SENSEI/O: REALISTIC UBIQUITOUS INDOOR OUTDOOR DETECTION SYSTEM USING SMARTPHONES

by

Mohsen Ali Mohsen Al-awami

A Thesis Submitted to the
Faculty of Engineering at Cairo University
in Partial Fulfillment of the
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MASTER OF SCIENCE
in
ELECTRONICS AND COMMUNICATIONS ENGINEERING

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Under the Supervision of

Associate Prof. Hossam A. H. Fahmy
Principal Adviser

*

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Approved by the
Examining Committee

Associate Prof. Hossam A. H. Fahmy, Thesis Main Advisor

Associate Prof. Tamer ElBatt, Member

Associate Prof. Moustafa Ameen Youssef, Member

Prof. Sherif Gamal Aly, Member

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In the name of Allah the most merciful the most gracious; all thanks to Allah the Lord of the Heavens and Earth and peace be upon Muhammad and his companions.

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Mohsen Ali Mohsen Al-awami,
Sep, 2014.

Abstract

A lot of indoor/outdoor location, tracking, context awareness and activity recognition technologies which have been proposed over the years are based on GPS receiver, Bluetooth, infrared, ultrasound and radio frequency RF (Wi-Fi and GSM) signals. These technologies provide varying levels of accuracy supporting different application needs. Actually, these upper layer applications are applied either in outdoor or indoor environments during identified and controlled areas which should be pre-known. Most of those proposed applications suffer from numerous problems and challenges such as accuracy is related and affected by ambient environment type, energy consumption aspects, continuous sensing and the deployment of special hardware and/or special calibration of the area of interest to provide an accurate performance.

In this thesis, we address the problem of realizing a realistic and ubiquitous indoor/outdoor detection system (SenseI/O) which is envisioned to be deployed on a large scale worldwide, with minimum overhead using heterogeneous devices. Thus, such efficient detection of the surrounding environment (indoor vs. outdoor) definitely serves those upper layer applications to improve their performance, make a clever decision about whether suitable to turn ON/OFF the used sensors which leads to reduce the energy consumption aspects as well. SenseI/O leverages the ubiquity of sensor-rich cell phones, e.g., accelerometer, proximity, light and system time clock as well as multiple radio interfaces; 3G Cellular and Wi-Fi . It tries to use the measurements of those sensors to infer the current user ambient environment. We propose a novel SenseI/O system which consists of four main modules and they are (1) Single smoothed cell tower, (2) Wi-Fi based, (3) Activity recognition and (4) Light intensity to ensure our aimed realistic and ubiquitous principles.

In order to present a realistic system applicable on most of smartphones, we designed *single smoothed 3G cellular module* which relies on single associated

cell readings rather than multiples visible cell towers readings. Moreover, to meet upper layer applications performance requirements, we present a fine-grained *rural, urban and indoor* environment detection instead of binary indoor/outdoor only. An *activity recognition module* is designed, where we employed a hierarchical multi-class classifier to infer current user activity type (e.g., In-vehicle, On-foot and Still) which represents direct approach to infer ambient user environment type even in complex places (e.g., Tunnels and underground stations).

We used *moving average sliding window* technique to smooth absolute single cell towers readings in order to eliminate such previous work challenges (e.g., Handover and corner effect). According to these single smoothed associated 3G cellular readings, we filtered ambient environment into two upper classes (clear and ambiguous) in order to facilitate inferring a fine-grained detection afterwards. In case of *ambiguity* detection, we designed a *Wi-Fi based module* which exploited indoor established Wi-Fi APs to resolve such ambiguity (esp. between Urban/Indoor) and infer accurately ambient environment. In addition, a unique pattern of *light intensity module* through indoor and outdoor areas is exploited to differentiate between such environments efficiently. Each module has an individual algorithm designed according to observed features. Finally, we utilized senseI/O into three main scenarios which rely on combinations of two or more modules to provide realistic and ubiquitous service.

We evaluated SenseI/O in every place of ambient environments such as *Rural outdoor* (open squares, long bridges, highways, wide and open residential areas), *Urban outdoor* (downtown, crowded metropolitan areas and narrow streets bounded by tall buildings), *Indoor* (inside buildings such as houses, malls, companies and universities) and *inside complex places* (e.g., Tunnels and underground stations). Our implementation of SenseI/O was by using different types of android smartphones equipped with different android version levels. Evaluation was in two levels: *level 1*, we evaluated each SenseI/O module individually and estimated the *detection ratio* compared with ground truth reference. *Level 2:* we evaluated three main SenseI/O scenarios through a long paths (2-5 Km) to infer a fine-grained detection and compare them with ground truth and other single modules. All evaluation results for both levels are listed in chapter 5 in detail.

Contents

List of Tables

List of Figures

List of Symbols and Abbreviations

Abbreviations

API Application Programming Interface .

APK Android Application Package File.

BS Base station.

BSSID Basic Service Set Identifier.

C Certainty Value.

CDF Cumulative distribution function.

Cmax Maximum Certainty Value.

dBm Decibel-milliwatts.

Env Environment.

EPU Environment Processing Unit.

Lux the SI unit of illuminance and luminous emittance.

FN False Negative.

FP False Positive.

GPS Global Positioning System.

GSM Global System for Mobile Communications.

I/O Indoor/Outdoor.

iOS iPhone Operating System.

MS Mobile Station.

OS Operating System.

R-IAR Readings of Indoor Area Range.

R-RAR Readings of Rural Area Range.

R-UAR Readings of Unknown Area Range.

RFID Radio-Frequency Identification.

RSSI Received Signal Strength Indication.

UWB Ultra-Wide band.

WAP-Avg Wi-Fi Access Points RSSI Average.

WAP-D Wi-Fi Access Points Density.

Wi-Fi APs Wi-Fi Access Points.

This thesis is dedicated to my family and friends.

Chapter 1

Introduction

1.1 Overview and Motivation

Over the last few years, the observation is generally that most of today's cell phones become high-end smartphones. In addition to having many advantages like developing basic communication functionality, record audio and photo-taking capabilities, the being truly ubiquitous, equipped with multiple sensors, and carried by people all day representes sufficient features which have already been developed as well. This continuous development makes it smarter and becomes most important platforms to use for more than just of basic communication functions. As it's known that these smartphones rely on sensing and contextual information to be used efficiently in improving performance of localization-based, navigation and tracking applications,...etc.

An effective pre-detection and classification systems for ambient environments will be required in order to optimize and enhance the performance of such upper layer applications that use smartphones efficiently.

Most of those upper layer techniques actually applied in indoor and/or outdoor environments. For instance, a lot of outdoor localization and tracking applications implemented in such highways, campus, parks and intra-city driving environments using GPS source and/or other internal equipped sensors to estimate an accurate location [34,39,43]. On the other hand, numerous indoor localization and tracking applications proposed solutions based on Wi-Fi access points, GSM-RSSI, bluetooth, ultrasound, infrared or RFID fingerprints were presented in [8, 28]. However, most of those upper layer related works applications simply suppose that the type of ambient environment has already been known.

Furthermore, in context of awareness and activity recognition schemes, it's naturally known that person's daily motion-styles in open outdoor regions differ from those in indoor regions. Moreover, activity recognition determinations rely on continuous sensing information of GPS source and internal sensors like accelerometer, compass and/or gyroscope to get an efficient estimation of user position and pedestrian tracking [10, 23] and other applications adopt some features like sampling frequency and duty cycled sensing to reduce the energy drain painful challenge [42]. Then the pre-determination of ambient indoor/outdoor environment type helps to predict the general style of user motion activity and leads to more realistic indication about user pedestrian and activity type classification.

Therefore, the pre-determination of the surrounding environment type accurately serves at upper layer applications to improve its performance, make a clever decision about whether it's suitable to turn on the used sensors or not and leads to conserving the energy as well.

In this thesis, we present a Realistic Ubiquitous Indoor Outdoor detection System for mobile applications, coined SenseI/O. The whole proposed system framework constrained by three main principles are the realistic, ubiquitous and energy consumption budget. In its core, the proposed system includes four modules which use lightweight sensors equipped in today's smartphones such as serving cell tower, Wi-Fi, activity recognition and light intensity. Briefly, each module uses one or more of the installed smartphone sensors like GSM, Wi-Fi, light, proximity and accelerometer.

During experiments, we observe that each module can present a unique pattern in indoor and outdoor environments respectively. These patterns should be expolited to make an accurate environment detection. Serving cell tower module exhibits a dramatic drop in received signal strength measurements when transition occurs through the rural outdoor, urban outdoor and indoor environments respectively. It's known that Wi-Fi access points are considered as indoor base stations and they are often available in common buildings such as malls, companies and universities, hence we observe that the detected indoor Wi-Fi model RSSI readings are stronger than those in urban outdoor areas. In addition to that, another observation is that the light model measurements from artificial light resources in indoor areas differ from those sunlight measurements in outdoor areas. Furthermore, indoor light intensity definitely provides a unique patterns not existing in outdoor environments which is considered as useful information to resolve the problem of traditional environments and buildings which suffer from the lack of such Wi-Fi access points.

The main purpose of activity recognition module is to determine user activity type (e.g. in vehicle, on foot or still) based on the gathered data from accelerometer sensor. For instance, if the type of user activity is in vehicle thus the ambient environment type will be outdoor with high level of confidence.

SenseI/O has to address a number of challenges including:

- the impossibility of getting all visible neighboring cell towers information on most of today's mobile models due to the lack of android API support and limitations of getting required number of visible neighboring cell towers in some environments.
- Furthermore, absolute cell tower readings have a significant fluctuations and variations in different places due to such fading, handover, corner effect and environment noises.
- The difficulty of classifying and distinguishing the urban outdoor from indoor areas due to cell tower readings , in urban environments, influenced by crowded and tall buildings which lead to dropping RSSI readings significantly to become similar to those in indoor environments.
- Unavailability of light sensor on most of today's mobile models in addition to that the ambient light intensity exhibits the same patterns in outdoor and indoor environments through a couple of hours a day.
- Challenge of buildings and environments which suffer from the lack of Wi-Fi access points.

1.2 Thesis contributions

In summary, we provide the following contributions in this thesis:

- We present a realistic SenseI/O system which has the following unique features:

1. We get RSSI information from the associated serving cell tower only, which is available in all of today's cell phones. This is more realistic than previous work [16, 19, 45] which assumes cell phones can get information from multiple cell towers simultaneously. This assumption is problematic since low-end phones and most of high-end phones connect only to serve cell tower due to lack of API support.

2. We resolve the long-standing ambiguity between the urban and indoor environments. Thus, we extend prior indoor/outdoor classification [24, 29, 45] to a fine-grained rural,urban or indoor environment detection.

- We present a novel ubiquitous multi-model sensor approach which includes four sensing modules (serving cell tower, Wi-Fi based , light intensity and activity recognition). Our system may utilize a subset of these sensing modalities to develope some of the detection scenarios depending on mobile devices types and environment complexity as will be shown later.

- We exploit Wi-Fi RSSI fluctuations to accurately distinguish urban/indoor environments.

- We leverage the acceleration sensor to differentiate between In vehicle/ On foot / Still user activities which has direct impact on the indoor/outdoor classification problem.

- For Wi-Fi-less traditional buildings, we exploit the availability of such light intensity module in today's smartphones to estimate an accurate indoor/ outdoor detection.

- Finally, we implement our SenseI/O system on different Android phones (Samsung S plus, Samsung Duos, LGE615 and T-mobile G1) and test it in diverse rural, urban and indoor environments.

1.3 Thesis Outline

The rest of this thesis is organized as follows:

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

Chapter 3 shows the overall system architecture of the senseI/O system, and covers overview of senseI/O blocks diagram.

Chapter 4 shows our proposed “senseI/O modules” designs and covers in detail our methods for detecting the user ambient environments.

Chapter 5 shows the senseI/O system performance evaluation in detail.

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

Chapter 2

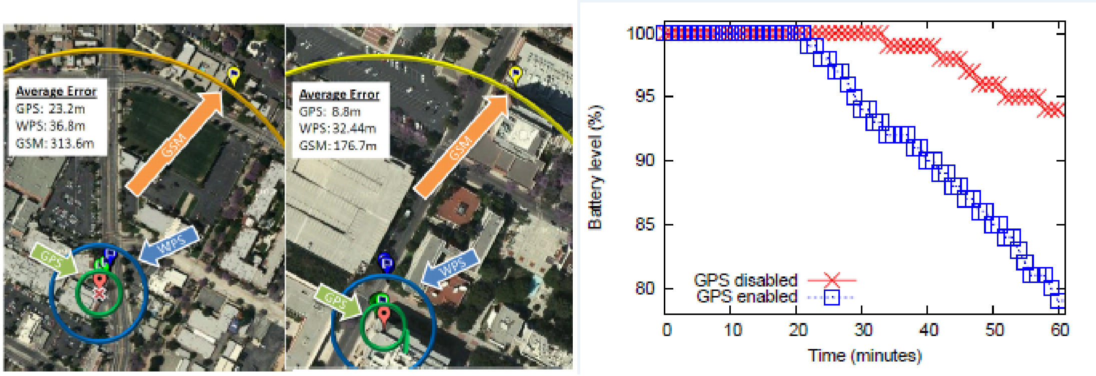
Background and Related Work

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

2.1 Background

As computing moves off the desktop into the hands of mobile users, it is becoming more important for mobile devices to be aware of the user's context. Important pieces of context include the user's location, activities, nearby people and devices, and mode of transportation. One important piece of context is related to whether the user is outside or not. This can be used to help infer the user's location (e.g. in a building) and her mode of activity (e.g. in a vehicle).

Inferring a prompt, primitive and accurate information on the ambient environment using an indoor/outdoor detection system makes most of upper layer mobile applications practical and realistic. Basically, many of upper layer applications which implicitly deal with such indoor/outdoor detection can be classified into four categories: localization and tracking, indoor positioning, context awareness and activity recognition and logical localization techniques.



(a) Accuracy of GPS,WPS, and GSM-based Positioning
(b) GPS power consumption life time in case of continuous sensing

Figure 2.1: Accuracy and power consumption trade-off in GPS-based localization applications

2.1.1 localization-based and tracking applications

An important feature of a modern mobile device is that it can periodically position itself using the built-in sensors. Not only for use locally on the device but also for remote applications that require tracking of the device. Examples of such applications are geo-based information applications [15] or proximity and separation detection for social networking applications [26]. To be useful, such position tracking has to be energy-efficient to avoid having a major impact on the power consumption of the mobile device. In this categroy, many emerging smartphone applications require position information to provide location-based or tracking services. Many of these localization-based and tracking applications often preferred built-in GPS sensor over its alternatives such as GSM/WiFi based positioning systems because it is known to be more accurate as shown in Fig. 2.1(a).

Unfortunately, these types of applications suffer from that the GPS source doesn't work properly to infer accurate user location in urban canyons and semi-outdoor places especially for pedestrian use. Furthermore, the GPS is considered as a useless tool in localization techniques in case of indoor environments because line-of-sight paths to GPS satellites are blocked [14, 22, 34]. However, GPS is still extremely power hungry where typical battery can be depleted in merely 6 hours in case of continuous GPS sensing as shown in Fig. 2.1(b). Also, GPS requires connecting with at least four satellites in case of clear sky and needs long time to wake up for conducting the GPS satellite scanning on mobile phones [23, 47]. So many related techniques tried to resolve this problem through queried GPS signal with a low duty cycle concept during user's transition from outdoors to indoors in order to reduce this challenge with small dropping in accuracy.

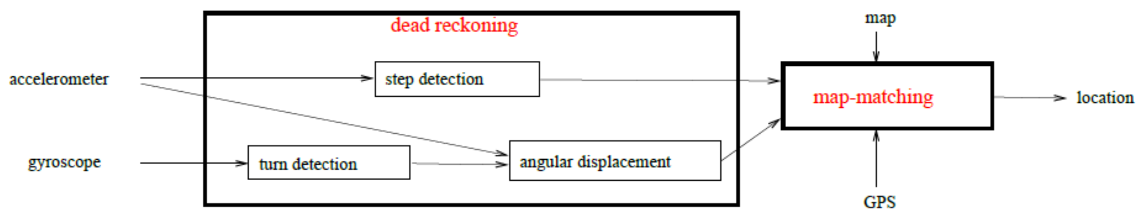


Figure 2.2: Accurate Outdoor Pedestrian Tracking System with Smartphones

Moreover, many of the newest related sensing works start to leverage other lightweight sensors equipped in smartphones to be used often more (e.g, accelerometer and gyroscope) rather than the expensive and problematic sensors which are used less frequently (e.g, GPS and Wi-Fi) [14]. However, other localization systems for outdoor pedestrians with smartphones perform better than the built-in GPS module of the smartphone in terms of accuracy through introducing a robust dead reckoning algorithm and an error-tolerant algorithm for map matching as shown in Fig. 2.2.

Then, our proposed solution (SenseI/O) helps localization-based upper layer applications to avoid those GPS drawbacks existing especially in urban environments and can also be used to turn it off directly inside indoor environments through an accurate prior, prompt and accurate decision whether it is a Rural, Urban or indoor environment. For tracking systems (SenseI/O) support that accordingly users decide cleverly when they can activate or deactivate GPS sensor to ensure tracking performance and definitely leads to reducing energy consumption challenges.

2.1.2 Indoor positioning systems

Many of the proposed mobile applications which work in indoor environments are performed mainly within specific indoor space settings such as offices, rooms and corridors of buildings or malls, where they do assume knowledge of the physical layout. So, can they perform these indoor positioning systems without pre-knowledge decision? Typically, many proposed related works exploit that both Wi-Fi access points and Wi-Fi mobile devices are becoming more ubiquitous as well as those short range scans of Bluetooth, Infrared, UWB or RFID readings to develop these positioning and tracking techniques [14, 22, 28]. All these applications also rely on the indoor/outdoor prior knowledge for a proper working scheme and collect required data from specific experiment test-beds include certain floors in specified buildings as in [13]. Then, answering the above question makes these

Sensor	*Approximate battery life (hrs)*	*Average power consumption (mW)*
Video camera	3.5	1258
IEEE 802.11	6.7	661
GPS (outdoors)	7.1	623
GPS (indoors)	11.6	383
Microphone	13.6	329
Bluetooth	21.0	211
Accelerometer	45.9	96
All sensors turned off	170.6	26

Table 2.1: Energy consumption of different smartphone sensors.

applications practical and realistic, so we need to apply a prompt system that give us a prior indication about the ambient environment type to enhance upper layer applications performance, leads to saving energy and extend smartphones battery life.

For example, WiFi-based indoor localization is attractive and used especially in many of the indoor positioning schemes, so it's necessary that before searching for WiFi access points, one may check whether it is inside or near buildings and adapt the scanning strategy accordingly. On the contrary, these sensors known as a battery hungry and require a continuous scanning to get accurate results reaching few meters as shown in table 2.1 which describe the amount of energy consumed by each sensor equipped in smartphone in case of continuous running until the battery was depleted. Moreover, the Wi-Fi sensing exhibits a little bit benefit in rural environments with long ranges (e.g, highways, bridges, tunnels), then a prompt prior-decision separates rural from urban/indoor environments without extra overheads will be useful to help user to decide when to activate and deactivate sensing which imply enhancing their performance and adopting scanning scenarios accordingly.

2.1.3 Context-aware schemes and activity recognition applications

Many of the context-aware and activity recognition applications rely on the nature of test-bed environments [11, 25, 33, 46]. **For example**, A context awareness via GSM Signal Strength Fluctuation system [11] demonstrates how a cell phone can infer contextual information which distinguishes between various states of movement such as walking, traveling in a motor car and staying still by monitoring the fluctuation of GSM signal strength levels, neighbouring cells information

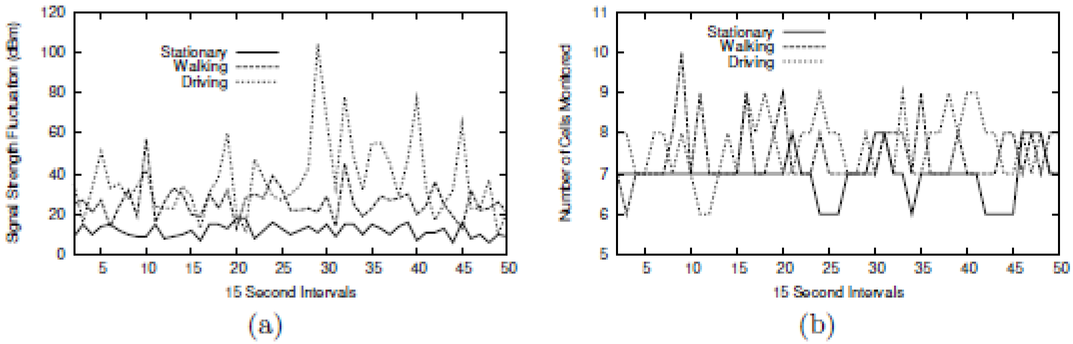


Figure 2.3: (a) Signal Strength fluctuation when stationary, walking and travelling in a motor car. (b) The number of distinct cells monitored during the 15-second intervals.

(up to 7 cells) and the number of distinct cells monitored over a given time interval. Also, they used an artificial neural networks to implement thier application in outdoor and indoor environments and collected datasets using Orange SPV C500 cell phones. Then, they expected that the list of neighbouring cells will typically vary minimally when the cell phone is static, however, whilst moving the rate of change will be more apparent, particularly in metropolitan environments with a large number of cells. **Hence**, a change to neighboring cells and signal strength levels typically occurs according to a change in the user context-aware which may rely on shape of surrounding environment as shown in Fig. 2.3. Furthermore, CROWDINSIDE [9] presented an automatic indoor floorplan generation according to users motion traces which are constrained by pedestrian trajectories of rooms and corridors using lightweight smartphones sensors such as accelerometer, compass and gyroscope as shown in Fig. 2.6 (b). **It's known** that indoor environments are controlled area and constrained by some rooms and corridors shapes which make mobility behaviors and pedestrian trajectories inside indoor environments differ from those in outdoor which are more freely with open roads and highways.

Also, proposed activity recognition applications are able to accurately and efficiently classify typical daily activities, postures, and environmental contexts based on data gathered from specific sensors and reported to central servers or aggregation nodes. For instance, PBN system (a practical on-body networking application) [21] for activity recognition classification. Data from multiple on-body sensors is reported to a mobile aggregator which makes classification decisions in real time. They break down target classifications of typical activities in which a user engages into many categories such as watching TV, driving, meeting with colleagues, and cleaning. PBN system consists of Crossbow IRIS on-body sensor

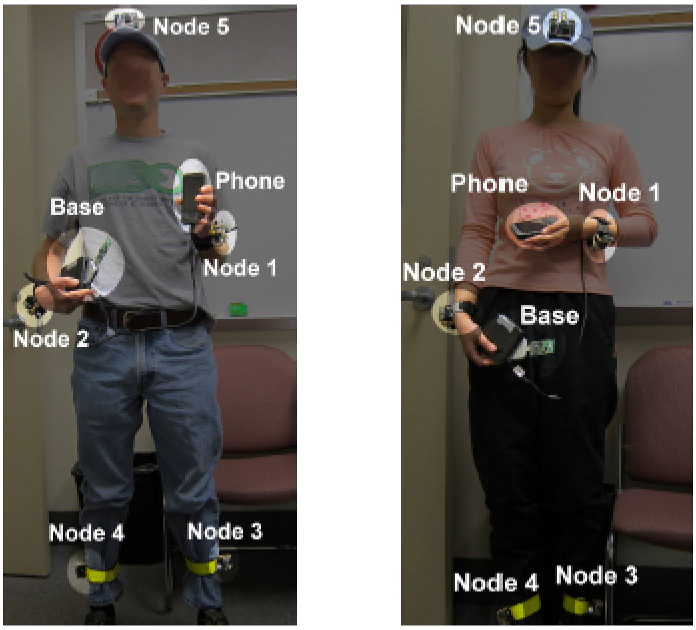


Figure 4: Subject 1. **Figure 5:** Subject 2.

Figure 2.4: PBN activity recognition experiment settings

motes and a TelosB base station connected to an Android HTC G1 smartphone via USB as shown in Fig. 2.4.

Pbn system tested on two subjects where each subject wore five Crossbow IRIS motes wirelessly linked to a TelosB base station and Android HTC G1 smartphone. Pbn system implementation was at indoor and outdoor environment, where on the phone, which they attached to the waist, they used of certain sensors like accelerometer, WiFi and GPS, with GPS active only they decide that the user is outdoors. So, they actually take a pre-decision that the ambient environment type is already known, then such (SenseI/O) pre-determination for ambient environment type (I/O) potentially gives sense sound about expected human behavior, enhances system accuracy and makes it looks like more practical.

2.1.4 logical localization applications

Consider GPS (latitude/longitude), the most popular physical localization method on mobile devices. While GPS can achieve high accuracy in outdoor environments, they do not work indoors. A variety of WiFi and GSM based alternates have been proposed for indoor operation [13, 27], each associated with distinct trade-offs between accuracy and scalability. While extensive research has been performed in physical localization, there have been few recent works which tries

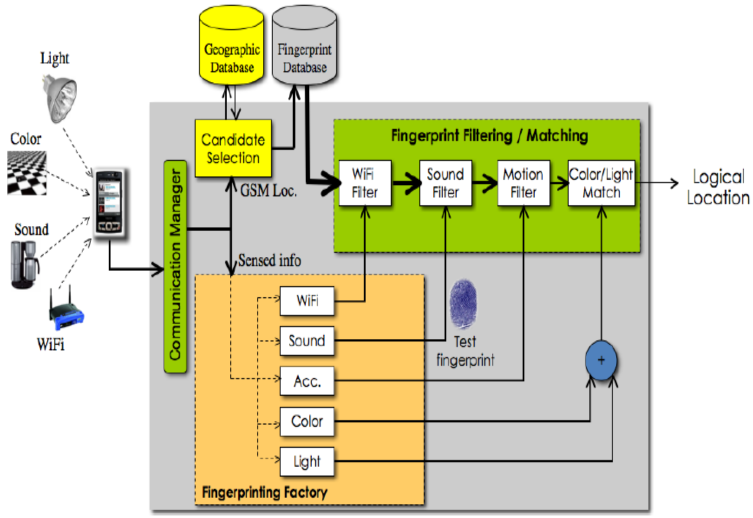


Figure 2.5: SurroundSense architecture: an example of logical localization based on fingerprinting ambient signals

to study the problem of logical localization by sensing the surrounding environment [12,30]. Increasing number of sensors on mobile phones presents new opportunities for logical localization. In fact, ambient sound, light, and color in a place convey a photo-acoustic signature that can be sensed by the phone's camera and microphone. Moreover, in-built accelerometers in some phones may also be useful in inferring broad classes of user-motion, often dictated by the nature of the place. A central server is normally needed to store such ambient fingerprints and answer queries from users as shown in figure 2.5. **Such** an approach is unlikely to be generalized to deal with universal indoor/outdoor detection. Hence, such systems may prefer to be supported by a primitive, prompt and non-painful indoor/outdoor knowledge to work properly and enhance localization performance.

It's argues that combining these optical, acoustic, and motion attributes, it may be possible to construct an identifiable fingerprint for logical localization.

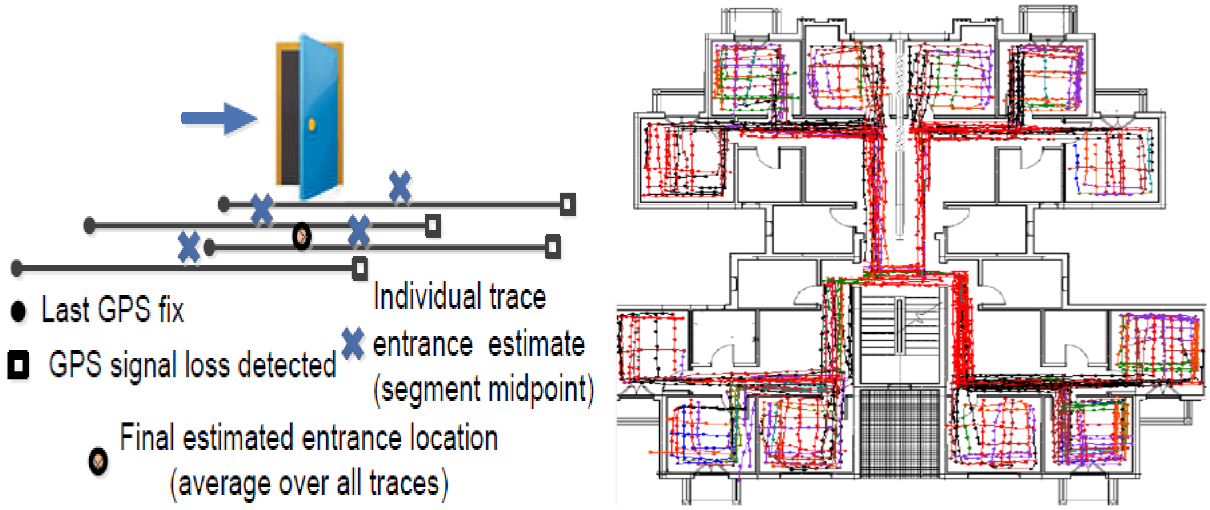
Our work primarily differs from them in that SenseI/O instantly detects the primitive ambient context without any labor-intensive site survey, any remote supports and user feedback. Those works may not only benefit from SenseI/O by taking the indoor/outdoor information as a primary filter, but also provide finegraind (Rural, Urban or Indoor) information for localization, tracking and context recognition.

2.2 Related work

All the above mentioned background performs a wide body of related works that implicitly deal with such indoor/outdoor detection. But, there have been many related approaches proposed explicitly which deal with such a problem.

- In CROWDINSIDE [9], they used GPS lock status not only to infer the ambient indoor/outdoor environment type, but in estimating the building entrances/ windows locations based on monitoring GPS signal availability status as well. They proposed that the required building locations (entrances/windows) will fall in intervals between last GPS signal fix and first GPS signal loss. Because GPS is usually high latency and consumes large amount of substantial energy especially in case of requiring the GPS to be always ON. Then, they also proposed querying GPS signal with a low duty cycle to detect the user's transition from outdoors to indoors in order to reduce these challenges, but this will affect on the accuracy and come to increase errors in estimating the required locations as shown in Fig. 2.6 (a). Furthermore, GPS act as a useful sensor in upper layer localization and tracking systems to estimate locations accurately or present an indication about ambient environment either indoor or outdoor. But, actually, in our objective (inferring ambient environment), we consider that the GPS sensor can give a limited information (i.e, signals are fix or loss only) and doesn't necessarily imply that the the user ambient environment is outdoor/indoor accordingly. This is because that losing GPS signal can occur in many places rather than when user is inside buildings such as inside tunnels, underground places (metro-stations) and semi-outdoors places. Moreover, in case of any user walking inside the building and passing near to a window/entrance, the GPS signal should be detected which means that the detected user ambient environment is outdoors while it's indoor environment in truth and this represents a wrong indication. GPS will not benefit in case of fine-grained and ubiquitous environment detection (Rural, Urban and Indoor) where fixing and losing signals will not be enough.

- Some works in image processing and pattern recognition [29,31] also study the problem of the indoor/outdoor image classification and automatic image tagging according to ambient environments. Those works can provide partial indication on indoor/outdoor environment, and such approaches cannot



(a) (b)

Figure 2.6: (a): Typical user motion traces inside buildings. (b) Estimating the building entrance location using GPS samples from different users.

directly be applied to our problem since they require explicit manual input from users. As taking photos normally incurs substantial human effort and energy cost, we can hardly rely on such classification approaches to build generic and automatic indoor/outdoor detection service. TagSense [35] classifies the ambient environments to automatically annotate images during the picture-click.

- TempIO [Tempio] classifies the ambient environment by comparing the environment temperature with the current outdoor temperature through the network query. Yet temperature sensors are not widely available on current mobile phones. Along with many other sensing resources, the temperature sensor if available on mobile phones can be used to complement our work.

- FLIGHT [flight] explores the fact that the light intensity changes with a stable period in the indoor environment and uses the feature to perform clock calibration.

- En-Tracked [23] focuses on outdoor pedestrian tracking using lightweight accelerometer to trigger GPS to reduce power consumption. GPS lock status can be used to indirectly infer the ambient environment [36], but it usually incurs substantial energy cost and high latency.

- IOdetector [45] is a closer explicit related work to our work which classifies the surrounding environment into three main categories and they are indoor,

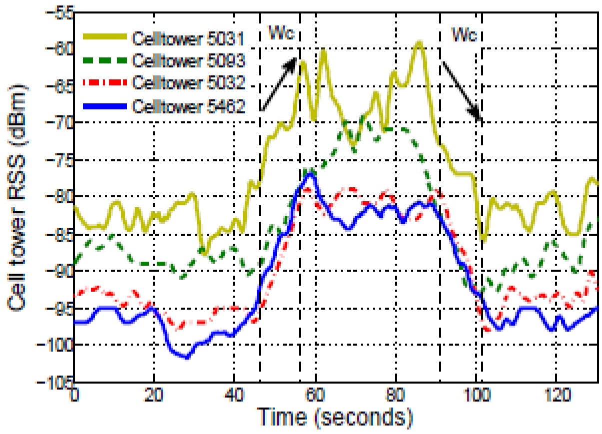


Figure 2.7: Multiple cell towers' RSS variation in environmental change.

semi-outdoor and outdoor based on signatures observed from lightweight sensors like light , magnesium and multiple cell towers signals during users transitions from inside buildings into outdoor and return back. They conducted experiments in controlled areas where data was collected from fixed routing traces (i.e., inside buildings and outside environments near to buildings) which makes it limited in usage (not ubiquitous). Furthermore, IOdetector is not considered a smartphone stand-alone system where it used extra devices like external sensors such as TelosB motes which are used to achieve a fine-grained control of the light sensors on the TinyOS platform. There are many disadvantages in IOdetector which they disregard them:

1. Light intensity sensor should be exposed in the space facing to the sun to be usable and provides detection result. While it's inside the pocket, screen faces the ground or light sensor unavailable in smartphone, then in this case the light intensity sub-detector will be useless.

2. Relying IOdetector on information that is recorded from all visible neighboring cell towers makes it unrealistic and suffers from two main problems: (a) it needs sufficient cell tower coverage to confidently detect the ambient context, and then it's difficult to ensure that at every environment. For example, rural environments actually require a number of 3G cell towers, to ensure sufficient coverage, less than the number of available cell towers at urban environments. In contrast, it's known that urban environments are covered by a large number of cell towers to ensure presenting communication service with high quality for all users, and then such environments may provide the required number of cell towers. But, it suffers from another problem where the variations of those cell tower signals when user

transit from urban into indoor areas or vice versa are not sufficient because signals dropping happen at urban areas make it look like those in indoor environments. (b) Also, recently, getting RSSI information on all visible 3G cell towers constrained to certain types of smartphones, where most high-ends smartphones types can't get these information due to lacking in API support.

3. The magnetism detector is only available when the user is moving around in such away the magnetic disturbance inside buildings can be detected.

Unlike IOdetector, SenseI/O proactively present a realistic and ubiquitous indoor/outdoor ambient environment detection using smartphones only without any external additional devices or remote supports. Where we rely on getting RSSI information from single serving cell towers rather than those of all visible cell towers (as shown in Fig. 2.7) which are considered realistic and available on all types of mobile devices either high-end or low-end types. Furthermore, we infer a fine-grained (Rural, Urban and Indoor) detection of ambient environment rather than indoor/outdoor detection only to meet upper layer applications requirements effectively.

Chapter 3

SenseI/O System Design

3.1 Overview

In this thesis, we introduce SenseI/O, "a Realistic Ubiquitous Indoor Outdoor Detection System using smartphones" which has large flexibility and scalability to run proactively on all of today's smartphones and provides a fine-grained (Rural, Urban and Indoor) ambient environment detection service for upper-layer applications. The main goal of our system is leveraging the realistic functions and capabilities allowed in lightweight and inexpensive sensors embedded in almost today's smartphones rather than those in baseline sensor (i.e, GPS receiver). The intuition behind our system, for it simply performs real time android application running on mobile devices that can be activated by any user or upper layer applications when needed, is that SenseI/O mainly achieves many practical design requirements like:

1. **Realistic:** getting information (RSSI) from a single associated serving cell tower rather than that from up to seven visible neighboring cells makes our system applicable on all types of today's android smartphones, even on low-end mobile devices. Furthermore, we infer a fine-grained (rural, urban or indoor) environment type rather than outdoor/indoor only which considered more realistic compared with previous related works.

2. **Ubiquitous:** presenting a multi-modal framework which contains four main modules aiming to improve system capabilities to cover most of user's states in a wide range of ambient indoor/outdoor environments kinds. Also,

these modules ensure that senseI/O is applicable on all mobile devices models. For instance, in light intensity module, if the light sensor is not available on any smartphone type, then senseI/O can trigger to the other module (e.g., Wi-Fi based or single cell tower modules) to ensure that indoor/outdoor detection service is available regardless of the smartphone type.

3. **Energy consumption:** such SenseI/O system, which many of upper layer applications would rely on, should run on mobile phones with constrained energy budgets because mobile phones mainly suffer from energy drain challenges. So, our SenseI/O should be energy efficient and use the inexpensive sensors resources of mobile phones more often. We build all sensing modules in our senseI/O framework based on lightweight sensor types like single cell tower, accelerometer, light and proximity which is almost known as energy negligible sensors even in case of continuous sensing [14,47], except Wi-Fi based sensing module equipped with wi-fi sensor which is known as a energy hungry sensor as shown in table 2.1. But, we impose some constraints on Wi-Fi sensing module to limit energy consumption challenges and reduce the demand energy like enabling/disabling Wi-Fi sensor for sensing within a specific interval period only, and senseI/O just cleverly calls Wi-Fi based module according to certain quired sensing scenarios to log required information that resolves specific problem and automatically after that switch to another module.

4. **Instantaneous:** as many other rapid applications should rely on our system, therefore this senseI/O system should have an instantaneous reaction and promptly distinguish the indoor/outdoor environment to be valid and acceptable to use. An outdated detection result may be less valuable for many upper layer instantaneous applications.

5. **Universal applicability:** to ensure that our SenseI/O system has a widely applicability on upper layer applications, so it should avoid relying on a priori knowledge or site survey, special additional and external devices or explicit user feedback.

Table 3.1 shows that our proposed SenseI/O system doesn't only simply infer binary indoor/outdoor detection as previous works [24,29,45] , but also provides a

Environment	Rural	Urban	Indoor
Site			
Site Example	Smart Village	Down Town	Comm. Building

Table 3.1: Environments types and the representative sites

fine-grained normal rural, urban, and indoor environment detection types. Furthermore, our senseI/O can infer user ambient environment type in abnormal places such as tunnels and underground metro stations which are considered a complex detection environments because it exhibits an environment signatures similar to those in other places as will described later. The main reason behind such fine-grained detection is to better meet requirements of upper-layer applications. In our work, we assumed that *Rural environments* represent the open and widely outdoor areas such as open squares, long bridges, highways, wide and open residential areas, wide sports fields and parks. Table 3.1 shows a Smart Village is a representative site example of rural environment type in our work which is considered a wide and open space of residential area which contains buildings of some local and international companies. The advantage of such site is that these buildings are spaced enough from each other and mid-rise where most of the buildings consist of two floors at most and these features potentially reduce dropping happening on 3G signal strength.

Also, *Urban environments* represent the downtown, crowded metropolitan areas and narrow streets bounded by tall buildings, hills and trees. Table 3.1 shows a downtown site example of urban environments type in our work which showing it's a crowded area bounded by tall buildings where it potentially leads to dropping 3G signal strength especially when user passing into branches of narrow streets.

We consider that any inside areas of any building such as houses, malls, companies and universities are *indoor environments*. Table 3.1 shows the gground floor corridor of our department inside communication building in Cairo university as representative site example of indoor environments.

So, the distinction of outside environments into rural and urban areas is considered sufficient, realistic and useful to serve upper layer applications which change their functionality accordingly. For instance, some outdoor upper localizations applications use GPS sensor to achieve high location estimation accuracy, but actually this can be achieved in rural outdoor area with high level confidence. But, it's difficult to be achieved in urban areas because GPS exhibits many drawbacks which make it works badly and hence provide inaccurate locations estimations [47]. **Then**, launching GPS component in such urban areas will be unnecessary and prefer that the ambient environment be known before. Our System Design is based on a data-collection approach, where measurements from used sensors equipped in mobile devices are collected from Rural, Urban and/or Indoor Areas. The intuition behind this is that a large number of measurements and traces can provide an enough description and enhance the certainty about type of those three surrounded environments.

In this chapter, we start to describe SenseI/O system architecture, introduce the whole system block diagram and end by explaining the first two phases in detail. In the following chapters, we describe each four modules individually, specify how to utilize the compound modules, and evaluate Sense I/O for inferring an effective output.

3.2 SenseI/O system architecture

Figure 3.1. shows that the SenseI/O system architecture consists of three main phases:

- **Activity Recognition Phase:** is responsible for recognizing current user's activity type based on data collected from accelerometer sensor available in the user's mobile devices. Section 3.4 provides more details about *Activity Recognition Phase*.

- **Environment Filtering Phase:** the goal of this phase is to provide an instantaneous *clear/ambiguous* primitive filtering environment type based on data collected from smoothed 3G single cell tower module. Section 3.5 provides more details about *Environment Filtering Phase.*

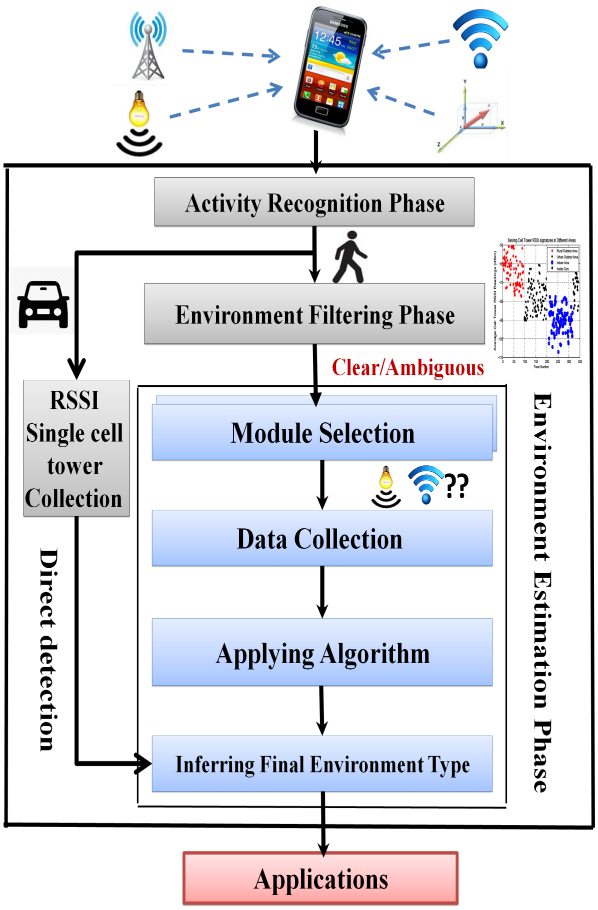


Figure 3.1: SenseI/O System Architecture.

- **Environment Estimation Phase:** is responsible for utilizing a suitable module and estimating the final fine-grained environment based on primitive output of the *Environment Filtering Phase*. In this phase, shortly, senseI/O starts to select a typical module, collect module measurements, apply module algorithm and infer the final detected environment type.

Description: SenseI/O architecture figure clearly explains the flow of our proposed system too. SenseI/O should start by calling first phase (Activity Recognition) to gather acceleration readings of accelerometer inertial sensor, and then EPU unit computes acceleration magnitude values accordingly. These values represent an input into activity recognition API supported by google play services, the expected outcomes from activity recognition phase are In-vehicle, On-foot or Still. Now, we have two expected approaches, according to activity type, the first one called *Direct Detection* if the detected activity output type is *In-vehicle*. In this case, EPU unit immediately invokes the single smoothed cell tower module and collects

RSSI readings, according to those readings, senseI/O rapidly determines the required fine-grained ambient environment type as one of the following three outdoor types *Rural, Urban or underground* (Tunnels and metro stations cases). The second, when the activity recognition phase outcomes are On-foot or Still, so the other approach will be invoked. In this case, EPU should need to utilize another module such as single smoothed cell tower to decide either the surrounding environment is clear or ambiguous (i.e., invoke Environment Filtering Phase). Afterwards, according to those outcomes, EPU unit invokes third senseI/O phase which is called *Environment Estimation,* where this phase contains the rest of senseI/O modules (i.e., Light intensity and Wi-Fi based). EPU should select one of these modules according to certain conditions (see section 3.3), then starts collecting its data and by applying related algorithm, senseI/O can finally provides final detected environments type.

3.3 SenseI/O System Block Diagram

Figure 3.2 shows inner view of senseI/O system. This system consists of four main blocks which represent sensing modules and they are Activity Recognition, Single smoothed cell tower, Wi- Fi based and Light Intensity. Also, one other software module (Virtual module) called environment processing unit (EPU) which is considered as control unit that organizes senseI/O system workflow. Each module relies on getting surrounding environment measurements on one or more types of embedded sensors in today's smartphones. For instance, all these modules collect their data from single sensor except intensity module which relies on three sensors, and they are light, proximity and time. Moreover, senseI/O should starts by accessing activity recognition module and then environment processing unit (EPU) selects cleverly which a next typical module will be used to provide final output. This selection generally is based on some grounds like:

- **User Activity Type:** according to the resulted user activity type (In-vehicle, On-foot or Still), the environment processing unit (EPU) selects cleverly which a typical next module will be used to provide final output. For instance, next selected module will be single smoothed cell tower when the detected user activity is inside vehicle (Direct detection case).

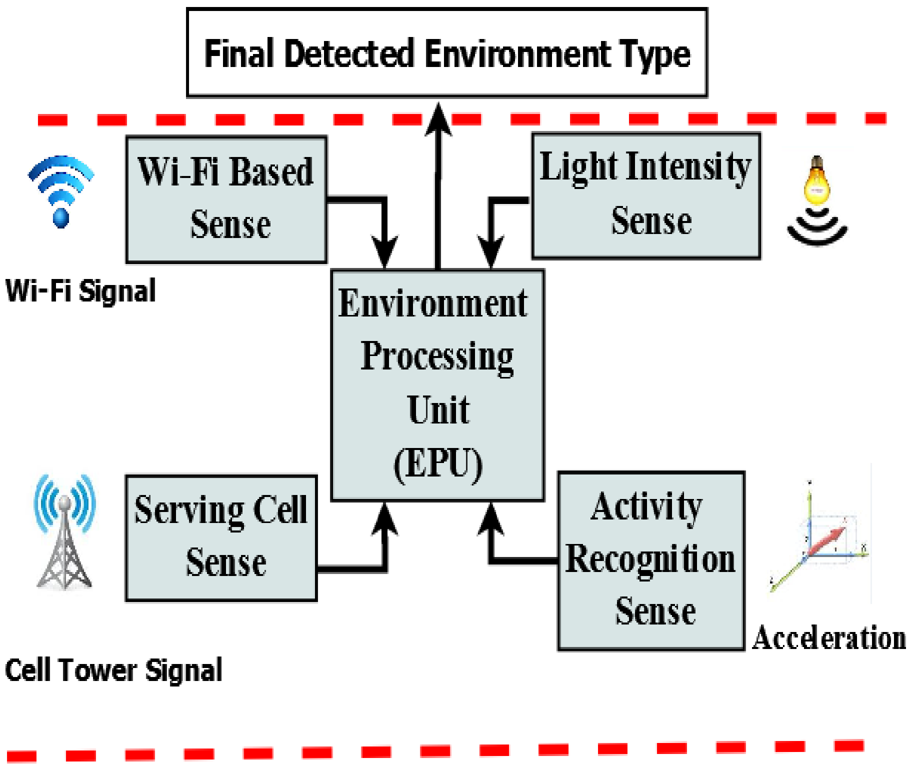


Figure 3.2: SenseI/O Proposed Modules Block Diagram

- **Environment Filtering Phase Result:** where the expected primitive output from this phase is either a clear or ambiguous environment type as described in Fig. 3.4. For instance, if the instantaneous output is clear that means the detected environment is highly probable either Rural outdoor or Ground-Indoor, and then the most candidate module will be selected by EPU is light intensity.

- **Environment limitations:** sometimes the nature of tested areas forces senseI/O system to use/deprecate some modules. For example, in case of tunnels, open squares, highways areas and/or traditional (Wi-Fi-less) areas, the Wi-Fi based module becomes less useful because Wi-Fi APs may be considered less density or perhaps the coverage don't exist. But the single smoothed cell tower and Activity Recognition modules will be required in such environments. On the contrary, through urban areas and inside buildings (e.g., Malls, Companies or Universities), Wi-Fi based module is useful to distinguish such urban areas from those indoor. Also, light intensity module is considered valid in such environments but to provide general indoor/outdoor detection not fine-grained urban/indoor, thus these two modules may be preferred to be required more than others.

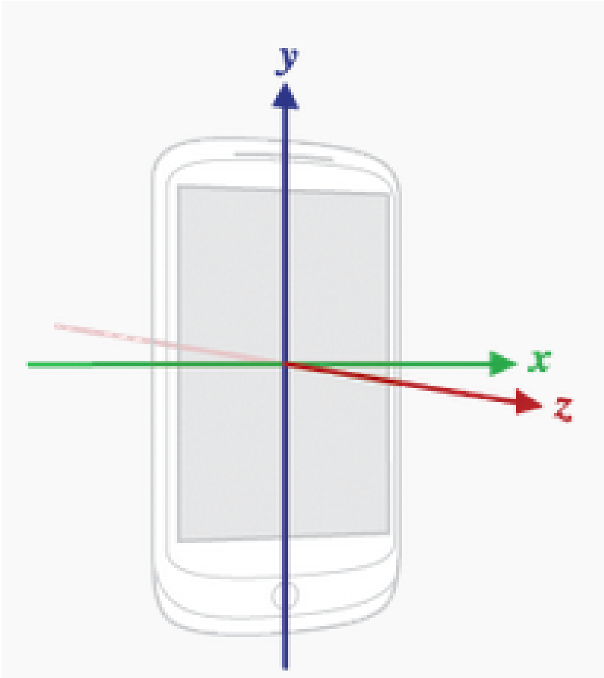


Figure 3.3: Coordinate system (relative to a device) that's used by the Accelerometer Sensor API.

- **Sensors Availability:** it's known that light sensor is unavailable on many of today's smartphones, so before selecting this module, sense I/O should check sensor availability first or jump to another typical module.

3.4 Activity Recognition Phase

This phase is implemented as a software service running on android mobile devices. It is responsible for querying the accelerometer sensor in the mobile devices and collecting their measurements. These measured values are defined in terms of the local coordinate system of the mobile devices (x, y and z) as shown in Fig. 3.3. Accelerometer sensor are queried at the SENSOR_DELAY_UI query rate which was experimentally found to be corresponding to approximately 50 sample per second on android mobile devices. This is the same rate used to detect the screen orientation change. This has the advantage of using nothing additional for the activity recognition over the normal energy for querying the inertial sensors. Then, we compute acceleration magnitude from those measured values and based on resulted values we classify current user activity into three main classes: In-vehicle, On-foot or Still as shown in next chapter in detail.

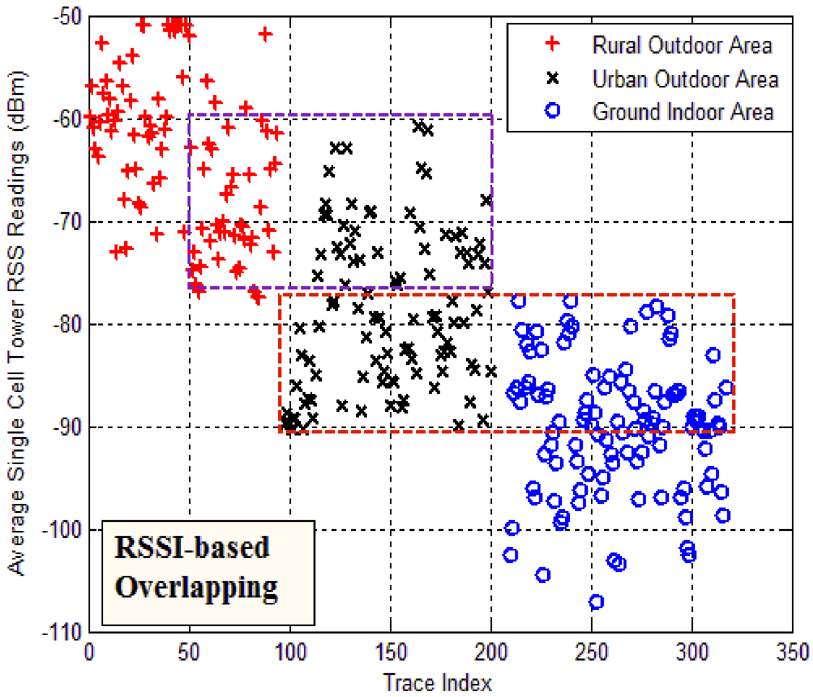


Figure 3.4: Illustration of the overlapping among Rural, Urban and Indoor environments based on single serving cellular RSSI measurements.

3.5 Environment Filtering Phase

The intuition behind this phase is that providing an instantaneous primitive filtering for surrounding environment whether clear or ambiguous based on single smoothed serving cellular RSSI collected readings. This phase is considered a very important one as it performs the first step of resolving ambiguity between indoor and urban environments, and accordingly senseI/O selects a typical module which is responsible to provide the final environment detection afterwards. This phase will be invoked only when the outcome of the previous activity recognition phase is On-foot or Still only.

Figure 3.4 describes more about such filtering. As we explained that our senseI/O aims not only to cover indoor/outdoor detection, but to present a fine-grained rural, urban and indoor environments detection as well. Then, based on experiments observations, we indeed proposed to study the relation between these environments and single 3G cellular RSSI readings to provide more precise and realistic distinction.

Methodology: all the absolute cellular RSSI measurements are collected from these environments separately using different android mobile phone models (Samsung Galaxy S1 plus, LG and Samsung duos) which is in hand with screen facing up and in pocket scenarios. Actually, we implement 305 experiments which cover 36 rural,urban and indoor different sites at Cairo and Alexandria cities. Each experiment consists of 90 RSSI values over period equal to 90 seconds (i.e., one value per second) with walking/stationary cases under different weather conditions during daytime and night. Afterwards, experiment average is estimated to get final value per experiment in each environment individually.

Observations: as shown in Fig. 3.4, dashed rectangles exhibit two clear RSSI-based environments overlapping and they are Rural/Urban and Urban/indoor. This may occur due to many reasons such as natur of places, changes in mobiles connectivity and/or variations of antenna gain across different mobile phone models. Therefore, this introduces realistic ambiguous problems in detection. In short, lower dashed rectangle, for instance, shows an overlapping between urban-outdoor and indoor areas, this will occur due to that obstacles such as tall buildings, hills and/or trees which increase in such urban areas and lead to dropping dramatically in single cellular RSSI measurements and look like those in indoor areas. Therefore, any transition from urban into indoor will be undetectable because there is no high variation achieved. Similarly, for overlapping between Rural-outdoor and urban-outdoor areas. On the other hand, no overlapping between Rural and indoor areas where single 3G cellular RSSI exhibits separated values which lead to presenting a clear detection when experiment is within such areas. Table 1 shows the tracing results of tested environments in detail.

Finally, based on these observations, we divided Surrounding environment into two main virtual and primitive categories which are *Clear* (Rural and indoor) and *Ambiguous* (Rural/Urban and Urban/indoor). It's known that both classes represent mainly outdoor/indoor environments, so querying another module to distinguish these classes is required. In short, it's known that light intensity module provides only general indoor/outdoor detection, then applying such module in case of the first class will be useful and efficient. In contrast, Wi-Fi based module is considered the suitable one that used to resolve ambiguity between Rural/Urban or Urban/Indoor, as it's known, the Wi-Fi APs density in rural areas are less than

Environment Type	Rural	Urban	G-indoor
-50 $\rightarrow$ -60 dBm	31	0	0
-60 $\rightarrow$ -70 dBm	34	15	0
-70 $\rightarrow$ -80 dBm	29	40	6
-80 $\rightarrow$ -90 dBm	0	48	47
-90 $\rightarrow$-100 dBm	0	0	48
-100 $\rightarrow$-110 dBm	0	0	7
Overall	94	103	108

Table 3.2: Confusion matrix for filtering different environments based on single smoothed serving cellular RSSI.

those in urban or approximately doesnot exist. Also, Wi-Fi received signals in indoor areas are stronger than those in urban environments.

Chapter 4

SenseI/O Modules

As described in the previous chapter that the SenseI/O system block diagram consists of four main sensing sub-systems or called modules, these modules complement each other to infer the final fine-grained user surrounding environments. Also, SenseI/O contains an additional virtual software unit called Environment processing Unit (EPU) to organize detection processing. In this chapter, we describe proposed senseI/O *activity recognition, single smoothed cell tower, Wi-Fi based and light intensity* modules from side of android application development [32], challenges, solutions, and algorithms in detail as follows.

4.1 Activity recognition: first step of I/O detection

In this module, we present simple, ubiquitous and accurate technique which attempts to infer user's physical activity based on sensing readings of accelerometer sensor equipped ubiquitously on most of today's smartphones and deploy it to produce an accurate indoor/ outdoor detection afterwards.

Figure 4.1 shows the method of classifying client activities and infer surrounding environments. Activity recognition classifier is divided into two main classification levels: the first level differentiates between shaken and fixed states of smartphones. For example, when smartphone being put on table or in the pocket of a stationary user either standing or setting down. The second level exhibits more efficient activities classification called: *Still, On-foot and Invehicle*. Once the type

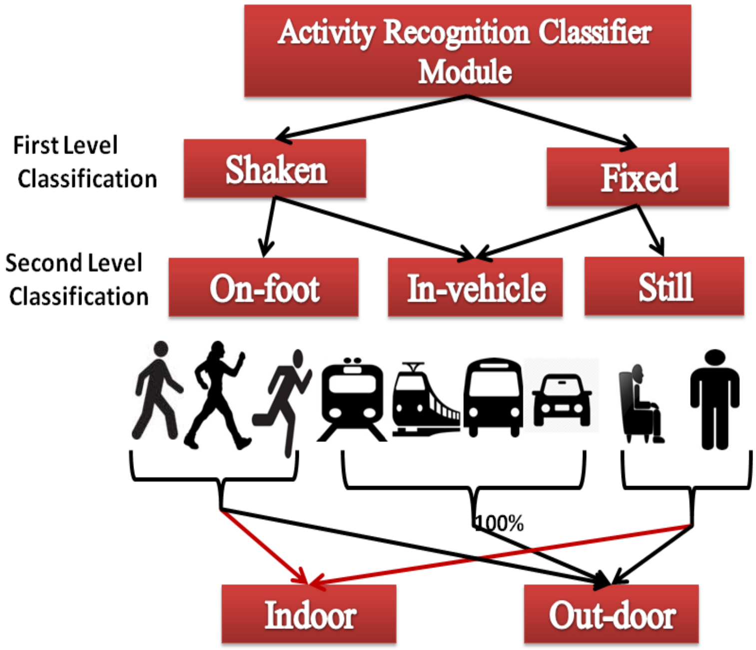


Figure 4.1: User activity recognition multi-level classifier.

of activity is identified , the senseI/O either returns the type of surrounding environment directly (through rapid detection method) or triggers another module to infer the final ambient environment type.

For instance, while the detected activity client is In-vehicle, senseI/O logically decides that the detected surrounding environment is outdoor with high confidence level, but if it's On-foot or still , hence SenseI/O will trigger to another module for proper detection. If detected client activity is Unknown, then senseI/O stays in the same state till user activity state changes.

Unlike previous works, we group seven activities such as transportation modes (e.g., Train, Metro, Car and Bus) [17], user on-foot motion modes (e.g., Walking, Jogging and Running) [10] and Stationary mode into those three main categories called: *Still, On-foot and In-vehicle* according to two main reasons. The first, inferring such fine-grained seven activities will be unnecessary due to our objective (Indoor/Outdoor Detection). The second is according to the similarities of acceleration magnitude readings, estimated of three coordinates acceleration (X, Y, Z) of smartphones, observed among them as shown in Fig. 4.2. This figure generally shows that the On-foot group activity types (Walking, Jogging and Running) have acceleration magnitude values similar to each other and larger than the other In-vehicle and Still activities, and In-vehicle group activity types (Train, Metro, Car

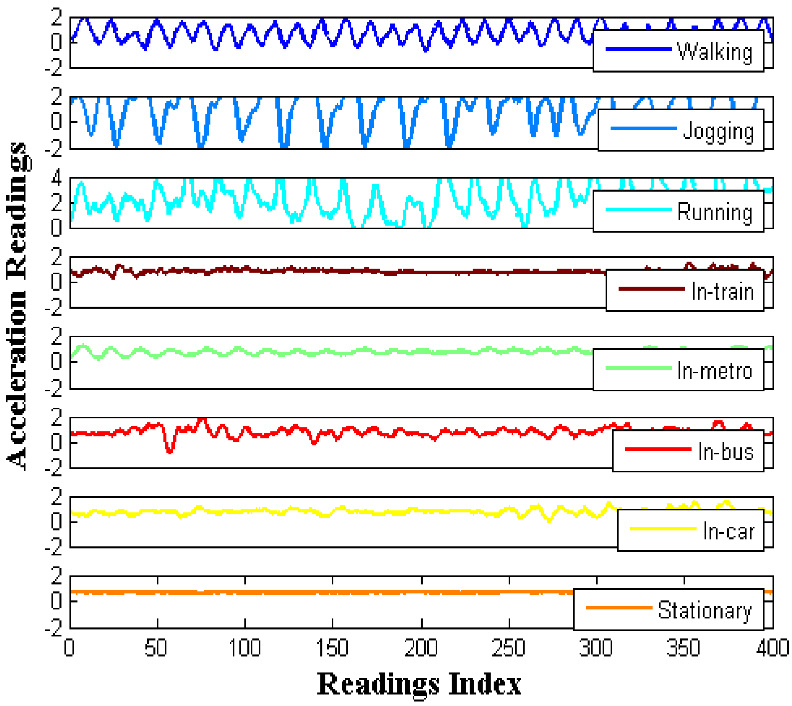


Figure 4.2: Classification between On-foot, In-vehicle and Stationary of user activities based on accelerometer sensor readings.

and Bus) have acceleration magnitude values similar to each other and closer to stationary activity type. So, we simply consider that detection of all inside transportation modes is *In-vehicle*, all of motions modes is *On-foot* and *Still* when the mobile is fixed.

Moreover, Figure 4.3 shows that the 3G smoothed RSSI cellular measurements drop dramatically inside some complex places (e.g., Tunnels and Underground stations) and look like those inside buildings. Such problems are accurately solved through exploiting such In-vehicle detection too.

SenseI/O system doesn't only simply exploit In-vehicle user activity detection to infer that the ambient environment is outdoor, but also utilize another senseI/O module called single smoothed cell tower which rely on 3G detected RSSI to infer a fine-grained Rural, Urban or Underground (Tunnels and Underground stations cases) areas as shown in detail in the following chapter.

4.1.1 Activity Recognition Android Application

This module is constructed based on *Google Play services* [41] which provides a very interesting, simple, and commercial API called *Activity Recognition client* [37] which is considered a part of Location Services. This API can open a gate of

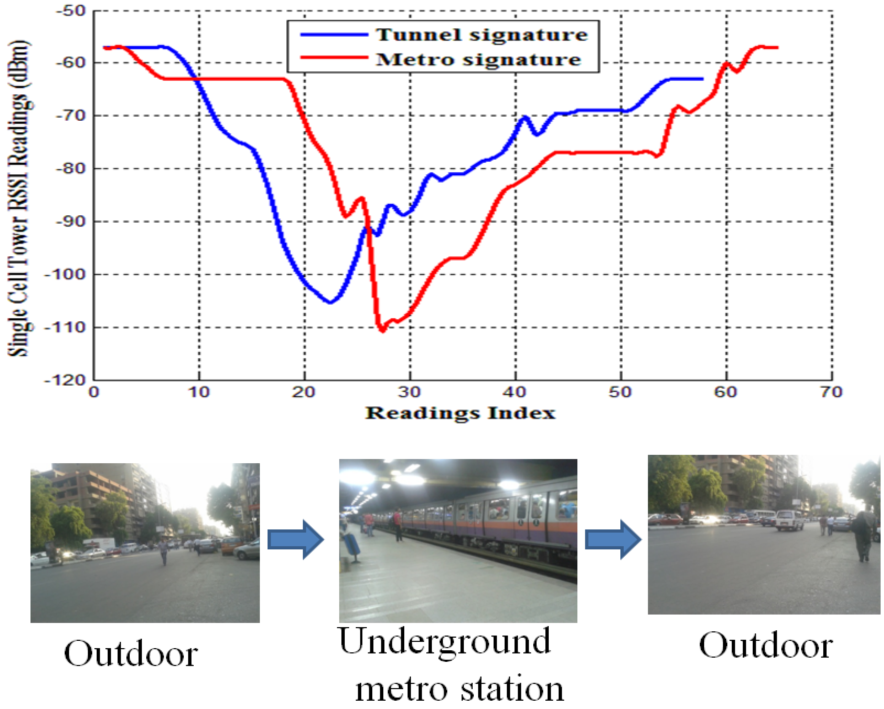


Figure 4.3: Resolving an observed 3G smoothed cellular detection problem inside some complex places (e.g, Tunnels and underground stations) using activity recognition module.

whole new kinds of applications on most android smartphones. Activity Recognition recognizes four activities 1] In-vehicle, 2] On-foot, 3] Still and 4] Unknown and provides each activity type with thier specific confidence levels. Also, we summarize *Activity Recognition client API* advantages as follows:

- Activity recognition application is considered ubiquitous and simpler than previous related work to infer current client activity type [17].

- Possibility of connecting/disconnecting, when this module invoked to recognize current client activity, the activity recognition client API immediately connects with the location services using built in *connect()* and *call Request Activity Recognition Updates* [6] methods. Similary activity recognition client API immediately disconnects the location services using built in *disconnect()* and *Stop Activity Recognition Updates* [6] methods when user needs to leave activity recognition module.

- We can choose a suitable interval in milliseconds to request activity recognition updates from *Location Services* during connecting state. So, we can maximize update intervals in order to save energy consumed or minimize them to increase user activity detection accuracy.

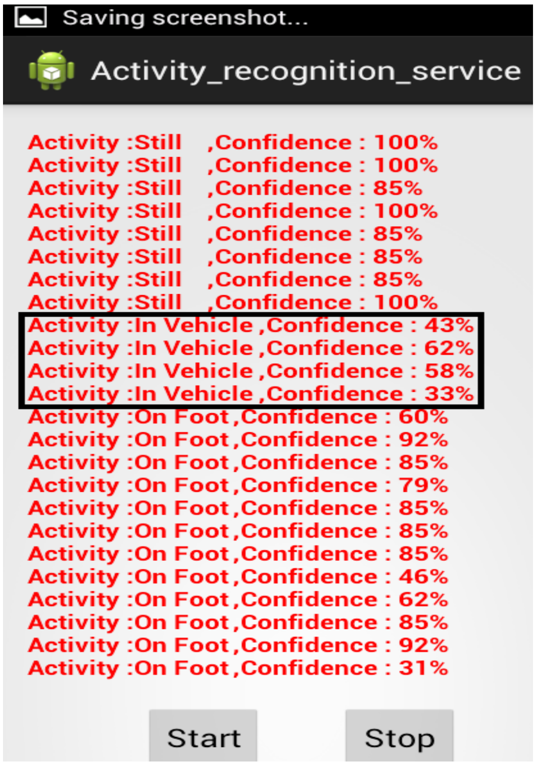


Figure 4.4: Activity recognition application screenshot explains false activity detection concept

Figure 4.4 shows an android application screenshot of activity recognition module where user activities and confidence levels are sent out periodically. Simultaneously, logged data is stored on designed database inside smartphones for next processing. Start and Stop buttons are for manually user control.

4.1.2 Optimized activity recognition module

False activity detection

During experiments, we observed that reliance on the activity recognition results directly is not proper and leads to inaccurate detection where *false activity detection* rates will increase. False activity detection implies that activity recognition module indicates false activity type due to rapid user activities fluctuations.

Black rectangule in Fig. 4.4, for example, clearly shows that the detected activity is On-foot while user is walking. Suddenly, when user decides to change his state and starts to slow down pedestrians, hence acceleration readings will drop and seem like those inside the vehicle according to figure 4.2. Then the detected activity will be In-vehicle rather than on-foot/Still for couple of times then being

Algorithm 4.1 Activity recognition module algorithm

>> C : Certainty value
>> C_{max} : Maximum certainty threshold

1. Detect the current recognized user activity
2. Previous detected user activity is saved and compared to the current detected activity
3. If both are similar
4. Increase C $\rightarrow$ C+1
5. Check if C equal Cmax
6. Final activity type is declared and C$\rightarrow$ 0
7. Else return to line 1
8. Else if both are not similar and (C < C_{max})
9. Put C$\rightarrow$0 and return to line 1
10. End

stable still afterwards. Similarly, when the user is *In-vehicle* and if the speed of the vehicle slows down due to traffic congestion, the detected activity will be *Still* type while in fact user still *In-vehicle*. This observation definitely affects detection accuracy sufficiently, so we optimize such module to rely on a couple of detected sequences activities instead of single activity.

We propose a certainty concept which implies focusing on a series of identical activities rather than single activity and decides final user activity when the number of these activities reaches specific threshold value called C_{max}. Current detected activity is saved and compared with the following detected activity type, C is increased when both the previous and current are similar. Otherwise, we reset C to 0, detection identified as error (False Detection) and clear these activities. Then, similar determined activites are merged and compared with the next detection. A final activity type is declared when C reaches C_{max} as described in activity recognition algorithm (algorithm 4.1).

4.2 Single smoothed cell tower RSSI for I/O detection

It's known, the correlation between single 3G cellular RSSI readings and surrounding environments varies according to the type of ambient environment. So, we aim to exploit such variation in our objective where it demonstrate the reason behind dividing surrounding environments into fine-grained areas such as Rural outdoor, Urban outdoor and Indoor. Then, we exploit this phenomenon to infer an accurate distinction for these environments based on those RSSI values.

4.2.1 Serving Single cell tower advantages

In this module, we first describe some single cell tower features which have been exploited in our work and the motivation to choose single cell tower:

- **Reliability:** as it's known that all kinds of mobile devices constantly search for the closest neighbor cell towers and sense their signal strengths, then lock on the strongest one called serving single cell tower. So, such devices can simply guarantee connect to at least one cell tower called serving cell tower and log its information any where as long as it is ON and connected to the base station.

- **Realistic**: most of mobile devices can't sense and log RSSI values of all visible cell towers simultaneously especially in high-end smartphones due to lack of API support. In addition, availability density of all visible cell towers in many places is very limited [18]. Therefore, reliance on sensing multiple cell towers needs sufficient coverage to detect the required number of surrounding cell towers (up to 7 cell towers) and confidently infer the ambient context. These challenges donot exist in case of single cell tower which are considered as an advantage exploited in our work to avoid such limitations on previous works and present a realistic system.

- **Availability:** single cell tower RSSI values are always available ubiquitously and can still be heard and log its information (e.g., Cell-ID and RSSI) even in difficult places like tunnels, stores and underground areas. However, (e.g., GPS) exhibits unavailable in indoor places and provides inaccurate performance in urban areas especially for pedestrian smartphone

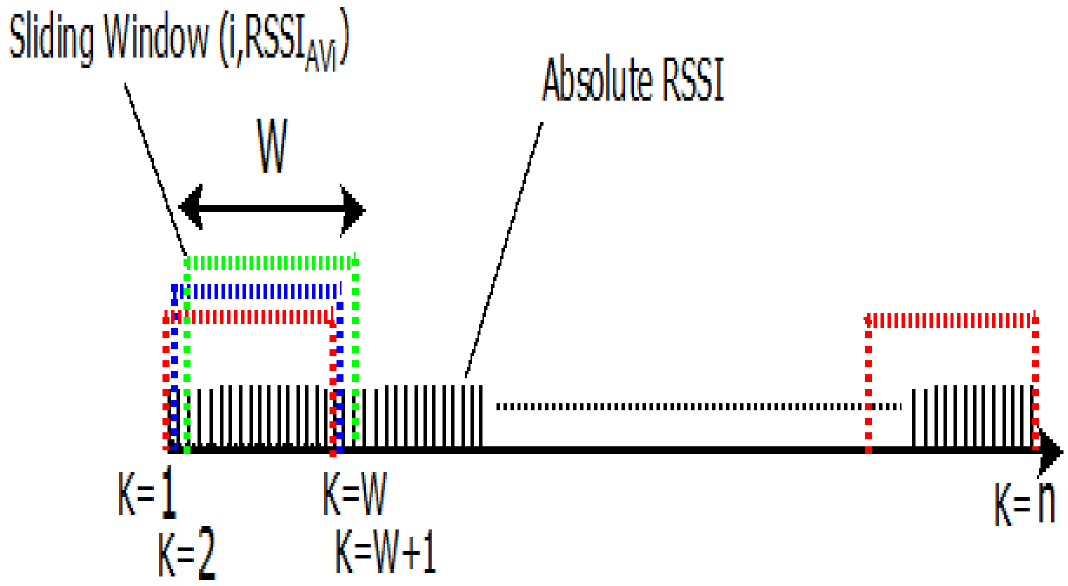


Figure 4.5: Moving average sliding window smoothing of single 3G cellular RSSI readings

usage [34]. Also (e.g., Wi-Fi) is a short range connectivity and may be unavailable in large open areas like highways, bridges and open squares.

- **Energy cost-less:** some sensors are extremely power-hungry especially for continuous scanning and consume much extra unnecessary energy in a problematic areas (e.g., GPS). In addition, it exhibits inaccurate performance in urban/indoor places which is well known. But, cost of sensing associated cell tower is negligible and mainly there is no extra energy consumption because mobile phones have to maintain connecting to associated cell tower for basic communications.

4.2.2 Serving single cell tower limitations

We first implement large number of experiments to sense single cell tower RSSI in numerous sites in Cairo such as open squares, bridges, highways and smart village (Rural-outdoor), through our university campus buildings, crowded areas and narrow streets (Urban-outdoor), inside stores, our college buildings ground floor and mosques (indoor). During these experiments, the key challenges we observe that single serving RSSI measurements suffer from two main limitations *handover and corner effect* [40] .

4.2.2.1 Handoff and Corner effects:

Handoff is the process of changing the channel (frequency, time slot, spreading code, or combination of them) of associated current connection while a call is in progress [44]. Handoff effect happens because such many mobile phones handover from one cell tower to another, this limitation clearly appears in case of in-vehicle user mobility where a number of occurrence handoffs will increase. Handoffs also happen due to many reasons like relative signal strength, relative channal capcity or MS moving out from connected BS range into another BS range as follows:

1. When the strength of the signal from the base station that the mobile is using starts to fall to a level where action needs to be taken. The cellular network looks at the reported strength of the signals from other cells reported by the mobile.

2. When the base transceiver station nears its capacity, which mobile is serving with, the network may decide to hand some mobiles over to another base transceiver station they are receiving that has more capacity, and in this way reduce the load on the base transceiver station that is nearly running to capacity.

3. When the user activity is In-vehicle and MS moving out from connected BS range of coverage into another BS range of coverage and so on [20], then such multiple handoffs will occure to ensure maintaining mobile device being associated to idenitifed base station.

Corner effect happens when user moves around environments and mobile phone may immediately pass near some obstacles such as corners which affect 3G cellular RSSI values to drop dramatically. These significant variation drops may look like false ambient environment detection. For example, while the user is in open areas, the detected RSSI readings are in rural readings range, then suddenly user passes near such big corner obstacle which make RSSI readings immediately drop to looks like those in urban or indoor readings range which gives false indication .

4.2.3 Moving average smoothing

Actually, we consider such handover and corner effect limitations as noises because they represent short-time rapid fluctuations (Milliseconds) and need some smoothing.

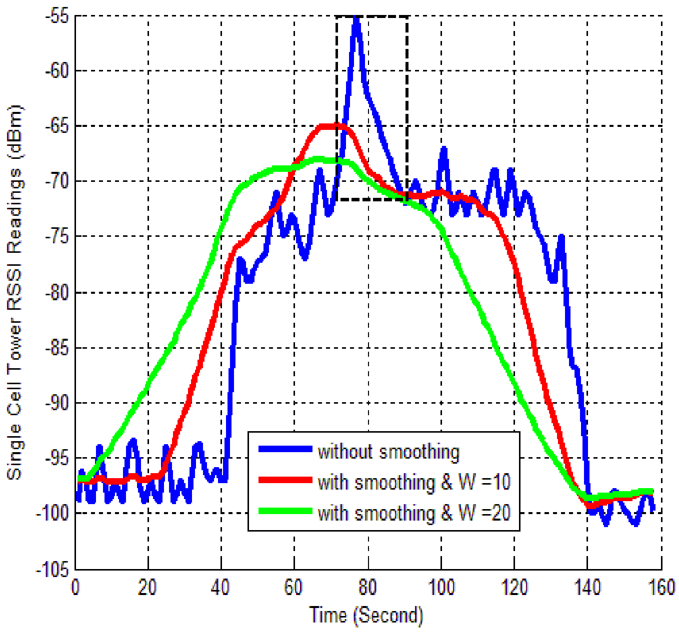


Figure 4.6: Effect of Moving average sliding window method on single cell tower readings to overcome handover and corner effect errors.

We remove this kind of noises using the most common noise removal method called *Moving Average Smoothing* [38]. We rely on the averaged value of the W RSSI samples defined as $RSSI_{AVi}$ rather than absolute samples. We denote i as index of slide window, W as sliding window size and K as index of absolute RSSI sample.

More precisely, if the input absolute RSSI values are $RSSI = RSSI_1, RSSI_2, .., RSSI_n$,n defined as total number of logged RSSI samples. The output of the moving average filter is: $RSSI_{AVi}$ = [$(RSSI_K + RSSI_{k+1} + RSSI_{k+2} + ... + RSSI_{k+w}) \,/\, W$], $1 \leq k \leq n$, as shown in Fig. 4.5. Figure 4.6 demonstrates the effect of handover and/or corner limitations where dashed rectangle clearly shows a spike in single 3G cellular RSSI readings and leads surely to erroneous decisions. After applying moving averaging smoothing, the spike is almost eliminated. Smoothing degree changes according to sliding window size, then we try to set W= 10, and W= 20. As shown in the Fig. 4.6, when sliding window size is large enough, we eliminate the spike more effectively. This section should close with the serving cell tower RSSI urban/indoor ambiguity problem that we demonstrate using Fig. 3.4, and how its a major challenge not studied before in the literature.

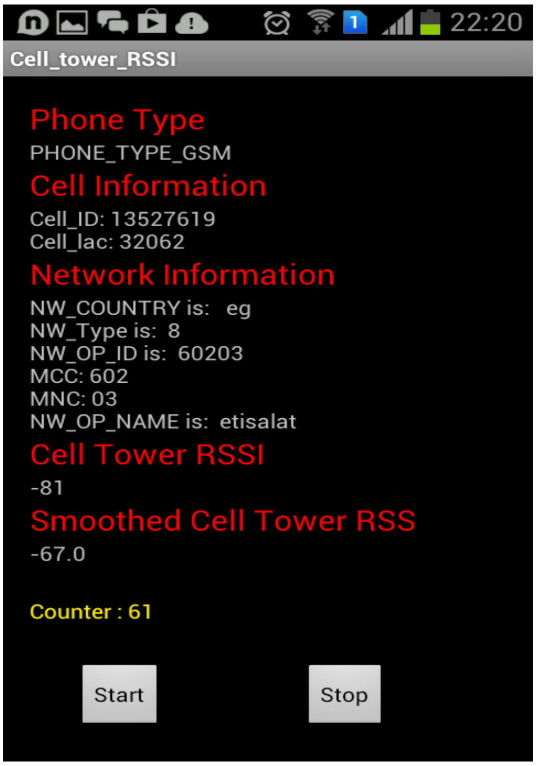


Figure 4.7: Single smoothed cell tower android application screenshot

4.2.4 Single smoothed cell tower android application

Figure 4.7 shows a screenshot of the developed single smoothed cell tower module android application where it's applicable to most brands of smartphones such as Samsung, HTC and LG [32]. The class we used was *TelephonyMananger* [5] where it provides access to information about the telephony services on the device. Applications can use the methods in this class to determine telephony services and states, as well as accessing some types of subscriber information. As shown, by using this module, we can get extra information related to single 3G cell towers, part of this information is fixed and the other is variable. Fixed information part is phone type (GSM or CDMA) and Networks information (Name, type, MCC, MNC and network operational name) while the variable part is associated cell information (Cell-ID and Cell-lac) and signal strength in dBm. Such smoothing operation is online, prompt and infrastructure-less (mobile-stand alone). When user activates such application a specific listener class called *PhoneStateListener* [4] immediately registered. Such listener class continuously retrieves information updates when such cell location or signal strength information changes. All this information will continuously be stored in a designed database or inside certain files inside device's memory for later processing.

4.3 Leveraging WiFi for the urban/indoor ambiguity problem

Motivated by the urban/indoor ambiguity problem faced by 3G RSSI solutions, which have not been addressed before in the open literature and we demonstrated using realistic results, we propose to bypass this hurdle using WiFi APs, typically deployed indoors.

4.3.1 Module Description

With the ubiquity of WiFi-enabled smartphones, and large scale access point deployment, WiFi-based sensing is one of the most promising indoor/outdoor detection signatures. Due to GPS limitations in urban/indoor environments, many urban tracking and indoor localization systems use WiFi received signal strength indicators (RSSI) updates to be one of the most attractive techniques due to it's reliance on ubiquitously deployed infrastructure.

In this module, we aim to collect Wi-Fi based sensing information (*i.e., BSSID, RSSI and SSID*) especially to present an accurate urban/indoor environments detection. As it's known, most high-end smartphones support Wi-Fi technology and nowadays most users automatically enable their Wi-Fi connections for self usage when becoming inside buildings like (homes, companies, universities and malls).

Then this will reduce the energy demand pain in our work. Furthermore, Wi-Fi sensing exhibits high power demand especially in case of periodic and continuous sensing and this acted as the most challenge which faced us during implementing Wi-Fi based sense module. Therefore, we present some solutions to reduce energy demand challenge through:

- We use less expensive sensors (e.g., accelerometer) more often, thereby adopt usage of expensive sensors (e.g, Wi-Fi) accordingly. More precisely, user has three main activities and they are *In-vehicle, On-foot and Still* provided by activity recognition module based on accelerometer embedded sensor on most smartphones that can be used to determine movement or orientation. Then the EPU unit on senseI/O system periodically monitors activity recognition output and should decide to enable/disable Wi-Fi sensing accordingly. Once the single serving cellular RSSI failed to detect surrounding environment and environment filtering phase exhibits an ambiguity case, then EPU first triggers activity recognition module to detect

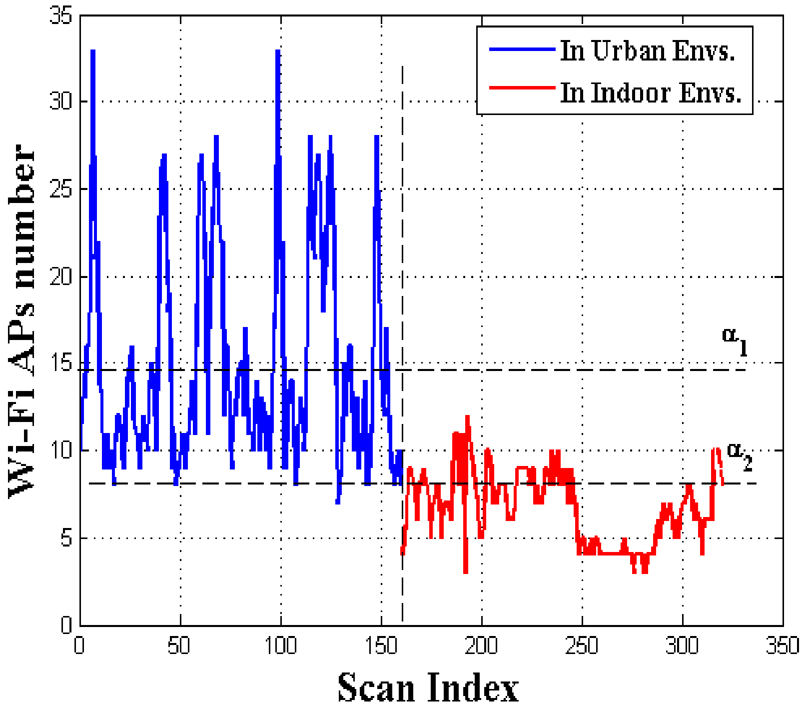


Figure 4.8: Distribution of all visible Wi-Fi access points number density at surrounding urban/indoor environments.

user activity type and wakes Wi-Fi sense if that detected user activity is On-foot or In-vehicle. Otherwise, if activity recognition movement is Still, EPU will trigger Wi-Fi sense to sleep.

- We use Wi-Fi based module through certain user movement scenarios (just through urban/indoor), for short scan periods and in case of lacking other modules. For example, in case of rural outdoor scenarios, light intensity module will be more useful than Wi-Fi becuase Wi-Fi RSSI will be non existent and difficult to be heard than those in urban/indoor environments as explianed next.

4.3.2 Android application

Figure 4.9 shows a screenshot of the developed Wi-Fi based sense module android application where it's applicable to most brands of android phones such as Samsung, HTC and LG [32]. The class we used was *Wi-Fi manger [3]* where this class provides the primary API for managing all aspects of Wi-Fi connectivity, it deals with several categories of items:

- The list of configured networks. The list can be viewed and updated, and attributes of individual entries can be modified.

- The currently active Wi-Fi network, if any. Connectivity can be established or torn down, and dynamic information about the state of the network can be queried.

- Results of access point scans, containing enough information to make decisions about what access point to connect to.

As shown in this android application, we try to get some information related to Wi-Fi based module, part of this information is BSSID (the address of the access point), (SSID) the network name and the final part is the detected signal level in dBm. The class we used to get all this information was *ScanResult* [2] which describes information about detected access points. Also, we can control Wi-Fi sensor and enable/disable it easily by using *wifiManager.setWifiEnabled()* method in order to extend battery life and reduce energy consumption. All the required parameters will be gathered with each scan and based on Wi-Fi proposed algorithm, the final detected ambient environment immediately will be inferred in real time as shown in the android application. All this information continuously will be stored in a designed database or inside certain files inside device's memory for later processing.

4.3.3 Module features

The intuition behind such module to identify that type of surrounding environment is one of the two following categories: urban or indoor. Our approach is based on some important Wi-Fi features to differentiate between them as follows:

1. **All visible Wi-Fi APs number:** the intuition is the number of all visible detected Wi-Fi nodes , based on their MAC addresses (BSSID) where each AP has unique MAC address, inside buildings will be less than those in urban outdoor environment because that mobile device inside building will be able to sense nearby and line of sight access points exist inside the same building only. In contrast, in urban outside areas, especially near to surrounding buildings and through narrow streets, mobile device is able to hear much more number of Wi-Fi access points.

2. **RSSI average of all visible Wi-Fi APs:** we can sense power strength (RSSI) of all visible Wi-Fi access points every scan at urban and indoor

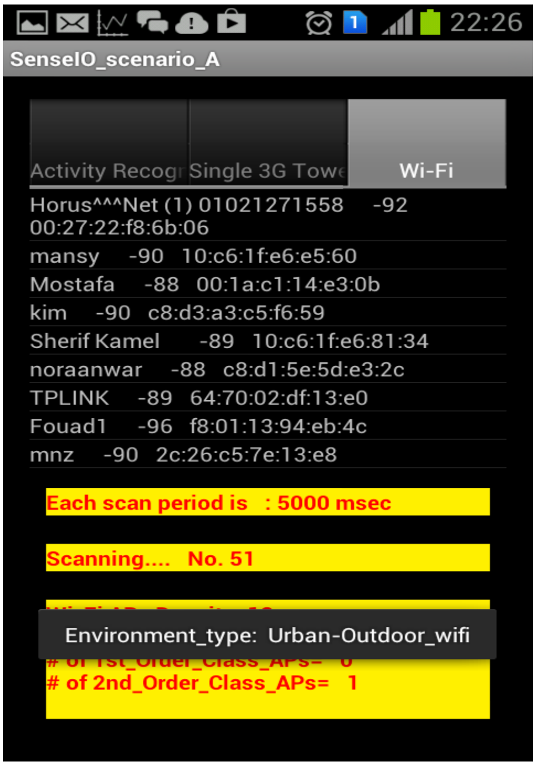


Figure 4.9: Wi-Fi based module android application screen shot

environments by using mobile devices. Then, this feature captures the intuition that these APs exhibit RSSI average in indoor areas stronger than in urban outside areas. This is because user inside the building will be nearby and line of sight with many of indoor nodes where correctness percentage varies according to user mobility scenario. On the other hand, APs exhibit very weak RSSI records but still heard by client's mobile when passing in urban outside areas like through buildings and narrow streets.

3. **Number of Wi-Fi APs in the 1st and 2nd classes:** we are able to measure, every scan, the received signals strength from all visible Wi-Fi access points. Then we aimed, in addition to estimating their average and number, to infer other useful features which classify Wi-Fi APs seen by smartphones user into two main classes called 1st and 2nd classes based on absolute RSSI value of each AP individually. Consequently, for each access point, if its RSSI value falls within the strong RSSI range, so it belongs to 1st APs class. Similarly, the AP which presents RSSI value within the lower RSSI range will belong into 2nd APs class. Hence, we count the number of Wi-Fi APs in each class to give us an indication whether the surrounding site is urban or indoor areas.

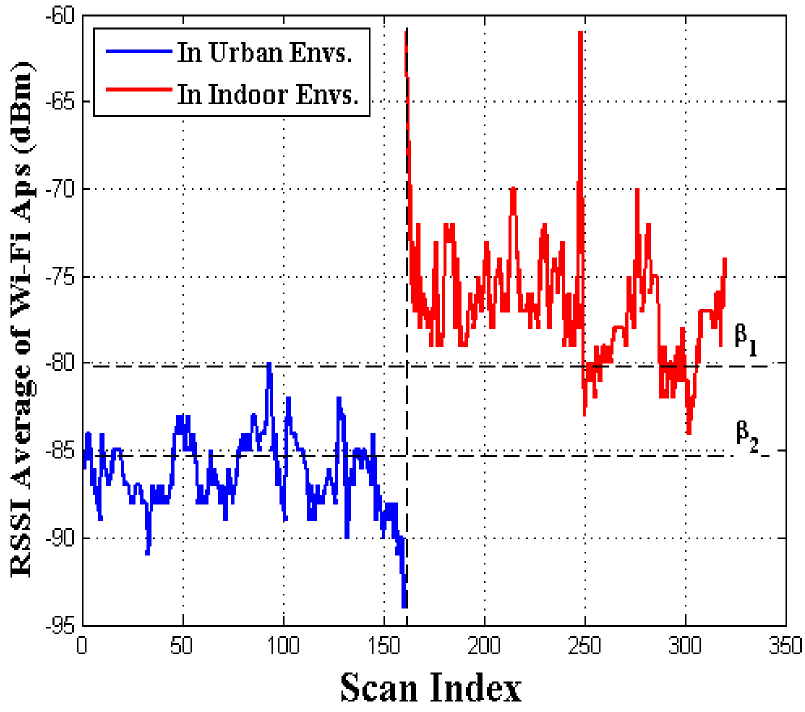
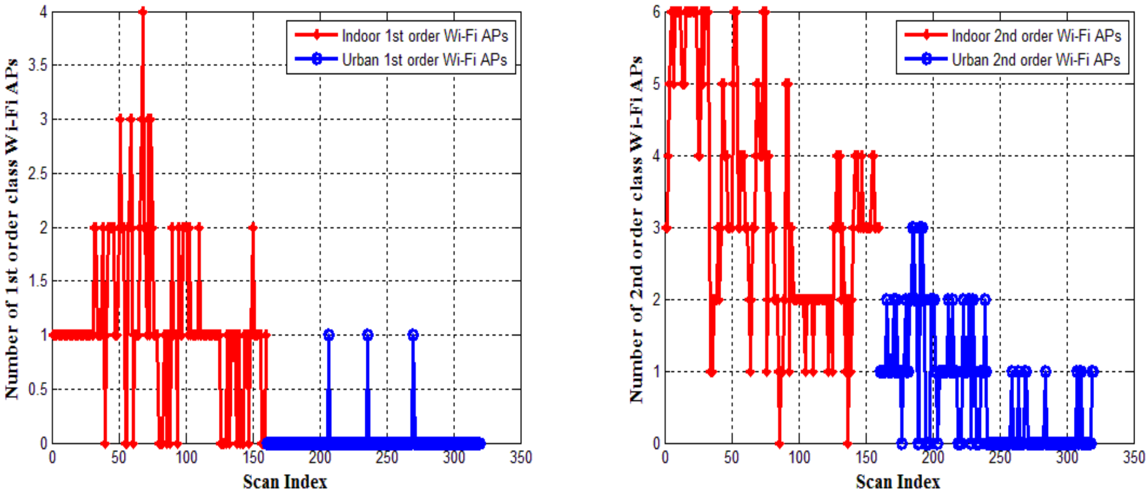


Figure 4.10: Distribution of RSSI average for all visibleWi-Fi access points at surrounding urban/indoor environments.

To infer these features, we developed an android application to log all visible Wi-Fi APs information (RSSI and BSSID) from surrounding urban/indoor environments. Then we experiment this application on many types of android smartphones to ensure avoiding the issue of varying measurements over different mobile models. During experiments, we implement more than 300 scans through 26 sites in indoor areas like (Malls, Universities, companies and Homes) and during the surrounding urban areas with different mobility scenarios (Still and walking).

Figure 4.8 shows how the Wi-Fi APs density varies significantly in urban and indoor areas respectively. This figure says clearly that, during the first 160 scans, urban sites exhibit all visible Wi-Fi APs density confined between thresholds $\alpha 1$ and $\alpha 2$, and sometimes upper than threshold $\alpha 1$ reach to 35 APs. In contrast, the other 160 scans, indoor sites often exhibit visible Wi-Fi APs density lower than threshold $\alpha 2$ reach some times less than 5 APs.

Figure 4.10 shows that average of all visible Wi-Fi APs RSSI exhibit distinctive signature in urban and indoor sites. We observe that most collected average values of all visible Wi-Fi APs RSSI in indoor sites are higher than $\beta 1$ threshold. This is seen logical because the majority of these nodes should provide strong



(a) (b)

Figure 4.11: (a): Distribution of the 1st order class Wi-Fi APs number at Urban/Indoor environments. (b): Distribution of the 2nd order class Wi-Fi APs number at Urban/Indoor environments.

RSSI readings to meet connectivity considerations. Unlike average values collected at urban sites where most of them are lower than $\beta 2$ because most detected signals are weak signals, but still can be heard, due to buildings structure and distances considerations.

Figure 4.11 shows the number of detected Wi-Fi APs belongs to 1st and 2nd classes during experiments implemented in many indoor and urban areas. In short, Fig. 4.11 (a) shows through the first 160 scans, in indoor areas, that the number of detected Wi-Fi APs belong to the 1st order class which is defined by RSSI values higher than (-69 dBm) varies between *one* AP and reaches *Four* APs sometimes. In contrast, through the second 160 scans in urban environments, the number of detected Wi-Fi APs belonging to the same class is usually *zero* AP and sometimes reaches *one* AP at most.

Similarly, Fig. 4.11 (b) shows through the first 160 scans, in indoor environments, the number of detected Wi-Fi APs belong to the 2nd order class which is defined by RSSI values within range (-80$\leq$ RSSI $\leq$ -70) *dBm* varies between *one* AP and reaches *six* APs sometimes. In contrast, through the second 160 scans, in urban environments, the number of detected Wi-Fi APs belonging to the same class is usually between *one* AP and sometimes reaches *three* APs at most.

During tracing all tested indoor and urban sites, we observe almost all indoor sites exhibit APs number of the 1st order class is larger than at urban sites.

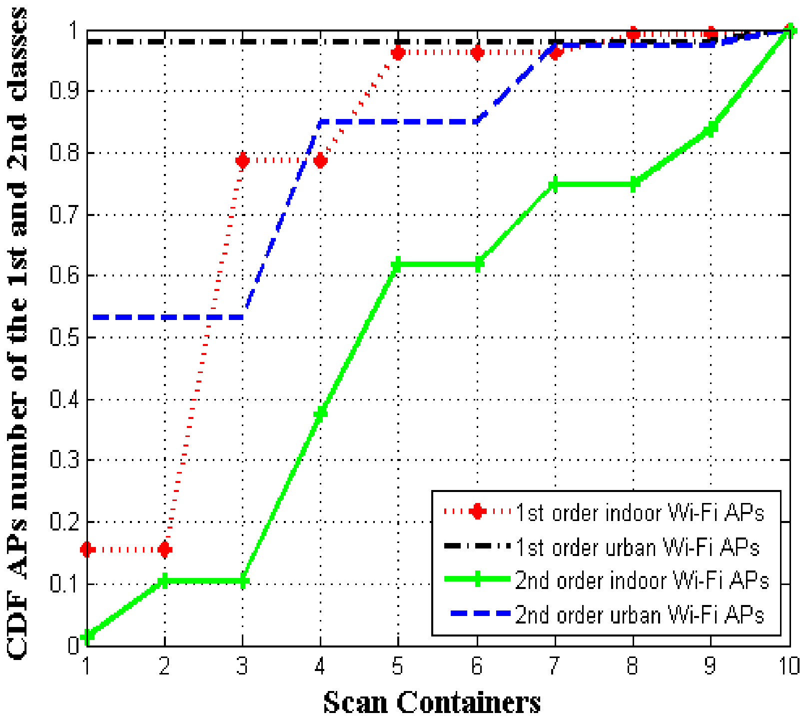


Figure 4.12: CDF number of Wi-Fi APs in the 1st and the 2nd order classes in urban and indoor environments.

This occurs because the probability of the expectation that the user, during indoor movements, becomes very close to such APs will be high. Furthermore, it is expected that the number of APs which have RSSI values belongs to the 2nd order class during indoor sites are larger than those in urban sites as shown in plotted Fig. 4.12. Figure 4.12 clearly shows the CDF plot of number Wi-Fi APs belongs to the 1st and the 2nd order classes at indoor sites versus urban sites.

Algorithm 4.2 Wi-Fi Based sense module algorithm

>> WAP_D: All visible Wi-Fi APs density per scan.
>> WAP_Avg: RSSI Average of All visible Wi-Fi APs per scan (dBm).
>> 1st_APs: Number of the 1st Order class Wi-Fi APs per scan.
>> 2nd_APs: Number of the 2nd Order class Wi-Fi APs per scan.

1. if (WAP_D$\geq \alpha 1$ & WAP_Avg $\leq \beta 2$)
2. Then, detected env is Urban-Outdoor with high level confidence.
3. elseif (1st_APs $\geq$1 or (2nd_APs$\geq$ 3 & WAP_Avg $\geq \beta 1$))
4. Detected Env is Indoor
5. elseif(WAP_D$\leq \alpha 2$ & 2nd_APs $\leq$ 3 & WAP_Avg $\geq \beta 2$)
6. Detected Env is Indoor.
7. elseif((WAP_D $\geq \alpha 2$ & WAP_Avg $\leq \beta 2$) or (2nd_APs $\leq$3 & WAP_Avg $\geq \beta 2$))
8. Detected Env is Urban-Outdoor.
9. End.

Based on these significant features, we construct Wi-Fi sense module algorithm as shown in algorithm 2.

4.4 Light detector: last resort for WiFi-less buildings

As a last line of defense against the urban/indoor ambiguity problem for WiFi-less buildings, we resort to the low-energy ambient light sensor onboard smartphones today.

4.4.1 Module Description

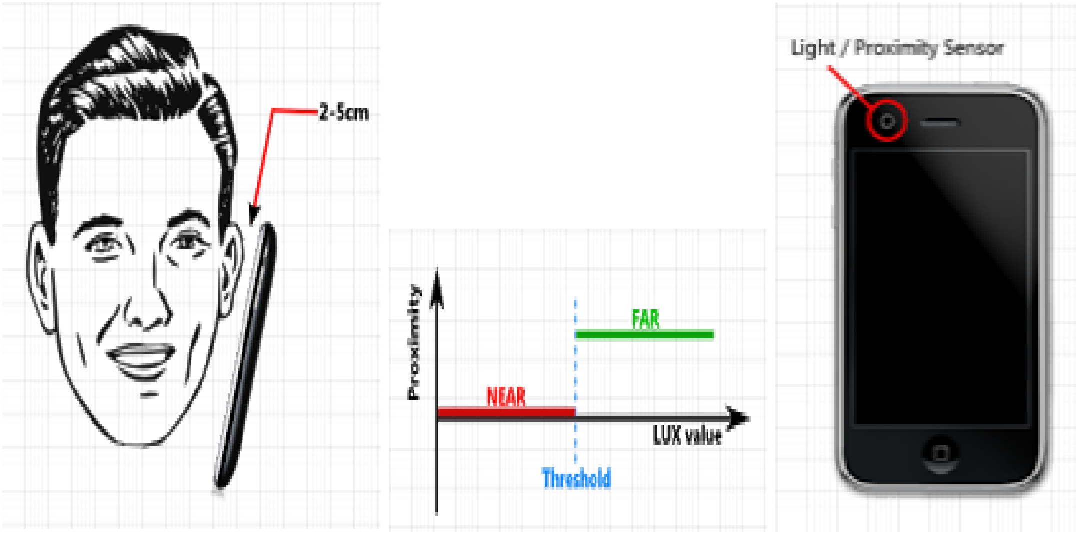
The Android platform provides numerous environment sensors that let us monitor various environmental properties. In this module, we use some of these sensors like light and proximity sensors equipped with Android-powered devices to monitor ambient light intensity and record relative measurements. Most environment sensors are hardware-based sensors where they will be available only if device manufacturers have built them into a device. Environment sensors are not always available on devices. Because of this, it's particularly important that you verify at runtime whether an environment sensor exists before you try to acquire data from it.

4.4.2 Related-used sensors

In this module, we used three main sensors are *light, proximity and system time clock* as follows:

4.4.2.1 Proximity Sensor

The proximity sensor is common on most smartphones, the ones that have a touchscreen [7]. This is because the primary function of proximity sensor is to disable accidental touch events. Proximity sensors would be useful to reveal the nearness of an object to the phone. We might often experience that screen of smartphones would turn off when we bring the phone to our ears when we are in a call and the screen will turn on when we take it back. This is because the proximity sensor recognizes the object near the phone, the optical proximity sensors can detect bodies in the vicinity of the device up to 5cm as shown in Fig. 4.13(a). Proximity sensor returns two binary values only for each data event either far or near as shown in Fig. 4.13(b). The position of light/proximity sensors are in the upper-left side on most of today's smartphone types as shown in Fig. 4.13(c).



(a) (b) (c)

Figure 4.13: (a): Proximity Sensor concept. (b): Proximity sensor outputs. (c): light/proximity sensors position.

In our work, we exploit this feature to give an indication whether the android device is in the pocket, on table with screen facing down or on the hand with screen up to ensure intensity record values correctness.

4.4.2.2 Light Sensor

Unlike most motion sensors and position sensors, which return a multi-dimensional array of sensor values for each sensor event, environment sensors returns a single sensor value for each data event. For example, light sensor return a single sensor value of ambient light intensity for each sensor event where unit of measured light readings is lx (Illuminance).

4.4.2.3 System time clock sensor

This sensor is common on most smartphones, it is responsible for returning the current date and time data according to the smartphone setting. In our work, we exploit such sensor and measurements to determine current user time either inthe daytime or at night to enhance light intensity module performance as it will be later.

(a) (b)

Figure 4.14: Light intensity android application screenshots

4.4.3 Light android application

Figure 4.14 shows a screenshot of the developed light intensity based sense module android application where it's applicable to most brands of android phones such as Samsung, HTC and LG [32]. The class we used was *Sensor manager [1]* 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 raw data acquired from the light, proximity, and system time clock sensors usually requires no calibration, filtering, or modification, which makes them easy to use. To acquire data from these 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.

As shown in this android application, we try to get some information related to light intensity module like maximum and current light measurements, proximity (Far or Near) and current system time clock. We always make sure to disable sensors that we don't need, especially when the application activity is paused. If

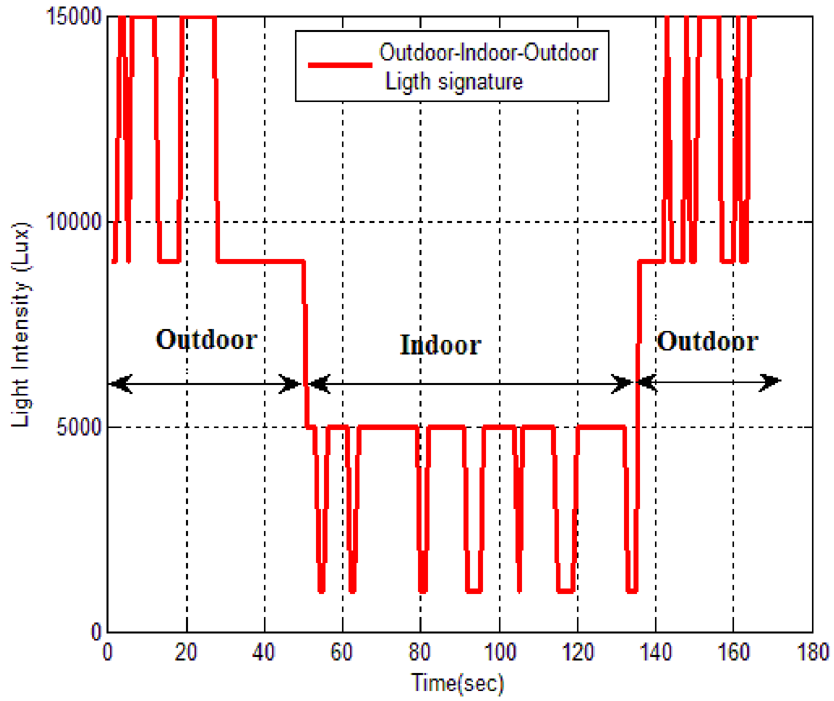


Figure 4.15: Light intensity pattern when user moves into indoor, then return out to outdoor during a sunny day with smartphone in hand and screen facing up.

it failed to do so, the battery could drain in just a few hours. We noted that the system will not disable sensors automatically when the screen turns off.

4.4.4 Light intensity module design

We normally observe that during daytime, brightness inside a building is much lower than outside because brightness source for outdoor sites is sunlight where intensity much higher than indoor light intensity that relies on artificial light 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. During experiments, we observe that environment sensors exhibit beneficial signature pattern when user moves from indoor out to outdoor areas or vice versa. Unfortunately, most of today's android smartphones don't support precise light intensity readings because full accessing to the light sensor on android OS platform is still locked. Thus, we rely on supported discrete light sensor readings levels only, where the light intensity value will round to the closest level. To further investigate that, we develop light intensity android application on different types of smartphones like (Samsung S plus, Samsung S2 and HTC Desire S), all have already been equipped with light and proximity sensors. Then, we conduct a set of

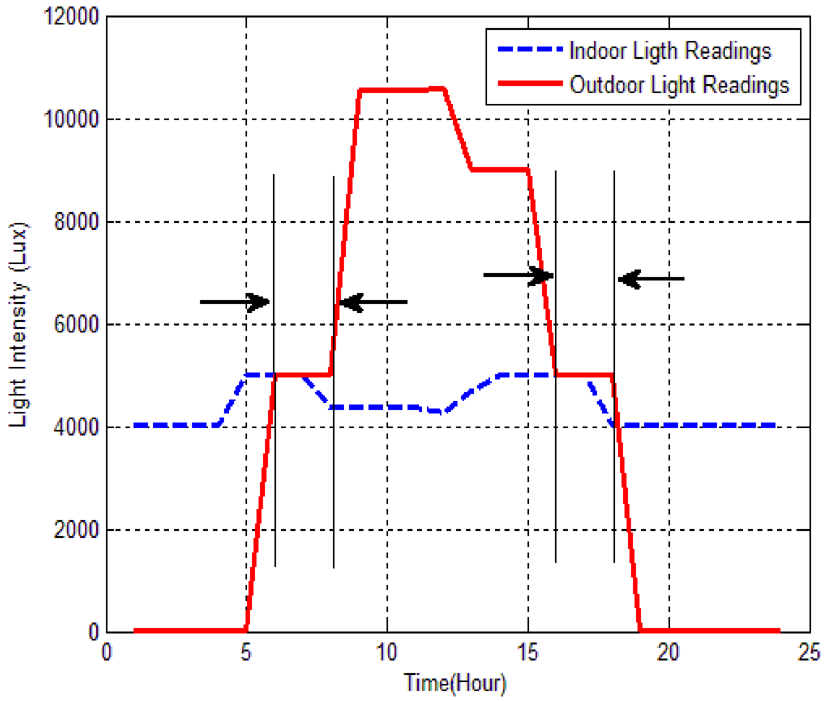


Figure 4.16: Light intensity readings signature all day (24 hour) with clear overlapping between outdoor and indoor environments.

experiments to collect light intensity readings at many indoor/outdoor sites during daytime and night periods under sunny/cloudy weather. For example, Samsung S plus smartphone provides five discrete reading levels (6,1000,5000,9000,15000) in case of mobile device in hand and screen facing up.

Figure 4.15 shows that the collected discrete readings clearly exhibit distinctive indoor/outdoor pattern during user transition with smartphone in hand and screen facing up. When user moves from outdoor to indoor at 50 sec the light readings significantly drop to be equal or less 5000 (Lux),then it raises up to be more than 5000 (Lux) when the user return again out to outdoor area.

Unlike previous work, we address and resolve some realistic challenges as follows:

- **Lack of fine-grained environment detection:** SenseI/O framework aims to present a fine-grained rural, urban and indoor environments detection. Unfortunately, light intensity module is limited to support such detection where light intensity sense module, in fact, can provide accurate indoor/outdoor detection only without additional distinction between rural/urban outdoor areas.

- **Ambiguity periods (namely dawn and dusk):** as shown in Fig. 4.16, we collect 24 hour light intensity readings to monitor light signature variations in indoor/outdoor environments all day by using discrete readings of mobile device only (Mobile stand alone) and discovered another challenge called ambiguous periods. This figure shows that at night (i.e., 1:00 to 5:00 and 18:00 to 24:00) smartphones provide outdoor light intensity readings where are much lower than in indoor ones. Similarly, in the daytime (i.e., 8:00 to 16:00) light intensity at outdoors is much higher than at indoors. These periods called *clear periods*, also we notice that there are *ambiguous periods* (i.e., 5:00 to 7:00 and 16:00 to 18:00) in the day where smartphones exhibit the same intensity levels in both indoor/outdoor environments and this leads to failing in detection. The major reason behind this is that, these periods represent critical times where outdoor environment brightness is much less. This ambiguity challenge wasn't investigated in previous work [45] because they used TelosB motes light sensor which precisely provides light readings (not discrete levels) to monitor light intensity all day. So, light module should first start checking current time by using *system clock* to check either *clear or ambiguous* periods.

Finally, based on those observations and challenges, we construct light intensity module algorithm as shown in algorithm 4.3.

Algorithm 4.3 Light intensity sense module algorithm

```
>> BL1 : First light intensity threshold
>> BL2: Second light intensity threshold
>> Li : Current light intensity measurement

Check light sensor availability on Smartphone
if available , check Proximity Smartphone status
 if FAR
  Check Current Time System clock
   if Clear Time
    Get Li
    if (Li > BL1) and Current Time is a Daytime
     The ambient Environment is OUTDOOR
    elseif (Li ≤ BL1) and Current Time is a Daytime
     The ambient Environment is INDOOR
    elseif (BL2 <Li ≤ BL1) and Current Time is a Night
     The ambient Environment is INDOOR
    elseif (Li ≤ BL2) and Current Time is a Night
     The ambient Environment is OUTDOOR
else (Light sensor unavailable, Ambiguity Time or In pocket)
Skip light intensity module
end
```

Chapter 5

SenseI/O Performance Evaluation

In this chapter, we evaluate the performance of SenseI/O framework through two main levels: (1) SenseI/O modules individually in order to assess their merits and limitations, (2) The entire SenseI/O system, under plausible scenarios.

The following details are the experiment setup, evaluates the performance of each module individually and the performance of specific scenarios of the whole system.

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 SenseI/O module over diverse scenarios. Some trips are made indoors (inside buildings, e.g., home, companies, universities and malls), others are made in rural areas (e.g., open areas, squares and bridges), others are made in urban areas (e.g., narrow streets, between tall buildings and crowded areas) and others are made in complex areas (e.g, tunnels and underground metro stations).

Usable Devices: We implemente and evaluate the SenseI/O prototype system on *Android Platform* and tested its performance on different types of mobile phones including Samsung Galaxy S1 Plus, Samsung Galaxy Duos GT-S7562, LG-E615 and T-mobile G1. These mobile phones are equipped with all sensors needed by SenseI/O, that is, proximity, time, accelerometer, 3G cellular, Wi-Fi.

The light sensor is available only in Samsung Galaxy S1 Plus device. In addition, these mobile devices support a variety of Android versions like 1.5, 2.3, 4.0.4 and 4.2.0, ensures the comparability and portability of SenseI/O to different O/S versions, phone vendors and models.

Datasets: to evaluate the performance of SenseI/O, we have collected 56 hours worth of data for different mobile user modes, namely riding transportation means, walking and stationary. This has been done in more than 52 different sites in the two largest cities in Egypt, namely Cairo and Alexandria. The measurements that we have collected comprise two different datasets.. The measurements that we have collected consist of two different datasets.

- Data collected by individual SenseI/O modules, namely single smoothed 3G cellular, Wi-Fi based, activity recognition and light intensity detector during winter 2014. Approximately 35 hours of data were collected over different rural, urban, indoor, tunnels and underground metro stations.

- Data collected for three specific SenseI/O test scenarios during summer 2014. This dataset constitutes approximately 21 hours collected from a number of paths of 2-5 km length, on the average.

5.2 Performance Results for Individual SenseI/O Modules

In this section, we compare the performance of the four major SenseI/O modules to the ground truth and select baseline schemes from the literature.

5.2.1 Performance of activity recognition

The approach of this module represents a typical system based on the accelerometer magnitude. We consider the following eight fine-grained user activities in our evaluation: *Stationary, Walk, Jogging, Running, Car, Bus, Metro and Train*. Unlike previous work, we omit the detection of these eight user activities, focusing instead on the detection of three main activities which are *In-vehicle, On-foot and Stationary* according to our objective (i.e., inferring indoor/outdoor detection) and the similarities on the acceleration magnitude values which are observed among those eight activities.

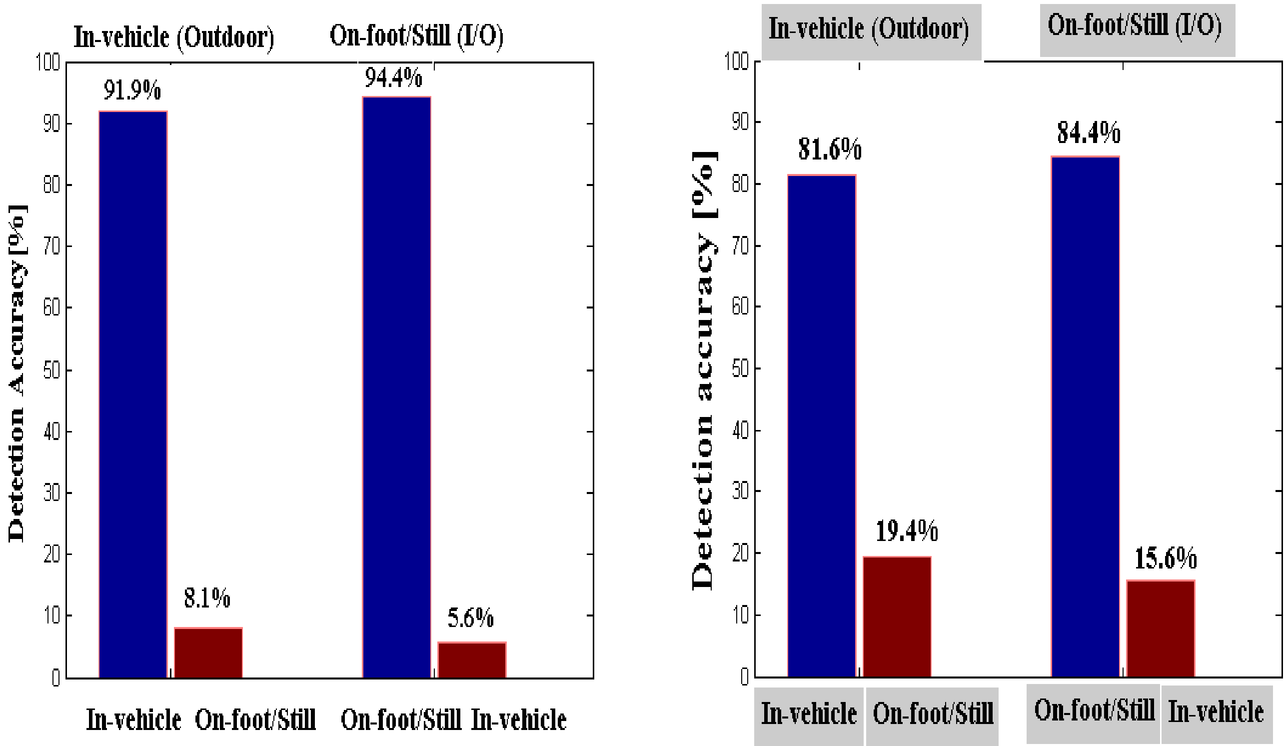
	In-vehicle	On-foot	Still	FP	FN	Correctness	Total
Train	146	0	12	7.6%	0%	92.4%	158
Metro	204	0	25	10.91%	0%	89.09%	229
Bus	153	0	15	8.9%	0%	91.1%	168
Car	119	0	17	12.5%	0%	87.5%	136
Walking	10	150	0	0%	6.25%	93.75%	160
Jogging	2	40	0	0%	4.76%	95.24%	42
Running	3	45	0	0%	6.25%	93.75%	48
Stationary	26	0	244	0%	9.62%	90.38%	270
Overall				9.97%	6.72%		1211

Table 5.1: Confusion matrix of classifying different personal user activities

We evaluate the performance of the two cases and they are : (1) normal activity recognition which directly relies on the module's outputs (i.e., before applying our designed certainty algorithm), (2): optimized activity recognition which relies on the outputs after applying certainty algorithm. The same data collection behavior is used for the both, tested through a large variety of everyday transportation lines for a period of several minutes per experiment for each participant. Moreover, because the phone in the pocket placement is considered noisy and not provided by *activity recognition API client*, the data is collected from only In-hand sensor placement regardless the screen is facing up or turning down to the ground. Furthermore, we have collected everyday transportation, on-foot motions and stationary activity data from four individuals. The participants were asked to collect such sensor data during their normal everyday behaviors and to record ground truth labels. The everyday data covers a total of over 20 different routes which were tested during various times and traffic conditions.

Table 5.1 shows the confusion matrix of classifying different personal user activities after applying optimized activity recognition certainty algorithm. The table clearly shows that the total number of tested traces for each activity type and the false detection (FP and FN) percentages. The overall FP (false positive means that the user in fact is in-vehicle whereas the detected activity is on-foot/stationary) and FN (false negative means that the user in fact is on-foot/stationary whereas the detected activity is in-vehicle) ratios are 9.97% and 6.72% respectively.

Figure 5.1 compares the detection accuracy of optimized activity recognition case with the detection accuracy of normal activity recognition case. The result shows that the optimized module is much better, where the detection accuracy ratio is enhanced in case of In-vehicle and On-foot/Still by approximately 7.3% and 8.8% respectively compared to the ground truth. Such enhancing leads to



(a) Optomized Activity Recognition Module

(b) Normal Activity Recognition Module

Figure 5.1: Detection accuracy evaluation of optimized vs. normal user activity recognition module in order to infer ambient Outdoor/Indoor environments.

increasing the opportunities of indoor/outdoor detection, where such In-vehicle activity detection should mean that the ambient environment is outdoors (outside buildings) with high level of confidence.

5.2.2 Performance of single smoothed 3G cellular

Environment type	Clear		Ambiguous
	Rural	Indoor	Rural/Urban,Urban/Indoor
Range	R_{RAR}	R_{IAR}	R_{UAR}
Value (dBm)	Higher -60	Lower -90	Between (-61 & -89)

Table 5.2: List of the thresholds used in the Smoothed 3G RSSI cellular filtering for ambient environments.

In this module, we omit the noisy absolute 3G RSSI measurements, focusing instead on single smoothed 3G RSSI measurements based on moving averaging sliding window method. As mentioned in chapter 2 that 3G RSSI measurements is problematic and suffer from sufficient ambiguity in detection especially in *Rural/Urban* and *Urban/Indoo*r environments. Therefore, we examine the detection performance of this module to report and evaluate the capability of resolving such challenge independently. We find it effective to distinguish *Indoor* environment from the *Rural/Urban* (Outdoor) environments.

A number of the used thresholds are applied to decide each ambient environment type and to differentiate clear from ambiguous ranges accordingly. These thresholds are found to be stable and their values are listed in table 5.2. The values of these thresholds are selected based on our experiments observations explained in Fig. 3.4 .

Figure 5.2 shows the evaluation results, once the mobile phones are in the rural/urban (outdoor) environments, the detection accuracy ratio is around 72%. When the phones are in the indoor environment, the detection accuracy is around 50.9% only whereas ratio 49.1% of traces is classified as a detection error, because the ambiguous problem is between indoor/urban-outdoor. The results clearly show that this module is *independently* ineffective to infer fine-grained rural, urban or indoor ambient environments or even indoors/outdoors. So, we decide to exploit this module only to infer a primary indication of the type of ambient environment (i.e., clear or ambiguous) as described in chapter 3.

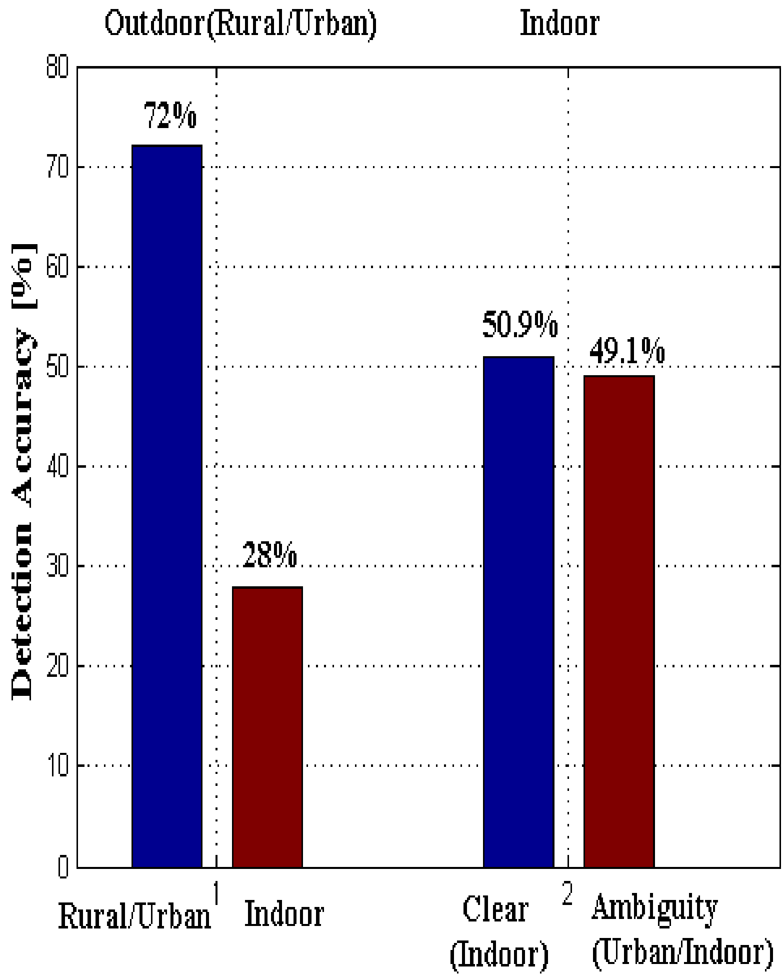


Figure 5.2: Single smoothed 3G cellular based detection between outdoor(Rural/urban) and indoor areas according to clear/ambiguity environments assumption.

5.2.3 Performance of Wi-Fi based

Symbole	$\alpha 1$	$\alpha 2$	$\beta 1$	$\beta 2$	1st_order_thr	2nd_order_thr
Value	15	8	-80 dBm	-85 dBm	1	3

Table 5.3: List of the thresholds used in the Wi-Fi based detection module algorithm.

In this module, we focus on collecting specific information parameters which are RSSI, SSID and BSSID per scan. This data is collected in specific environments are urban/indoor environments only, in order to resolve the ambiguous detection challenge as described in chapter 3. We experiment and evaluate this module independently over 36 urban/indoor sites which include buildings (e.g., houses, companies, malls and universities) in 2 different cities in Egypt (Cairo and Alexandria). Data is collected by different individuals when the phone is kept in hand and in pocket for a number of trips with different paths of surrounding indoor/urban environments. Some trips are made outside buildings (i.e., through urban areas near to buildings) and others are made inside mentioned buildings. A number of thresholds are applied to the designed Wi-Fi based algorithm to effectively decide ambient environment type. These thresholds are found to be stable and their values are listed in Table 5.3. The values of these thresholds are selected according to our experiments observations explained in section 4.3 .

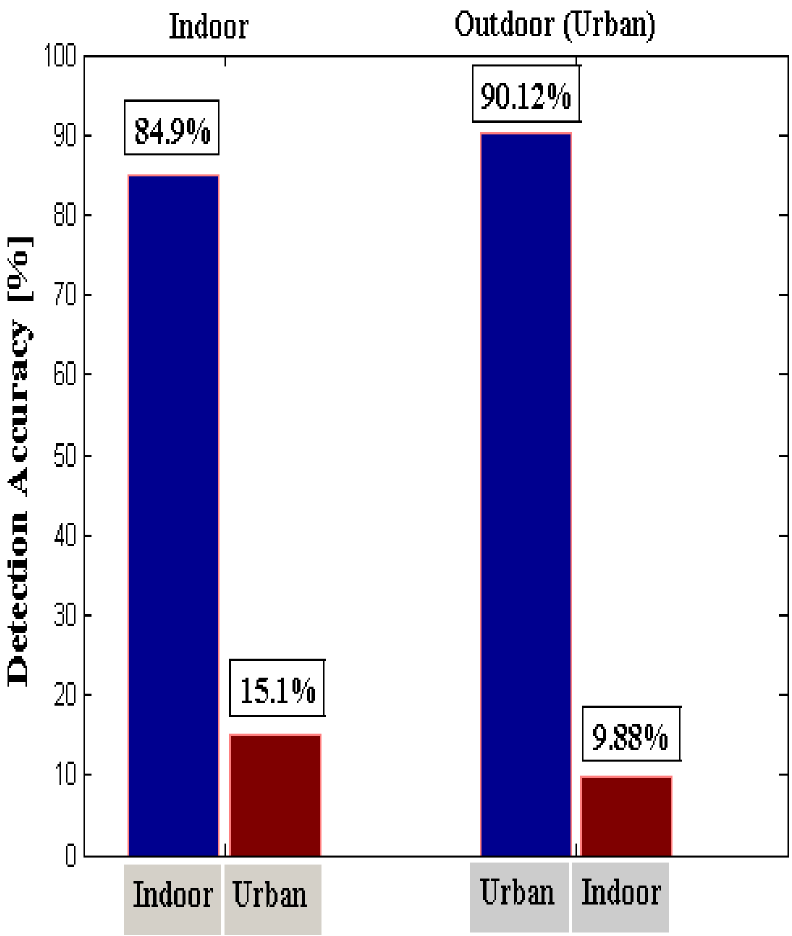


Figure 5.3: Wi-Fi based module detection accuracy for Urban-Indoor environments.

Figure 5.3 shows the result of applying the Wi-Fi based module algorithm on measured Wi-Fi measurements (RSSI, BSSID and SSID). Once mobile phones are in urban (outdoor) environments, the detection accuracy ratio is around 90.12%, whereas when mobile phones are in the indoor environments, the detection accuracy ratio is around 84.9% only. An average error ratio is arround 7.5% in both indoor/urban experiments. This average error detection significantly decreases when the Wi-Fi APs are available-rich and more ubiquous in the ambient environment.

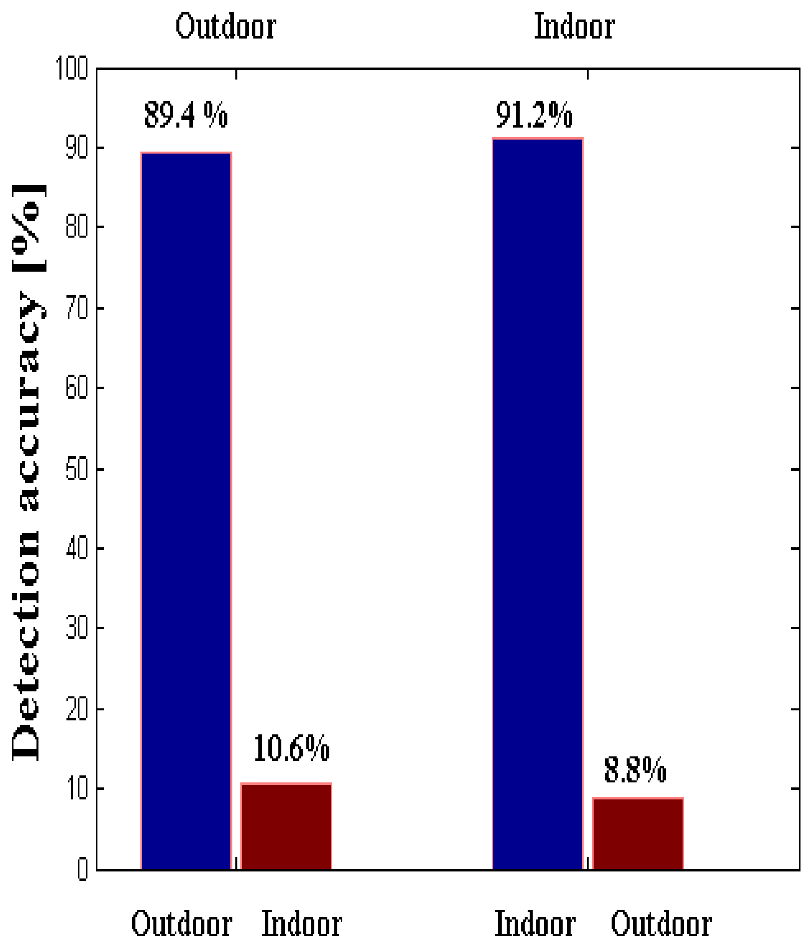


Figure 5.4: Detection accuracy evaluation of light intensity module for Indoor/Outdoor ambient environments.

5.2.4 Performance of light intensity

Light intensity module represents a useful detection module only when some conditions are met : (1) The availability of clear paths between mobile phones and ambient light sources (i.e., when proximity sensor readings are Far, not in pocket), (2) guaranteeing that used smartphones should be equipped by light sensors, (3) avoiding ambiguous time periods as described in section 4.4. Figure 5.4 depicts the detection accuracy of the light intensity module independently. We find out that this module can effectively distinguish the indoor environment from the outdoor environment. But, it can't satisfy our precise objective to infer a fine-grained Rural/Urban (outdoor) and indoor detection. The collected data, which are light, proximity and current time readings for every scan, is applied to the designed algorithm. Mobile phones should be placed in-hand with screen facing up to sky during all experiments. Figure 5.4 shows light module evaluation results, once mobile phones are in indoor environment, the detection accuracy ratio is around 91.2%. Also, when they are in outdoor environment, the detection accuracy ratio is around 89.4%.

5.3 Overall SenseI/O Detection Performance

Based on the state-of-the-art, each of the SenseI/O four major modules could provide an I/O detection services, yet, has its own limitations and challenges. For instance, the serving cell smoothed RSSI module works on virtually all smartphones, yet, it fails to distinguish rural/urban and urban/indoor areas. Also, In addition, the light intensity module is simple, accurate and energy-efficient, yet, it fails to perform when the phone is in the pocket or purse. Wi-Fi based module accurately can resolve an urban/indoor ambiguity. However, it fails to provide a detection for the ambient rural environments because of lacking APs density and suffer from energy consumption aspects. Finally, WiFi-based I/O detection resolves the urban/indoor challenge, yet, exhibits high energy consumption and cannot detect rural areas due to the lack of adequate APs density.

Motivated by the above limitations, SenseI/O hosts all four modules to get the bast of all worlds and collectively overcome their individual limitations.

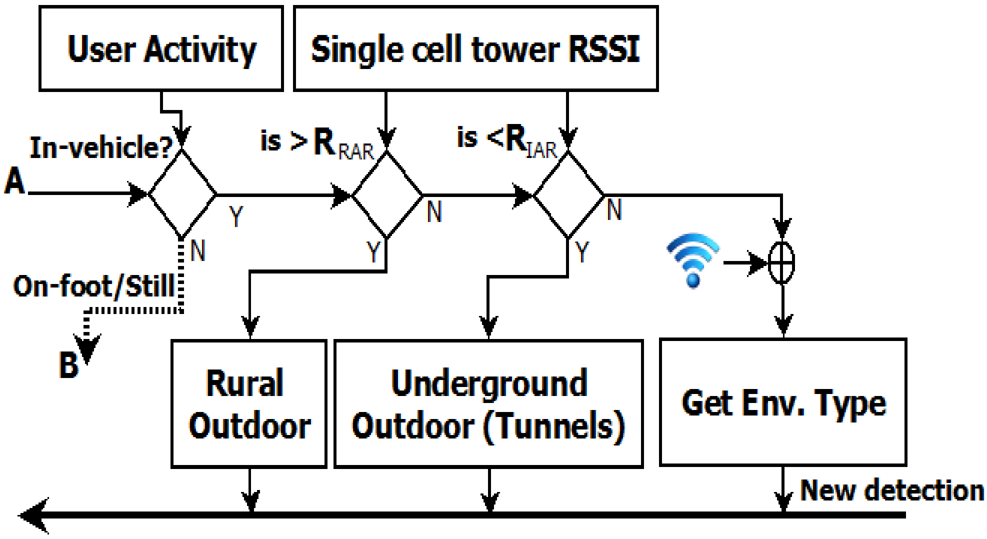
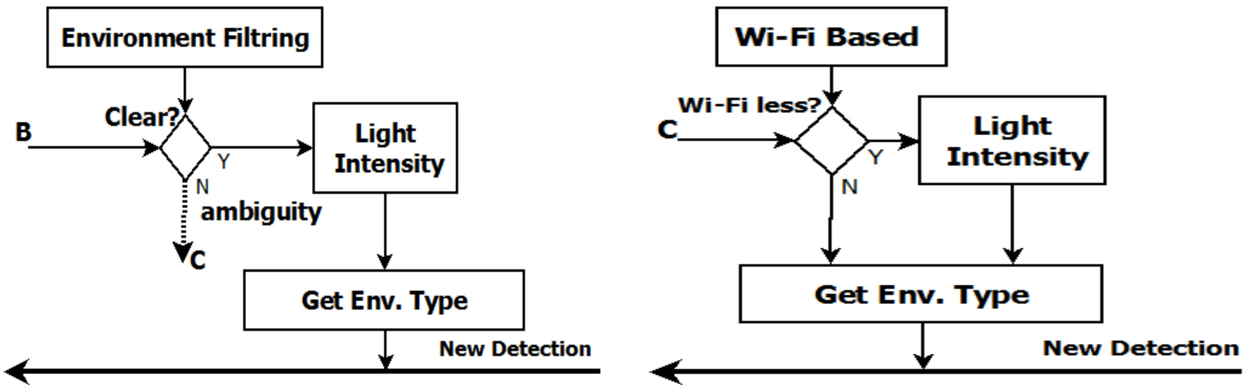


Figure 5.5: SenseI/O behavior under Scenarios A.

We test SenseI/O under three scenarios, namely A, B and C, tailored to unveil its main strengths and showcase its salient features. For instance, Scenario_A utilizes three modules which are activity recognition, Single smoothed 3G and Wi-Fi based. It can cover all user behavior under condition that only the user activity is *In-vehicle* which means that the ambient environment is highly outdoors. Then, the rest of scenario_A modules will be utilized in order to provide a fine-grained outdoor detection such as Rural, Urban and complex places (e.g., Tunnels) as shown in Fig. 5.5 . Otherwise, when the user activity is *On-foot/Stationary*, both scenarios B and C will directly be invoked. Also, these scenarios should require additional modules in order to overcome their individual disadvantages and provide ubiquitous detection as shown in Fig. 5.6 .



(a)

(b)

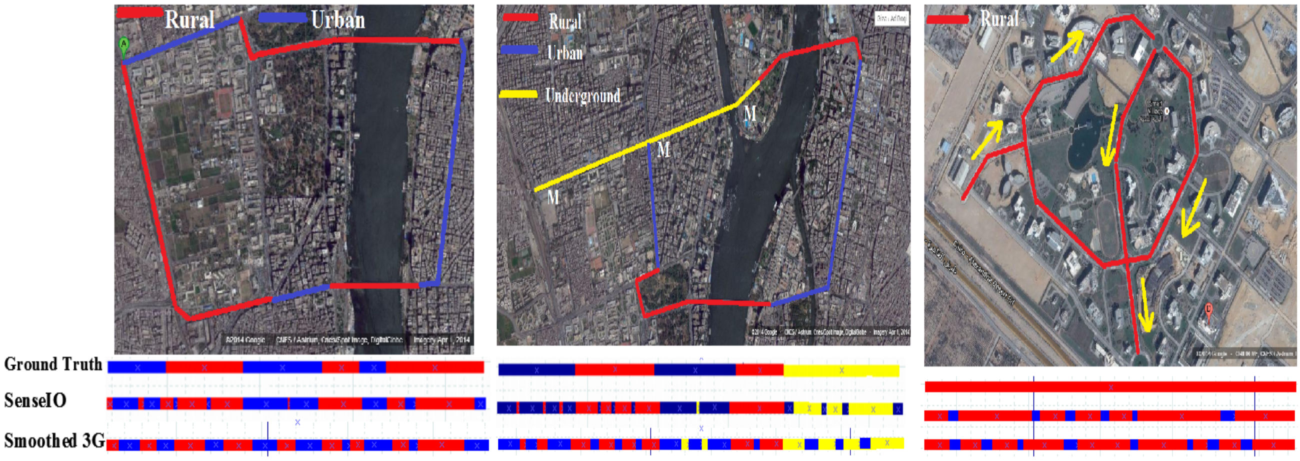
Figure 5.6: (a): SenseI/O behavior under Scenarios B. (b): SenseI/O behavior under Scenarios C.

SenseI/O exploits the output of environment phase to separate scenarios B from C as shown in table 5.2. For instance, if the output of environment phase is *clear*, based on the detected RSSI values, then scenario_B will be selected and the ambient environment is initially either *Rural-outdoor or Indoor*. But, because RSSI readings have less detection accuracy, so it will be not enough. Afterwards, scenario_B would use the light intensity module, which effectively provides indoor/outdoor classification output, in order to enhance detection certainty and reduce errors.

Similarly, if the output of environment phase is *ambiguous*, this means the scenario_C will be selected and the ambient environment is initially either *Urban-outdoor or Indoor*. Afterwards, scenario_C uses Wi-Fi based module to resolve such ambiguity because Wi-Fi sensor is available on all smartphons types more than light intensity. But, in case of traditional regions where Wi-Fi APs mostly do not exist, light intensity will be used instead.

5.3.1 SenseI/O scenarios evaluation

We consider some trips to evaluate the performance of SenseI/O scenarios A, B and C. During scenario_A, we experiment 3 separate traces (path1, 2, 3) while the user is In-vehicle according to the Fig. 5.5. Figure 5.7 shows the results of the tested environments using scenario_A compared to the ground truth for each path. During data collection of each path, the participants are in-vehicle (bus, car and



(a) Path1 (b) Path2 (c) Path3

Figure 5.7: (a): SenseI/O scenario_A path 1 with rural/urban areas. (b): SenseI/O scenario_A path 2 with rural, urban and underground metro stations. (c): SenseI/O scenario_A path 3 in a rural area.

metro) where the length of each path reaches to several Kms. Experiments are repeated on same paths at different times and under different weather conditions.

	Readings per path	Detection Ratio [%]					
		SenseI/O Scenario_A			Smoothed 3G Cellular		
		Rural	Urban	Underground	Rural	Urban	Underground
Path1	365	91.6	89.7	——	81.5	78.6	——
Path2	510	93.14	88.9	87.55	82.2	75.9	80.3
Path3	539	92.6	—-	——	80.2	——	——

Table 5.4: Detection accuracy matrix for fine-grained detection of different ambient environments between SenseI/O scenario_A and Smoothed 3G Cellular compared to ground truth.

Table 5.4 explains the amount of collected readings per path and the detection accuracy ratios of the Scenario_A and Single smoothed 3G cellular. Also, these ratios are compared with the ground truth for all these 3 paths.

Figure 5.8 shows the final aggregate values of the detection accuracy ratios for the both (scenario_A and smoothed 3G cellular) which included different outdoor environments such as Rural, Urban and Underground in all 3 tested paths.

Similarly, during scenario_B, we experiment the trace shown in figure 5.9 (a) while the user is On-foot/Stationary according to figure 5.6. The corresponding trace is in *Smart Village* in *Cairo* which represents a Rural/Indoor environment. Through this trace,we collected 479 of Single 3G cellular and light intensity readings from rural-outdoor areas and inside some buildings (Ground and upper

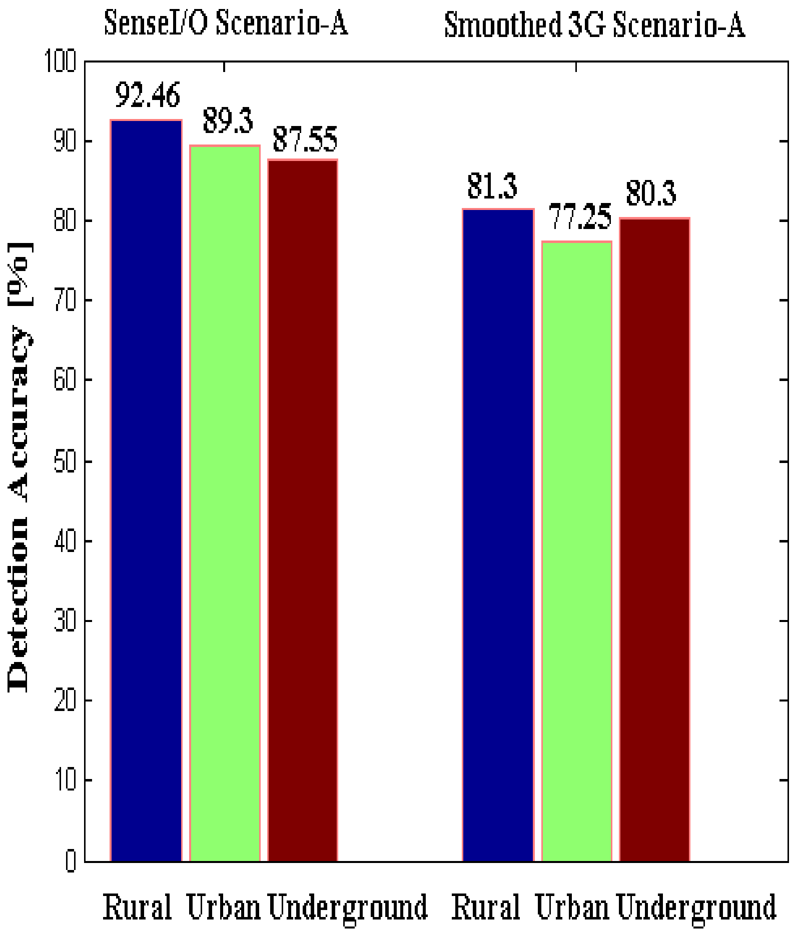
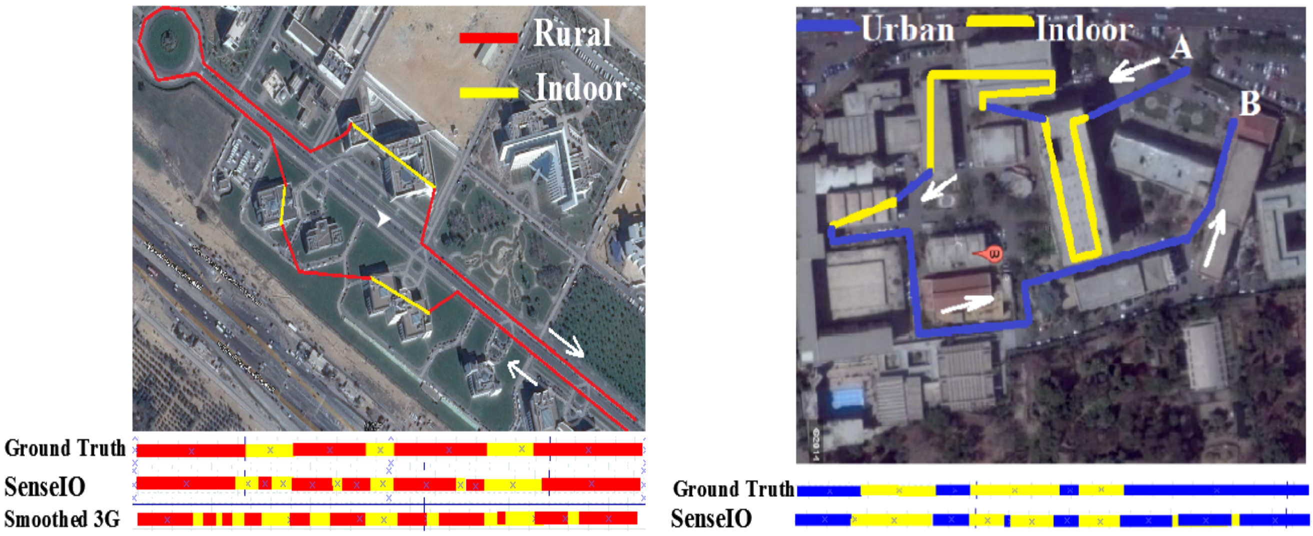


Figure 5.8: Detection accuracy of SenseI/O scenario_A vs. smoothed 3G scenario_A only for different outdoor areas such as Rural, Urban and Underground.

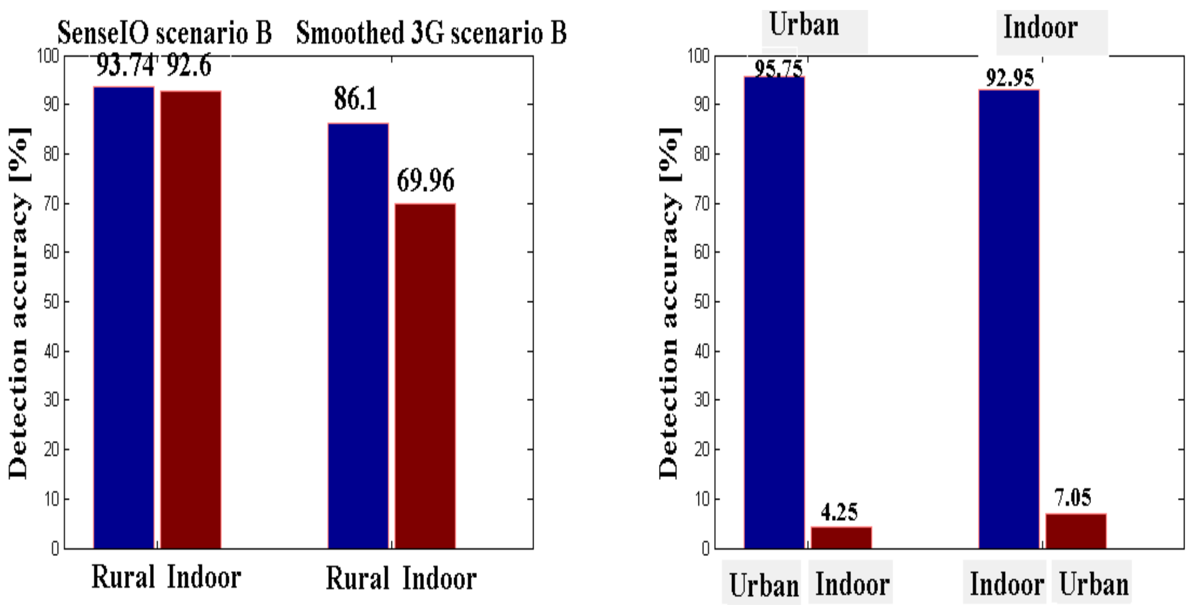
floors). Figure 5.10 (a) shows that the detection accuracy results of scenario_B are approixametly enhanced by 8 % in case of Rural-outdoor and by more than 20% in Indoor environments compared to the Single 3G cellular through the same tested environments.

Finally, during scenario_C, we experiment the trace shown in figure 5.9 (b) while the user is On-foot/Stationary according to figure 5.6. The corresponding trace is in *Cairo University Campus* which represents *Urban/Indoor* environments. Through this trace,we collected 303 of Single 3G cellular and Wi-Fi readings through urban-outdoor areas and inside some buildings (Ground and upper floors). Figure 5.10 (b) shows that the results of the tested environments using scenario_C satisfied high detection accuracy above 95% in case of urban areas and around 93% in indoors compared to ground truth.



(a) (b)

Figure 5.9: (a): Corresponding trace of the SenseI/O scenario_B in Rural/Indoor environments. (b): Corresponding trace of the SenseI/O scenario_C in Urban/Indoor environments.



(a) (b)

Figure 5.10: (a): Detection accuracy for SenseI/O scenario_B vs. smoothed 3G. (b): Detection accuracy for SenseI/O scenario_C.

Chapter 6

Conclusion And Future Work

6.1 Conclusion

In this thesis, we presented *SenseI/O* a realistic ubiquitous indoor outdoor detection system using smartphone. Our system employs the ubiquity of lightweight sensors equipped in sensor-rich today's smartphones to address upper layer challenges and resolve it as well. SenseI/O tries to use measurements of these sensors to infer current user ambient environment type. By intelligently utilizing a novel multi-models technique consists of four main models to infer not only binary indoor/outdoor environments but also fine-grained (Rural, Urban and Indoor). The developed system serves upper layer applications, makes a clever decision whether it's suitable to turn *ON/OFF* used sensors to minimize energy budget aspects and improve their performance. Furthermore, such fine -grained detection of surrounding environment is definitely considered a practical solution that makes those upper layer applications more realistic and practical in use.

We have also shown that using a utilized scenarios *(A, B and C)*, it becomes more accurate and possible to be applicable for most upper layer applications worldwide.

6.2 Future Work

In our experiments, however, we find that the current environment state of user being is usually related to the previous state. The stateless SenseI/O does not consider previous states and thus may suffer from noises. So, several interesting issues remain for future work including (1): developing SenseI/O to consider alternatively a *stateful* integration of these four modules which makes decisions on top of both current and previous observations. (2): the stateless SenseI/O provides us instant detection results. Users can activate SenseI/O on need basis. Therefore, functionality ensures the energy efficiency of stateless SenseI/O. So, expanding study of energy-accuracy trade-off aspects in both stateless and stateful will consider another interesting issue.

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