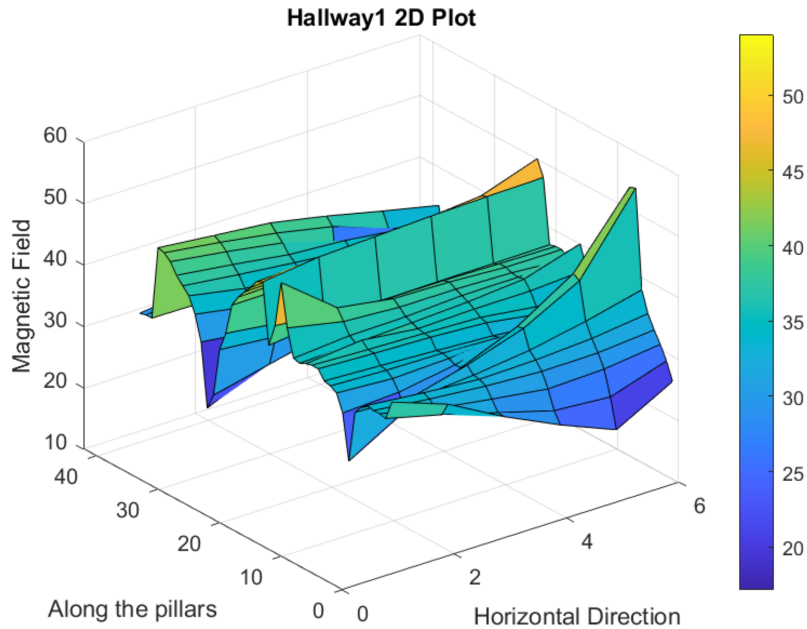

Figure 4.4: 2D signature plot of a hallway

ilarity. To make Fingerprinting work with pattern recognition, we have to use a distance matrix. This distance matrix would show how closely the two time series or patterns are related to each other, i.e., the minimal the distance between the two time series, the more they are similar to each other. We have an option to use a famous euclidean distance that matches the data points sequentially. A varying length time series and the two time series which lag each other will never show similarities if we use euclidean distance. Our system provides a time series that varies across the axes, so we have to use another distance-based matrix. Dynamic Time Warping does the job for us. It warps the series across time and finds the closest match possible for the two time series. Section 4.3 describes in detail the working of DTW.

4.3 Dynamic Time Warping (DTW)

Dynamic Time Warping(DTW) a well known technique that is used to match and align two time series sequences that have visible similarity in patterns but varies in length and height of an instance. It has a known applications in speech processing [30], sensor data classification [42] and many other time series analysis. DTW tries to achieve a better allignment among the two time series by compressing or stretching either of the series. In general, consider two signatures, $T = \{t_1, t_2, ..., t_A\}$ and $S = \{s_1, s_2, ..., s_B\}$ of different lengths. The goal is to find the best match between the two signatures by some alignment w, the optimal warping path. The warping path is given by $w = w(1), w(2), ..., w(n)$, where $w_n = [i(n), j(n)]$ is the set of matched samples, where i and j corresponding to the time axes of two sequences respectively. Fig. 4.5 shows how the two distance based matching algorithm, i.e., Euclidean and Dynamic Time Warping works to wrap the two time series and how DTW performs better and care-full in matching two time series. The objective of the warping function is to minimize the overall

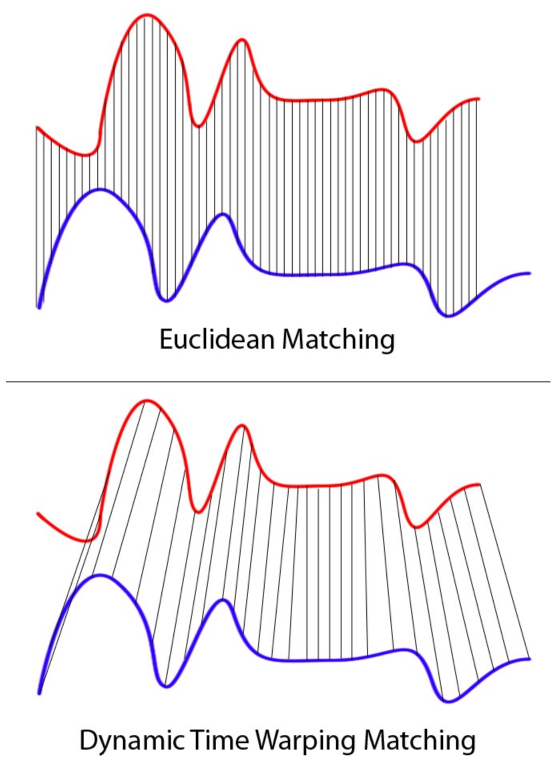

Figure 4.5: Difference in matching schemes and how DTW captures the distance [31]

cost function given by

$$D = \sum_{n=1}^{N} \delta(w(n)) \tag{4.1}$$

where $\delta(w(n))$ is the squared distance between the sample points given by

$$\delta(w(n)) = (i(n) - j(n))^2 \tag{4.2}$$

To generate a warping path, a cost matrix is constructed. This matrix represents the minimum cost required to reach a particular point (i, j) from $(1, 1)$. This minimization problem is usually solved using the dynamic programming approach, whereby a cumulative or accumulated distance $\gamma(i, j)$ is computed as the sum of $\delta(w(n))$, the distance obtained from the current set of points and the minimum of the cumulative distances of the adjacent elements or neighbors. This is given by

$$\gamma(p,q) = \delta(w(n)) + min[\gamma(p-1,q), \gamma(p-1,q-1), \gamma(p,q-1)] \tag{4.3}$$

$$\gamma(i,j) = \delta(w(n)) + min[\gamma(i-1,j), \gamma(i-1,j-1), \gamma(i,j-1)] \tag{4.4}$$

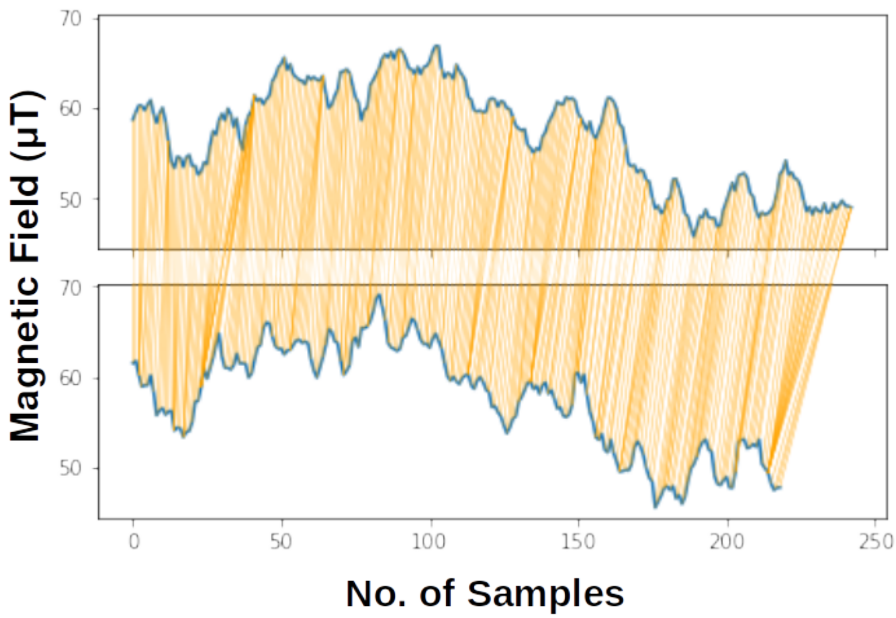

Figure 4.6: DTW path mapped over two signatures of same hallway of CEP

After performing the time warping, the closest match is obtained by the lowest cumulative distance between the signatures.

Fig. 4.6 shows how the DTW finds matching path between two signatures of a corridor that we took in second floor of CEP building. We see as long as the algorithm encounters similarity, it follows parellel paths, and as it encounters dissimilarity it picks the path with minimum euclidean distance between the further points, this is how we could summarize the concept of Dynamic Time Warping.

4.4 Application Of DTW

Though the collected datasets for multiple locations show a visible sense of uniqueness, they should also show uniqueness through computation as well. Hence we took a test signature of a known location and computed its DTW distance among the signatures of four random locations. The table 4.1 shows the distance values. We can observe that the test signature has a minimum DTW distance to the $Location\_3$; hence we can say that the test signature belonged to $Location\_3$.

Pillar Number	**DTW distance**
Location_1	39.55
Location_2	42.85
Location_3	38.58
Location_4	67.04

Table 4.1: DTW distance of test signature with 4 different signature patterns

The motive of collecting datasets is to classify the pattern among them to the location they belong to. This dataset could be tested to belong to a particular hallway as well. In order to check the accuracy of DTW along the signatures of hallways and to classify the signature belonging to hallways, we picked a few hallway signatures as well and checked the DTW distance along the hallways as well. For this experiment, we employed subjects to capture datasets across the hallways of the Laboratory building, and the CEP building table 4.2 shows the accuracy of DTW across the hallways where explain the rest.

Subject	Lab	CEP
S_1	28/30	25/30
S_2	28/30	27/30
S_3	23/25	24/25
S_4	25/30	24/30
A_H	90.4	87

Table 4.2: Number of times signatures correctly classified out of total collected by subjects

Here in the table A_H is the accuracy of the DTW based classifier that we employed to predict locations of signatures in the two buildings and shows how many times it correctly predicted those signatures.

$$A_H = \frac{\sum_{s \in S}(C(s))}{\sum_{s \in S}(E(s))} \tag{4.5}$$

C(s) represents the samples predicted correctly and *E(s)* is the total test samples that we took

4.5 Chapter Summary

This chapter builds the foundation of this project, describing the properties of magnetic signature; how these properties are used for establishing a fingerprinting approach in localization. We then learnt the detailed working of DTW and how we plan to apply it in our project.

Next, we'll see how our classification system was built. Followed by its system architecture.

CHAPTER 5
Classification System

The classification system that we developed was inspired by the one proposed by the author in [38] to compare the test signature across the signature of the hallway in order to find a correct matching portion of that test signature in the entire hallway signature and get the corresponding location. Starting with incorporating fingerprinting method to store a set of locations in the database and then comparing the test signatures with the fingerprints we have in the database, we could get a person's location. This chapter will talk about the above-mentioned statements in detail. We'll look into the steps involved in classification, classification methodology, and the system architecture we implemented. Further, we would learn the error estimation procedure we used for performance evaluation.

5.1 Steps involved in classification

5.1.1 Data Collection

The first step of the procedure was to get the dataset ready. Hence, we collected the magnetic field datasets using the Usage tracker application installed in the phones provided to all the volunteers, and the datasets were collected along the hallways of all the three buildings mentioned in section 3.5 in chapter 3. The method was developed to mimic the actual scenario where our users would capture the data to find their location inside the building. Apart from the procedure, the data was collected. Users are supposed to cover a certain portion, i.e., the user needs to walk a certain distance in order to get localized. This minimal distance will be discussed in the error estimation section. For the data collection part, we collected data walking across the hallways in both directions so as to capture the scenario where the person is moving in any of the provided directions. These collected datasets were then labelled according to the hallways of the building it was captured at, and storing the metadata includes the properties like volunteers name, volunteer's ID, Phone used, Height, and walking speed. An average walking speed was captured by using a pedometer application and was appended to the details of all users prior to collecting the data. Some datasets were collected as a part of experimentation and were labelled according to the experiments they were part of. The detailed information about the number of datasets collected is mentioned in table 3.2.

5.1.2 Database Creation

After the collection of datasets (hallway signatures) was done, the signatures were divided into smaller length signatures using the sliding window procedure (detailed explanation in section 5.2) and stored these smaller signatures along with their labelled length in a separate database which will be our primary database for classification. Again, three different databases were created using the same methodology but with varying lengths of data in it labelled accordingly for the experimentation of performance. These databases don't require information about the volunteer who collected them but require information about speed, as the window length would vary according to the speed of a person. The databases were divided to be used in two different categories. The general database holds the labelled dataset for all sorts of signatures, irrespective of the time, speed, and sensor model it was captured from. And the other databases were specific to the experiments they were captured for. Hence the second step of the procedure was to make databases of required datasets. Specifically, Each hallway signature was divided into the same number of smaller signatures as its length, i.e., if a hallway is 10 meters, the hallway signature for that hallway would be divided into ten strides of data.

5.1.3 Classification

For every hallway, we had around thousands of signatures to test our system upon and to capture the location based on designed experiments. Based on the experiment we were working upon, we randomly picked 20% of signatures along with their labels. Now at the time of classification, we noted the DTW distances of all the test signatures with the remaining training signatures, and then signatures with minimum distance were picked. The location in this picked signature was the predicted location of the test signature. This was how the classification procedure worked for our system.

5.2 Sliding Window based classifier

As our goal of this project is to locate a person inside the hallway, all we have is a magnetic field signature of hallways and a distance matrix(DTW) that finds similarities between two such signatures. We developed a system that could divide the existing hallway signature into smaller strides of defined window size, store them in a separate file, and compare the test signature that our end-user would provide to all those smaller signatures. The comparison was simply made by finding the minimal DTW distance value and predicting the location based on the fingerprinting procedure, i.e., predicting the most similar signature and coming up with the location it belonged to. This way, we were able to localize a person inside a building's hallway. The location provided was in meters as the windows were stridden in such a manner that it represents a meter of data captured.

Fig.5.1a shows the striping mechanism of our system, and Fig.5.1b is a test signature we get from a user. And on the visual comparison, one could see the test signature has a higher similarity with the window W2; hence we could say that a person is somewhere near a location where the W2 signature could be formed. In our case, the W2 is 1 meter away from W1, and W1 is a starting point of reference in the hallway. So we could say the person is two meters away from the referencing point we picked for our hallway signature. This referencing point is stored as a label prior to doing any division.

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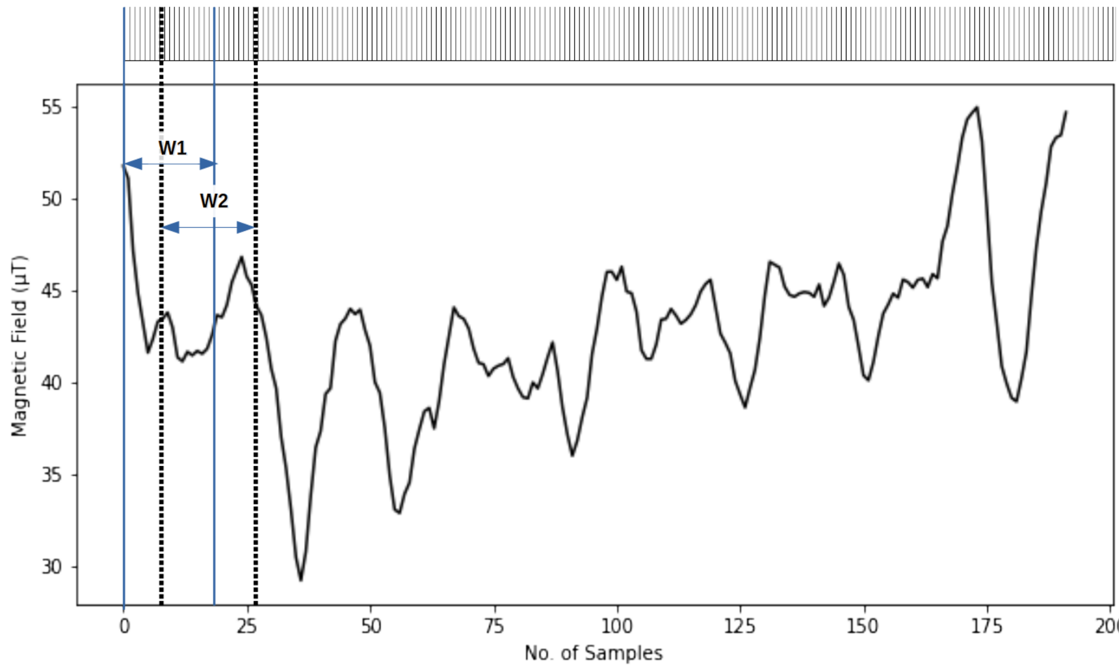
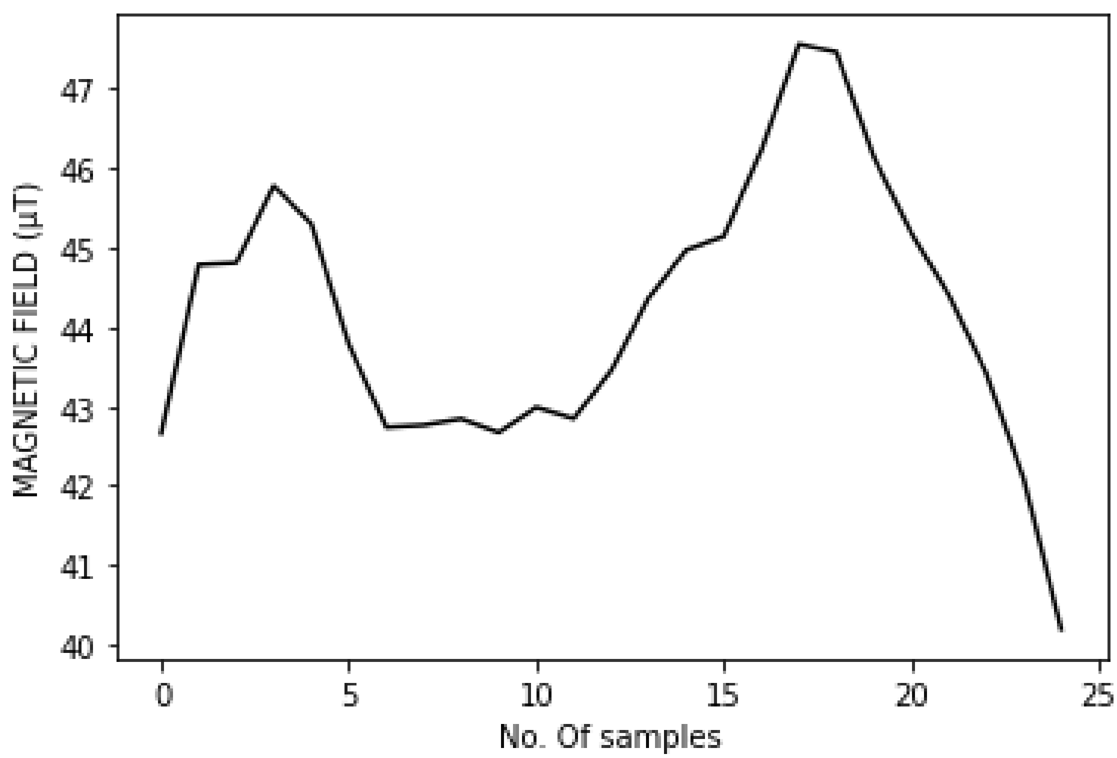
5.3 System Architecture

Fig. 5.2 shows the architecture of our system. The data collection part represents all the scenarios where a person captures the data, and the captured data holds the location of a person's average walking speed of a person. This dataset could be the signature of the entire hallway or a test signature to predict a location. The collected data is then sent for data preprocessing. All the data, whether a hall-



(a) Plot shows How the windows are created and moved across the dataset



(b) Test Signature Window to be compared with the entire hallway signature

Figure 5.1: Working of sliding window based DTW

way signature or a test signature, is sent for cleaning and labelled according to the hallway, time of capturing, walking speed and sensor model used for capturing. The data is divided to store only the vector of magnetic field values in all the X, Y and Z directions. This step is responsible for the selection of data based on experimentation or for sending data to the general database. After the database is created, the hallway signatures are sent to a sliding window divider which takes the speed of the user as an input as well. The divider is responsible for creating smaller signatures and making them available for classification, and after division, the system also labels the window data. Finally, the test signature and the divided smaller signatures are sent to the classifier, and the location is predicted.

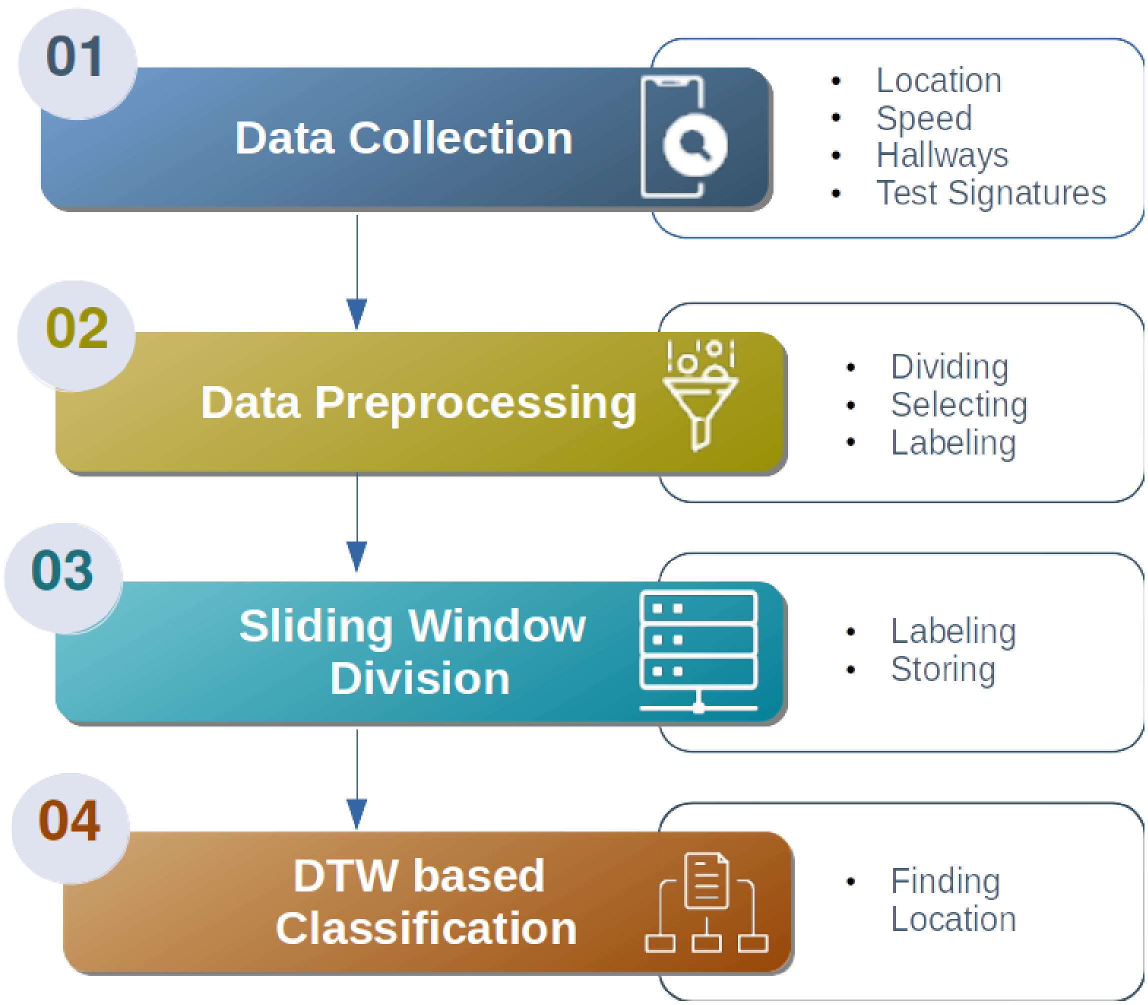


Figure 5.2

5.4 Estimation Error

The error in our system was generated by getting the difference between the predicted location L_P and the actual location L_A labelled in the dataset. To get a record for all such errors, we picked all the signatures of the ground floor of the lab building from the database where person collected data at an average walking speed of 1m/s and then divided them into smaller signatures following the sliding window procedure into three categories(10m, 20m and 30m). The categories were selected in a manner to find a minimal amount of distance a person needs to walk to get localised, and the person needs to walk a certain distance to provide our system with magnetic field data that could form a pattern. Our system randomly picked around 500 signatures of all the three categories, or we could say all the window lengths. As the sampling rate was 2hz, we collected a data point every 0.5 seconds. Also, as mentioned above, for this estimation, the data was collected by a person who walked at an average speed of 1m/s. The system has got two samples for every meter, and the sliding window was stridden after two samples. Division of signatures in this manner mimics the scenario where the user would walk for 10 meters or 20 meters to produce enough samples to be compared and get classified to produce the location.

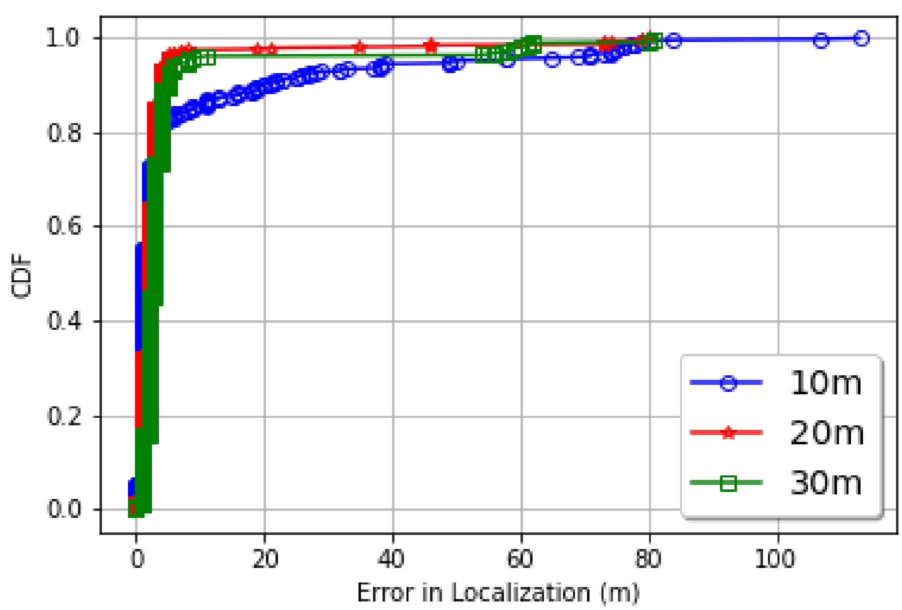


Figure 5.3: Estimated Location Error with variety of Window Length

In this manner, we were able to produce enough smaller signatures for all the locations inside the hallway for our classifier, out of which we randomly picked

500 signatures for testing. We classified them and predicted the locations for all the random signatures. For all these predicted locations the difference with the actual distance was calculated, and stored in a list of differences, which we represent here as an error in prediction. This estimated error is also represented in meters. The estimation error is a key measure for our performance analysis. Fig. 5.3 shows the performance of the system in all the categories based on the window length that we used. Here, you can see how almost 80% of the time, the estimation error of localization is lesser than 8-10m when the window length(W_l) is kept to hold 10 meters of samples. When the W_l is kept to be 20 meters around 96% of the time, the system predicted location within 5 meters of range, whereas in the case of 30meter it was 92% certainty of estimating within 5 meters.

5.5 Chapter Summary

The chapter provided a brief description of a sliding window-based classifier that divides the hallway signatures into test signatures and stores them in a database to be utilized further for comparing test signatures and generating DTW distance. I showed the fundamental steps required to develop this system, and the steps involved in classification are presented through system architecture. The motive of this chapter was to introduce the usage of CDF with error estimation to show the resultant performance of our system. In the next chapter, I use these CDF plots and will show performance analysis in varying conditions and experimental results of all those factors.

CHAPTER 6

Performance Evaluation

To estimate the location and calculate the estimation error, this chapter shows a detailed procedure of how the classification was done and what results were generated. I'll start by describing the challenges we faced, and then the chapter will further discuss the actual performance evaluation.

6.1 Challenges

Throughout the course of this project, we have come across many challenges, and one of the motives of this project was to address these challenges. In this chapter, we will discuss all those challenges and our approach to addressing them.

6.1.1 Built-in Sensor Models Variation

Due to variation in sensor models, the intensities captured by them vary, creating uncertainty in sensor readings, which leads to getting minor changes in the intensity of data. As mentioned in chapter 3 we used a smartphone with varying sensors; these sensors captured a variety of different readings based on the maximum ranges and sensitivity it poses. Fig. 6.1 shows the variation in patterns captured by two different sensors for the same location. These variations are caused when the number of voltages provided to the sensors in various phones while capturing the data, as mentioned in detail in section 3.1 of chapter 3

6.1.2 Distance from ferromagnetic entity

Distance may be a factor in sensing a variety of readings, i.e., a person may face an issue in capturing a crisp pattern as it moves away from the referencing ferromagnetic entities inside an indoor environment. We captured data using a robot, keeping all other factors like speed and height constant, and we noted the drop in magnetic field value as it was moved away from one of the pillars towards a

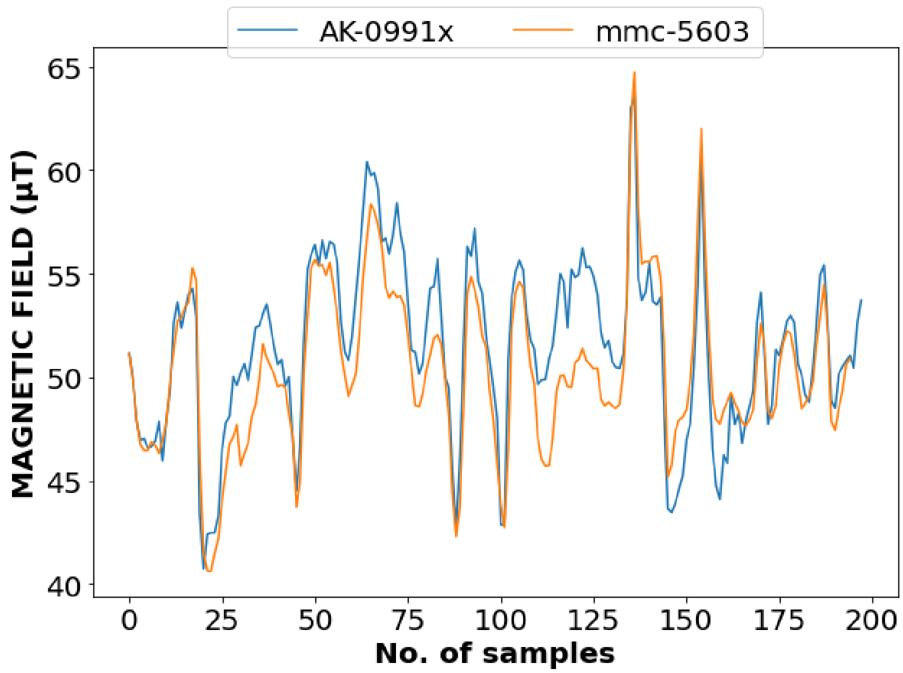


Figure 6.1: Variation captured in sensors

non-ferromagnetic entity. Fig. 6.2 shows the result captured by multiple phones used with a robot.

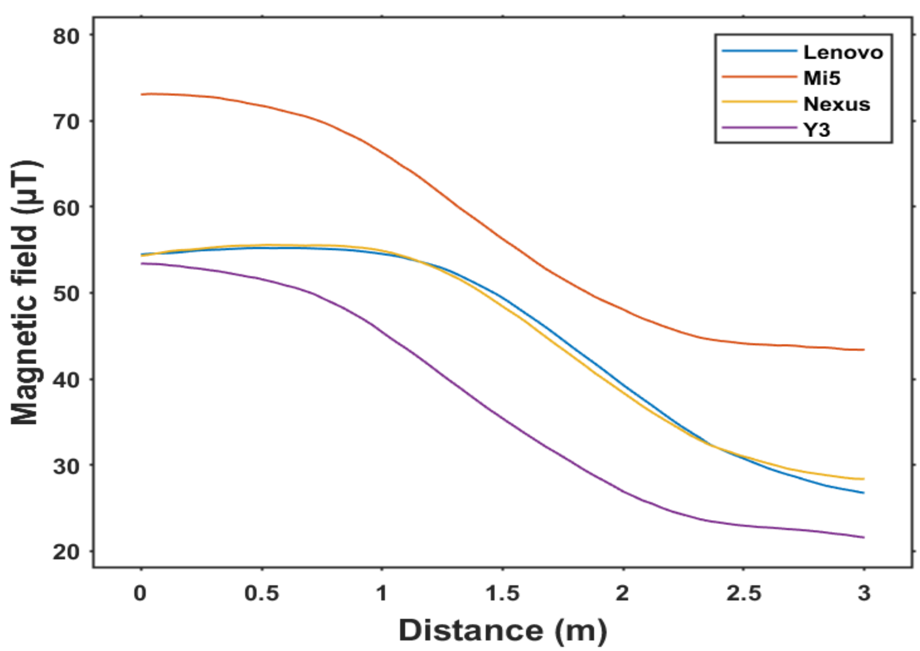


Figure 6.2: A Drop in intensity of magnetic field magnitude observed using a robot

6.1.3 Long Term Variations

The magnitude of the magnetic field may show minor changes over a certain period of time. Existing work has also shown that magnetic field data exhibits temporal stability over a period of time[38, 37, 47]. This may be challenging to us to classify such a dataset. We noted the changes in magnitude for over a month and even a year and noted the changes in magnetic signature.

6.2 Working with these Variations: SUTL study

Having to address the above-mentioned challenges, we have to take datasets of all possible situations covering every challenge that we faced earlier and conduct several experiments to capture the performances of all such challenges. The study was divided in such a way that it could show the performance of the classifier in diverse factors.

First, the diversity of smartphone brands poses a big challenge for magnetic field-based indoor positioning. Specifically, these phones are built-in with magnetic field sensor models that vary in their specifications, such as resolution, sensitivity, specificity, and accuracy. Second, variations (if any) of magnetic fields across time and space(location) may impact the location estimation. Lastly, users with different walking speeds could contribute to the changes in the magnetic field intensity, in turn affecting the estimation. This study looks at how a specific location estimation algorithm performs when considering the SUTL (sensor, user, time and location) diversity factors.

For conducting the performance evaluation across the diversity parameters mentioned, we used our proposed classifier and checked the estimation error, plotted the estimation error in the form of CDF plots and the results generated to show how accurately our classification system performs across the given SUTL diversity.

6.3 Device Diversity

To analyse the impact of different smartphones and the sensors built in them, we conducted a data collection experiment across 15 students from the campus. The usage tracker app installed in all phones collected not only the sensor data but also metadata such as phone brand and model number. The idea was to identify the number of unique smartphone brands. We observed 10 unique smartphone brands being used built-in with eight different magnetometer models. Table 3.1 lists the models and their specifications. For performance evaluation, we choose eight different sensor models. However, for the sake of clarity, we already illustrated the magnetic field signature across one hallway when measured with two phones having different sensor models in (Fig. 6.1). Variation in that figure shows st480 model present in Lenovo phone shows magnitude differences of few μ Tesla across the samples.

To estimate the location and calculate the estimation error, we implemented a windowed DTW between a short test signature collected using eight different models and then stored the signatures in our database along with the sensor models that we used, a set of almost 500 test signatures along with the labelled locations were picked randomly from the stored signatures, these test signatures were classified and the locations were predicted. The entire experiment of classification was done for all the mentioned sensor models separately, and a CDF plot was generated, which is shown below in Fig. 6.3.

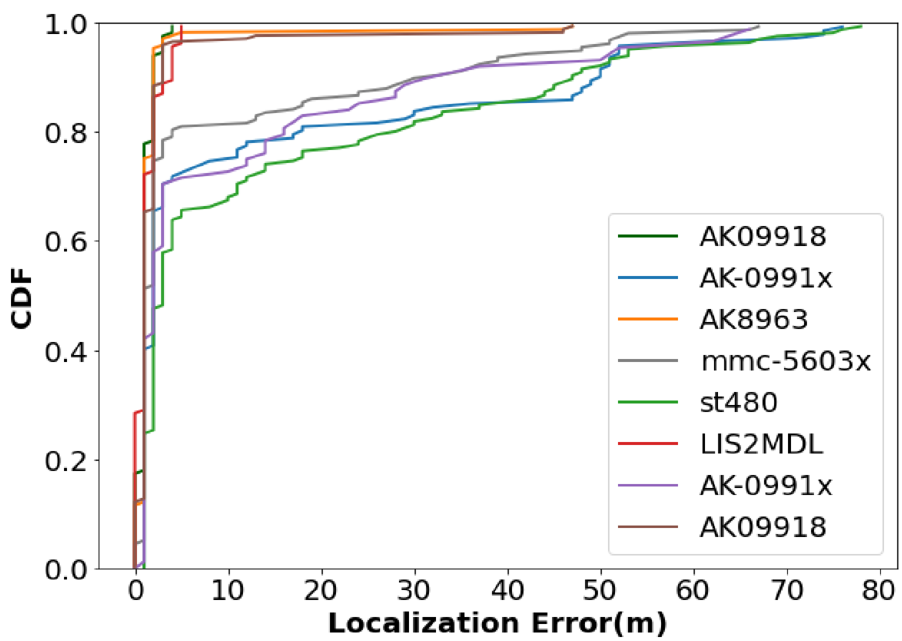


Figure 6.3: Impact of sensor diversity on estimation errors.

The CDF graph of the localization error indicates that heterogeneity in the sensor models does have an impact. For example, the Lenovo phone with the st480 model produces errors of estimates larger than 30 m 80% of the time, whereas Redmi 5 (AK09918, Brown curve) results in errors less than 5 m for the same probability. This is an 80% difference in the error. Reasons for this could include a) changing magnetic field data from different smartphones due to the sensor resolutions and accuracy and b) populating the database and training with data from a particular smartphone model.

We further compare the average estimation errors incurred by using three sensor models across the three experimental buildings. Fig. 6.4 depicts the results.

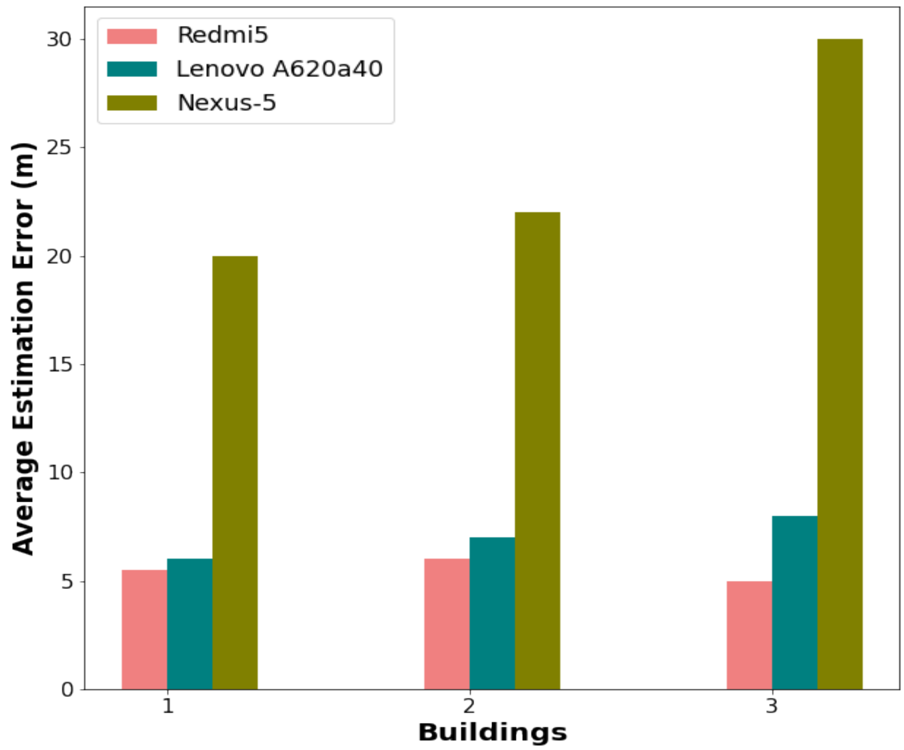


Figure 6.4: Average estimation errors of three devices with different sensors models.

As we can see, Redmi-5 (AK 09918) performs the best. Following this is the Nexus-5. The worst performing phone was Lenovo which had the st480 model.

6.4 User Diversity

For user diversity, five students walked around the corridors holding the phone (Redmi-5) near waist height. We instructed the student to walk at his/her own speed. We measured the walking speeds using a built-in pedometer application. Fig. 6.5 illustrates the data collected by two users walking at different speeds.

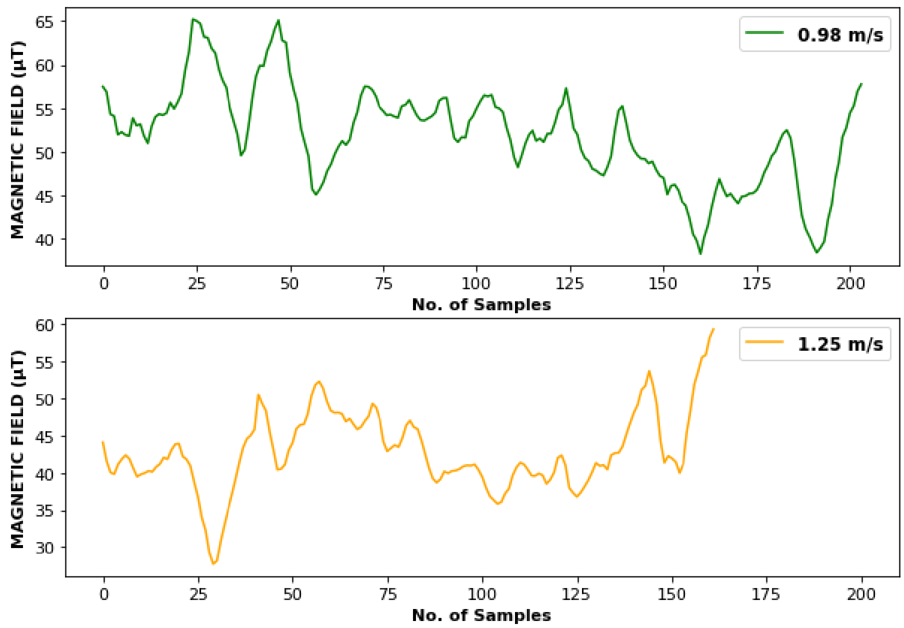


Figure 6.5: Users walking at different speeds. The data shows variations in the magnitude.Also, the student walking at 0.98m/s collected around 200 samples whereas student who walked at 1.25m/s collected around 160 samples.

The speed variations causes the data from one user to lead or lag the data from another user when plotted across time. We show this is in Fig. 6.6.

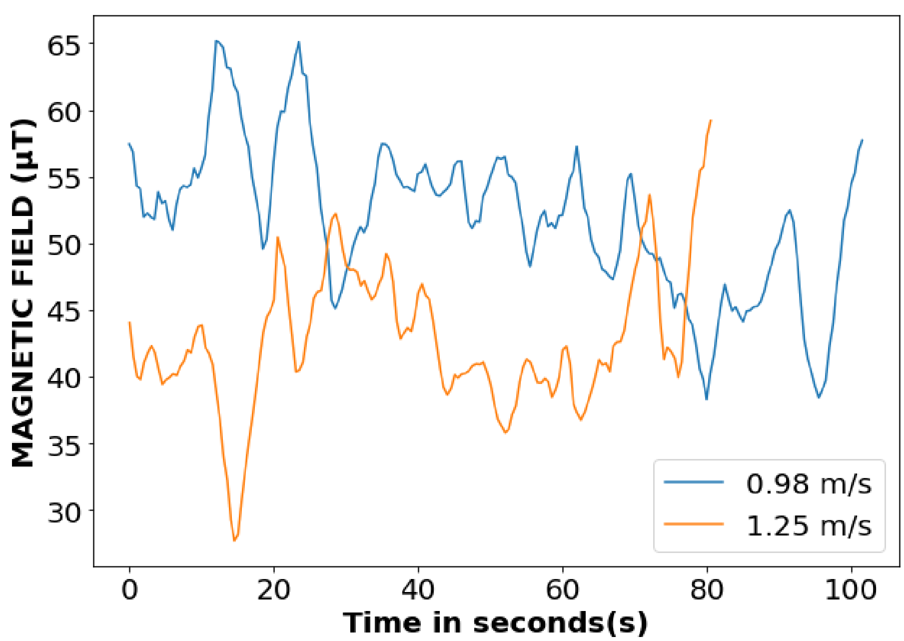


Figure 6.6: As we can see, the data at 0.98m/s lags the data collected at 1.25m/s.

The same windowed DTW was implemented on the data collected by the users for estimating the location.

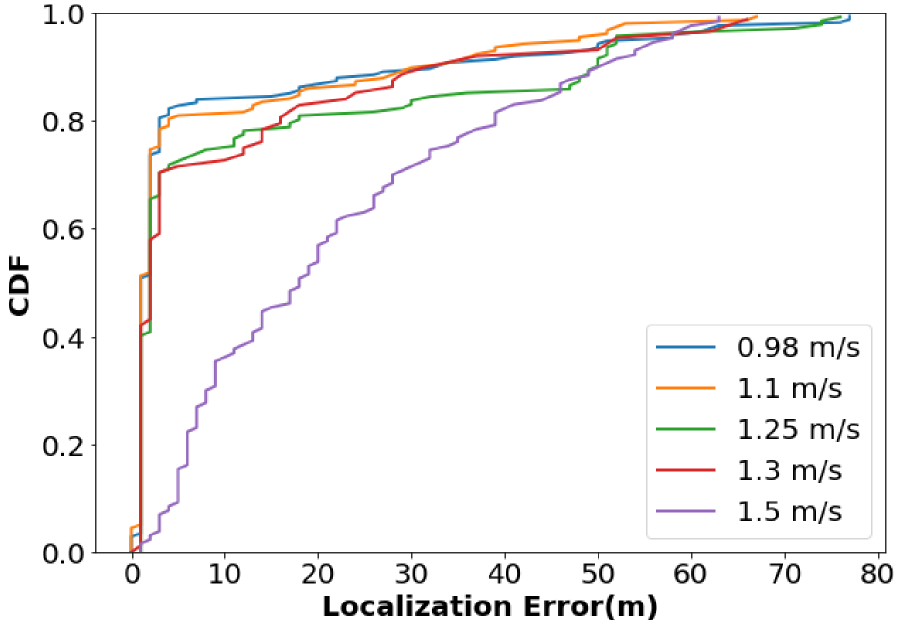


Figure 6.7: Impact of user diversity on estimation errors.

The CDF results in Fig. 6.7 show that the performance of the DTW estimation is affected as walking speed changes. We noticed that as speed increased, the probability of getting less than 5m errors reduced. This could be due to the fact that fast walking induces hand and body movements resulting in the addition of noise in the measured data, which resonates with the estimates.

6.5 Time Diversity

As mentioned earlier in challenges that it is important to study the long-term behaviour of magnetic field data. We have a separate database to discuss the variation of the magnetic field throughout time.

Our data collection spans a duration of over a year (Feb'21 - Present). To understand the long-term variation, we show a data set collected in Apr'21 and another of the same location in Apr'22, one year apart, using Nexus 5 Phone and the same user.

As displayed in Fig.6.8, the intensity of the magnetic field data varies over certain samples. These changes may also be attributed to the sensor functioning at varying speeds of the user.

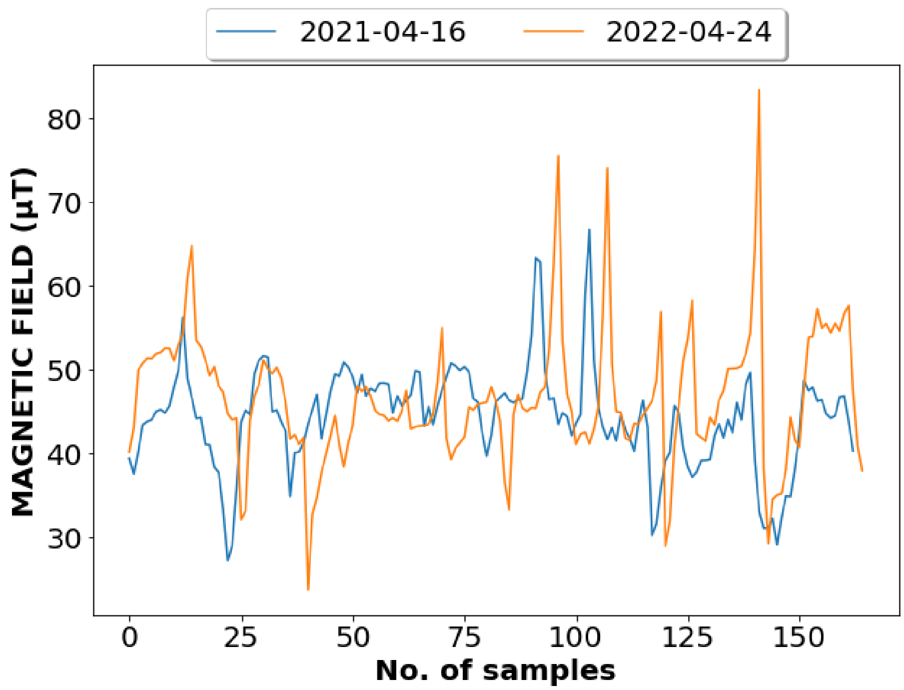


Figure 6.8: Signatures collected on days spanning over a year

We computed the estimation errors wherein the test data was taken from year 2022 and windowed DTW matching was performed using stored signatures collected in 2021.

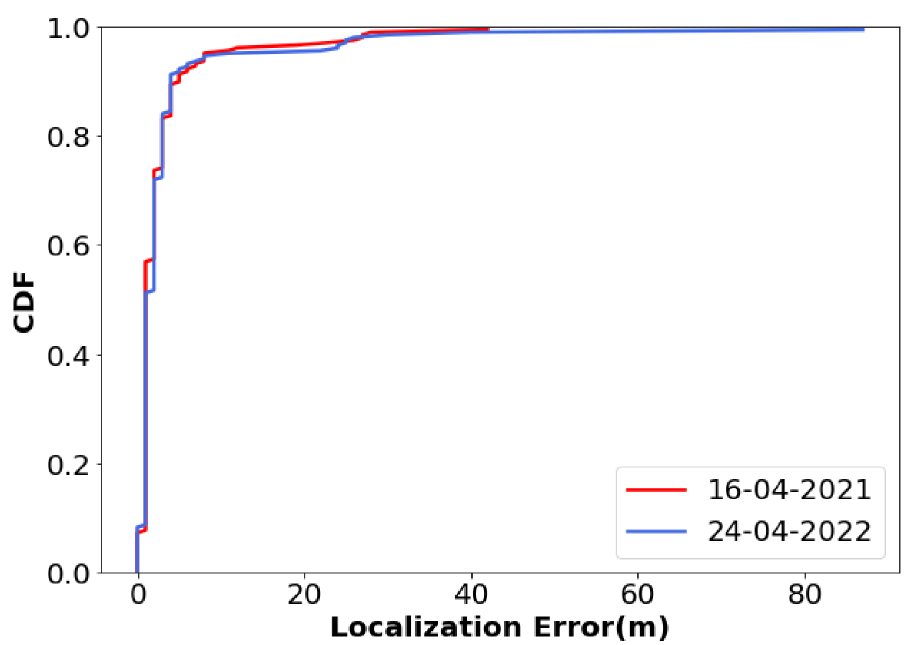


Figure 6.9: Impact of time diversity on estimation errors.

The CDF result in Fig.6.9 shows that even though there were changes in intensity, the estimation remained intact over time across the same building and same phone.

6.6 Location Diversity

The spatial/location diversity looks at whether the magnetic field data varies across different locations. It is interesting to re-look at Fig. 3.3. The hallways in (a) and (b) look very similar in terms of the type of pillars; however, the signatures are different, as shown in Fig. 6.10. Similarly, the hallway in (c) is entirely different from (a) and (b) and thus presents a unique signature. The theoretical underpinnings of this phenomenon are well explained in [37].

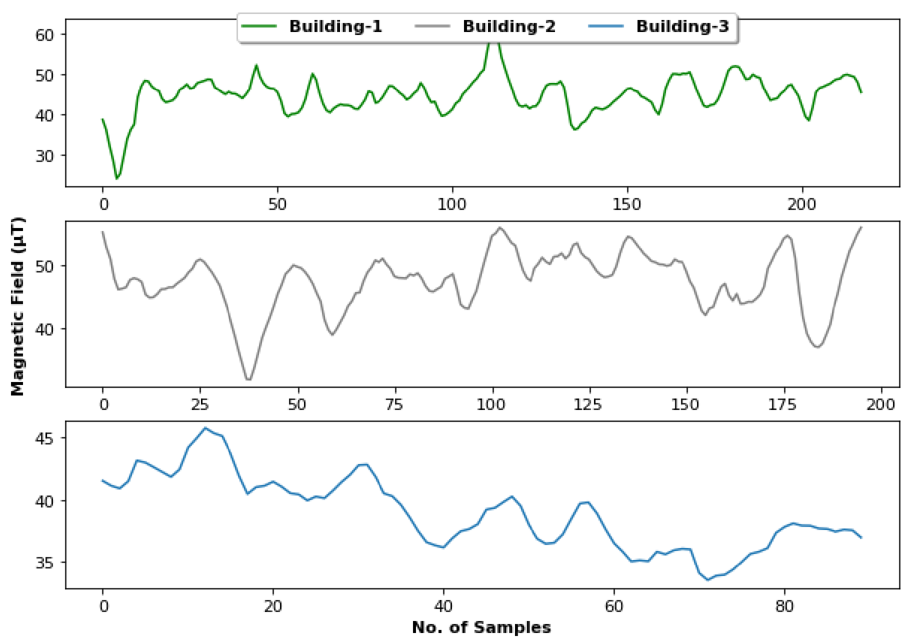


Figure 6.10: Signatures corresponding to hallways in three different buildings in the campus

Although, every location has unique signatures, there may be several locations where the signatures of two different hallways might look similar. For example in Fig. 6.10, 100-150 samples of building-1 look similar to samples 90-125 of building-2. Next, we shall look at how this similarity impacts the location estimation errors. The CDF results in Fig. 6.11 shows that hallways in location-1 give errors of less than 5m 90% of the time in contrast to 8m in building-2. Overall the estimation performance of location-2 is poorer than location-1 and location-3.

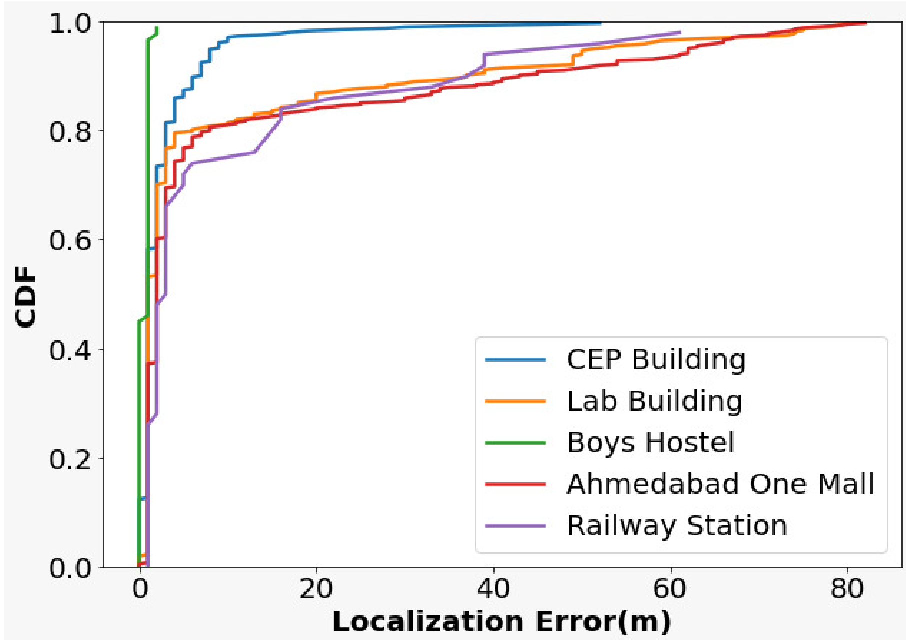


Figure 6.11: Impact of location diversity on estimation.

Chapter Summary

In this chapter, I presented the challenges faced during data collection, including challenges like built-in sensors of different phones and distance from the ferromagnetic entity. Then in the further sections, I have described the SUTL study, which shows how the system performs with diverse scenarios like Device, User Speed, Time and locations. The next chapter concludes the entire thesis work and presents the scope of future work.

CHAPTER 7

Conclusion And Future Work

Conclusion

In this thesis, I have presented an ambient magnetic field based indoor localization system, which is reliable and a robust solution to indoor localization and positioning. Dynamic time warping has the greatest influence on the proposed system. I provided a detailed description of how DTW is used for finding similarities among two time series of varying properties and its application in our project. We learned the uniqueness and stability of magnetic field signature, where we saw how fingerprinting works and the application of DTW in fingerprinting. I have addressed the challenges we encountered during the collection of data and showed how these factors affect performance evaluation. I have discussed the procedure of data collection in the later chapters. Then we introduced to the SUTL study, a performance matrix that played a crucial role in discussing the results our system provided. SUTL Study discusses the diversity in sensors inside devices, user's speed, and variation with time and location.

Future Work

As this project is in a naive state, it has a scope for improvement, and some additional functionalities are to be developed further. We could work on developing a platform that would help us in collecting data of multiple locations through crowd-sourcing. We can test and implement the system in multiple locations with massive datasets. Apart from working with just Magnetic Fields, we could further develop a stable localization system that uses both the magnetic fields and the WiFi present indoors. The end goal of this project is to come up with a platform that could provide not just locations to the person but also provide him with a path that could navigate him across the hallways inside huge buildings. Hence, we could also develop a platform that shows such navigation to him on his phone.

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