“Seamless Indoor Outdoor Navigation for Smartphone Users”

A Project Work

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FACULTY OF ENGINEERING AND TECHNOLOGY

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Certificate of Recommendation

This is to certify that the dissertation entitled "**Seamless Indoor Outdoor Navigation for Smartphone Users** " has been carried out by Kuheli Manna(University Registration No.: 154254 of 2020- 2021 , Examination Roll No.: MCA2360041) under my guidance and supervision and be accepted in partial fulfilment of the requirement for the Degree of Master of Computer Application. The research results presented in this work have not been included in any other paper submitted for the award of any degree in any other University or Institute.

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The foregoing project report entitled "**Seamless Indoor Outdoor Navigation for Smartphone Users** " is hereby approved as a creditable study of an engineering subject carried out and presented in a manner satisfactory to warrant its acceptance as a prerequisite to the degree for which it has been submitted. It is understood by this approval the undersigned do not necessarily endorse or accept every statement made, opinion expressed or conclusion drawn therein but approve the report only for the purpose for which it has been submitted.

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All information has been obtained and presented in accordance with academic rules and ethical conduct.

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Abstract

As mobile technology continues to evolve, the demand for context-aware applications has grown substantially. One crucial aspect of context awareness is accurately detecting whether a user is indoors or outdoors, as it allows personalized and location-based services. This project presents a novel approach for indoor-outdoor detection using a fusion of Wi-Fi, GPS, and Android sensor data to enhance the accuracy and reliability of context-aware mobile applications.

To ensure our desired realistic and ubiquitous principles, we offer a unique indoor-outdoor system comprised of four primary modules: (1) GPS, (2) Wi-Fi, (3) Magnetism, and (4) light intensity. The GPS sensor on Android devices provides precise outdoor location information, while the Wi-Fi sensor continuously scans for nearby wireless networks. By analyzing the characteristics of Wi-Fi signals, the system can detect indoor locations with high accuracy. The android sensors, including accelerometer, light, magnetometer, and orientation sensors, enhance the detection system's accuracy. Extensive real-world experiments were conducted in various indoor and outdoor environments to evaluate the proposed approach. The results demonstrate the system's robustness and effectiveness, achieving accurate indoor-outdoor detection under different scenarios.

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LIST OF ABBREVIATIONS AND SYMBOLS

AP	access point
API	application programming interface
APK	Android Application Package File
GPS	Global Positioning System
GSM	global system for mobile communication
IO	Indoor outdoor
NA	Not applicable
RF	radio frequency
RFID	radio frequency identification
RSSI	received signal strength Identification
Lux:	SI unit of illumination and light emission.
dBm	Decibel-mill watts
BSSID	Basic Service Set Identifier
SSID	service set identifier

Chapter 1

Introduction

The past decade has witnessed the flourishing of Smartphone technology and its application for indoor-outdoor localization. Smartphones have developed at a rapid speed in recent years, and they are becoming crucial equipment in daily life. Since navigation has been an essential requirement of daily life, smartphones are widely used for navigation purposes nowadays. A location-based service has to be consistent in providing navigation in both indoor and outdoor locations. Accurate indoor and outdoor localization is in high demand for improving human daily life. One of the most fundamental items of this contextual information is whether the device is in an indoor or outdoor environment because it makes a significant difference if a user is standing in front of a shopping mall or inside a shopping mall. For determining the current position of a mobile device, location-aware mobile applications need some capabilities. In the outdoor environment, smartphone positioning system depends on Global Navigation Satellite Systems (GNSS) including the Global Positioning System (GPS). GPS is one of the most reliable positioning systems when it comes to differentiating between indoor and outdoor environments. In an outdoor context, GPS has a high rate of accuracy because it can easily reach most the satellites. GPS needs to have a direct line of sight between satellite and phone antenna, a smartphone inside an indoor environment will have a harder time discovering satellites. That's why GPS is often not effective in indoor environments [1].

Accurate indoor localization methods rely on several localization techniques such as sensor networks, RFID, WI-FI, ultra-wideband (UWB), Bluetooth, cellular signals, etc. Wi-Fi-based indoor positioning is one of the most popular positioning systems that have lots of pre-installed Wi-Fi access points [2]. Besides, by using Wi-Fi for indoor positioning there is no need for additional peripherals and almost all smartphones are equipped with Wi-Fi features. From nearby WI-FI access points, we can obtain receive signal strength (RSS) that is used to characterize the fingerprint. Compared with the outdoor environment, the accuracy of Wi-Fi-based technology can not satisfy the expectation of indoor users because there are many points of interest (POIs). When GPS is not used, Wi-Fi is a very common system, but certain locations have a scattered Wi-Fi signal. Thus Wi-Fi localization is a good indoor localization method; however, it cannot guarantee, that there are enough Wi-Fi fingerprints for localization [3]. However, the number of Wi-Fi AP is growing, and the characters associated with Wi-Fi AP represent resources that could be helpful in the future specifically indoor-outdoor detection Modern smartphones are now provided with numerous varieties of sensors. The most prominent sensors that most smartphones have are an accelerometer, magnetometer, gyroscope, light sensor, proximity, microphone, and camera. We can detect various environmental aspects Using this sensor data [4]. These sensors detect the user's movement, providing vital data about user steps, direction, and orientation. Utilizing the data from these sensors can enhance the accuracy and reliability of indoor-outdoor detection.

In this project, we propose the indoor/outdoor detector: Seamless Indoor-Outdoor Navigation for Smartphone Users using Wi-Fi, GPS, and smartphone sensors with careful consideration of the user's Environment. We primarily make use of four sensing resources: GPS, magnetic field, light sensor, and Wi-Fi. In this approach, we examine in depth the adequacy of the devices and techniques such as Wi-Fi Aps RSSI, GPS Signal-to-Noise-ratio (SNR), the number of connected APs or satellites, Magnetism, and illumination. Through 2 monthly experiments, we observe that the light intensity, GPS signal, WIFI signal, and the intensity of the magnetic field all individually exhibit distinct patterns in the indoor and outdoor environment. These patterns are feasible for accurate classification of the ambient environment. More preciously, light signals display distinct patterns when they are captured inside and outside the building. Similarly, the RSSI from a Wi-Fi AP by a device changes dramatically from the outdoor to indoor environments and the intensity of the magnetic field also varies significantly inside a building. In this observation, we combined four sensing components and developed an extensible indoor/outdoor detection app.

1.1 Motivation:

Indoor-outdoor detection is a powerful mechanism that bridges the gap between our physical and digital worlds, enhancing our interactions with technology and our environment. In the last two decades, many approaches have been proposed for Indoor/Outdoor detection and most research has been focused on a general method employing semi-supervised machine learning and using light intensity, cellular signal strength, and sound intensity [5]. This IODetector is quite poor because the system is invariant to changes in relevant factors like environments, weather conditions, seasons, latitude, and devices, which ultimately hurts the accuracy of the IO detection. Motivated by the above observations, we propose a new approach to IO detection which aims to show accurate indoor-outdoor detection by combining GPS, Wi-Fi, and Android sensor data so that it can significantly improve the navigation experience for users. Since Smartphones are widely available, most smartphones are accomplished with a wide range of sensors. Therefore users already own smartphones with GPS, Wi-Fi, and various sensors, there is no need to provide additional equipment to users. Hence our approach is seamless, Real-time, and cost-effective. As is presented in this project, if a user is walking down a busy street then GPS will accurately track the user’s location. But suddenly users step into a building this is where Wi-Fi comes to the rescue with a Light sensor. The fusion of GPS, Wi-Fi, and Android sensors is key to a world of infinite possibilities where navigation is seamless, and where buildings and open spaces are seamlessly connected.

1.2 Contribution:

We have designed a seamless indoor-outdoor detection system by combining Wi-Fi, GPS, and Android sensors, which have been divided into four components such as light detector, magnetism detector, Wi-Fi RSSI detector, and GPS SNR detector. By evaluating the confidence levels from these four sensing units, we intellectually aggregate their detection results and guarantee an accurate, optimized result. In Chapter 4, we will describe the design details of each component. We are also storing different types of sensor data in a CSV file in different scenarios, such as indoor, outdoor, indoor-to-outdoor, and outdoor-to-indoor. By analyzing these data sets, we are fixing the confidence level of those four sensing components. Using this technology, we can accurately determine a user’s situation and improve overall user satisfaction.

To summarize, the contributions of the study are as follows-

1. We implement an Android app named sensor-data-collection-application that collects sensor data from devices, such as GPS, Wi-Fi, magnetometer, accelerometer, proximity, and ambient light sensors, and conduct experiments to collect data samples in various real daily scenarios. A data set containing a large number of labeled data samples is constructed.
2. We have also implemented another Android app named IO detection for indoor-outdoor detection based on data sets from the sensor-data-collection application. This app detects the user’s environment (indoor or outdoor) and opens another app for Localization based on this detection. If the user is found in an indoor area, an app for indoor localization is opened, and if the user is found in an outdoor area, Google Maps is open for outdoor navigation.

1.3 Project Outline

The rest of the project is organized as follows:

Chapter 2 shows the background and related work done in localization, positioning, and environment techniques.

Chapter 3 shows the Experiment design and describes the experiment and data collection procedure.

Chapter 4 shows our proposed work, logic, and workflow for detecting the user's ambient environment.

Chapter 5 shows the Experiment result including system performance evaluation in detail.

Chapter 6 concludes the project and discusses the possible future directions through which we plan to extend our work.

Chapter 2

Background and Related Works

In this chapter, we start by explaining a wide research works that have represented an important implicit background to our proposed work and end by discussing on most explicit related work.

2.1 GPS

Even though GPS is the sensor with the most energy consumption, it is still the most reliable sensor when it comes to differentiating between indoor and outdoor environments. GPS signals are highly dependent on the line-of-sight (LOS) paths between the device and GPS satellites. It is distinguished that GPS signals are poor in indoor environments as the LOS paths of GPS signals are blocked [6]. In the outdoor context, GPS has a high rate of accuracy because it can easily reach most satellites as the LOS paths of GPS signals are not blocked. Based on these facts, the localization accuracy of GPS or the availability of GPS signals has been exploited to detect whether a device is in an indoor or outdoor environment [7] [8].

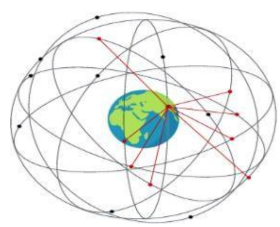


Figure 1. Illustration of a 24 GPS satellite constellation in motion relative to the Erath's rotation (Source: Wikipedia).

Nowadays almost everyone can own a GPS receiver because the cost of GPS technology has significantly decreased over the years due to evolution in technology. Its intuitive nature and easy implementation make GPS an attractive tool for many researchers. Using GPS SNR value as an indicator for indoor-outdoor transition is proposed in [9]. GPS signals are usually available outdoors where the sky is directly visible, and are often weak or unavailable indoors when the sky is obscured by ceiling and walls. Thus, the estimated accuracy of GPS localization can be used to detect if a user is indoors [10, 6].

2.2 Wireless signals

According to Vathsangam et al., [11], one of the suitable and cost-effective candidate techniques is using existing Wireless Received Signal Strength (RSS) -based indoor positioning methods. Despite the robustness of the Wi-Fi localization method, there is a challenge in evaluating Wi-Fi signals because of their variety from time to time. The Wi-Fi signals hardly can be stable hence there is many complexities in the indoor environment and it is difficult to get precise and flexible signal from wave propagations [12]. Wi-Fi location determination consists of two primary methods, signal strength propagation models and fingerprinting techniques [2]. The fingerprinting technique represents a reliable way of getting accurate position information inside Wi-Fi networks but its data acquisition stage makes it slow, static, and hard to scale. WiFiBoost [13] used a machine learning meta-algorithm that combined an adequate ensemble of simple classifiers to improve the overall performance.

2.3 Multiple sensors

The following sensors are chosen to identify the indoor-outdoor state that might be related to the environmental exposure of the user.

2.3.1 Light Sensor:

A light sensor, also known as a photo sensor, is a sensor that measures the intensity of light in its surrounding environment. Light sensors operate based on the principle of the photoelectric effect. Light sensors can be exploited to automatically adjust the lighting in indoor spaces depending on the ambient light level. By comparing the light intensity readings from the sensors, it is possible to detect indoor or outdoor environments. In the daytime, the sun provides around 10,000-80,000lx when it's shining fully [14, 15], compared to between 300 lx to 750 lx emitted by indoor lighting [16], and between 0.27 lx to 1.0 lx provided by the moon under a clear sky [14]. From this, it is effective for indoor-outdoor estimation both in the daytime and nighttime.

2.3.2Accelerometer:

Accelerometer can record the motion patterns and dynamics that relate to various activities and environments. Indoor and outdoor environments often have different motion patterns. For example, walking or running outdoors may involve faster changes in direction and variation in the ground compared to indoor movement [17].

2.3.3 Magnetometer:

The magnetometer plays a vital role in the indoor navigation system. It is designed to measure the Earth's magnetic field, which is useful in navigation applications. This sensor is sensitive to disturbances caused by electronics, magnets, and metals, and hence, the magnetometer variance is a good indication of nearby structures and electronics, which happen mostly in an indoor environment [18].

2.3.4 Proximity:

A proximity sensor is a device that can detect or presence of nearby objects and for this, it does not need any physical contract [19]. By utilizing proximity sensors it is possible to develop a system that can detect indoor-outdoor environments.

2.3.5 Aggregated Sensor

Depending on the types and capabilities of the sensor, there may be situations where a single sensor might not be able to tackle all application scenarios. The data coming from multiple sensors such as accelerometers, proximity, and light sensors, wireless receivers [6], and magnetometers were exploited for IO detection. Moreover, indoor-outdoor determinations rely on continuous sensing information from GPS sources and internal sensors like accelerometers and gyroscopes to get an efficient estimation of user position and pedestrian tracking [20]. IODetector [5] combined data from three lightweight sensors (light, cell tower signal strength, and magnetic sensors) to develop an extensible IO detection framework that did not require a training phase. There are some cases where these IODetector components fail to detect the right IO state because of the non-adaptive nature of their respective thresholds. As an alternative, [21] proposes an approach to IO detection that is based on semi-supervised learning. Note that the supervised learning-based classifier approach has the same fundamental limitation as IODetector in that a supervised learning-based classifier model trained in one environment may not be accurate in other environments.

Chapter 3

Experiment Design

3.1 Overview

The existing methods cannot estimate indoor/outdoor with high accuracy. We aim to the improvement of the precision of indoor/outdoor estimation by using GPS, Wi-Fi, and Android sensors.

3.2 Task Definition

To create an exact indoor-outdoor detection algorithm, we divided our work into two parts. The first one is the data collection part which is information coming from physical sensors in the device that could be influenced by the environment. For that, we have developed an Android app for data collection. In The second part, we analyzed these data sets and we developed another Android app that can easily detect indoor and outdoor based on our analysis. Let's see in detail below.

3.3 Data Collection Application development

We have developed an Android application for data collection. This Android app is implemented using Android Studio. This app needs to access multiple sensors on the smartphone and save the sensor readings to a CSV file. The class we used was SensorManager where this class lets developers access the device's sensors and provides the primary API for managing all aspects of sensors enabling, disabling, and collecting information. The collected data consist of the number of GPS satellites, the GPS signal-to-noise ratio, the number of Wi-Fi networks around the user, the highest signal strength of the Wi-Fi networks around the user, luminance, the magnetic flux density, proximity, angular velocity, and linear acceleration. To acquire data from GPS, the class we used was LocationManager. Then, we register a GPS listener in the GpsStatus.Listener method, and start handling incoming data in the onGpsStatusChanged() callback method that can used for receiving notification when GPs status has changed. We picked Wi-Fi Manger for the Wi-Fi scan because it provides the primary API for managing all elements of Wi-Fi connectivity, including a list of configured networks, presently active Wi-Fi networks, and access point scans. To acquire data from other sensors, we first need to create an instance of the SensorManager class, which we can use to get an instance of a physical sensor. Then, we register a sensor listener in the onResume() method and start handling incoming sensor data in the onSensorChanged() callback method. This application provides a user-friendly interface that allows users to interact with the app. This app includes various features such as data visualization, file manager settings, configuration settings, dark mode turn on turn off the feature, and Google map visualization.

It is already maintained that this application is user-friendly so that the user can easily specify whether he/she is indoors or outdoors. To start data collection user has to press the start button and also specify whether he/she is in an indoor or outdoor environment Labeling would be done in this circumstance. Thus, the user can modify data labels or remove the collected data if they make any mistakes. If the user wants to terminate data collection, then he/she has to press the 'save and exit' button. This button saves the collected data to their respective named CSV file. The file name format of CSV files is determined by the date and time. The process of data collection can be 10 minutes, 30 minutes, or unlimited time depending upon the user. The user can stop data collection at any time. This makes the process of starting and stopping the data collection fast and simple for the user.

3.3.1 Data collection

In this data collection process, the users, carrying smartphones, walk around inside the building or outside the building as usual for daily activities. Their smartphones record relevant information from various positions. To evaluate our IO-Detector approach, using a custom Android app, we collected different samples of sensor data with a fair distribution between two environments: the Jadavpur University campus and a residential area. For each site, we collected light signal six times, magnetism signal four times, GPS signal two times and Wi-Fi signal two times on average with different sampling rates. To assess the accuracy of different approaches, the Android app relies on an interface for volunteers who participated in the data collection to manually input (indoor/outdoor) ground-truth information. There were a total of three members who participated in the data collection process and various models of smartphones are used for data collection. The users collected the data in their daily lives in both urban and rural areas. This ensures the diversity of the data set.

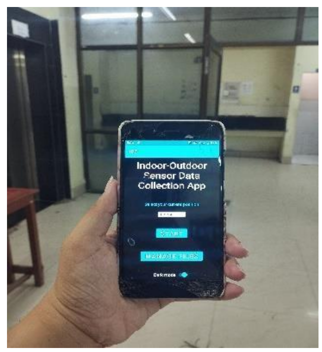


Fig. 2. Data logging process. The picture shows a user configuring the data logging session.

Table 1
Example of collected data instance.

" sensor_data ":
" Gps_lat ": 22.49569877,
" Gps_long ": 88.3725543,
" Gps_accuracy ": 7.62,
" Gps_snr_average": 27.53999,
" Gps_satellites ": 5,
" Gps_snr_Trend ": 4.2222233,
" wifi_AP_No ": 17,
" wifi_Max_RSSI ": -48,
" wifi_Avg_RSSI ": -85,
" 1st_AP": 1,
" 2nd_AP": 4,
" magnetic_x ": 32.156255,
" magnetic_y ": -36.487503,
" magnetic_z ": -15.000001,
" mag_veriance ": 0.7068694,
" light ": 303.155347,
" proximity ": 5.0,
" accelerometer_x ":-1.72905,
" accelerometer_y ": 4.02,
" accelerometer_z ": 8.95005
" Result": "outdoor",

3.3.2 Overview of the data set

The dataset contains a series of recorded readings that are captured at regular intervals by the sensors. For example, magnetometer datasets may include 3-axis magnetic values(x, y, z) while light datasets may provide light values. GPS datasets may include latitude, longitude, altitude, accuracy, and timestamp values. Each sensor reading is normally correlated with a timestamp that describes the exact time when the measurement was recorded. This dataset may indicate the frequency at which the sensor readings were sampled. For example, Wi-Fi datasets normally have a lower frequency compared to accelerometer, magnetometer, proximity, etc. This is because Wi-Fi scans, which involve measuring the RSS of nearby access points, are typically performed every 10 to 30 seconds or even longer intervals. Higher data frequency as a result in larger datasets requires more storage capacity.

3.4 IO-detector

3.4.1 Module Description

In this project, we introduced the IO-Detector which is a combination of “IO” (including indoor-outdoor) and “detector”, signifying the capability to distinguish between indoor and outdoor environments. The intuition behind our system is that simply performs real-time Android applications running on smartphones that can be activated by any user when needed. The main goal of our system is to provide accurate indoor-outdoor detection results. IO-detector classifies the surrounding environment into three main categories: indoor, semi-outdoor, and outdoor, based on signatures observed from various physical sensors like light, magnetism, GPS, and multiple Wi-Fi AP signals during user transitions from inside buildings into outdoor and return. We conducted experiments in controlled areas where data was collected from fixed routing traces that can provide enough description and enhance the certainty about the type of those surrounding environments. IO-Detector mainly achieves many practical design requirements:

- High accuracy –as we are using Wi-Fi, GPS, light, and magnetic sensors. Therefore if any of these module does not perform well then the other module configures the user's ambient environment. For example, sometimes indoor GPS does not provide SNR value. Thus GPS is inactive. In this situation, Wi-Fi can play an important role but if there is no Wi-Fi AP then Wi-Fi can’t find Wi-Fi fingerprint. For that, there is only one way left which is indoor-outdoor detection using smartphone sensors. In this project, we proposed two sensors Light and magnetometer. There may be a case where light is not available but the magnetic field always works. Combining all four modules we can say this approach is highly accurate.
- Universal applicability- IO-Detector has large flexibility and scalability to run proactively on all of today’s smartphones and smartphones are widely available. That ensures its wide applicability.
- Real-time –IO-Detector continuously monitors and updates the indoor-outdoor status as a user or device moves and the environment changes.

3.4.2 IO-detector Application Development

We have developed another Android application for Indoor-outdoor detection. This Android app is also implemented using Android Studio. It applies to most brands of Android phones such as Samsung, Redmi, and LG. This app needs to access location and Wi-Fi services on the smartphone for detecting the ambient environment. Therefore this app needs permission for Location access. If the user isn't allowed to permit access to location service then this app will show a prompt and once again it ask the user to permit location service. In the case of Wi-Fi, this app will ask the user to please turn on Wi-Fi. This application also stores relevant data in a CSV file concerning detection results. After opening this app it shows nearby Wi-Fi lists with their SSID, BSSID, Capabilities, level, and frequency. This list is constantly sorted by the RSSI showing the access point with a higher level of signal strength at the top of the list. To start Wi-Fi scanning user has to press the scan button. After the scan button is pressed relevant Wi-Fi list will be updated if there is an update and whenever the scan button is pressed the user will be shown that scanning is in progress. It gives the user a user-friendly atmosphere. For indoor-outdoor detection, the user has to press the start button and press button to show the user whether it is outdoors or indoors. If the IO-Detector finds that the user's environment is indoors, then it will open an indoor localization app to help the user find his/her path. In the case of outdoor it directly open Google map to help the user navigate. It will show in detail in the proposed work section the tasks that will be performed in the background of this application after the button is pressed.

Chapter 4

Proposed work

In this section, we introduced the system architecture and design details for each component in IO-Detector. Then we use a Light sensor, magnetic field sensor, Wi-Fi, and GPS to determine indoor and outdoor states. Each of these four components works independently to estimate a state and a confidence value. The final state is determined after adding all the confidence values. Figure 4.1 presents the system architecture of the IO-Detector.

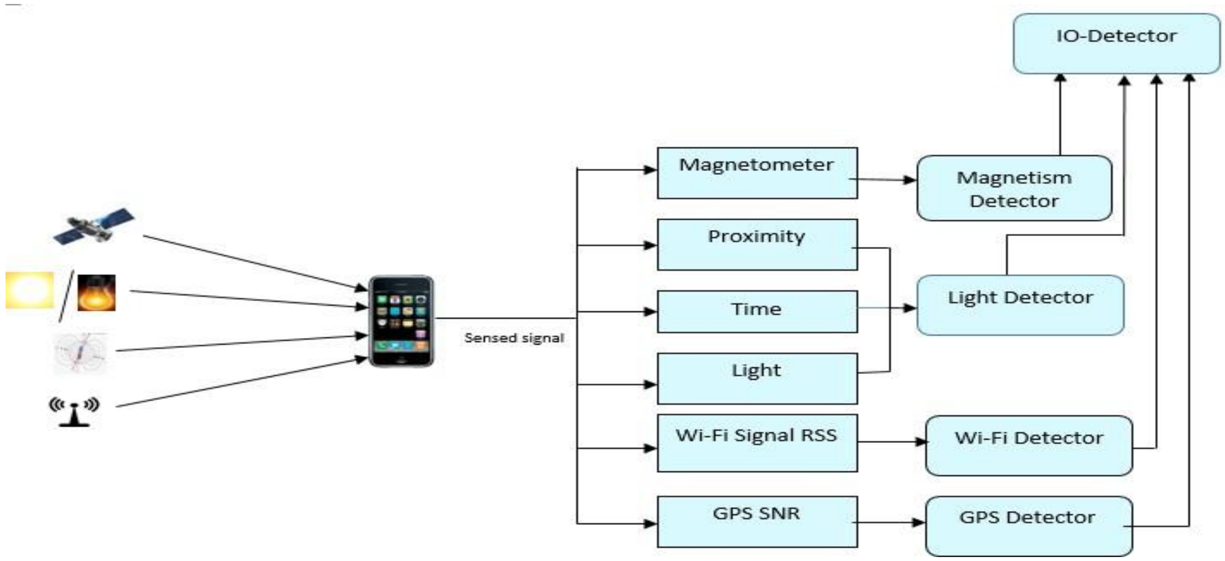


Figure 4.1 System architecture of IO-Detector.

4.1 System overview

In this project, we introduced an IO-detector, "Seamless Indoor Outdoor Navigation for Smartphone Users" which has large flexibility and scalability to run actively on all of today's smartphones. We aim for the improvement of precision of the indoor/outdoor estimation by using four modules that are maintained in System architecture. Fundamentally, the IO-Detector is built based on four experimental observations: (1) In the daytime, outdoors, light intensity is typically above 2000 Lux; (2) When the user's context changes from outdoors to indoors, the Wi-Fi signal strength increases due to neighbor access points; and (3) Magnetic field sensed by the phone tends to change rapidly when the user is moving indoors where there are possibly many appliances, electric currents and metallic objects nearby, compared to outdoors. (4) In the outdoors, the SNR of all GPS signals is more than 20dB and the GPS module of the terminal can communicate with more than 3 satellites. The indoor/outdoor estimations by the 4 physical quantities mentioned above are carried out in parallel. In addition, the estimation reliability is maintained in each estimation. If each estimated result is different, the estimated result with the highest reliability is adopted. In the rest of this section, we will describe the design details of each component. To reveal the signal features with different environments, we empirically study the patterns of the light signal, Wi-Fi signal, GPS SNR, and magnetism signal in different environments. All of the signals are collected in different environments under different weather conditions, including sunny, cloudy, and rainy days, and at different times of the day. The light signal and magnetism are collected with different orientations of the light sensor and magnetic sensor, Wi-Fi signal and GPS signal are collected when the user walks from outdoors to indoors and vice versa.

4.2. Light Detector

The primary source of light for light detection is the Sun. Light Detector is designed to capture and measure the intensity of light, and it can detect sunlight as well as other sources of light. In outdoor and semi-outdoor environments, the sun emits electromagnetic radiation across the broad spectrum including visible light which is the primary light source in the daytime. Indoors, artificial light sources play a crucial role in light detection.

4.2.1 Light intensity

Light intensity refers to the amount of light energy present per unit area that is measured in units such as lux, foot candles, or watts per square meter. We normally observe that during the daytime, the intensity of light inside a building that relies on artificial light is typically much lower than in an outdoor or semi-outdoor environment that is based on sunlight, even on cloudy or rainy days. The major reason is that the intensity of sunlight within the visible spectrum is normally much higher than that from ordinary lighting lamps. That’s why the luminous flux of sunlight is much higher than that from artificial light sources during the daytime. Outdoors, there is direct exposure to sunlight, and there are typically no walls, ceilings, or other structures blocking the light path, allowing light to spread more freely and reach larger areas. Therefore, we can accurately distinguish the indoor environment from the outdoor environment by using the observed light intensity.

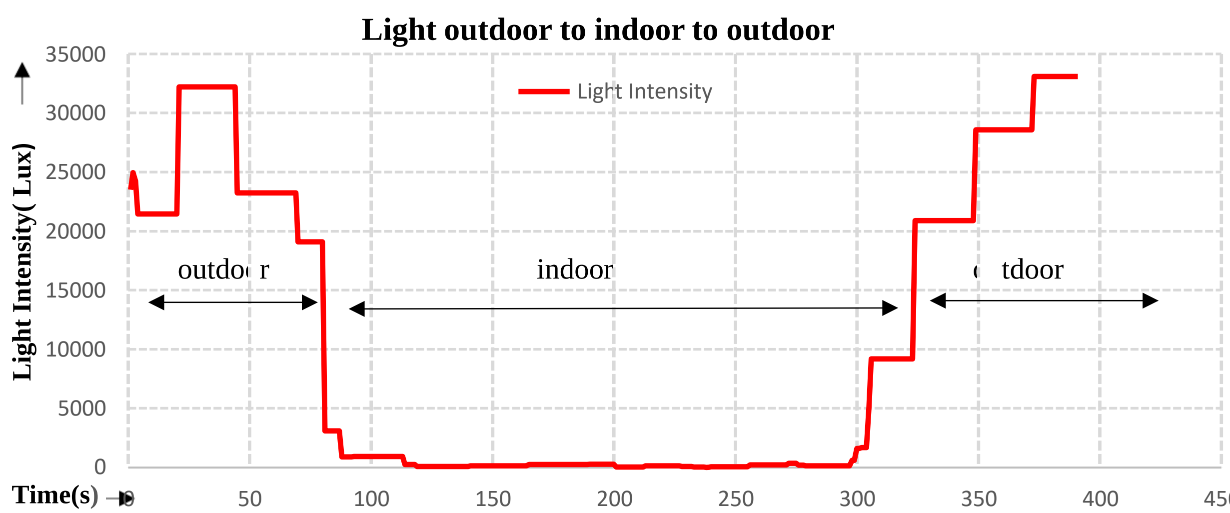


Figure 4.2.1. Light intensity pattern when the user moves indoors, then returns out outdoors during a sunny day with a smartphone in hand and screen facing up.

There may be Additional information is needed to make the light information more useful. First, the phone might be in the pocket of the user, which would mean the light sensor is obstructed and no light measurement is available. For this scenario, we included the proximity sensor, and the idea is to determine when the information from the light sensor is reliable. It might often happen that when we are on a call, the screen of our smartphones will turn off automatically when we bring the phone to our ears, and the screen will turn on when we take it back. This is because the proximity sensor recognizes the object near the phone. Secondly, the clouds can significantly affect the amount of light received from the sun. To address this issue, information about the weather was included. Lastly, the sun is not available 24 hours a day. This changes depending on the time and place the user is. To further improve the possibility of inferring information from the light sensor, information about the part of the day was collected. Even though a simple approach would be to divide the day into 2, daytime and nighttime, Based on sunrise time and sunset time, it is decided whether it is daytime or night. In our work, we exploit time clock sensors and measurements to determine current user time either in the daytime or at night to enhance light intensity module performance as it will be later.

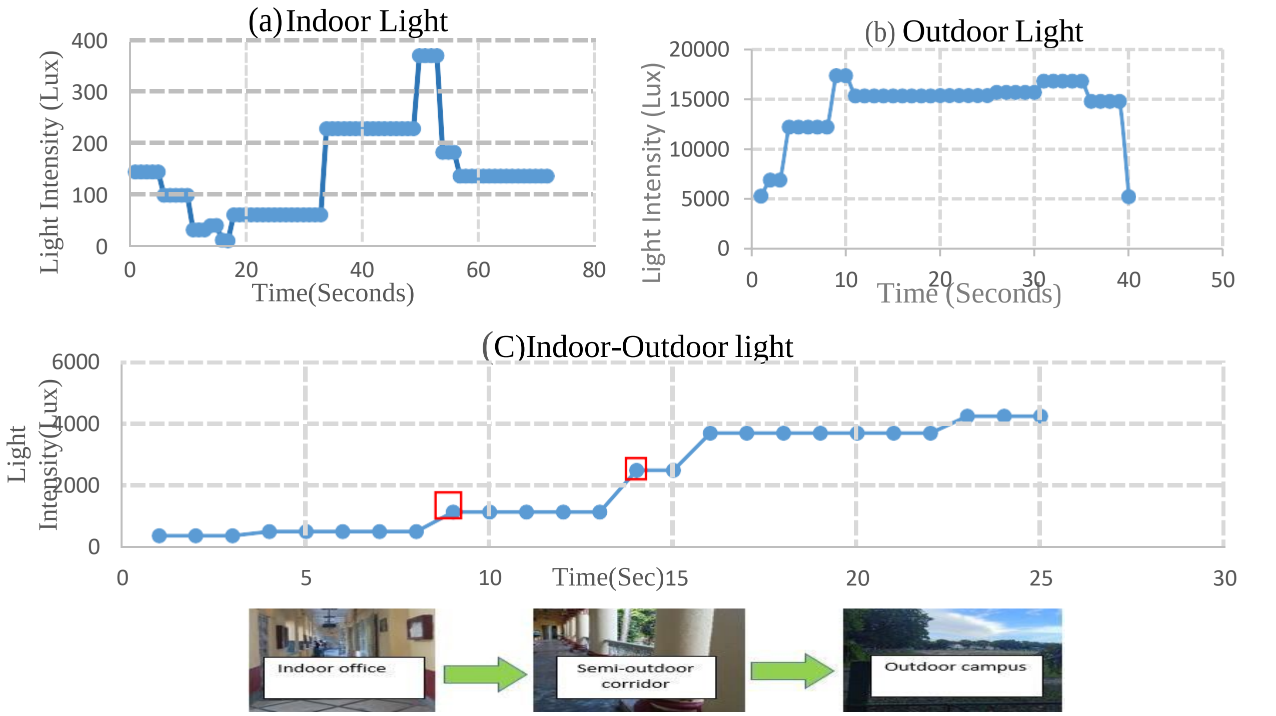


Fig. 4.2.2. Light intensity exhibits a periodic pattern in the indoor environment during the daytime as shown in (a), whereas the Periodic pattern in outside buildings during the daytime is shown in (b). The overall trend of light intensity is shown in part (c).

In this experiment, the light sensor of the terminal measures the intensity of light every 1 second. The intensity of light has a large difference in values between indoors and outdoors in the daytime and also at night. In the daytime, the outdoor illumination is about 3000-80000 lux, which is shown in Fig 4.2.2(b). In contrast, the indoor illumination is about 70-800 lux, which is shown in Fig 4.2.2(a). From Figure 4.2.2(b), the light intensities in both outdoor and semi-outdoor scenarios are above 2,000Lux and much higher than that in the indoor environment in the daytime (from 8:00 AM to 5:00 PM). In the nighttime, the outdoor streetlight is about 1-5 lux, and the brightness of the full moon is about 0.01- 0.1 lux. In the night outdoors, illumination is almost 0 lux shown in fig 4.2.3. The illumination of the general indoor fluorescent lamp is about 20-800 lux. From this, it is thought that the illumination is effective for indoor/outdoor estimation both in the daytime and the nighttime. In addition, the light intensities in the indoor and outdoor environments are both relatively stable.

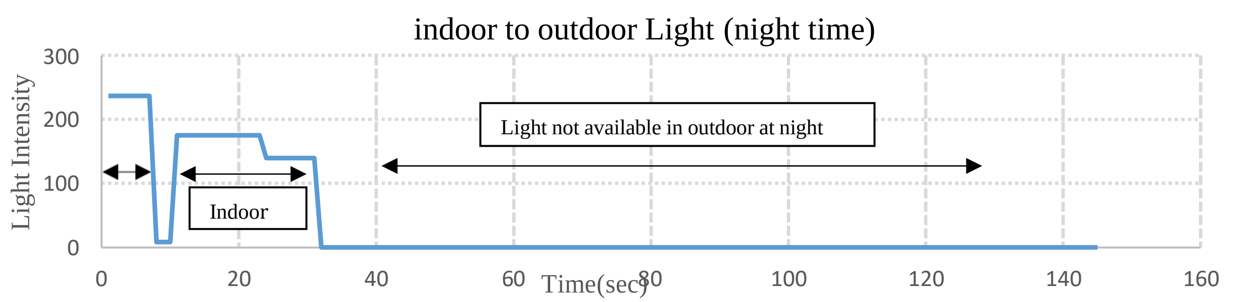


Figure 4.2.3. Light intensity pattern when the user moves indoors, then returns outdoors during the nighttime with a smartphone in hand and screen facing up.

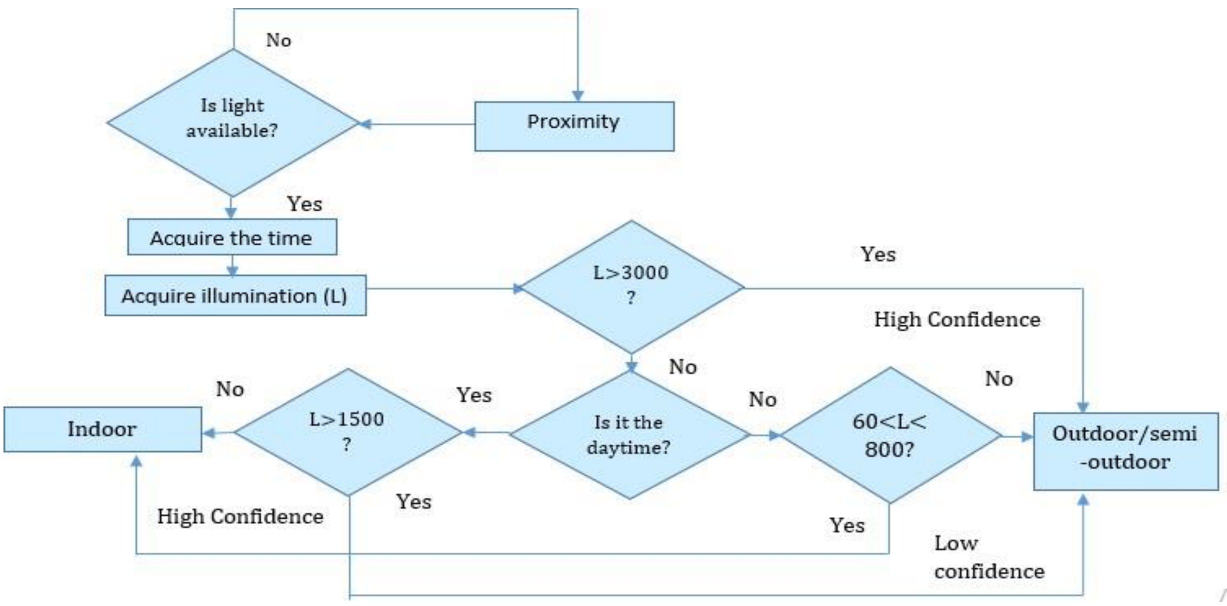


Figure 4.2.4: Light intensity sense module flowchart

Finally, based on those observations and challenges, we construct a light intensity module algorithm as shown in algorithm 4.2.4. From the 4.2.4 flowchart, we try to get some information related to the light intensity module like maximum and current light measurements, proximity (Far or near), and current system time clock.

During experiments, we collect 24-hour light intensity readings to monitor light signature variations in indoor/outdoor environments all day by using discrete readings from mobile devices only. Even when the light sensor is back to the sun, the light intensity is relatively high as well (e.g., around 3,000Lux). Figure 4.2.1 indicates that outdoor illumination becomes higher than indoor illumination in the daytime and figure 4.2.3 indicates that indoor illumination becomes higher than outdoor illumination in the night. Before and after sunrise and sunset respectively, no light from the sun is perceivable in the atmosphere, which would mean that any light perceived by the light sensor is artificial light or moonlight. After a few minutes of sunrise, the outdoor illumination gradually increases from 0 lux to 10000 lux. Lighting estimation has great credibility between 8:00 AM and 4:00 PM. The estimation by brightness is unreliable near dawn and nightfall Because of the influence of the buildings' shadows, the terminal's orientation, and clouds. The major reason behind this is that these periods represent critical times when outdoor environment brightness is much less. The limitation of the light detector is that the light signal is not always available. Not only that using light sensors we cannot confidently distinguish the outdoor and semi-outdoor environments.

4.3 Magnetism Detector

Magnetic field is an invisible for created by magnetic objects or electric currents that surround us, shaping our environment and influencing countless aspects of our daily lives. It possesses both strength and direction, and its effects can be observed through the behavior of magnetic materials and the interaction between charged particles. Earth itself has a magnetic field which play a crucial role in various aspect. The disturbance of the earth's magnetic field inside buildings can be utilized as fingerprints for indoor localization. The quantity of magnetism is easy to use for the estimation because there is a large change in the quantity of magnetism indoors. Though the previous setting including the measurement in the building is necessary to use magnetism for indoor positioning estimation, only the observation of the change in the quantity of magnetism is necessary for the indoor/outdoor estimation.

(a)

(b)

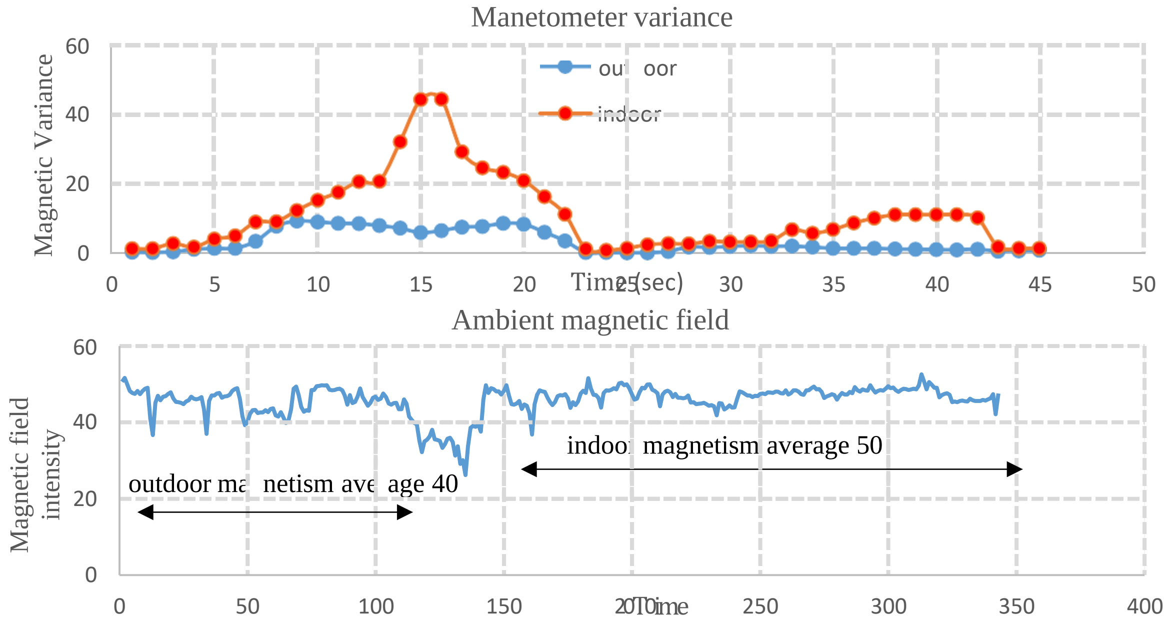


Fig. 4.3.1 The variation of magnetic field intensity. The magnetism signal varies significantly when the user moves to indoor environments but keeps relatively stable when the user gets to outdoor environments.

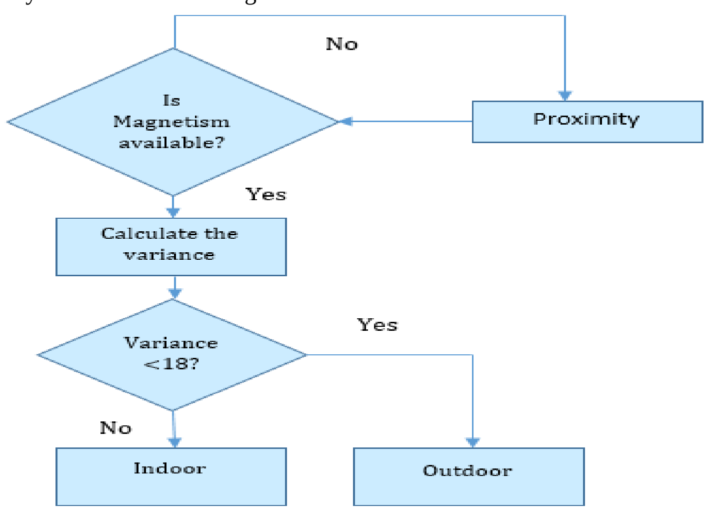


Figure 4.3.2: Flowchart of estimation by magnetism

The magnetometer variance is a good indication of nearby structures and electronics, which happen mostly in an indoor environment. Figure 4.3.1(a) plots the magnetic field intensity and its variance in two different scenarios indoor and outdoor. The magnetism sensor of the terminal measures the quantity of magnetism every 1 second and calculates the variance of the magnetism every 10 seconds. We find that the intensity of the magnetic field in the indoor environment varies dramatically. In indoors, we find that the variance is very high when the user moves (from the 1st second to 23th second). When the user is walking through the corridor, the magnetic field intensity also shows significant variance (from 23 seconds to 30 seconds). From here we have estimated a threshold. In outdoors, If the variance of magnetism is less than the threshold, it is estimated to be outdoor. And if more than or equal to the threshold, it is estimated to be indoor. The threshold of the variance is set to 18. Fig. 4.3.2 shows the flowchart of the indoor/outdoor estimation using a Magnetometer.

The estimation by magnetism cannot provide accurate results if the terminal is covered in a bag or a pocket. Therefore the covered situation of the terminal is estimated by a proximity sensor. The magnetic variance is below the threshold for some cases, both indoors and outdoors. In these cases, the IO-Detector component magnetism detector fails to detect the right IO state.

4.4 GPS detector

A "constellation" of 31 evenly spaced satellites known as the GPS (Global Positioning System) orbits the Earth and enables users to determine their exact geographic location. These satellites can tell us exactly where we are. Each GPS satellite has an onboard computer, an atomic clock, and a radio. Since it knows its orbit and time, it constantly informs about its changing position and time. On the ground, every GPS receiver has a microprocessor that "triangulates" its position by controlling it from three satellites. Once the GPS receiver calculates its distance from three or more satellites, it can determine the user's actual location. GPS signals are always available. Of 31 GPS satellites in Earth orbit, 27 are in use. The minimum number of GPS satellites required for normal operation is 24, which means that at least seven satellites are redundant. But on Earth's surface, it is defined that at least nine satellites are always available to send GPS signals to receivers. Due to this redundancy, receivers can obtain stable GPS signals anywhere on Earth, and at least three or four signals will be sufficiently strong for IO-Detection. Most of the time, in an indoor environment, the availability of GPS satellites is not more than three. Not only that sometimes there are no satellites available indoors due to lack of line-of-sight path to satellites. That's why GPS does not detect indoor environments accurately. But, if the satellite count becomes Less than three or three then it can identify the indoor environment. Although calculating the number of GPS satellites can give glimpses about indoor and outdoor environments but main detection result is implemented based on GPS SNR value.

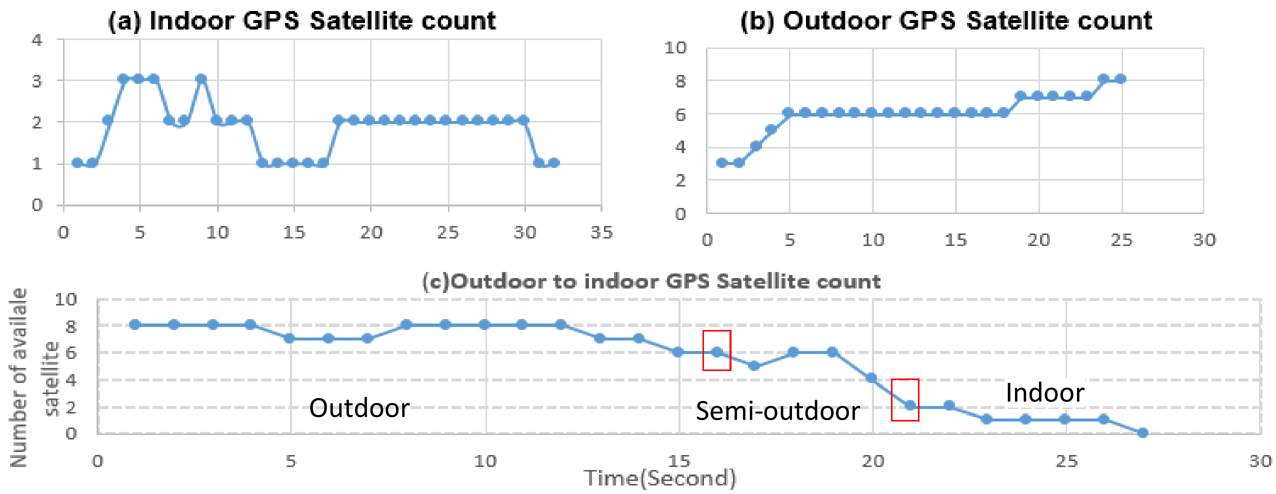


Figure 4.4.1 Number of visible GPS satellites that are communicated with receivers inside a building as shown in (a). Whereas the number GPS satellite pattern is communicated with receivers outside the building as shown in (b). The number of GPS satellite pattern that is communicated with receivers when the user moves outdoors, then return indoors as shown in (c).

In Figure 4.4.1(a), in an indoor environment, one to three signals from the GPS satellites are measured. Similarly, in semi-outdoor and outdoor environments, this range becomes greater than 4. Typically, in Figure 4.4.1(c), this range lies between 4 and 6, which indicates a semi-outdoor environment, which is shown using two rectangles. In this experiment, we also observed that the highest number of signals coming from GPS satellites in outdoor Environments is 10. The total number of signals that come from GPS satellites finds distinct patterns in indoor/outdoor environments. Figure 4.4.1 (c) indicates the decreased rate of signal that comes from GPS satellites as the user walks from outdoor to indoor environments

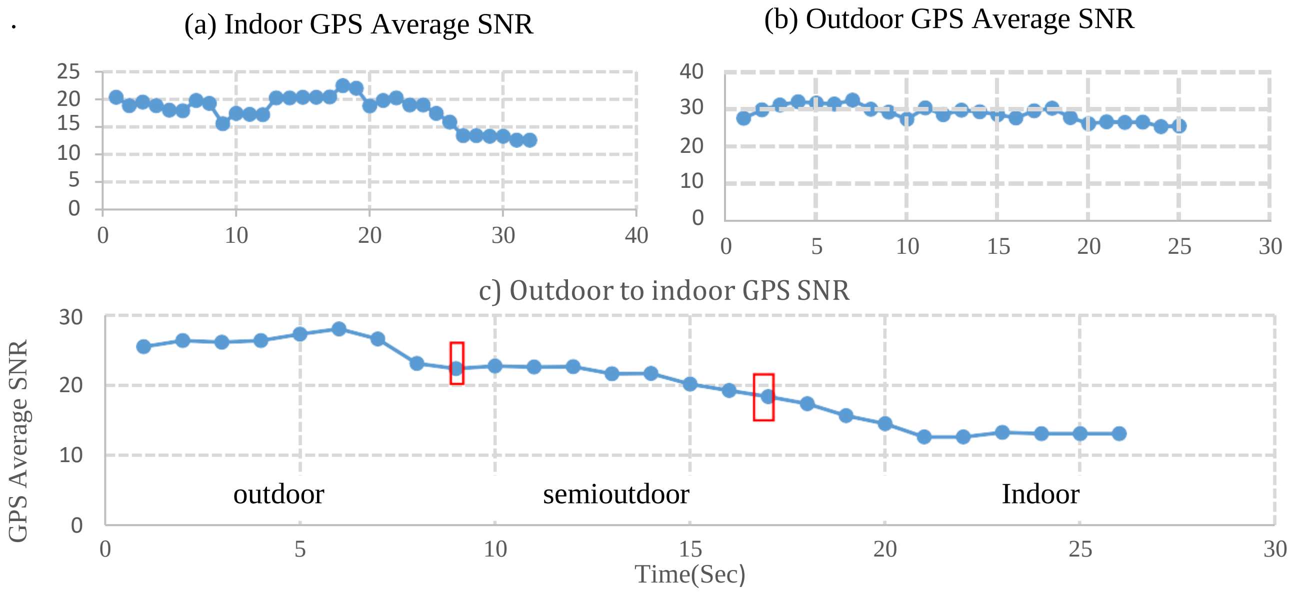
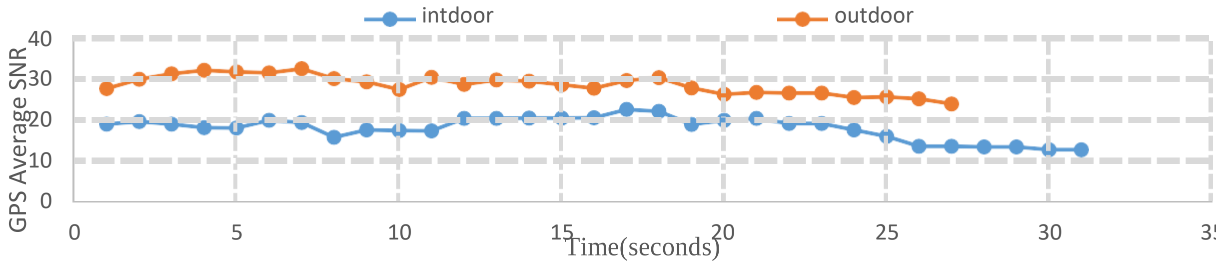
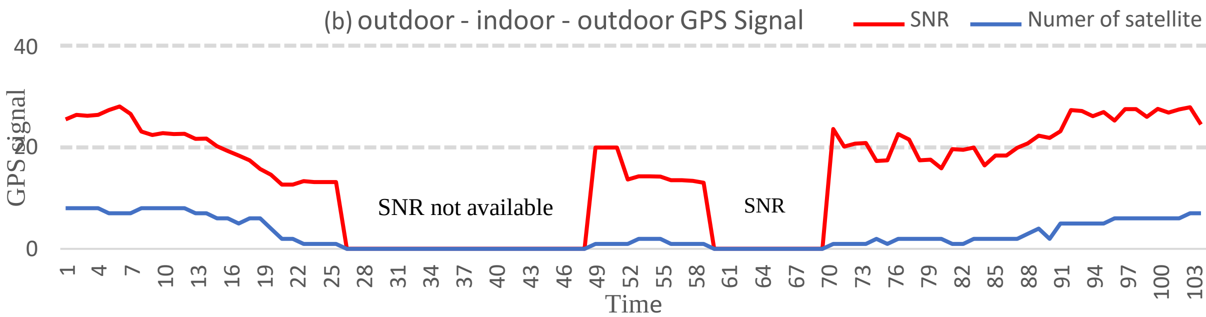


Figure 4.4.2 Average GPS signal-to-noise-ratio pattern in an indoor environment as shown in (a). Whereas the Average GPS signal-to-noise-ratio pattern is outside the building as shown in (b). Average GPS SNR pattern when the user moves outdoors, then returns indoors as shown in (c).

As the term indicates, SNR is a ratio of signal power to the noise floor of GPS observation and has conventionally been used only as a measure of receiver tracking efficacy or for comparison of signal strengths between channels and satellites. SNR is calculated using the code tracking loop. Tracking loops are used in a closed loop to follow continuously the code and carrier parameters of the incoming signal. The SNR of all GPS signals is measured every 1 second, and the average SNR of GPS is measured every 10 seconds. If the SNR average of GPS is more than 20 dB and the GPS module of the terminal can communicate with more than 6 satellites, it is judged that positioning is possible and the state remains in the outdoors state, which is shown in figure 4.4.2 (b). In the outdoor environment, the SNR becomes much higher, varying from 25 to 42 due to the clear line-of-sight paths between the phones and GPS satellites. In the semi-outdoor environment, although we may sometimes observe GPS signals from more than four satellites, typically the SNR of GPS signals is not high enough to ensure accurate localization. Figure 4.4.2 (a) shows that the average SNR of GPS indoors is less than 18 and the GPS module of the terminal can communicate with less than 3 satellites.



(a) Average GPS SNR measurement in different scenes. The GPS SNR readings are discrete but different for different environments.



(b) GPS signal pattern when the user moves indoors, then returns outdoors with a smartphone in hand and screen facing up. The average SNR and number of GPS satellites communicated with receivers are jointly plotted in this graph.

4.4.3 GPS signal measurement

The GPS module can work with more than four visible satellites. However, even with four satellite signals, the localization accuracy varied dramatically in our experiment. With more than six visible satellites, the localization error is around 20 meters. We also observe that more visible satellites (e.g., >9) yield less marginal improvements in localization accuracy. With 10 GPS satellites, the localization error can be within 10 meters. In the indoor state, GPS positioning is stopped because GPS is not available. Moreover, GPS can sometimes get a satellite fixed indoors (e.g. when the user is close to a door or window). Figure 4.4.3 (b) plots the GPS signal pattern and its average SNR in an example scenario in which a user walks outside of the office, passing through a corridor. In particular, the user walks from the 1st second to the 15th second in an outdoor environment, continues walking from the 15th second to the 70th second inside the building, then walks along the corridor from the 70th second to the 80th second, and after that, the user comes outside the building and stops walking from 85 seconds to 100 seconds. In Figure 4.4.3(b), in the first 15 seconds, we find that the average SNR of GPS in the outdoor environment is higher than 20 dB. Between 15 and 27 seconds, the average SNR value decreases dramatically. After 27 seconds, the average SNR becomes null due to the unavailability of GPS satellites. Between 50 and 60 seconds, the SNR of GPS is available due to one or more satellite communications with receivers. After 60 seconds, the SNR once again disappeared due to no satellite being available. From 70 seconds to 85 seconds, the user passes through a corridor, which is a semi-outdoor environment. In this situation, the average value of SNR is around 19–22 dB. After 85 seconds, when the user starts working in outdoor environments, the SNR of GPS dramatically increases due to the greater number of satellites communicating with receivers. We find that the average SNR is very high when the user moves from the 1st second to the 15th second and from the 85th second to the 100th second. Hence, indoors, when GPS is not available, other indoor positioning techniques take place. In summary, the experiment results demonstrate that GPS availability and localization accuracy are highly correlated to the type of environment. Yet solely reading such availability from the GPS module itself can take up to minutes and consume much extra energy in scanning the satellites.

4.5. Wi-Fi AP Detector

With the ubiquity of Wi-Fi-enabled smartphones and large-scale access point arrangements, Wi-Fi-based detecting is one of the most promising indoor/outdoor detection signatures. Due to GPS limitations in indoor environments, the indoor localization system depends on the received signal strength (RSSI) of each Wi-Fi access point. Wi-Fi received signal strength indicator (RSSI) upgrades are one of the most attractive techniques due to their dependence on the ubiquitously deployed infrastructure. The accuracy of the Wi-Fi location relies on the number of access points. This module employments the complete Wi-Fi infrastructure, which incorporates not only Wi-Fi routers but also versatile phones and tablets. By utilizing Wi-Fi access points, this system can effortlessly find all Wi-Fi-powered devices' locations and monitor their movements inside the building.

This Wi-Fi AP Detector does a Wi-Fi scan every second and lists all the access points detected. Every list row shows the access point's SSID, BSSID, current RSSI, and frequency. The number of Wi-Fi APs makes a significant difference between indoor and outdoor environments, as shown in Figure 4.5.1. During experiments, we implemented more than 250 scans through different sites in indoor areas like Universities, and homes and in the surrounding outdoor areas with different mobility scenarios (standing and walking). The number of all visible detected Wi-Fi nodes is calculated based on their MAC addresses (BSSID), where each AP has a unique MAC address. Figure 4.5.1 says clearly that, during the scan, outdoor sites exhibit all visible Wi-Fi AP density confined between thresholds α1 and α2, and sometimes higher than threshold α1 reaching 39 AP. In contrast, indoor sites often exhibit a visible Wi-Fi AP density lower than threshold α2, sometimes less than 5 APs.

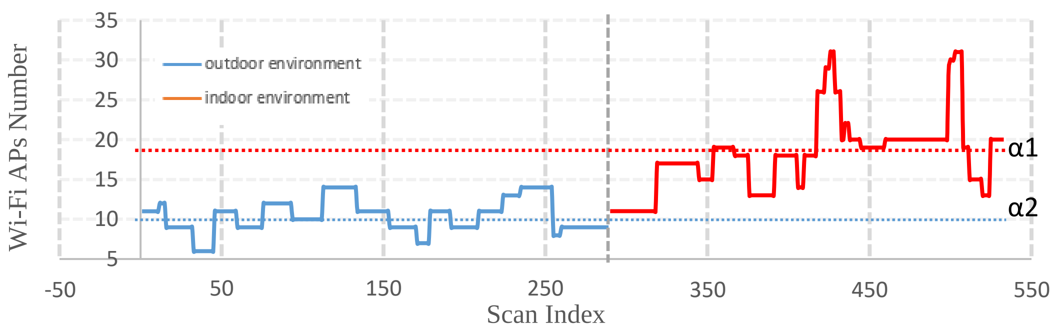


Figure 4.5.1: Distribution of all visible Wi-Fi access points number density at surrounding urban/indoor environments

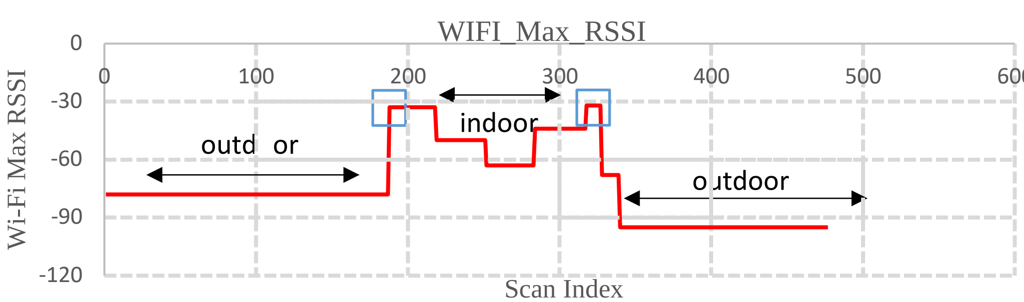


Figure 4.5.2: Distribution of Maximum RSSI for all visible Wi-Fi access points in surrounding outdoor and indoor environments

The Wi-Fi detector module collects all the RSSI obtained and finds the maximum and average values of RSSI. APs exhibit higher RSSI in indoor areas than in outdoor areas. This is because users inside the building will be nearby and in line of sight with many of the indoor nodes, where the correctness percentage varies according to the user mobility scenario. On the other hand, APs exhibit very weak RSSI records but are still heard by clients' mobiles when passing by outside areas like buildings and narrow streets. Figure 4.5.2 shows that in an indoor environment, the maximum RSSI value is higher than -67 dB, which indicates a strong Wi-Fi signal. As shown on a chart, the X-axis represents time, and the Y-axis represents the signal level in dB. But using this maximum RSSI, we cannot reach any decision because sometimes, when the Wi-Fi router is close to the outdoor scene, the maximum RSSI range falls under -55 dB to -69 dB. The RSSI higher than -50 indicates we are very close to or in the same room as the Wi-Fi router. The possibility of which is very low. But combining the maximum RSSI, the average RSSI, and the number of detected Wi-Fi APs (less than -67 dB) gives us a clear indication of the indoor environment. Which is shown in the IO detection algorithm. From Figure 4.5.4, we can understand the difference between extremely strong, strong, and weak signals.

Table 2: Wi-Fi RSSI range

RSSI range	Observation	statement
RSSI<-90 dBm	Extremely weak signal	Approaching or drowning in the background transmissions and causing serious interference with the signal.
RSSI<-80 dBm	Not a good signal	Minimum signal strength for basic connectivity
RSSI<-70 dBm	Okay	Minimum signal strength required for decent packet delivery
-67dBm <RSSI<-55 dBm	fairy strong signal	Minimum signal strength for most business applications.
-55 dBm <RSSI<-30 dBm	Very strong signal	The client would see the AP or vice versa.
RSSI>-30dBm	Excellent	Maximum achievable signal strength.

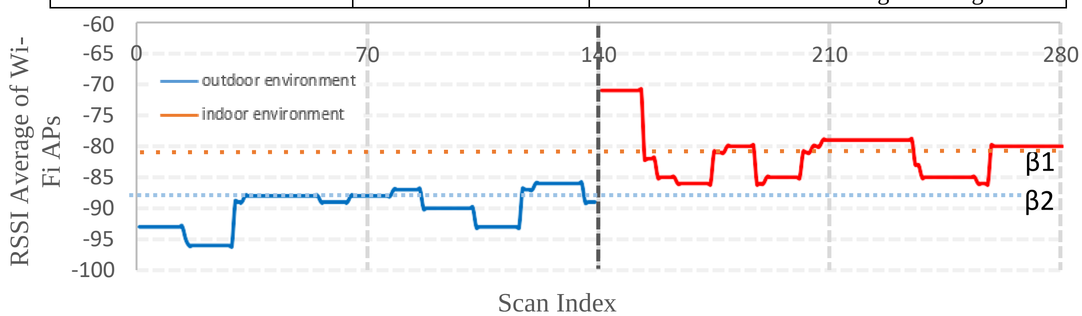


Figure 4.5.4: Distribution of the RSSI average for all visible Wi-Fi access points in surrounding outdoor and indoor environments

We can measure, in every scan, the received signal strength from all visible Wi-Fi access points. Then we aimed, in addition to estimating their average and number, to infer other useful features that classify Wi-Fi APs seen by smartphones. For each access point, if its RSSI value falls within the strong RSSI range, it is called the 1st AP class. Figure 4.5.3 shows that the average of all visible Wi-Fi APs RSSI exhibits distinct signatures for indoor and outdoor environments. We observe that the most commonly collected average values of all visible Wi-Fi APs RSSI in indoor sites are higher than the β 1 threshold. This is seen as logical because the majority of these nodes should provide strong RSSI readings to meet connectivity considerations. Unlike average values collected at outdoor sites, most of them are lower than β2 because most detected signals are weak signals that can still be heard due to buildings' structure and distance considerations. During tracing all tested indoor and outdoor sites, it has been observed that almost all indoor sites exhibit an APs number of the 1st order class (which has an RSSI higher than -67 dB) that is larger than at outdoor sites. This occurs because the probability of the expectation that the user, during indoor movements, will become very close to such APs is high.

4.6 Overall estimation

This proposed method uses the estimation by illumination, the estimation by magnetism, the estimation by GPS, and the estimation by Wi-Fi AP concurrently and acquires each estimation result's reliability. Each of the four subdetectors has unique advantages and disadvantages. For example, a light detector requires the mobile phone to be exposed to space. If mobile phones are inside a bag or pocket, a light detector cannot provide accurate detection results. The Wi-Fi detector needs sufficient Wi-Fi AP signals to detect the ambient context. The magnetic detector is only available when the user is moving around, such that the magnetic disturbance inside the building can be exploited. The GPS detector sometimes stops working in an indoor environment. We refer to the four individual detectors as subdetectors and integrate them to output an arbitrated decision. As described in the IO-Detector algorithm, each subdetector outputs the possible environment types and associated confidence levels for them. For each possible environment type, we sum the confidence levels from the four subdetectors. If the four estimation results are different, the proposed method considers the result with the highest reliability to be the estimation result. For example, in the outdoor state, the method of estimation always relies on GPS because the reliability of GPS in the outdoors is higher than other estimation methods. Similarly, indoors, the estimation method depends on Wi-Fi. Whenever Wi-Fi is unavailable, the estimation method relies on either light intensity or magnetism variance. For example, in the case of rural outdoor scenarios, a light intensity module will be more useful than Wi-Fi because Wi-Fi RSSI will be nonexistent and more difficult to hear than those in urban or indoor environments.

Finally, based on those observations and challenges, we construct the IO-detection algorithm as shown in algorithm 4.6.

Algorithm 4.6 IO-Detection algorithm

>> Li: Current light intensity measurement.
>> Mg: Current Magnetism intensity measurement.
>>Mag_Variance: Calculate magnetism variance every 10 seconds.
>>GPS_SNR: GPS signal-to-noise-ratio per sec.
>> GPS_Count: All visible GPS satellites per scan.
>> Avg_ Trend: Calculate Average SNR Trend per 10 sec (dB).
>> WAP_D: All visible Wi-Fi APs density per scan.
>> Max_RSSI: RSSI max of All visible Wi-Fi APs per scan (dB)
>> WAP_Avg: RSSI Average of All visible Wi-Fi APs per scan (dB)
>> 1st_APs: Number of Wi-Fi AP whose RSSI>-67 per scan.

1. Check Proximity sensor availability on Smartphone
2. if available, Get Li, Get Mg, and Check the Current Time System clock
3. if (Li >=2000) and Current Time is a Daytime
4. OUTDOOR CONFIDENCE =+6
5. Else if (Li ≤ 900) and Current Time is a Daytime
6. INDOOR CONFIDENCE =+6
7. Else if (Li > 900 && Li<=1500) and Current Time is a Daytime
8. SEMIOUTDOOR CONFIDENCE =+6
9. if(GPS_SNR>=23 && GPS_Count>=4)
10. OUTDOOR CONFIDENCE =+8
11 Else if (GPS_SNR>=18 && GPS_Count>2 && GPS_SNR<21)
12 SEMIOUTDOOR CONFIDENCE =+7
13. Else if ((GPS_SNR<18 && GPS_Count<=3) OR (GPS_Count>4 && GPS_SNR>18 & GPS_Trend>6.5))
14. INDOOR CONFIDENCE =+8
15. if ((WAP_D ≥8 & 1st_Aps>=3) OR (Max_RSSI≥ -50 & WAP_Avg ≥ -80))
16. INDOOR CONFIDENCE =+9
17. if (Mag_Variance<18)
18. OUTDOOR_ CONFIDENCE =+3
19. else INDOOR CONFIDENCE=+3
20. if(INDOOR_ CONFIDENCE >OUTDOOR_ CONFIDENCE && INDOOR_ CONFIDENCE >SEMIOUTDOOR_ CONFIDENCE)
21. Detected Environment is Indoor
22. if(OUTDOOR_ CONFIDENCE> INDOOR_ CONFIDENCE && OUTDOOR_ CONFIDENCE >SEMIOUTDOOR_ CONFIDENCE)
23. Detected Environment is Outdoor
24. if(SEMIOUTDOOR_ CONFIDENCE >OUTDOOR_ CONFIDENCE && SEMIOUTDOOR_ CONFIDENCE> INDOOR_ CONFIDENCE)
25. Detected Environment is Semi-outdoor
26. End.

Chapter 5

Experiment result

5.1 Experimental Setup

Throughout our experiments, measurements are collected using different mobile users walking multiple trips over different paths to assess the performance of each IO-Detector module over diverse scenarios. Some trips are made indoors (inside buildings, e.g., homes, universities, and malls) and others are made in outdoor areas (e.g., open areas). We implemented and evaluated the IO-detector prototype on the Android Platform and tested its performance on a smartphone as an Android application (Realme-8). This phone is equipped with all the sensors required for IO-Detection such as proximity, time, light sensor, accelerometer, Magnetometer, GPS, and Wi-Fi.

Outdoor Semi-outdoor Indoor

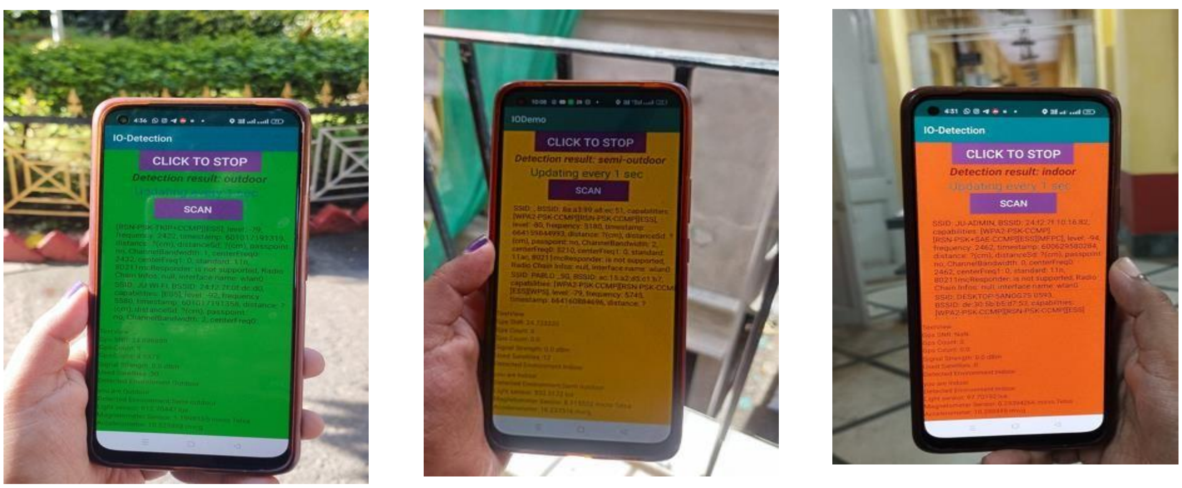


Fig. 5.1 IO-Detector application

5.2 Performance

For the evaluation of the estimation accuracy, it is necessary to record the correct location of the terminal (correct answer data). At every movement between outdoors and indoors, I select the correct answer data by selecting the current position button and storing it. Therefore we made the process to record indoor or outdoor, and at every movement between indoor and outdoor, the user selects the current position using the current position button and records whether it is indoor or outdoor. This record becomes the correct answer data. We compare the estimated result with this correct answer data and calculate the precision ratio. In this section, we show the detection performance of the four individual subdetectors as well as the aggregated IO-Detector.

5.2.1. Performance of Subdetectors.

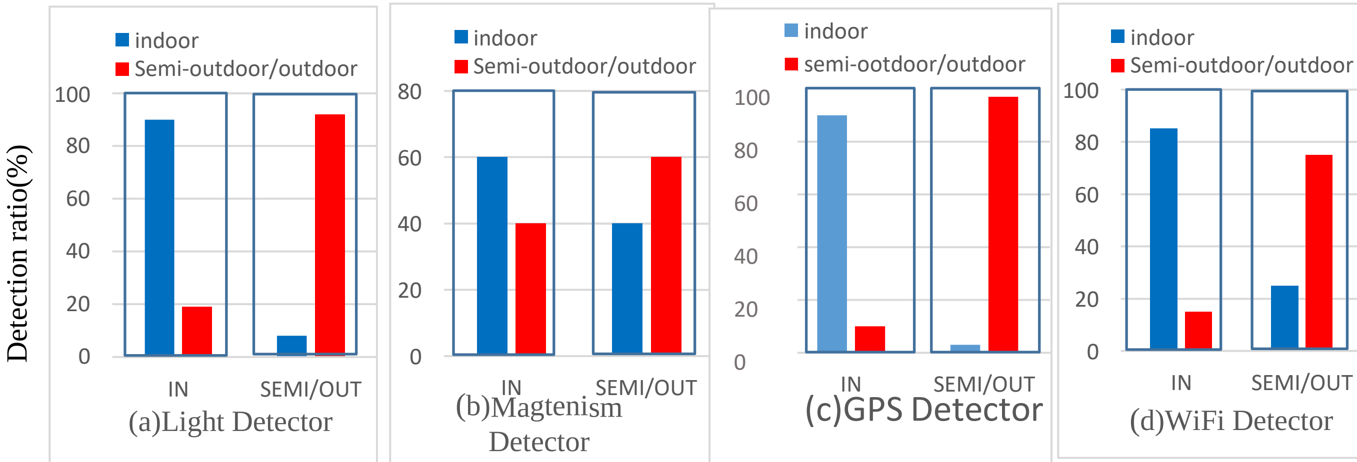


Fig. 5.2. Detection performance of 4 subdetectors. For each subdetector, we report the performance under 3 kinds of scenarios. For example, we test the light detector in indoor environments and outdoor/ semi-outdoor environments, respectively.

To evaluate the contribution of each detector (i.e., light detector, GPS detector, Wi-Fi detector, and magnetism detector), we examine the detection performance independently in Figure 5.2 using correct answer data. Each detector reports the environment type with the highest confidence level after the local computation. The light detector is available when there are clear paths between mobile phones and ambient light sources. Figure 5.2(a) shows the detection performance of the light detector. We find that the light detector can effectively distinguish the indoor environment from the outdoor environment. In Figure 5.2(a), in the indoor environment, the detection accuracy is around 90%. When the phones are in the outdoor environment, the detection accuracy is around 92%. However, it was not able to be estimated with accuracy at the time without a clear illumination difference between indoor and outdoor such as evening. This is because a false estimate of the indoors occurs by the very small difference of the illumination when the subject stopped in the shade for a long time. Figure 5.2(b) shows the detection performance of GPS detectors that can significantly differentiate between indoor and outdoor environments. The GPS detector provides high accuracy for both indoor and outdoor environments with average power consumption. GPS detectors provide a detection accuracy exceeding 90%. Figure 5.2(c) shows the detection performance of the Wi-Fi detector that classifies the indoor environment from the outdoor environment. Figure 5.1 shows the result of applying the Wi-Fi-based module algorithm on measured Wi-Fi measurements (RSSI, BSSID, and SSID). Our experiments mainly cover the campus. In such experiment settings, the Wi–Fi–based detection performs with 85% accuracy. An average error ratio is around 7% in both indoor and outdoor experiments. This average error detection significantly decreases when the Wi-Fi APs are available and more ubiquitous in the ambient environment. We obtained quite a close performance of the Wi-Fi detector compared with that of the light detector. We note that both the light detector and Wi-Fi detector can effectively classify the indoor environment from the outdoor environment. On the other hand, the magnetism detector can enhance the detection capability of the IO-Detector in classifying the outdoor environment. Figure 5.2(d) plots the performance of the magnetism detector. The estimation only by the magnetism was able to attain around 60% of the precision ratio on average. Because it was estimated to be the outdoor by mistake indoor with the magnetic variation, the precision ratio did not rise.

Table 3: Scenario of the evaluation experiments

Ex. No.	Date	Time	Place	Environment	Weather
Ex.1	24/7/23	17.37-17.40	Central library to impact center Jadavpur University	outdoor	sunny
Ex.2	24/7/23	16.31-16.35	Within the campus	indoor	sunny
Ex.3	23/7/23	17.48-17.54	home	Indoor	Cloudy/rainy
Ex.4	23/7/23	18.17-18.22	Outside the Residential House	outdoor	Cloudy/rainy
Ex.5	25/7/23	10.04-10.10	Within the campus	Semi-outdoor	sunny

Table 4: Result of the evaluation experiments

Detected Environment	Ex. No.	No of detected Environment	No. of Error environment Detection	Proposed method accuracy
INDOOR	Ex.2	70	3	95.71%
	Ex.3	283	26	90.81%
Outdoor	Ex.1	83	6	92.77%
	Ex.4	240	5	97.91%
Semi-outdoor	Ex.5	40	16	60%

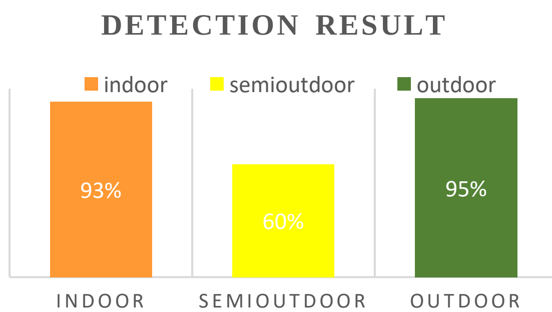


Fig. 5.3. Detection precision

4.2.2. Performance of Aggregated IO-Detector.

The evaluation experiment is based on 5 scenarios in Table 3. In these scenarios, the subject walks holding the terminal in his hand. Table 4 shows the results of the experiments. The data collected process of Ex.1 was conducted in an outdoor environment as shown in Table 3. Similarly, other experiments were conducted in their designated environment as maintained in Table 3. Of the 83 detected environment samples in Ex.1, six detected samples indicated error environments. From this, we calculated the proposed method accuracy of Ex.1 which is 92.77%. Similarly, we have calculated the detection accuracy for our proposed methods for the rest of the experiments. From Table 4, we get the detection accuracy of each environment for each conducted experiment. Since a semi-indoor environment is not available everywhere that's why we exclude it from overall detection accuracy. By adding these four indoor/outdoor detection accuracy we get the overall detection accuracy. The overall detection accuracy of the IO-Detector is about 95% which is higher than other independent estimations. When the four subdetectors are aggregated as the IO-Detector, there is improvement in detection accuracy for all different types of indoor/outdoor environments, but not much. Because the proposed Aggregated IO-Detector method can use the other estimate technique in a situation in which one estimated technique is weak, the method can keep estimation with high precision. For example, it is the situation such as at the time of the outdoor movement with no Wi-Fi AP found in the estimation by the Wi-Fi-detector and the smartphone is in the subject's pocket which indicates the estimation by magnetism is difficult or the situation in the evening in the estimation by the illumination. In this case, Estimation by GPS Detector provides high accuracy. Compared with less than 80% detection accuracy of individual detectors, in the aggregated IO-Detector both the precision and the recall are consistently above 90% for the indoor and outdoor environment type. The experiment results suggest that the IO-Detector accurately classifies the indoor/outdoor environments for most cases.

Chapter 6

Conclusion and Future Work

Conclusion:

This project work presents a novel and effective approach for indoor-outdoor detection in mobile context-aware applications. The proposed system utilizes a fusion of GPS, Wi-Fi, and Android sensor data to achieve accurate and reliable detection of users' indoor and outdoor locations. By analysing the characteristics of Wi-Fi signals and combining them with GPS location data, the system can accurately detect indoor locations, while the GPS sensor provides precise outdoor location information. Additionally, the Android sensor suite, including accelerometer, light intensity, magnetometer, and orientation sensors, further enhances the system's accuracy and robustness.

The extensive real-world experiments conducted in various indoor and outdoor environments demonstrated the effectiveness and robustness of the proposed approach. The system achieved accurate indoor-outdoor detection under different scenarios, providing a strong foundation for the development of personalized and location-based services in context-aware mobile applications.

Future Work:

While the presented indoor-outdoor detection system shows promising results, there are several avenues for future research and improvement:

1. **Battery Efficiency:** Mobile devices' battery life is crucial for users, and the proposed system's reliance on multiple sensors could impact energy consumption. Future work should focus on minimizing the system's energy consumption without sacrificing detection accuracy, possibly through sensor data fusion techniques or power-efficient algorithms.
2. **Dynamic Environment Adaptation:** Investigating ways to adapt the system to dynamically changing environments, such as moving between indoor and outdoor spaces rapidly, will be beneficial. This may involve developing adaptive thresholds or using context-aware methods to adjust the system's behavior based on the user's context.
3. **Multi-User Scenarios:** Extending the system to support multi-user scenarios, where multiple users are in the same vicinity, could open up new possibilities for collaborative and interactive context-aware applications.
4. **Privacy and Security:** As the system relies on various sensors, ensuring user privacy and data security becomes paramount. Future work should address these concerns and implement measures to protect user data while maintaining the system's functionality.
5. **Scalability and Generalization:** Evaluating the system's performance in larger-scale deployments and different geographical regions is essential to assess its generalization and scalability.
6. **Integration with Applications:** Finally, integrating the developed indoor-outdoor detection system into real-world context-aware applications will be crucial to fully evaluate its practical usability and user experience.

By addressing these future research directions, the proposed indoor-outdoor detection system can be further advanced and contribute significantly to the development of context-aware mobile applications with enhanced personalization and location-based services.

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