# IODetector: A Generic Service for Indoor Outdoor Detection

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## Abstract

The location and context switching, especially the indoor/outdoor switching, provides essential and primitive information for upper layer mobile applications. In this paper, we present IODetector: a lightweight sensing service which runs on the mobile phone and detects the indoor/outdoor environment in a fast, accurate, and efficient manner. Constrained by the energy budget, IODetector leverages primarily lightweight sensing resources including light sensors, magnetism sensors, celltower signals, etc. For universal applicability, IODetector assumes no prior knowledge (e.g., fingerprints) of the environment and uses only on-board sensors common to mainstream mobile phones. Being a generic and lightweight service component, IODetector greatly benefits many location-based and context-aware applications. We prototype the IODetector on Android mobile phones and evaluate the system comprehensively with data collected from 19 traces which include 84 different places during one month period, employing different phone models. We further perform a case study where we make use of IODetector to instantly infer the GPS availability and localization accuracy in different indoor/outdoor environments.

## Categories and Subject Descriptors

C.2.4 [**Computer Communication Networks**]: Distributed Systems – *Distributed Applications*; C.3.3 [**Special-Purpose and Application-based Systems**]: Real-time and embedded systems

## General Terms

Design, Implementation, Measurement

*Keywords*

Indoor and Outdoor Detection, Mobile Phones, GPS Availability

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## 1 Introduction

Current mobile phones are becoming important platforms that serve the ubiquitous sensing and communication needs of people [16]. The sensing and communication modules on mobile phones are usually developed to provide location and context-aware services. However, they may have heterogenous availabilities and perform differently in different environments. An effective indoor/outdoor detection scheme can provide primitive environment information for a variety of mobile applications, and thus potentially improve the performance of mobile phones. For example, in location-based applications, people usually source GPS for an accurate location reference when they are in the outdoor environment. In contrast, GPS performs poorly without line-of-sight paths to satellites when mobile devices are inside buildings [5, 30]. In mobile data services, mobile phones normally observe more WiFi Access Points (APs) with strong signals inside buildings whereas it is unlikely to have good WiFi connections in outdoor environments. Therefore, knowing indoor or outdoor can help to make smarter decisions on whether to turn on GPS or to perform AP scanning. In the context and activity recognition applications, the knowledge of the surrounding indoor/outdoor environment potentially leads to more accurate recognition.

Although many applications may benefit from accurate and prompt indoor/outdoor information, the research study towards generic indoor/outdoor detection surprisingly lacks. Many location related works simply assume a clear pre-knowledge on the indoor/outdoor environment has been known, but such an assumption hardly holds in practice. The unavailability or performance degradation of GPS is sometimes used to infer the indoor/outdoor environment, yet such an approach suffers from low accuracy, high energy consumption, and long response time.

In this paper, we present the **I**ndoor/**O**utdoor **Detector** (IODetector): a generic and light-weight service for the indoor/outdoor detection for mobile applications. Constrained by the energy budget on mobile phones, we primarily make use of three types of lightweight sensors, i.e., light sensor, cellular module, and magnetism sensor. Through one month experiment, we observe that the light intensity, the cell tower signal, and the intensity of magnetic field all individually exhibit distinct patterns in the indoor and outdoor environments. Those patterns turn out to be viable for an accurate classification of the ambient environments. More precisely, light signals exhibit distinct patterns when they are captured inside and outside buildings respectively. The reason behind is that the natural and man-made light sources contain inherent difference in nature. The received signal strength from a cell tower by a mobile phone changes dramatically from the outdoor to indoor environments as the dividing walls block the line-of-sight paths between the mobile phone and the cell tower. The intensity of magnetic field varies significantly across different places inside buildings due to the ambient electric appliances and steel structures while remains much less fluctuated across an outdoor environment. Motivated by those facts and observations, we target at achieving the indoor/outdoor detection by exploiting the three lightweight sensing resources.

Translating such an idea into a practical indoor/outdoor detection service entails a wide range of challenges, as the three aforementioned sensing resources show distinct pros and cons in different surrounding environments. The ambient light intensity may vary over time and is potentially influenced by various factors (e.g., people movement, phone pose, and cover of sight). The absolute cell tower signal strength may vary significantly at different places and across different mobile phone models, making it difficult to confidently set a uniform rule for the indoor/outdoor classification. The magnetometer readings are error-prone without careful calibrations. We develop practical solutions and address above challenges in IODetector. In particular, we extract unique identifiable indoor lighting features to detect the indoor/outdoor environment, and leverage particular light intensity patterns to improve the detection accuracy (§3.2). We exploit the abrupt period of the cell tower signal strength rather than its absolute value to distinguish the indoor/outdoor context that is invariant across different places and phone models. We track the cellular signals from multiple visible cell towers so as to enhance the robustness of the indoor/outdoor detection (§3.3). We take advantage of the magnetic disturbance inside buildings and make use of the movement status from accelerometers to ensure the detection performance (§3.4).

We constructively combine the three sensing components and develop an extensible indoor/outdoor detection framework. By taking other ambient sensing readings and evaluating the confidence levels of three sensing units, we intellectually aggregate their detection results and guarantee optimized reliance on those sensing units. The developed IODetector then works as an underlying service module that can be invoked by upper-layer applications to provide instant indoor/outdoor information (§3.5).

We implement and evaluate IODetector with the Android platform using different mobile phone models. We test IODetector in 19 traces including 84 different sites in our campus and city areas, and demonstrate quite encouraging results with various scenarios. Since IODetector only relies on lightweight sensors, the low energy cost allows continuous tracking of indoor/outdoor state transitions. In particular, we perform a case study and show that we can utilize IODetector to cheaply and accurately infer the current availability and accuracy of the GPS module for mobile phones.

The rest of this paper is organized as follow. In §2, we first detail the background and motivation of this work. We describe the technical solutions of IODetector in §3. We present the evaluation results in §4 and review related works in §5. Finally, we conclude the paper in §6.

## 2 Background and motivation

The indoor/outdoor detection can provide essential and primitive information for upper-layer mobile applications. For example, before turning on GPS, one may first check whether it is outside a building to ensure the GPS performance. Another example is that before searching for WiFi access points, one may check whether it is inside or near buildings and adapt the scanning strategy accordingly. Many other applications, including automatic image annotation [24], context and activity recognition [10], indoor localization [7], may also rely on the indoor/outdoor knowledge for a proper working scheme. If the detection overhead (depending on the application profile) is sufficiently small, most location and context-aware applications will greatly benefit from such indoor/outdoor detection.

While practically useful, the problem of indoor/outdoor detection has not been thoroughly studied yet. Existing localization and tracking applications may indirectly infer the ambient environment with the availability and accuracy of the GPS signal. It is well known that localization and tracking systems perform poorly in the indoor environment as the line-of-sight paths to GPS satellites are blocked. The unavailability of GPS signals and the the decreasing number of the visible satellites can thus infer the indoor environment [25]. Typical GPS modules, however, draw substantial amount of energy and take minutes to warm up and conduct the GPS satellite scanning on mobile phones [30]. As a result, detecting indoor/outdoor environments solely with GPS can be slow and inefficient. There are some other works relying on dedicated devices to assist the ambient environment detection. The deployment cost of such infrastructure-based approaches significantly limits the flexibility and scalability for general purpose detection [27]. On the other hand, some recent works study the problem of logical localization by sensing the surrounding environment [4, 19]. By painstakingly fingerprinting ambient signals (e.g., sound, floor color, user movement, etc), the mobile phones can learn the ambient environment through an intensive site survey. A central server is normally needed to store such ambient fingerprints and answer queries from users. Such an approach is unlikely to be generalized to deal with universal indoor/outdoor detection. Many works in image processing and pattern recognition study the problem of the indoor/outdoor image classification and automatic image tagging [23, 24, 28]. Such approaches cannot directly be applied to our problem, since they require explicit, manual input from users.

In this work, we propose IODetector, a lightweight indoor/outdoor detection framework, which independently runs on each mobile phone and provides generic service to upper-layer applications. As a basic component which might be frequently invoked by many applications on energy-constrained mobile phones, IODetector needs to meet several stringent design requirements.

- **High accuracy.** As a generic framework that many

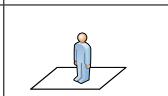
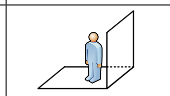
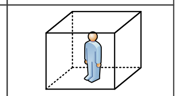
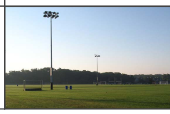
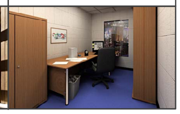
| Environment | **Outdoor** | **Semi-outdoor** | **Indoor** |
|---|---|---|---|
| Definition | Outside a building | Near a building | Inside a building |
| Example |  |  |  |
| Scene |  |  |  |

**Figure 1. Three indoor/outdoor environment types and the representative scenes.**

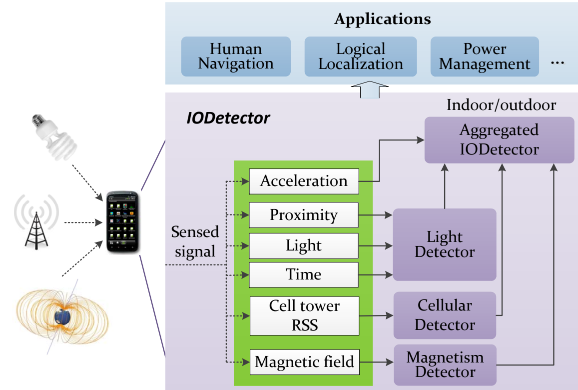



**Figure 2. System architecture of IODetector.**

other applications would potentially rely on, IODetector should accurately detect the indoor/outdoor environment.

- **Prompt response.** IODetector should promptly distinguish the indoor/outdoor environment. An outdated detection result may be less valuable for many instantaneous applications.
- **Energy efficiency.** Being a generic service running on the mobile phones with constrained energy budgets, IODetector should be energy efficient, and better use only inexpensive sensing resources on mobile phones.
- **Universal applicability.** IODetector should avoid relying on a priori knowledge or site survey, special sensors or explicit user feedback to ensure wide applicability.

Before we present the design of IODetector in detail, we formally define the indoor/outdoor environment types studied in this paper. To provide fine-grained context information for upper-layer applications, we classify the environment into three categories, i.e. outdoor (outside a building), semi-outdoor (close to or semi-open building), and indoor (inside a building). Figure 1 illustrates representative scenes for those three different environment types. The reason to introduce the category of semi-outdoor is mainly due to potential application needs. For instance, GPS may not necessarily perform well even if it is outdoor. The reason is that the number of visible line-of-sight satellites might be insufficient in many semi-open environments. In such cases, we may not prefer to launch the GPS component. On the contrary, the situation could become different for other types of applications. One typical example is that mobile phones normally can find WiFi APs in indoor environments. Yet in most semi-outdoor environments, mobile phones may still detect a number of APs with good connections. Additionally, Some rooms with large window could be treated as semi-outdoor, since it is possible to receive good GPS signal in such environment, although it can be less accurate as in fully outdoor environments. Thus, the designed IODetector does not simply output a binary result (i.e., indoor or outdoor) for upper-layer applications. Instead, it provides finer grained classification on the indoor/outdoor scenes and thus better meets different application needs.

# 3 System design

In this section, we first introduce the system architecture and the design details for each component in IODetector. Then we specify how to aggregate the outputs obtained from each component to construct a comprehensive and effective indoor/outdoor detector.

## 3.1 System overview

Figure 2 illustrates the system architecture of IODetector. To meet stringent design requirements, IODetector utilizes a series of lightweight sensors for the indoor/outdoor detection. IODetector primarily makes use of three types of lightweight detectors: *light detector*, *cellular detector*, and *magnetism detector*. Light detector adopts light sensors to capture ambient light signals to determine the surrounding environment type. It also utilizes other two lightweight sensors, the proximity sensor and the system time clock, to assist the detection. Cellular detector detects the attenuation of cellular signals caused by obstacles (e.g., walls). It normally indicates the entrance/exit of the device to/from an indoor environment. Magnetism detector exploits the dramatic disturbance of magnetic field inside or in the vicinity of buildings during the movement of the mobile phone. It thus can distinguish the indoor/semi-outdoor environments from the outdoor environment. Note that each component of IODetector shows unique advantages and disadvantages in different environmental contexts. They process the sensor data and report the respective *partial* detection results. IODetector then aggregates those results and generates a final decision, which is provided to upper layer applications through a service interface. In the rest of this section, we will describe the design details of each component.

In order to reveal the signal features with different environments, we empirically study the patterns of light signal, cell tower signal and magnetism signal in different environments for 2 weeks. All of the signals are collected in 31 different environments under different weather conditions, including sunny, cloudy and rainy days, and at different times of the day. The studied sites include indoor offices, homes, stores, outdoor campus, some downtown areas, etc. For each site, we collect light signal 6 times, magnetism signal 4 times and cell tower signal 4 times on average with different sampling rates. The light signal is collected with different ori-

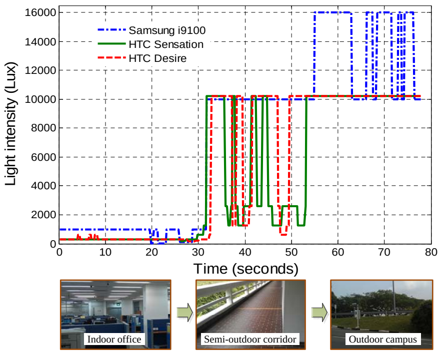



**Figure 3. Mobile phone light sensor readings in different scenes.**

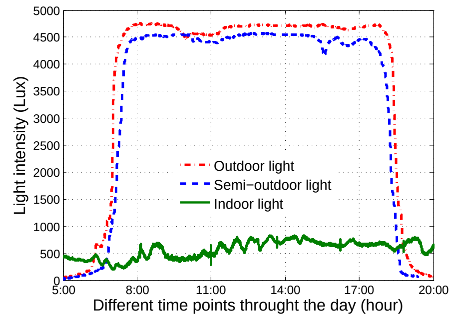



**Figure 4. Outdoor and indoor light variation throughout the whole day.**

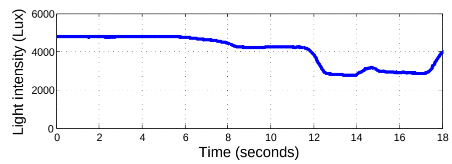



**Figure 5. Light intensity during the rotation in the outdoor environment.**

entations of the light sensor and the cell tower signal is collected when the user walks from outdoor to indoor and vise versa.

## 3.2 Light detector

In outdoor and semi-outdoor environments, the sunlight is the primary light source in the daytime. In the indoor environment, however, we normally rely on artificial light sources (e.g., fluorescent lamps). In this subsection, we study how to take advantage of various light sources for the indoor/outdoor detection.

### *3.2.1 Light intensity measurement*

Our primary observation for light detector is that the light intensity inside buildings is typically much lower than that in either the outdoor or semi-outdoor environment even in cloudy or rainy days. Such a phenomenon can still be observed when the light sensor is rotated towards the ground. The major reason is that the intensity of sunlight within the visible spectrum is normally much higher than that from ordinary lighting lamps. In addition, light sensors can also detect the light in the invisible spectrums (e.g., infrared and ultraviolet). As a result, even when the brightness of sunlight and artificial light looks similar, the luminous flux from sunlight is much higher than that from artificial light sources during the daytime. Therefore, the indoor environment can be accurately distinguished from the outdoor/semi-outdoor environment by using the observed light intensity.

To verify the statement above, we conduct a set of experiments. We measure the light intensities in different environment types under different weather conditions. In Figure 3, we plot the light sensor readings from three different types of mobile phones (HTC Desire S, HTC Sensation G14, and Samsung Galaxy S2 i9100). Current Android platform, however, only provides coarsely quantized light sensor readings for upper-layer applications. For instance, Samsung Galaxy S2 i9100 only provides five quantized levels (10, 100, 1000, 10000, and 160000), and the light intensity will be rounded to the closest quantized level. From Figure 3, we can see that readings of the light intensity from all three mobile phones are discrete and coarse. Yet the readings still show clear and consistent transition behaviors in the experiments. When the user moves outside of the office at 30sec, the light sensor readings increase significantly at all the three mobile phones.

To further investigate the effectiveness to utilize the light intensity to distinguish the indoor environment, we further collect light intensities in three different environments using three TelosB motes in a cloudy and rainy day. Since it is flexible to achieve a fine-grained control of the light sensors on the TinyOS platform, we can record instant light intensities during the entire experiment. We note that the results and observations obtained in this experiment can also be used to improve the system performance. On one hand, recent works have shown that mobile phones can be directly connected to the sensor motes [10]. On the other hand, we believe that the light signal intensity fidelity obtained with the cheap onboard sensor on TelosB can be easily achieved if we unlock the full access to the light sensor on the Android OS platform. In this experiment, the sampling rate of the light sensor is set to be one sample per second. From Figure 4, the light intensities in both the outdoor and semi-outdoor scenarios are above 2000Lux and much higher than that in the indoor environment in the daytime (from 8:00AM to 17:00PM). We also find that during the night (from 20:00PM to 5:00AM), the outdoor light intensity is much smaller than indoor light intensity. In addition, the light intensities in the indoor and outdoor environments are both relatively stable. This observation is consistent with the indoor lighting standards and measurements [2], which shows that in the vast majority of cases the indoor light intensity is within the interval from 100Lux to 1000Lux.

In practical scenarios, the mobile phone does not necessarily face to the sun and the phone may be dynamically rotated. To examine the robustness of our method, we record the detected light intensity when rotating a TelosB mote in Figure 5. The light sensor initially faces to the sun and is gradually rotated until being towards an opposite direction. Figure 5 shows that even when the light sensor is opposite to the sun, the light intensity is relative high as well, e.g., around 3000Lux. Compared with the light intensity ob-

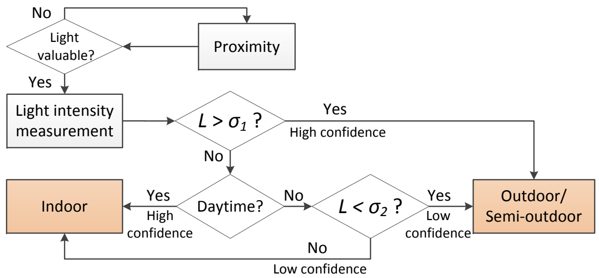



**Figure 6. Detection flow of light detector.**

served in the indoor scenario as shown in Figure 4, we can still distinguish them easily. Therefore, the detection of the light intensity is robust to the mobile phone dynamics.

### 3.2.2 *Detection process in light detector*

Since mobile phones may be placed in pockets or bags, the light sensors may not be always available . We use proximity sensors on mobile phones to detect the presence of nearby objects which may block the light sensor. We associate a confidence level $C_L \in [0,1]$ for the detection result. Different light signals will lead to different detection confidence levels.

Figure 6 summarizes the work flow of the light detector component. We denote $L$ to be the detected light intensity. The light detector first queries the proximity sensor to check whether the light sensor is currently available for accurate detection. If the light sensor is available, the light intensity $L$ is then compared with a threshold $\sigma_1$. If $L > \sigma_1$, light detector confirms an outdoor/semi-outdoor environment detection with a high level confidence $C_L = 1$; if $L \leq \sigma_1$, it needs to further differentiate whether it is an indoor environment or an outdoor/semi-outdoor environment at night. To this end, light detector refers to the system clock. If the clock indicates a daytime, the detector infers the environment to be indoor with a high confidence. If not, light detector compares $L$ to a threshold $\sigma_2$. If $\sigma_2 < L \leq \sigma_1$, it indicates an indoor environment with a confidence level $C_L = \frac{\sigma_1 - L}{\sigma_1}$; if $L \leq \sigma_2$, the mobile phone is in an outdoor/semi-outdoor environment with a confidence level $C_L = \frac{\sigma_2 - L}{\sigma_2}$.

From Figure 4, the sunlight intensity in both daytime and night is distinguishable from that of indoor lights. According to our empirical study, we set the threshold $\sigma_1$ to 2000Lux and $\sigma_2$ to 50Lux.

In addition to the light intensity, we also observe that the indoor fluorescent light powered by the alternating current (AC) power exhibits a periodical pattern. We measure the frequency of indoor fluorescent light flicker and find that the flicker of indoor fluorescent light intensity is relatively stable in various conditions [17]. This pattern can be further used to classify indoor/outdoor environment. By using FFT, we can extract the frequency of light flicker. If the frequency matches the AC power frequency, it highly indicates an indoor environment. We leave the details of the approach for future elaboration due to the page limitation.

Light detector is designed to differentiate the indoor environment from outdoor/semi-outdoor environments. High light intensity normally indicates outdoor/semi-outdoor environments; while extremely low light intensity suggests an indoor environment. The limitation of the light detector is that the light signal is not always available. In addition, we cannot confidently distinguish the outdoor and semi-outdoor environments by merely using light sensors.

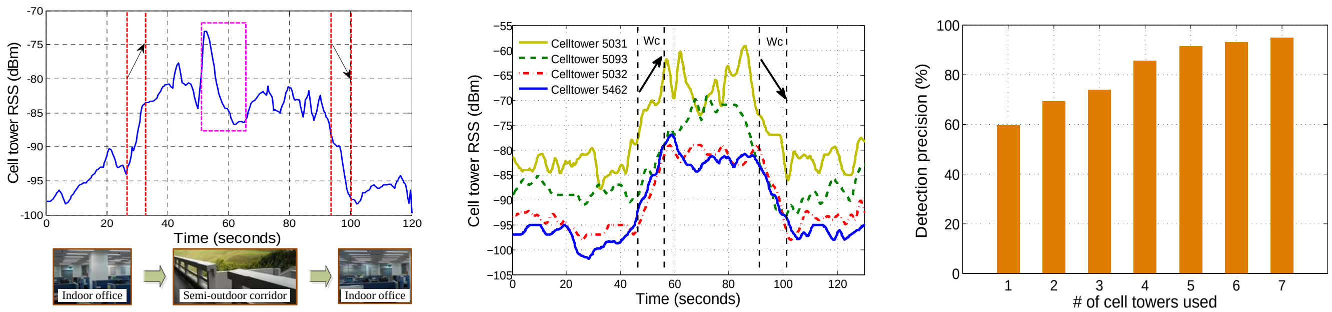
## 3.3 Cellular detector

Mobile phones maintain connections to nearby cell towers to support the primary functionality, i.e., the telephone calls. The marginal energy consumption of collecting received cellular signal strength (RSS) is thus negligible. Previous works utilize the information about visible cell towers and their signal strength for localization and tracking [29]. Such approaches, however, suffer from low accuracy due to various factors. One primary issue is the dividing wall effect, which refers to the fact that the dividing wall significantly blocks the cellular signal and hence leads to dramatic signal strength drop when people get into indoor environment. Unlike the localization work where the dividing wall effect is undesired, in this paper, we embrace and exploit the resulting cellular RSS variations for indoor/outdoor detection.

In this paper, we choose to look at the cell tower signal over other wireless signals (e.g., WiFi) mainly due to the following considerations. First of all, cell tower signal is available with no additional energy cost since mobile phones have to maintain connectivity to cell towers for basic communication, and cellular networks have almost universal coverage, both outdoor and indoor. Continuous scanning of other wireless signals (e.g., WiFi), however, consumes much extra energy and above all, doing so outdoors may lead to unnecessary energy consumption due to poor signal availability in outdoor environments. Meanwhile, for those high frequency band signals like 2.4GHz WiFi signal, because of the short wavelength, they may severely suffer from the shielding effect of surrounding objects or even the human body itself [36] which will bring in too much noise to the detection system. On the contrary, the cell tower signal of much longer wavelength can easily diffract around these objects. Thus the shielding effect of human body is much weaker than the dividing wall effect and will not mislead the system.

### 3.3.1 *Associated cell tower signal strength*

We aim to find the correlation between the RSS variations of cellular signal and the surrounding environment transitions. We first measure the cellular RSS in several representative places such as offices and homes (indoor), corridors and paths in the vicinity of building (semi-outdoor), and plaza and football field (outdoor). We find that the absolute value of the cellular RSS provides limited information for the detection. It varies across different places, times, and phone models. In contrast, the RSS variation within a short period of time normally indicates the context transition. In our experiments, we observe a significant variation of the cellular RSS when the ambient environment changes due to the user mobility. For instance, when the user walks into an office building from the outside, the cellular RSS significantly drops due to the dividing walls that block the line-of-sight paths to cell towers. Therefore, we exploit the abrupt variation of the cellular signal strength rather than its absolute value to distinguish the indoor/outdoor context that is invari-




(a) Single cell tower's RSS variation in environmental change.

(b) Multiple cell towers' RSS variation in environmental change.

(c) Detection accuracy with the varied number of cell towers.

**Figure 7. Cell tower signal strength variation for indoor/outdoor detection.**

ant across different places and phone models.

To enhance the communication quality, mobile phones usually connect to the cell tower with the strongest RSS. Figure 7(a) shows the RSS value from the connected cell tower when the user walks out to the corridor, and returns back to the office. The user walks outside at 30sec. We can see that the RSS rises by approximately 15 dB. Then at about 90sec, the user comes back to the office and the RSS drops back within ten seconds. Such a sharp cellular RSS variation can be used to detect the ambient environment changes. On the other hand, since the antenna gain may vary across different mobile phone models, it is hard to accurately map different RSS values to different environments. Adopting the RSS variation can avoid the detection error that would arise if the absolute RSS value were used, especially when applied on diversified devices and environments. In short, our cellular detector is independent of mobile phone models and environments which ensures the universal applicability.

However, we notice that using RSS information of the single associated cell tower suffers from two inherent limitations. First, mobile phones may handover from one cell tower to another. Such a handover normally introduces a significant cellular RSS variation. In this case, the RSS variation may not necessarily imply an indoor/outdoor transition. Second, due to the corner effect [31], the cellular RSS may dramatically change in the semi-outdoor environment. For example, in Figure 7(a), the RSS suddenly drops by about 15 dB at 50sec when the user turns around at a corner. The corner effect usually happens in the semi-outdoor environment due to the change of the line-of-sight to cell towers.

### *3.3.2 Visible cell tower signal strength*

A mobile phone is normally within the coverage range of multiple cell towers and tethers to the one with the strongest signal strength. Instead of using the single associated cell tower, we take a full advantage of all visible cell towers to improve the detection accuracy [37]. In particular, we measure the signal strengths of all of cell towers and track their variations. Thereby we naturally solve the inherent handover problem since the cell tower that the phone may connect to is also among the observed cell towers. In addition, with a rich set of RSS from multiple cell towers, we can mitigate the problem of the corner effect. Actually, since the evident corner effect usually indicates a semi-outdoor environment, we can exploit such a property to refine the detection.

We denote the RSS from cell tower $i$ at time $t$ as $R_i(t)$, $1 \leq i \leq n$. We track the RSS variation within a time interval $\Delta$, and denote the variation of cell tower $i$ as $V_i(t) = R_i(t+\Delta) - R_i(t)$. We refer $N_+(t)$ as the number of cell towers whose RSS increases more than $\nu$, i.e., $N_+(t) = |\{i|V_i(t) \geq \nu, 0 \leq i \leq n\}|$; we also denote by $N_-(t)$ the number of cell towers whose RSS decreases more than $\nu$, i.e., $N_-(t) = |\{i|V_i(t) \leq -\nu, 0 \leq i \leq n\}|$. In some cases, we will also see that $\frac{N_+(t)+N_-(t)}{n} < 1$, since the RSS of many cell towers remains quite stable and the differences do not exceed $\nu$. We define $N_0(t) = n - N_+(t) - N_-(t)$ to represent the stability of cell tower RSS. In our experiments, we set $\Delta = 10$sec and $\nu = 15$dB.

Intuitively, if a user moves from an indoor environment to an outdoor environment, the RSS of cell towers will increase, and vice versa. In addition, the more cell towers whose RSS exhibits the same trend, the more confident the detection will be. We correspond the detection results with different confidence levels $C_C$. Say that we find $N_0(t) = 1$, $N_+(t) = 1$, $N_-(t) = 4$, and $n = 6$, then the cellular detector will confirm the ambient environment as the indoor environment with confidence level $C_C = N_-(t)/n = 0.67$. The cellular detector will also report the confidence level for semi-outdoor/outdoor environment as $N_+(t)/n = 0.17$.

Figure 7(b) illustrates the RSS of multiple cell towers when the user walks out to the corridor (at 45sec), and returns to the office (at 90sec). In Figure 7(b), we see that the RSS of all four cell towers rapidly climbs up, which implies that the user has moved from indoor environment to the outside. At 90sec, the RSS of all 4 cell towers drops sharply, which means that the user walks back to indoor office. During the period from 60sec to 70sec, the RSS of the associated cell tower varies significantly, while other cell towers remain relatively stable. In this case, the majority rule helps filter out bursts and reduces detection errors.

We note that the visible cell towers are not necessarily from the same GSM network operator. A phone may detect cellular signals from multiple GSM networks which ensures sufficient number of visible cell towers. In our experiment, mobile phones typically see 4$\sim$6 cell towers at one time. Figure 7(c) plots the detection precision of cellular detector with the varying number of cell towers. We find that

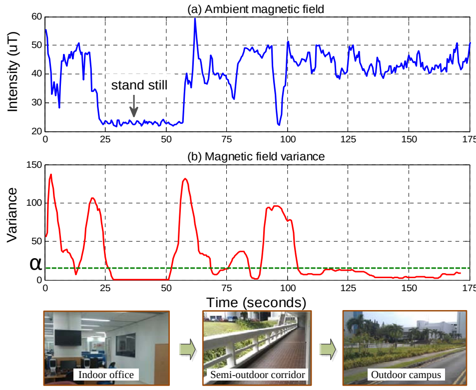



**Figure 8. The variation of magnetic field intensity.**

the detection precision increases as the number of visible cell tower increases and it is satisfactory when the number of cell towers is more than 4. Since mobile phones need to maintain connections to cell towers, the energy consumption of cellular detector is almost negligible. The major limitation is that the cellular detector may perform poorly without sufficient number of visible cell towers in some cases.

## 3.4 Magnetism detector

Many steel structures and electric appliances disturb the geomagnetic field and generate the electromagnetic fields in the indoor environment [26]. The disturbance of the Earth's magnetic field inside buildings can be utilized as fingerprints for the indoor localization [7]. However, such a localization approach requires a labor-intensive fingerprinting and cannot be applied for the indoor/outdoor detection directly. In this section, we seek to explore useful characteristics of the magnetic fields in different ambient environments that may help to enhance the indoor/outdoor detection.

The magnetic field exhibits distinct patterns in indoor/outdoor environments. In the indoor environment, the Earth's geomagnetic field varies at different positions due to the disturbance of steel structures and electric appliances inside buildings. For instance, the intensity of the magnetic field near the equator and near the pole varies from 0.25 to 0.65gauss ( i.e., 25 to 65$\mu T$). In comparison, a strong refrigerator magnet has a field of around 100 gauss (two orders of magnitude higher) [1]. Therefore, the intensity of magnetic fields shows a high variance across different places near and inside buildings than that in the open space.

Figure 8 plots the magnetic field intensity and its variance in an example scenario in which a user walks outside of the office, passing through a corridor. In particular, the user walks from 0sec to 25sec, stops walking from 25sec to 50sec inside the building, and then walks along the corridor from 50sec to 100sec. In the end, the user walks along the road. In Figure 8(a), we find that the intensity of magnetic field in the indoor environment varies dramatically. Figure 8(b) plots the variance averaged over $\tau$ seconds to filter out noises. We find that the variance is very high when the user moves (from 0sec to 25sec). When the user is walking through the corridor, the magnetic field intensity also shows significant variance. In contrary, after the user comes outside after 100sec, the variance drops significantly. Therefore, by choosing a suitable threshold $\alpha$, we could distinguish the indoor/semi-outdoor from the outdoor environment.

We vary the threshold $\alpha$ from 0 to 40 with step length 2 and statistically analyze the detection accuracy using the collected data described in §3.1. If the threshold is small, most indoor/semi-outdoor environments will be correctly classified, while many outdoor environments will be wrongly detected as the indoor/semi-outdoor environment. On the other hand, if the threshold is too large, most outdoor environments will be correctly classified but we will miss the detection of many indoor/semi-outdoor environments. Therefore, we select an empirical threshold 18 to achieve a balance. In our implementation, we first refer to accelerometer to detect whether the mobile phone is moving. If so, magnetism detector samples the magnetism sensor, and uses the variance averaged over $\tau = 10$ seconds to detect the environment. When the user stops walking (from 25sec to 50sec) the variance becomes very small. When the user is moving, we confirm the detection of an indoor/semi-outdoor environment if the field variance is larger than $\alpha$; otherwise the detection result is an outdoor environment. Since a larger $\tau$ yields a higher detection robustness, we set the confidence level of magnetism detector $C_M = \tau/10$.

## 3.5 Aggregated IODetector

Each of the three detectors shows unique advantages and disadvantages. They best fit different scenarios. For instance, the light detector can rapidly detect the ambient environment. The light detector, however, requires the mobile phone to be exposed in the space. If the phone is inside pocket or bags, the light detector cannot provide accurate detection results. The cellular detector needs sufficient cell tower coverage to confidently detect the ambient context. The detection response is also slower. The magnetism detector is only available when the user is moving around such that the magnetic disturbance inside buildings can be exploited. We call the three individual detectors as sub-detectors and integrate them so as to output an arbitrated decision.

At first, we directly aggregate the instant detection results of all three sub-detectors. We let each sub-detector report a detection profile, i.e., a triplet of confidence levels for the three possible environment types, and sum the confidence levels from all three sub-detectors. The environment type with the highest summed confidence level will be output as the final detection result. Such a combination makes stateless decision, i.e., the detection output is solely determined by the current environment status and the instant sensor readings. We call it stateless IODetector in the following.

Figure 9 shows the aggregation processing of stateless IODetector. We denote the detection profile from the three sub-detectors as $[D_L(t), C_L(t)]$ (light), $[D_C(t), C_C(t)]$ (cellular), and $[D_M(t), C_M(t)]$ (magnetism), where $D$ is the output detection result from each sub-detector and $C$ is the set of associated confidence levels for the three possible environment types. As described in §3, each individual sub-detector outputs the possible environment types and associate confidence levels for them. For example, each detection profile of light detector can be denoted as $[D_L, C_L] = \{(indoor,\ C_{L,indoor}), (semi\text{-}outdoor,\ C_{L,semi-outdoor}), (outdoor,\ C_{L,outdoor})\}$. For

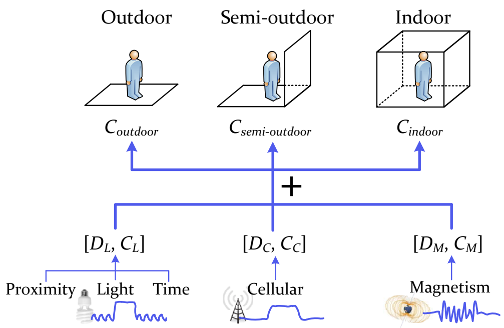



**Figure 9. Stateless IODetector.**

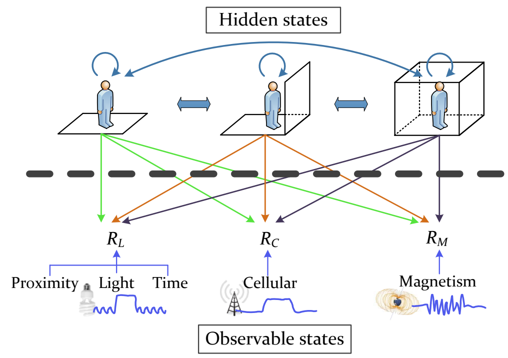



**Figure 10. Stateful IODetector.**

each possible environment type, we sum the confidence levels from the three sub-detectors and obtain the triplet of overall confidence levels $C_E \in \{C_{indoor}, C_{semi-outdoor}, C_{outdoor}\}$. The environment type with the highest overall confidence level will be reported as the final detection result.

The stateless IODetector provides us instant detection results. Users can activate IODetector on need basis. Thus the significant out-of-the-box functionality ensures the energy efficiency of stateless IODetector. In our experiments, however, we find that the current environment state of human being is usually related to the previous state. For example, during the movement from indoor to outdoor, the user has a good chance experiencing the semi-outdoor environment. The stateless IODetector does not consider previous states and thus may suffer from noises. In the following, we alternatively consider a stateful integration of the three sub-detectors which makes decisions on top of both current and previous observations.

In order to do so, we let all sub-detectors continuously perform detection and return sequential results. Figure 10 sketches an illustrative example of stateful IODetector. We make use of the Hidden Markov Model (HMM) [30] to integrate the sub-detectors. The HMM models a Markov process with underlying hidden states. Every hidden state emits observable states with particular conditional probability distribution called the emission probability distribution. The HMM traverses the states and the transitions among the hidden states are governed by the transition probabilities. With the HMM, we estimate the most likely sequence of hidden states that may produce the sequence of observable states. We use the first-order HMM in which the current environment state is only affected by the immediate previous state. We denote the hidden state at time $t$ as $H(t)$ $\in$ {*indoor*, *semi-outdoor*, *outdoor*} and the observed results from the three sub-detectors as $R_L(t)$(light), $R_C(t)$(cellular), and $R_M(t)$(magnetism), where $R$ is the output environment type with the highest confidence level from each individual sub-detector. For example, the detection result from light detector is $R_L \in$ {*indoor*, *semi-outdoor/outdoor*}. IODetector incorporates the detection results from all the sub-detectors and treats them as the observable state $B(t) = [R_L(t), R_C(t), R_M(t)]$. IODetector will thus infer the most likely hidden state $H(t)$ from the previous hidden state $H(t-1)$ and the current observable state $B(t)$. The transition and emission probabilities determine the inference result.

**Transition probability.** We determine the transition probabilities based on the experimental observations and the characteristics of IODetector. Since the detection period of IODetector is set to 10 seconds, when a user is previously indoor, the current environment state is highly likely indoor and might be semi-outdoor but is not likely outdoor because the user unlikely moves directly from indoor to fully outdoor environment. It is similar when a user is outdoor. When the user is semi-outdoor, however, he could be able to directly move indoor or outdoor, or he may stay semi-outdoor. We denote the transition probability from environment $H_1$ to $H_2$ (elaborated as I:*indoor*, O:*outdoor*, and S:*semi-outdoor* in the following) as $T(H_1, H_2)$. Based on above observations, we determine the transition probabilities as follows:

1) $T(S,I) = T(S,S) = T(S,O) = p_1 = 1/3$.
2) $T(I,I) = T(I,S) = p_2 = 1/2$.
3) $T(O,O) = T(O,S) = p_3 = 1/2$.
4) $T(O,I) = T(I,O) = p_4 = 0$.

**Emission probability.** The emission probability $E(B,H)$ is the likelihood that an observable state $B$ is observed in $H$ environment. We set the emission probability according to the training data as described in §3.1. Table 1 shows the emission probability of each hidden state (*indoor*, *semi-outdoor* and *outdoor*) to each observable state in detail.

**Viterbi algorithm.** We apply the Viterbi algorithm [32], a dynamic programming algorithm, to estimate the most likely environment type in the HMM according to the detection results of the three sub-detectors. As the scales of both hidden and observable states are small, the computation cost can be easily accommodated on commodity mobile phone platforms.

For the stateful IODetector, we do not keep all the sensors on. We use the accelerometer as a trigger. Only when the accelerometer detects the user movement, IODetector activates the sensors and starts to infer the new environment state from the HMM. When the user is stationary, the user environment state is deemed unchanged and all sensors are deactivated, and so is the HMM processing.

Applying the HMM, stateful IODetector further explores the sequential observations and provides stateful detection results, which are robust to noisy measurements [30]. Its detection accuracy, which we show in §4.2.2, is better than stateless IODetector. However, stateful IODetector may con-

| Detector | Observable state | Indoor | Semi-outdoor | Outdoor |
|---|---|---|---|---|
| Light detector | Indoor | 0.9 | 0.11 | 0.11 |
| | Semi/outdoor | 0.1 | 0.89 | 0.89 |
| Cellular detector | Indoor | 0.82 | 0.16 | 0.16 |
| | Semi/outdoor | 0.18 | 0.84 | 0.84 |
| Magnetism detector | Semi/indoor | 0.88 | 0.88 | 0.17 |
| | Outdoor | 0.12 | 0.12 | 0.83 |

**Table 1. Emission probability settings.**

| Environment type | Representative places | Total |
|---|---|---|
| **Outdoor** | 12 campus sites, 11 downtown areas | 23 |
| **Semi-outdoor** | 15 campus sites, 12 downtown areas | 27 |
| **Indoor** | 10 office rooms, 18 stores, 6 restaurants | 34 |

**Table 2. Experimental sites**

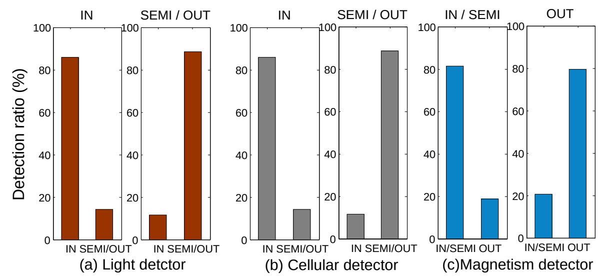



**Figure 11. Detection performance of three sub-detectors.**

sume extra energy since it has to perform continuous detection. We show the energy consumption of IODetector in §4.2.2 and §4.3.3. Users can choose either stateless or stateful IODetector which is more suitable for the application scenarios.

# 4 Evaluation

We implement a prototype system on the Android platform with different types of mobile phones. We collect sensor data at 19 traces including 84 different sites over a one-month period of experiments. The following details the experiment methodology and the results.

## 4.1 Experimental methodology

**Mobile Phones.** We implement IODetector on the Android platform and test its performance using three different types of mobile phones (Samsung Galaxy S2 i9100, HTC Desire S, and HTC Sensation G14). All types of mobile phones are equipped with light sensors, proximity sensors, magnetism sensors, accelerometers, etc. The Samsung Galaxy S2 i9100 has a 1 GB RAM and dual-core 1.2 GHz Cortex-A9 processor, the HTC Desire S has a 768 MB RAM and 1 GHz Scorpion processor, and the HTC Sensation G14 has a 768 MB RAM and dual-core 1.2 GHz Scorpion processor. As IODetector is independent of platforms, we believe that the proposed indoor/outdoor detection method can be simply implanted to other mobile computing platforms, such as Apple iOS and Windows Phone.

**Sensor motes.** We use TelosB motes integrated with light sensors to measure the light signals with higher fidelity. We modify TinyOS code to directly read the voltage on the light sensor S1087-01. The sensitivity range of the light sensor is from 300nm to 1200nm with a full coverage of the visible light spectrum and a partial coverage of the infrared and ultraviolet spectrum. At the current stage, we connect the TelosB mote to the mobile phone for the enhanced light fidelity, and we look forward to a similar performance solely using the mobile phones if we unlock the full access to the on-board light sensors on the Android OS platform.

**Experiment environment.** We experiment with 19 different walking traces and collect sensor readings from 23 outdoor segments (covering football fields, downtown squares, etc.), 27 semi-outdoor segments (covering corridors and paths near buildings), and 34 indoor segments (including offices and shopping malls) mainly in campus and city areas (summarized in Table 2) during the period 5:00 to 22:00 in 30 days with different weather conditions. The users walk along these traces and the mobile phones perform continuous detection for the experimental sites along the traces. These sites are different from the environments where we collect prior data and learn the IODetector philosophy.

## 4.2 System performance

In this section we show the detection performance of the three individual sub-detectors as well as the aggregated IODetector. We also compare the performance of the stateless and stateful IODetectors.

### *4.2.1 Performance of sub-detectors*

One may query three different detectors independently and select an arbitrary one in practice. To evaluate the contribution of each detector (i.e., light detector, cellular detector, and magnetism detector), we examine the detection performance independently in Figure 11. Each detector reports the environment type with the highest confidence level after the local computation.

The light detector is available when there are clear paths between mobile phones and ambient light sources. Figure 11(a) depicts the detection performance of light detector. We find that the light detector can effectively distinguish the indoor environment from the semi-outdoor/outdoor environment. In Figure 11(a), when mobile phones are in the indoor environment, the detection accuracy is around 83%. When the phones are in the semi-outdoor/outdoor environment, the detection accuracy is around 88%. Figure 11(b) shows the detection performance of cellular detector that classifies the indoor environment from the semi-outdoor/outdoor environment. We obtain quite a close performance of cellular detector compared with that of light detector. Our experiments mainly cover the campus and city areas where most sites are covered by at least 5 cell towers. In such experiment settings, the cell tower based detection performs with 82% accuracy.

We note that both light detector and cellular detector can effectively classify the indoor environment from the semi-outdoor/outdoor environment. On the other hand, the magnetism detector can enhance the detection capability of IODetector in classifying the semi-outdoor and outdoor environment. Figure 11(c) plots the performance of the magnetism detector. The magnetism detector can successfully distinguish the indoor and semi-outdoor environments from the outdoor environment with an accuracy around 80%.

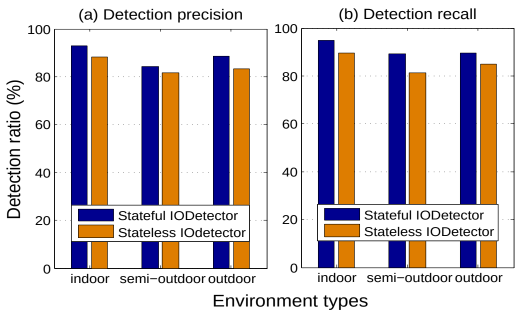



**Figure 12. Detection precision and recall of stateless IODetector and stateful IODetector.**

### 4.2.2 *Performance of aggregated IODetector*

As described in §3.5, there are two approaches to constructively combine the results from the three sub-detectors.

**Detection accuracy.** In Figure 12, we show the detection accuracy of both stateless and stateful IODetectors. We report the average detection results, including detection *precision* and *recall* [8], in different scenarios.

As shown in Figure 12, the overall detection accuracy of stateless IODetector is about 82%. When the three sub-detectors are aggregated as the stateful IODetector, there is improvement of detection accuracy for all different types of indoor/outdoor environments but not much. According to the experiment results, for both stateless and stateful IODetectors, the detection precision and the recall for the indoor detection are slightly higher than the detection results for the other two environment types. Nevertheless, compared with less than 83% detection accuracy of individual detectors, in the aggregated IODetector both the precision and the recall are consistently above 88% (90%+ for the indoor environment). The experiment results suggest that IODetector accurately classifies the indoor/outdoor environments for most cases. For the stateful IODetector, with the optimization of the HMM parameters, the detection accuracy could be further improved.

In Figure 13, we show one of the walking traces in that we experiment with in NTU campus. The experiment was done in a rainy day. The detection results from stateless and stateful IODetectors can be seen in Figure 13(bottom). The detection results of both IODetectors are accurate. When we look at their detection results separately, there are some differences. In some segments, the stateless IODetector suffers from mis-detection of some semi-outdoor environments, which are usually in the trace between indoor and outdoor environments. In some segments, although the ambient environment is not changed, the detection result of statless IODetector may vary. The detection result of stateful IODetector is relatively more stable due to the effect of the HMM. Considering the previous state, the HMM filters out some noise and avoids the mis-detection of semi-outdoor environments during user movements. However, the stateful IODetector may give inaccurate results for frequent environment changes as it reacts insensitively to the sudden change of environment types and there are extra energy consumptions for stateful IODetector due to its continuous operation.

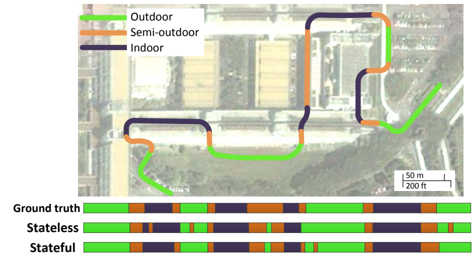



**Figure 13. An experiment trace in the university campus.**

| Sensors | Samsung i9100 | HTC Desire | HTC Sensation |
|---|---|---|---|
| No sensor | 18.3 | 15.4 | 18.1 |
| Magnetism 2Hz | 18.0 | 14.9 | 17.8 |
| Light 400Hz+FFT | 17.8 | 15.0 | 17.5 |
| Celltower 2Hz | 18.1 | 15.1 | 17.9 |

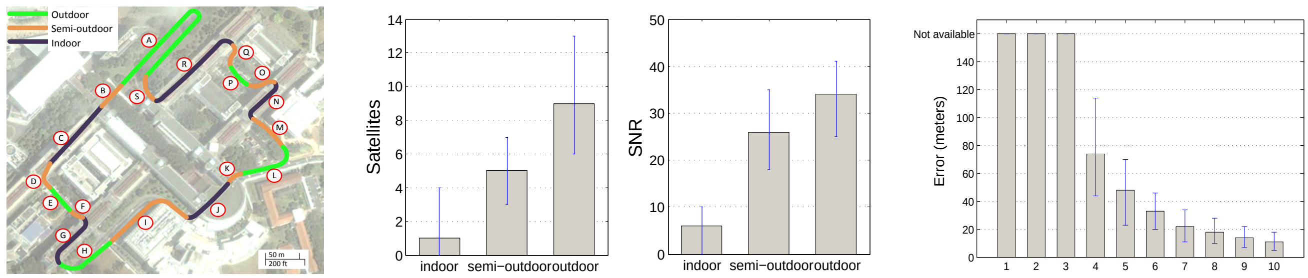
**Table 3. Battery duration for different sensor settings (in hours).**

**Detection latency.** The detection latency of IODetector is bounded by the time consumed by three sub-detectors. The light detector is fast, sampling at 400 Hz that is sufficient to capture the alternating light intensity. We set the same detection window length of 10 seconds for both cellular detector and magnetism detector. Considering that three detectors can run in parallel, it typically takes 10 seconds to warm up and then starts reporting detection results. After that, IODetector can keep tracking the indoor/outdoor transitions according to the application requirements.

**System overhead.** We measure the energy consumption of continuously sampling light sensor, magnetism sensor and cellular signals. We measure the battery duration with the screen set to the minimum brightness in the experiments. Table 3 shows the measured battery lifetime when the mobile phones continuously sample different sensors. In Table 3, we find that the battery durations for sampling magnetism sensor at 2Hz and sampling light sensor at 400Hz with the FFT are quite close to the battery duration without sampling any sensors. Sampling the cellular signal consumes little extra battery power as well. Thus although the stateful IODetector needs to perform continuous detection, the low energy consumption makes it affordable for the users.

## 4.3 Case study: inferring GPS availability

In this subsection, we conduct a case study and demonstrate how IODetector can be used to provide indicative information on the GPS availability. Nowadays, many smartphones are equipped with commodity GPS modules that provide localization and navigation services for mobile applications. Traditional works [30] study how to adaptively use GPS/GSM/WiFi signals for energy-efficient localization or tracking. Such approaches, however, either assume the preknowledge of the ambient environment, or infer it passively with high overhead and low efficiency. Serving as a generic and lightweight service, IODetector can be used to provide cheap and instant triggers for switching on/off the GPS component so as to achieve both high location accuracy and energy efficiency.




(a) GPS experiment trace in the university campus.

(b) Number of visible satellites and SNR of GPS signals in different environments.

(c) GPS accuracy for different number of available satellites.

**Figure 14. Indoor/outdoor dependent GPS performance.**

### *4.3.1 Indoor/outdoor dependent performance*

For accurate localization, GPS normally needs more than 4 clear line-of-sight paths to GPS satellites. In the outdoor environment, with a sufficient number of paths to satellites, commodity GPS modules can achieve a localization accuracy within 20m. In the shadow of tall buildings, some line-of-sight paths to satellites would be blocked and GPS may only receive signals from a small number of satellites. Some received GPS signals might be from the reflecting walls leading to the multi-path problem. In such scenarios, the localization accuracy degrades dramatically. In the indoor environment, there is normally no line-of-sight path to satellites. As a result, GPS takes minutes to scan the satellites without finding any strong signals from satellites and the localization error can be up to 400m. In addition to the inaccuracy, it usually causes high responsive latency and extra power consumption. As the GPS performance differs significantly in the indoor and outdoor environments, mobile phones greatly benefit from a priori knowledge of the ambient environment types with minimal overhead.

### *4.3.2 GPS availability and localization accuracy*

We evaluate the localization accuracy and energy consumption of a mobile phone GPS component along with a walking path in our experiment. Figure 14(a) plots the experiment path in our campus. We mark the route segments from A to S. The total length of the walking path is approximately 1600m, with 620m outdoor, 380m semi-outdoor, and 600m indoor segments, respectively. We query GPS for location information when we travel along the circular path with different mobile phone models under different weather conditions during the one-month experiments.

Figure 14(b) plots the number of visible satellites as well as the SNR (signal to noise ratio) of the GPS signals in the indoor, semi-outdoor, and outdoor environments, respectively. In Figure 14(b)(left), we find that in the indoor environment the mobile phones normally receive less than 2 GPS signals, though the mobile phones can sometimes capture slightly more GPS signals near windows. In the outdoor environment, the phones normally receive signals from more than 6 GPS satellites even in cloudy and rainy days. The number of observed satellites varies in between in the semi-outdoor environment (e.g., corridors and paths in the shadow of buildings). Figure 14(b)(right) plots the SNR of the received GPS signals. The SNR value is a normalized value from the android API indicating the signal to noise ratio of the received satellite signal. The SNR greater than 20 is usually high enough for the mobile phone to calculate accurate location, and typically, the greater, the better. In Figure 14(b)(right), we observe that in the indoor environment the SNR of the GPS signals vary from 0 to 10. In the outdoor environment, the SNR becomes much higher varying from 25 to 42 due to the clear line-of-sight paths between the phones and GPS satellites. In the semi-outdoor environment, although we may sometimes observe more than 4 GPS signals, typically the SNR of GPS signals is not high enough to ensure accurate localization.

Figure 14(c) plots the summarized GPS localization error against the number of visible satellites. We find that the GPS modules can obtain more accurate localization results with more visible satellites. According to the experiment results, with less than 4 visible satellites GPS service is generally unavailable. The GPS module is able to work with more than 4 visible satellites. However, even with 4 satellite signals, the localization accuracy vary dramatically in our experiment. With more than 6 visible satellites, the localization error is around 20m. We also observe that more visible satellites (e.g., >9) yield less marginal improvements in the localization accuracy. With 10 GPS satellites, the localization error can be within 10m.

In summary, the experiment results demonstrate that the GPS availability and localization accuracy are highly correlated to the environment types. Yet solely reading such availability from the GPS module itself can be up to minutes and consume much extra energy in scanning the satellites.

### *4.3.3 IODetector-augmented GPS: IO-GPS*

We can simply leverage IODetector to infer the GPS with accurate indoor/outdoor awareness. In our IOdetector augmented GPS (IO-GPS) scheme, mobile applications invoke IODetector for the indoor/outdoor detection before switching on the GPS module. If the mobile phone is outdoor, the applications can confidently call GPS for an outdoor localization; if it is indoor, the applications may postpone the GPS localization and resort to a variety of alternative indoor localization techniques [35]. In this experiment, We track the localization accuracy and energy consumption of the traditional GPS and the IO-GPS scheme.

**IO-GPS localization accuracy.** We follow the path in Figure 14(a) at a walking speed and collect the GPS local-

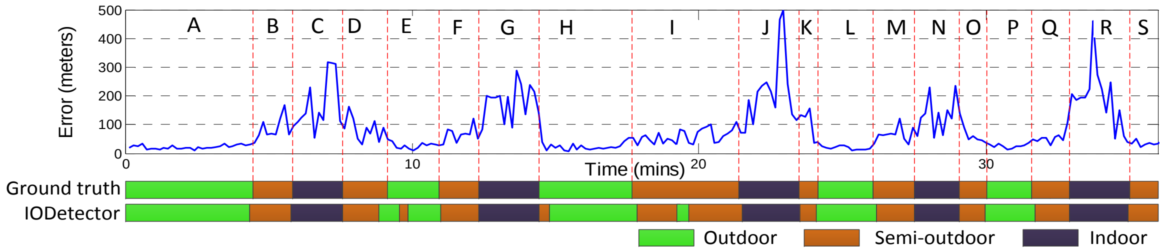



**Figure 15. GPS localization accuracy of an example instance along the walking path.**

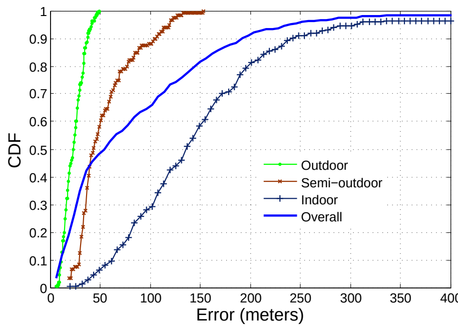



**Figure 16. CDF of localization error.**

| Environment | Samsung i9100 | HTC Desire | HTC Sensation |
|---|---|---|---|
| Indoor GPS | 9.2 | 6.6 | 8.7 |
| Semi-outdoor GPS | 9.8 | 7.2 | 9.7 |
| Outdoor GPS | 10.1 | 7.3 | 9.8 |
| Stateful IODetector | 17.3 | 14.4 | 16.8 |

**Table 4. Battery consumption comparison (in hours).**

ization data. We repeat the experiment 10 times and report the average results. We use stateful IODetector to estimate the environment type. Figure 15 presents one example instance. In Figure 15, we observe that the GPS localization error varies across different path segments. We see apparent variation on GPS localization error due to the indoor/outdoor environment transition. For example, when we move from segment G to H (indoor $\rightarrow$ outdoor), we see a big dive of the localization error; when we move from P to Q then to R (outdoor $\rightarrow$ semi-outdoor $\rightarrow$ indoor), we observe a two-stage jump of the localization error. Consistent with the above measurement, in the indoor environment the GPS localization error is much larger than that in the semi-outdoor or outdoor environment. The path segment J has a particularly high error because the segment is underground and the GPS component detects almost no satellite signals.

Figure 16 summarizes the localization error from the 10 experiments and we take a fine-look at the localization error in outdoor, semi-outdoor, and indoor areas, respectively. The median localization error in the outdoor environment is around 24m with the maximum error within 50m in our experiments. In the semi-outdoor areas, the median error is around 44m while the 90th percentile can be up to 100m. In the indoor environment, the median localization error is around 140m with the 90th percentile of 235m. The overall localization error presents the performance of the traditional GPS. We find that the median localization error is around 55m with a long tail up to 400m. In our experiment setting, users walk around campus with comparable route segments inside buildings and outdoor environments. Yet the researches on human activity pattern show that people spend around 89% of the time in the indoor environment [13].

Without discriminating the indoor/outdoor environment, blindly using the traditional GPS scheme would perform similarly to that in the indoor cases for most of the time. Augmented by IODetector, the IO-GPS performance would be closer to that in the outdoor/semi-outdoor environment. In Figure 15(bottom), we compare the indoor/outdoor detection results with the ground truth along the experiment path. We can see that IODetector provides promising detection accuracy. In particular, IODetector successfully detects the indoor cases from the semi-outdoor and outdoor cases. For outdoor/semi-outdoor detection at some places, IODetector cannot provide the most accurate result. We revisit the places such as the path segments D and E, where IODetector misclassifies the semi-outdoor and outdoor environments. We find that D and E are located at a corner passing by a two-storey building. It is even difficult to manually label such places as ground truth, yet we believe the misclassification results of IODetector in such corner cases would introduce little influence to the GPS localization service.

**Energy consumption.** We measure the power consumption when we run the GPS module during the experiment. We measure the battery life with the screen set to the minimum brightness. Table 4 summarizes the battery life of three different mobile phone models in different environments. We also present the battery duration for running stateful IODetector for the indoor/outdoor detection. In Table 4, the first 3 rows show the energy consumption of mobile phones when GPS is turned on for indoor, semi-outdoor and outdoor environments. We find that GPS drains the battery rapidly in all the environments. The energy consumption of GPS is especially high in the indoor environment where the GPS module continuously scans the satellite signals and rapidly depletes the battery energy. With the awareness of the indoor/outdoor environment, IO-GPS may avoid unnecessarily switching on the GPS module and save the energy consumption in the indoor environment.

## 5 Related work

Though there have not yet been generic approaches proposed for explicit indoor/outdoor detection, there exist a wide body of related works that implicitly deal with such a problem.

**Environment detection.** GPS lock status can be used to indirectly infer the ambient environment [25], but it usually incurs substantial energy cost and high latency. ABL [15] proposes the approach that allows mobile sensors to localize themselves by exploiting their ambient physical environment signals. FLIGHT [17] explores the fact that the light intensity changes with a stable period in the indoor environment and uses the feature to perform clock calibration. TempIO [14] 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 recourses, the temperature sensor if available on mobile phones can be used to complement our work. TagSense [24] classifies the ambient environments to automatically annotate images during the picture-click. Some works in image processing and pattern recognition [23, 28] also study the problem of classifying images according to ambient environments. Those works can provide partial indication on indoor/outdoor environment. 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.

**Localization and tracking.** Many works study GPS/GSM/WiFi localization schemes. StarTrack [3] provides a comprehensive set of APIs for the development of mobile localization and tracking applications. Zhou *et al.* [37] use cell tower sequences to track the buses and make bus arrival time prediction for the waiting passengers. LANDMARC [22] proposes a location sensing prototype system that uses RFID technology for locating objects inside buildings. EnTracked [12] focuses on outdoor pedestrian tracking using lightweight accelerometer to trigger GPS to reduce power consumption. Jurdak *et al.* [9] complement GPS duty cycling with short-range radio contacts to balance positioning accuracy and energy consumption. VTrack [30] studies reducing energy consumption using inaccurate WiFi positioning schemes to measure road traffic condition. Chung *et al.* [7] present an accurate positioning system based on the magnetic signatures in the indoor environment. Above approaches primarily focus on obtaining accurate physical locations and track the targeted objects. They can potentially benefit from the indoor/outdoor awareness of IODetector, e.g., adaptively switching on/off the GPS modules in localization.

**Context awareness and activity recognition.** A number of works have studied use of sensors to recognize user activities and detect ambient context. Yan *et al.* [34] design and build FALCON to remedy slow app launch using contexts to predict the next app to launch. CenceMe [21] exploits sensors on mobile phones to automatically infer people's ambient context and then allows users to share that through social networks. Mercury [18] monitors patients using wearable sensors in indoor medical environments. EEMSS [33] presents an energy efficient sensor management framework which uses minimum number of sensors on mobile devices to monitor user status. Jigsaw [20] supports continuous sensing applications on mobile phones to infer human activities and ambient context. PBN [10] proposes user activity detection system using sensors on both mobile phones and on-body wireless sensors. Such works either implicitly assume the activity context or passively infer the ambient context. Unlike those works, our work proactively detects the indoor/outdoor environment using various lightweight sensors (e.g., light sensor, cellular signal, and magnetism sensor) without any remote supports.

SoundSense [19] classifies general sound types (e.g., music, voice) to achieve context recognition. SensLoc [11] collects WiFi beacons to extract useful patterns to infer contextual information. Kobe [6] aids the mobile classifier development by automatically extracting high-level semantics from raw sensory data while balancing energy, latency and accuracy. Our work primarily differs from them in that IODetector instantly detects the primitive ambient context without any labor-intensive site survey and user feedback. Those works may benefit from IODetector by taking the indoor/outdoor information as a primary filter for context recognition.

## 6 Conclusions

We present the design and implementation of an indoor/outdoor environment detection system, which efficiently takes input from a variety of lightweight sensors to derive the indoor/outdoor information. By intelligently aggregating the sub-detectors, IODetector achieves prompt and accurate detection results in various time and environments. We comprehensively test IODetector through a prototype implementation and evaluate the system based on different Android mobile phone models. We particularly conduct a case study where we make use of IODetector results to infer the GPS availability and accuracy under various indoor/outdoor environment.

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## References

[1] Earth magnetic field. `http://en.wikipedia.org/wiki/Earth_magnetic_field`.

[2] Lux. `http://en.wikipedia.org/wiki/Lux`.

[3] G. Ananthanarayanan, M. Haridasan, I. Mohomed, D. Terry, and C. A. Thekkath. Startrack: a framework for enabling track-based applications. In *Proceedings of the 7th International Conference on Mobile Systems, Applications, and Services (MobiSys '09)*, pages 207–220, 2009.

[4] M. Azizyan, I. Constandache, and R. Roy Choudhury. Surroundsense: mobile phone localization via ambience fingerprinting. In *Proceedings of the 15th Annual International Conference on Mobile Computing and Networking (MobiCom '09)*, pages 261–272, 2009.

[5] P. Bahl and V. N. Padmanabhan. RADAR: an in-building RF-based user location and tracking system. In *Proceedings of the 19th IEEE International Conference on Computer Communicaitons (INFOCOM '00)*, pages 775–784, 2000.

[6] D. Chu, N. D. Lane, T. T.-T. Lai, C. Pang, X. Meng, Q. Guo, F. Li, and F. Zhao. Balancing energy, latency and accuracy for mobile sensor data classification. In *Proceedings of the 9th ACM Conference on Embedded Networked Sensor Systems (SenSys '11)*, pages 54–67, 2011.

[7] J. Chung, M. Donahoe, C. Schmandt, I.-J. Kim, P. Razavai, and M. Wiseman. Indoor location sensing using geo-magnetism. In *Proceedings of the 9th International Conference on Mobile Systems, Applications, and Services (MobiSys '11)*, pages 141–154, 2011.

[8] M. Junker, R. Hoch, and A. Dengel. On the evaluation of document analysis components by recall, precision, and accuracy. In *Proceedings of the 5th International Conference on Document Analysis and Recognition (ICDAR '99)*, pages 713 –716, 1999.

[9] R. Jurdak, P. Corke, D. Dharman, and G. Salagnac. Adaptive gps duty cycling and radio ranging for energy-efficient localization. In *Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems (SenSys '10)*, pages 57–70, 2010.

[10] M. Keally, G. Zhou, G. Xing, J. Wu, and A. Pyles. Pbn: towards practical activity recognition using smartphone-based body sensor networks. In *Proceedings of the 9th ACM Conference on Embedded Networked Sensor Systems (SenSys '11)*, pages 246–259, 2011.

[11] D. H. Kim, Y. Kim, D. Estrin, and M. B. Srivastava. Sensloc: sensing everyday places and paths using less energy. In *Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems (SenSys '10)*, pages 43–56, 2010.

[12] M. B. Kjærgaard, J. Langdal, T. Godsk, and T. Toftkjær. Entracked: energy-efficient robust position tracking for mobile devices. In *Proceedings of the 7th International Conference on Mobile Systems, Applications, and Services (MobiSys '09)*, pages 221–234, 2009.

[13] N. E. Klepeis, W. C. Nelson, W. R. Ott, J. P. Robinson, A. M. Tsang, P. Switzer, J. V. Behar, S. C. Hern, and W. H. Engelmann. The national human activity pattern survey (nhaps): a resource for assessing exposure to environmental pollutants. *Journal of exposure analysis and environmental epidemiology*, 11(3):231–252, 2001.

[14] J. Krumm and R. Hariharan. Tempio: inside/outside classification with temperature. In *Proceedings of 2nd International Workshop on Man-Machine Symbiotic Systems*, 2004.

[15] N. D. Lane, H. Lu, and A. T. Campbell. Ambient beacon localization: using sensed characteristics of the physical world to localize mobile sensors. In *Proceedings of the 4th Workshop on Embedded Networked Sensors (EmNets '07)*, pages 38–42, 2007.

[16] N. D. Lane, E. Miluzzo, H. Lu, D. Peebles, T. Choudhury, and A. T. Campbell. A survey of mobile phone sensing. *IEEE Communications Magazine*, 48(9):140–150, Sept. 2010.

[17] Z. Li, W. Chen, C. Li, M. Li, X.-Y. Li, and Y. Liu. Flight: clock calibration using fluorescent lighting. In *Proceedings of the 18th Annual International Conference on Mobile Computing and Networking (MobiCom '12)*, pages 329–340, 2012.

[18] K. Lorincz, B.-r. Chen, G. W. Challen, A. R. Chowdhury, S. Patel, P. Bonato, and M. Welsh. Mercury: a wearable sensor network platform for high-fidelity motion analysis. In *Proceedings of the 7th ACM Conference on Embedded Networked Sensor Systems (SenSys '09)*, pages 183–196, 2009.

[19] H. Lu, W. Pan, N. D. Lane, T. Choudhury, and A. T. Campbell. Soundsense: scalable sound sensing for people-centric applications on mobile phones. In *Proceedings of the 7th International Conference on Mobile Systems, Applications, and Services (MobiSys '09)*, pages 165–178, 2009.

[20] H. Lu, J. Yang, Z. Liu, N. D. Lane, T. Choudhury, and A. T. Campbell. The jigsaw continuous sensing engine for mobile phone applications. In *Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems (SenSys '10)*, pages 71–84, 2010.

[21] E. Miluzzo, N. D. Lane, K. Fodor, R. Peterson, H. Lu, M. Musolesi, S. B. Eisenman, X. Zheng, and A. T. Campbell. Sensing meets mobile social networks: the design, implementation and evaluation of the cenceme application. In *Proceedings of the 6th ACM Conference on Embedded Networked Sensor Systems (SenSys '08)*, pages 337–350, 2008.

[22] L. M. Ni, Y. Liu, Y. C. Lau, and A. P. Patil. Landmarc: indoor location sensing using active rfid. *ACM Wirelelss Networks*, 10(6):701–710, Nov. 2004.

[23] A. Payne and S. Singh. Indoor vs. outdoor scene classification in digital photographs. *Pattern Recognition*, 38(10):1533–1545, Oct. 2005.

[24] C. Qin, X. Bao, R. Roy Choudhury, and S. Nelakuditi. Tagsense: a smartphone-based approach to automatic image tagging. In *Proceedings of the 9th International Conference on Mobile Systems, Applications, and Services (MobiSys '11)*, pages 1–14, 2011.

[25] L. Ravindranath, C. Newport, H. Balakrishnan, and S. Madden. Improving wireless network performance using sensor hints. In *Proceedings of the 8th USENIX Conference on Networked Systems Design and Implementation (NSDI'11)*, 2011.

[26] A. Rowe, V. Gupta, and R. R. Rajkumar. Low-power clock synchronization using electromagnetic energy radiating from ac power lines. In *Proceedings of the 7th ACM Conference on Embedded Networked Sensor Systems (SenSys '09)*, pages 211–224, 2009.

[27] A. Smith, H. Balakrishnan, M. Goraczko, and N. Priyantha. Tracking moving devices with the cricket location system. In *Proceedings of the 2nd International Conference on Mobile Systems, Applications, and Services (MobiSys '04)*, pages 190–202, 2004.

[28] M. Szummer and R. W. Picard. Indoor-outdoor image classification. In *Proceedings of IEEE International Workshop on Content-based Access of Image and Video Databases*, 1998.

[29] A. Thiagarajan, J. Biagioni, T. Gerlich, and J. Eriksson. Cooperative transit tracking using smart-phones. In *Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems (SenSys '10)*, pages 85–98, 2010.

[30] A. Thiagarajan, L. Ravindranath, K. LaCurts, S. Madden, H. Balakrishnan, S. Toledo, and J. Eriksson. Vtrack: accurate, energy-aware road traffic delay estimation using mobile phones. In *Proceedings of the 7th ACM Conference on Embedded Networked Sensor Systems (SenSys '09)*, pages 85–98, 2009.

[31] N. D. Tripathi, J. H. Reed, and H. F. VanLandingham. Handoff in cellular systems. *IEEE Personal Communications*, 5:26–37, 1998.

[32] A. Viterbi. Error bounds for convolutional codes and an asymptotically optimum decoding algorithm. *IEEE Transactions on Information Theory*, 13(2):260–269, 1967.

[33] Y. Wang, J. Lin, M. Annavaram, Q. A. Jacobson, J. Hong, B. Krishnamachari, and N. Sadeh. A framework of energy efficient mobile sensing for automatic user state recognition. In *Proceedings of the 9th International Conference on Mobile Systems, Applications, and Services (MobiSys '11)*, pages 179–192, 2009.

[34] T. Yan, D. Chu, D. Ganesan, A. Kansal, and J. Liu. Fast app launching for mobile devices using predictive user context. In *Proceedings of the 10th International Conference on Mobile Systems, Applications, and Services (MobiSys '12)*, pages 113–126, 2012.

[35] Z. Yang, C. Wu, and Y. Liu. Locating in fingerprint space: wireless indoor localization with little human intervention. In *Proceedings of the 18th Annual International Conference on Mobile Computing and Networking (MobiCom '12)*, pages 269–280, 2012.

[36] Z. Zhang, X. Zhou, W. Zhang, Y. Zhang, G. Wang, B. Y. Zhao, and H. Zheng. I am the antenna: accurate outdoor ap location using smartphones. In *Proceedings of the 17th Annual International Conference on Mobile Computing and Networking (MobiCom '11)*, pages 109–120, 2011.

[37] P. Zhou, Y. Zheng, and M. Li. How long to wait?: predicting bus arrival time with mobile phone based participatory sensing. In *Proceedings of the 10th International Conference on Mobile Systems, Applications, and Services (MobiSys '12)*, pages 379–392, 2012.