No Need to War-Drive

Unsupervised Indoor Localization

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ABSTRACT

We propose *UnLoc*, an unsupervised indoor localization scheme that bypasses the need for war-driving. Our key observation is that certain locations in an indoor environment present identifiable signatures on one or more sensing dimensions. An elevator, for instance, imposes a distinct pattern on a smartphone's accelerometer; a corridor-corner may overhear a unique set of WiFi access points; a specific spot may experience an unusual magnetic fluctuation. We hypothesize that these kind of signatures naturally exist in the environment, and can be envisioned as internal *landmarks* of a building. Mobile devices that "sense" these landmarks can recalibrate their locations, while dead-reckoning schemes can track them between landmarks. Results from 3 different indoor settings, including a shopping mall, demonstrate median location errors of $1.69m$. War-driving is not necessary, neither are floorplans – the system simultaneously computes the locations of users and landmarks, in a manner that they converge reasonably quickly. We believe this is an unconventional approach to indoor localization, holding promise for real-world deployment.

Categories and Subject Descriptors

H.3.4 [**Information Storage and Retrieval**]: Systems and Software; C.2.4 [**Computer-Comunication Networks**]: Distributed Systems

General Terms

Design, Experimentation, Performance

Keywords

Location, Mobile phones, Sensing, Landmarks, Recursion

1. INTRODUCTION

Despite innovative research [1–9,9–16], indoor localization is still not in the mainstream. In trying to trace the reasons, we distilled two main messages: (1) Indoor spaces require fairly high location accuracy because the contexts vary at finer spatial granularity. For instance, $5m$ location error outdoors may still indicate the same street, but $5m$ indoors may mean two different aisles in a grocery store. An inventory-management application may very well require aisle-level precision. (2) While such precision is attainable with pervasive WiFi systems, they come at a prohibitively high cost, mostly in the form of meticulous (signal) calibration. Such calibration is not necessarily a one-time cost since RF fingerprints could change, perhaps due to changes in layout and objects in the environment. Attempts to simplify the calibration process have been successful, but at the expense of reduced location accuracy. This zero sum game between accuracy and calibration overhead has been an important hurdle to deploying indoor localization systems. This paper is tasked to break away from this tradeoff, and achieve *meter* level accuracy with zero calibration. Although a high bar, we believe this is feasible and make an attempt to do so.

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Our scheme cuts across isolated ideas in mobile computing. We introduce these ideas first, and then describe the value in making them compatible.

(1) A few recent schemes have demonstrated the ability to compute the motion trajectory of a mobile phone, using its accelerometer and compasses [2, 17]. This has been called urban dead-reckoning. Due to noise in the mobile sensors, the dead-reckoned trajectories are accurate in the beginning, but diverge from the truth over time. Therefore, outdoor localization schemes like CompAcc [2] have triggered periodic GPS measurements to recalibrate the user's location. Unfortunately, GPS is unreliable indoors, rendering dead-reckoning based approaches useless. Nonetheless, if one can identify other means of recalibration, dead-reckoning could be applicable even indoors.

(2) Urban sensing and activity recognition literature have demonstrated the ability to recognize ambiences and user behavior. For instance, inertial sensors can detect when a user is walking, turning into a corridor, or climbing up the stairs [18]; microphones and magnetometers can detect ambient sounds and magnetic fluctuations [14, 19]. While these signatures have been primarily used for various forms of context-awareness, they lend themselves to localization as well. For example, these signatures can be treated as "landmarks", useful to recalibrate indoor dead-reckoning.

(3) Past work has mostly relied on signal calibration [1, 3] to develop WiFi based localization. We observe that WiFi can be valuable even without calibration. For instance, one can use

overheard WiFi APs to partition an indoor space into smaller sub-spaces. Thus, a landmark signature need not be unique in the entire building – so long as it is unique within a WiFi sub-space, it can be recognized without ambiguity.

UnLoc combines these 3 ideas (dead-reckoning, urban sensing, and WiFi-based partitioning) into a framework for unsupervised localization. The core idea is recursive but not complicated. Briefly, mobile users move naturally in the building collecting accelerometer, compass, gyroscope, and WiFi readings. By assimilating data from these devices, UnLoc detects sensory signatures (e.g., a corridor turn) that are unique within their respective WiFi sub-spaces. Now using the same collected data, UnLoc dead-reckons the devices starting from a known reference location, say the entrance of the building. Since dead-reckoning provides a rough location to the phone, it is also possible to roughly localize the signatures based on when the phone senses them.

Now, the locations of these signatures – also called *landmarks* – can be made more accurate by combining the rough estimates from multiple phones. These landmarks can then be used to improve dead-reckoning of subsequent phones, which in turn can refine the landmark locations. This recursive process continues to improve localization accuracy over time. Observe that, the system does not need calibration – the first few users may experience inferior location accuracy, but a little more data brings the system to convergence.

Of course, translating this idea-sketch into a functional system entails a variety of challenges: (1) Dead-reckoning is non-trivial in indoor environments where metals and electrical equipment significantly affect the compass bearing[1]. (2) Extracting the accurate location of the landmarks from multiple erroneous locations is problematic, since the errors may not be all equal. Some notion of confidence on the errors need to be built, so that the estimates can be suitably weighted before combination. (3) Identifying landmark signatures from the sensed data warrants unsupervised learning on sensor features. (4) Finally, the system needs to be optimized for energy, to avoid a significant battery drain during localization. This paper addresses these challenges one step at a time, prototypes on a testbed of Android Nexus series phones, and evaluates with 3 volunteers naturally walking in 2 university buildings and 1 shopping mall. Performance results show median localization accuracy of $1.69m$ when UnLoc runs online, and $0.89m$ when the locations are computed offline. The system quickly reaches convergence in less than 2 man-hours, and remains robust to dynamic changes in the environment. We believe this could be a promising direction, and with rigorous testing and tuning, a potential candidate for the real-world.

Our main contributions may be summarized as follows:

- **We identify an opportunity to simultaneously harness sensor-based dead-reckoning and environment sensing for localization.** Our approach does not require calibration or installation of additional infrastructure.

- **We design a practical scheme that employs unsupervised learning to extract unique sensor signatures – called landmarks.** We show that adequate landmarks exist inside buildings such that dead-reckoning is practical and reasonably accurate.

- **We develop UnLoc on the Android OS, and evaluate across 3 different indoor spaces, including the North Gate shopping mall in Durham.** We achieved less than $2m$ error without any pre-deployment effort; in fact, we used the map of the building only to compute ground truth for evaluation.

[1]Prior work demonstrated dead-reckoning mostly for outdoor environments.

The subsequent sections expand on each of these contributions, beginning with architectural overview and intuition, followed by measurement, design, and evaluation.

2. ARCHITECTURE AND INTUITION

We begin with a high level overview of UnLoc, focussing mainly on the core building blocks and intuitions (Figure 1). We will postpone the discussion on actual algorithms and engineering details to the next section. In fact, *we will even make a simplifying assumption that the building floorplan is available to UnLoc.*

Of course, this assumption need not hold in our final system – its sole purpose is ease of explanation. Once we have developed the core framework, we will discuss how the assumption can be relaxed.

Human Motion Traces

Consider the example where we intend to localize users in a shopping mall. When users visit the mall, the UnLoc app running on their smartphones collect time-stamped sensor readings. These readings (mainly from accelerometer, compass, gyroscope, and WiFi APs[2]) are assimilated in a central repository. UnLoc must operate on this data to track each user's location. For now, we perform this offline.

Seed Landmarks (SLMs)

As a first step, UnLoc looks into the floorplan of the building and identifies some "*seed landmarks*". These seed landmarks are essentially certain structures in the building – stairs, elevators, entrances, escalators – that force users to behave in predictable ways. These predictable behaviors can be translated to sensor signatures. For instance, building entrances are characterized by a visible drop in the GPS confidence when the user moves from outdoors to indoors; elevators exhibit a distinct accelerometer signature, emerging from the start and stop of the elevator. If a user, Alice, used the elevator in the mall, UnLoc expects her trace to contain the elevator signature embedded in it. Let us assume that this signature occurs in Alice's trace at time t_i. Since the location of the elevator is known within the floorplan, UnLoc can precisely localize Alice at t_i. In similar ways, Alice can be precisely localized at other time-points when she passed through any of the other landmarks. The next step, then, is to localize her while she moved between these landmarks – for this, UnLoc adopts techniques from urban dead-reckoning.

Dead Reckoning

Urban dead-reckoning [2] is an established idea that uses the accelerometer and the compass to track a mobile user.

[2]Sound and light measurements could also be useful, but we do not activate them for energy-efficiency.

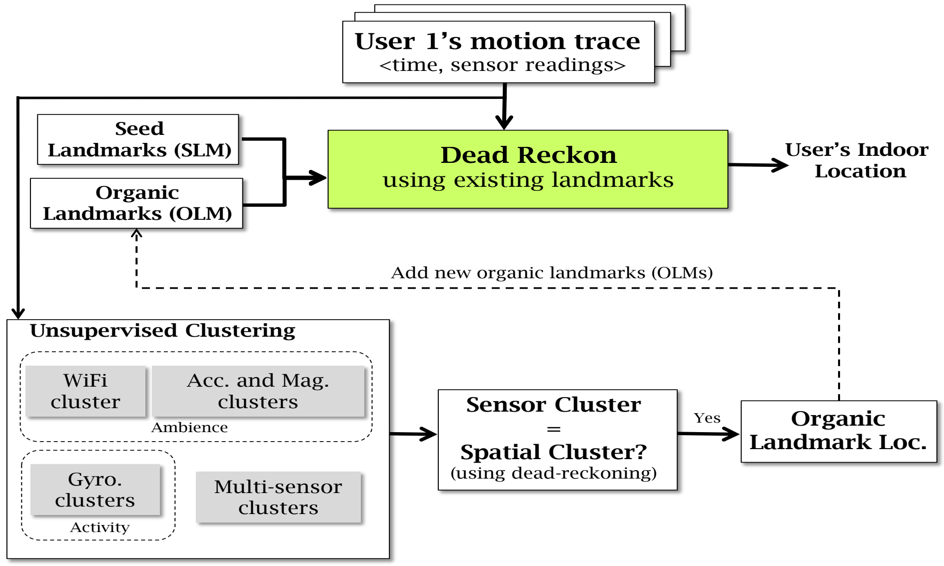

Figure 1: UnLoc architecture – motion vectors are computed from recorded sensor readings, and the user's location computed via dead-reckoning. The dead-reckoning error is periodically reset using landmarks in the environment. Further, the same sensor readings are mined to identify signatures of new landmarks. These landmarks help in improving localization accuracy for subsequent users.

The key idea is simple. Based on the accelerometer readings of the mobile phone, it is possible to count the number of steps a person has walked, and therefrom derive the displacement of the person. Based on the compass, the direction of each of these steps can be tracked[3]. Merging these, the <*displacement, direction, time*> tuple forms the human's motion vector. Pivoting these vectors at the seed landmarks, UnLoc tracks the location of Alice. Although the tracking operation is crude (because the noisy sensors accumulate error over time), the error gets reset whenever Alice crosses any of the landmarks. Thus, in the steady state, Alice's localization error exhibits a saw-tooth behavior – over time, the localization error grows and then sharply drops to zero at the landmark, and then grows again. Observe that increasing the density of landmarks will cause the error to reset frequently, thereby curbing the error growth. UnLoc will attempt to accomplish this by organically extracting additional landmarks from the indoor environment

Organic Landmarks (OLMs)

In addition to seed landmarks, UnLoc postulates that any indoor environment will offer some ambient signatures across one or many sensing dimensions. These signatures can be in the magnetic domain, wherein metals in a specific location may produce unique and reproducible fluctuations on the user's magnetometer, near that location. Signatures could also be WiFi-based – a spot may overhear a set of WiFi base stations, but the set may change at short distances away from that spot. A few (dead) spots inside a building may not overhear any WiFi or GSM/3G signals, which by itself is a signature. Further, even a water-fountain could be a signature – users that stop to drink water may exhibit some common patterns on the accelerometer and magnetometer domains. Whenever these pattern surface on Alice's trace, it could be an opportunity to recognize her location. Of course, even though these signatures can become useful landmarks, they cannot be known *a priori*, and will vary across different buildings. They have to be learnt dynamically.

Towards learning these landmarks, UnLoc subjects the sensor data (gathered from all phones) to a clustering algorithm (Figure 1). Actually, various features of this data are extracted and the clustering runs on this high dimensional space – detailed in the next section. Once the clustering operation has completed, each of the resulting clusters is expected to contain similar sensor patterns. Now, since each sensor reading is associated with time-stamps, it is possible to find their corresponding locations via dead-reckoning. UnLoc computes these locations to check whether all members of a cluster fall within a small area – Figure 2. If they do, then UnLoc deems it a new landmark. Since these landmarks were discovered automatically, without any external supervision, we call them *organic landmarks* (OLMs). If no OLMs are found, UnLoc waits for more traces and continues scanning for OLMs.

Simultaneous Localization and Mapping

Both SLMs and newly discovered OLMs are used to improve dead-reckoning for subsequent users, which in turn improves the location estimates of the SLMs/OLMs themselves. This circular process pushes the entire system to better accuracy and UnLoc continues to improve over time. The evaluation section will quantify this behavior, for different users and buildings.

2.1 Intuitions and Supporting Measurements

The success of UnLoc hinges on at least 3 performance-related expectations: (1) Dead reckoning can attain desired levels of accuracy, if periodically recalibrated by landmarks. (2) Indoor environments indeed offer the requisite number of landmarks. (3) The locations of the landmarks can be computed from rough estimates of multiple devices (i.e., the dead-reckoning errors are indeed independent). We discuss our intuitions in

[3]However, as we will find in the next section, magnetic fluctuations in the environment will derail the compass readings, forcing us to shift to gyroscopes.

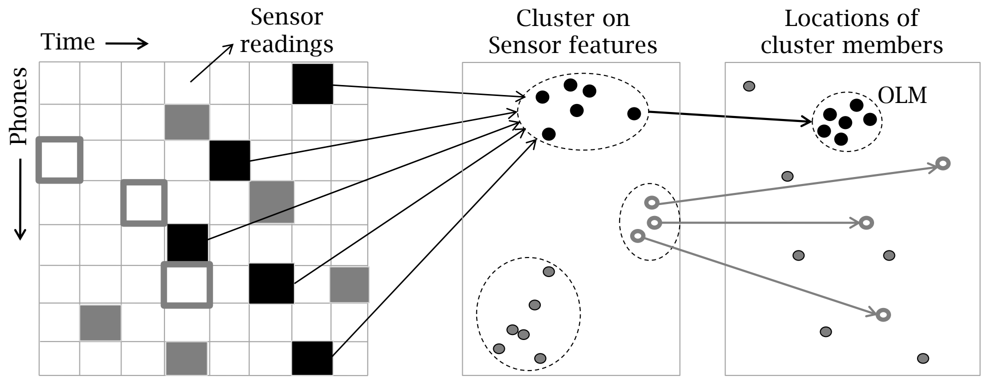

Figure 2: Matrix showing sensor readings collected by devices across time. Readings are clustered and location of cluster members computed. If all cluster members fall within a small region, UnLoc deems it an OLM.

each of these, and present supporting measurements wherever relevant.

(1) Dead-Reckoning Accuracy

We performed some initial experiments in the computer engineering building at Duke University. Volunteers were asked to carry NexusS phones in their pockets, and walk naturally in one wing of the building. The UnLoc app running on the phones records the accelerometer and compass readings, and extracts from them the $<$*displacement, direction, time*$>$ tuples. To record ground truth, we marked different doors and windows in the buildings with a distinct number[4] – when a user passed by that number, she entered it into her phone. Since we know the mapping between the number and the door/window, we are able to extract the ground truth (almost accurately). We gathered 10 traces, each starting from the entrance of the building. We performed trace-based analysis to understand how the dead-reckoned path diverges from the true path, with varying number of landmarks.

Figure 3 shows the accumulated error over time (light gray curve) when using pure dead-reckoning with zero landmarks. Evidently, the error accumulates dramatically fast, and is completely unusable. Hence, we simulate landmarks by periodically reseting the user's location to the correct location – the black curve shows the results. While the performance improves, the mean localization error is still $11.7m$, greater than our target. On analyzing the data, we observed that the magnetic field in indoor environments is heavily distorted by metallic and electrical equipments in the (engineering) building. Thus, although these magnetic fluctuations are beneficial for finding landmarks, they derail dead-reckoning by injecting heavy error in the compass. UnLoc appeared impractical at this point.

Fortunately, newer smartphones are embedded with gyroscopes that measure the angular velocity of the phone in 3 dimensions and are not affected by the magnetic field. We carefully processed the gyroscope readings to compute the angular changes during walking, i.e., how the user turned. However, gyroscope readings are relative and we needed to combine it opportunistically with the compass to estimate the user's absolute walking direction. We will report several technical challenges of this operation in section 3, including compass offsets and gyroscope drifts. However, once we harnessed the gyroscope and the compass in tandem, the dead-reckoning error reduced appreciably (blue curve in Figure 3). When re-calibrated by periodic landmarks, the average error dropped further to $1.2m$, offering us confidence to build a fuller system.

[4]Recall that GPS is unavailable indoors.

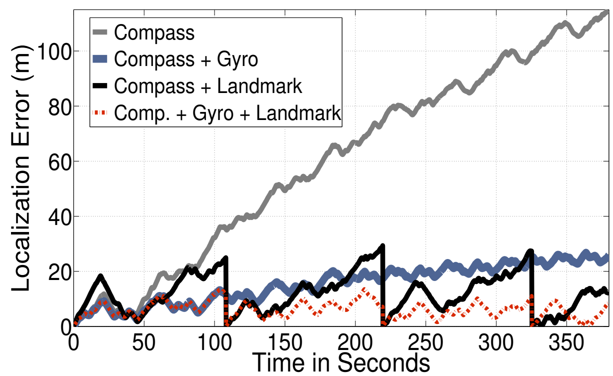

Figure 3: Error from dead-reckoning reduces with gyroscope, and further with landmarks.

In addition, once a landmark is encountered, the user's path can be retraced and corrected between the last two landmarks. Although this does not help in realtime tracking of the user, it helps in offline analysis, and more importantly, for improving the location estimate of organic landmarks.

(2) Landmark Density

It is natural to question *why indoor environments would exhibit sensor signatures to be used as landmarks?* While there is of course no guarantee, our observation is that an indoor environment is rich with ambient signals, like sound, light, magnetic field, temperature, WiFi, 3G, etc. Moreover, different building structures (e.g., stairs, doors, elevators) force humans to behave in specific ways. If one "combs" through all these sensor signals and their high-dimensional combinations, we postulate that some signatures are likely to emerge. The intuition is essentially rooted in diversity, i.e., the chances that all of the signals are similar and no pattern "shows up as different", seems unlikely. Further, these signatures need not be unique in the entire building – so long as they are unique within the WiFi sub-space, they can be valid landmarks. We performed a small scale measurement study to verify this intuition – the results follow.

• **WiFi Landmarks**:
Consider an area within which all locations overhear a distinct set of WiFi APs. An indoor space is likely to have many such areas of varying sizes. Figure 4 shows the distribution of the sizes of these areas. While most of the areas are quite large – explaining why simple WiFi based localization is not very accurate – there are a few areas (at the left side of the X axis) that are very small. UnLoc aims to exploit these small areas as a landmark. If one of this small areas overhears a set of WiFi APs, denoted W, then a mobile phone overhearing the same set can be assumed to be within that area. Since the area is small, the localization error of the phone will be small too, enabling a location recalibration. Our measurements show that in two floors of the engineering building, we find 8 and 5 such WiFi landmarks, each of area less than $4m^2$. Thus WiFi APs can offer landmarks to enhance dead-reckoning.

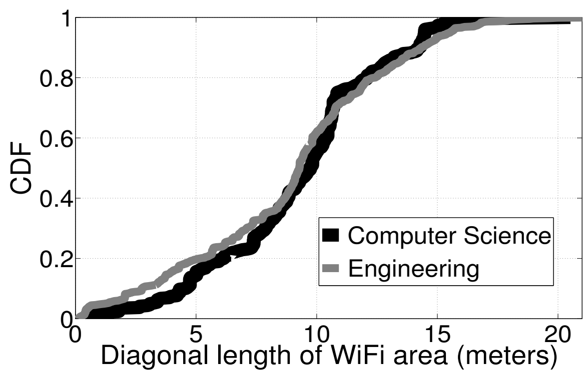

Figure 4: Some WiFi areas are very small (tail of distribution), and hence, an ideal landmark.

• **Magnetic/Accelerometer Landmarks**:
In search of signatures in other sensing domains, we executed K-means clustering on accelerometer and compass measurements (we present the algorithm and parameter details later). For each cluster, we mapped their members to their corresponding physical locations (using ground truth). For most clusters, we found that their member-locations were widely scattered in space, and hence, were unusable as a landmark. However, members of a few clusters proved to be tightly collocated in space as well. For example, we discovered a unique/stable magnetic fluctuation near our networking lab. We found another spot with a distinct accelerometer signature – a pair of symmetric bumps in opposite directions (Figure 5).

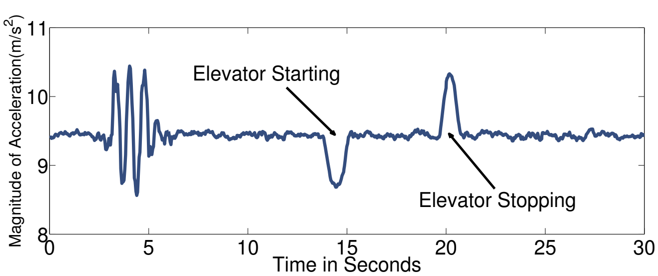

Figure 5: Accelerometer signature inside the elevator (caused by the elevator starting and stopping).

Although UnLoc need not understand the semantic meaning of these signatures, out of curiosity we analyzed the data, and discovered that they were caused by the elevator starting and stopping. In fact, the direction of the bumps (upward or downward) even indicated whether the user went upstairs or downstairs. These spatially collocated patterns were natural landmarks, and when we assimilated all sensing dimensions, the number of landmarks proved to be 6 and 8 for each floor. In fact, when we combined accelerometer and compass together – a higher dimensional signature – we found even more landmarks due to turns in the building. In sum, the organic and seed landmarks together seemed to offer the needed density to support indoor dead reckoning.

(3) Computing Landmark Locations

Perhaps an important pitfall in UnLoc lies in computing the locations of the landmarks. Figure 6(a) is intended to explain the problem. In this example, assume that UnLoc has combined the user's sensor data, clustered on them, and discovered 3 sensor signatures (in distinct WiFi areas), that can be used as landmarks. Now the locations of these landmarks need to be computed, but there is no ground truth to learn that. One way to estimate the location of a landmark is to use dead-reckoning, but that will not be accurate since dead-reckoning itself is erroneous. Our approach is to compute the landmark location by combining all the (dead-reckoned) estimates of a given landmark. The intuition is that dead-reckoning errors have been observed to be random and independent, due to the noise in hardware sensors and human step sizes [2]. By combining these errors from adequate measurements, one could expect the estimated mean to converge to the actual landmark location. Figure 6(b) illustrates the opportunity through a simple centroid calculation.

Figure 8 visualizes data from real measurements to verify independence in dead-reckoning error – each line joins the estimated landmark location to the actual location. Visually, the errors appear uncorrelated. Of course, this is a preliminary overview of the inner workings of the system – we later discuss the algorithmic details of this error combining process, and measure performance in greater detail.

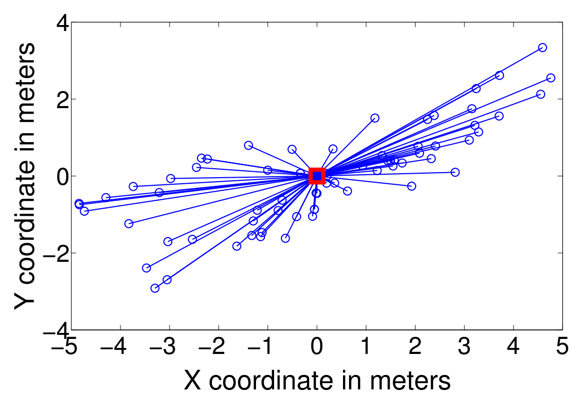

Figure 8: Uncorrelated errors from multiple dead-reckoning estimates.

3. DESIGN DETAILS

This section describes the algorithms and engineering details underlying UnLoc.

3.1 Seed Landmarks

If the building's floorplan is known (which is often necessary to visualize the user's location), then UnLoc can infer the lo-

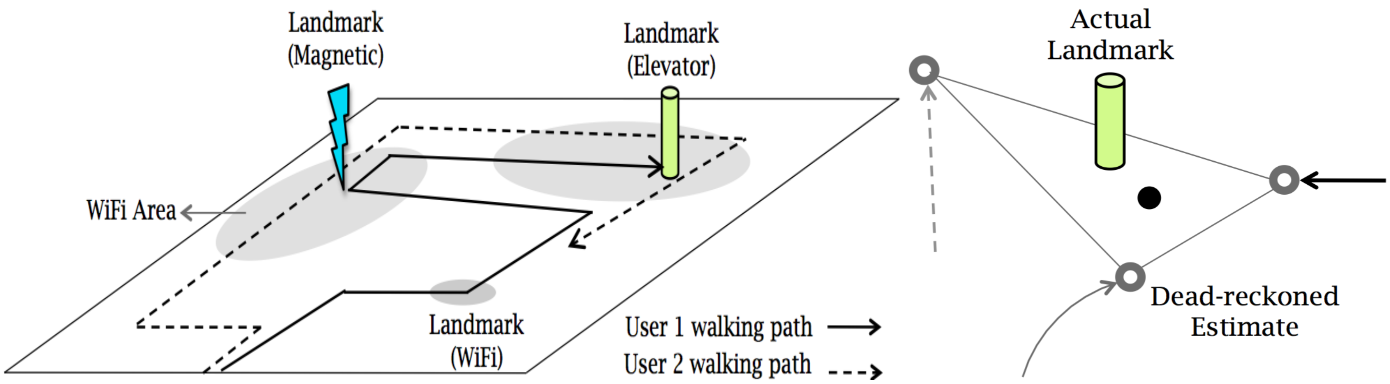

Figure 6: (a) UnLoc users walk and periodically encounter landmarks – refines landmark locations, corrects own location. (b) The solid circle showing the centroid of the dead-reckoned estimates. Multiple erroneous estimates leading to a better approximation of the landmark location.

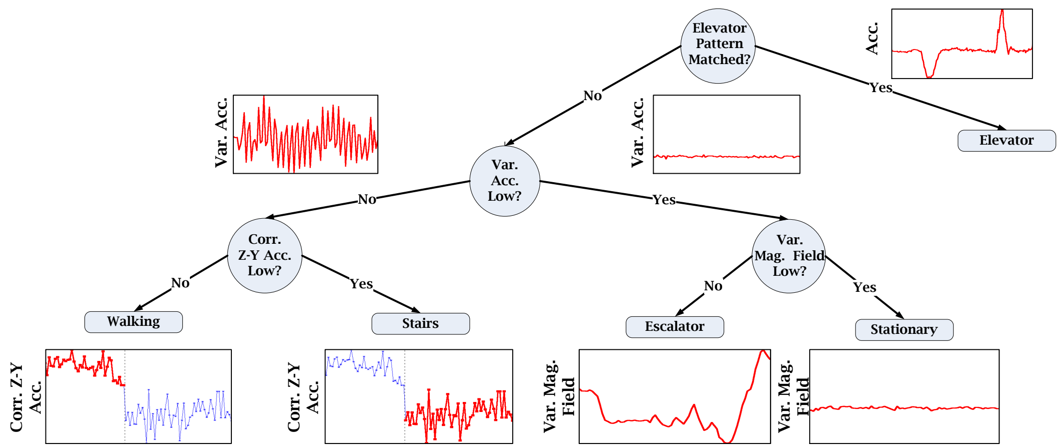

Figure 7: Decision tree for detecting Seed LandMarks (SLMs). The top level separates the elevator based on its unique acceleration pattern. The second level separates the constant velocity classes (stairs and escalator) from the other two classes (walking and stairs) based on the variance of the acceleration. The third level uses the variance of magnetic field to separate the escalator from the stationary case and the correlation between the Z and Y acceleration components to separate between the stairs and walking cases.

cations of doors, elevators, staircases, escalators, etc. This implies that the location of seed landmarks (SLMs) are immediately known. As long as the smartphone can detect these SLMs while passing through them, it can recalibrate its location. Thus, the goal of the SLM detection module is to define sensor patterns that are global across all buildings.

Elevators, Staircases, and Escalators

This class of SLMs are based on using the inertial sensors. These sensors have the advantage of being ubiquitously installed on a large class of smart phones, having a low-energy footprint, and being always on during the phone operation (to detect the change of screen orientation). We focus on three particular examples that are common in indoor environments: elevators, escalators, and stairs. Figure 7 shows a classification tree for detecting the three classes of interest and separating them from walking and being stationary. We note that a false positive leads to errors in estimating the location of the SLM while a false negative leads to missing an opportunity for recalibration. Therefore, high detection accuracy with low false positive/negative rates are highly desired.

Elevator: A typical elevator usage trace consists of normal walking period, followed by waiting for the elevator for sometime, walking into the elevator, standing inside for a short time, an over-weight/weightloss occurs (depending on the direction of the elevator), then a stationary period which depends on the number of the floors the elevator moved, another weight-loss/over-weight, and finally a walk-out. To recognize the elevator motion pattern, we developed a Finite State Machine (FSM) that depends on the observed state transitions. Different thresholds are used to move between the states. Evaluation over 22 traces show that the thresholds are robust to changes in the environment and can achieve 0.6% and 0% false positive and negative rates, respectively.

Escalator: Once the elevator has been separated, it is easy to separate the classes with constant velocity (escalator and stationary) from the other classes (walking and stairs) using the variance of acceleration. Now, to separate the escalator from stationarity, we found that the variance of the magnetic field can be a reliable discriminator. Of course, a user may sometimes climb up the escalator – we find that magnetic variance also differentiates between this and an actual staircase-climb (see Figure 9).

Stairs: Once the scenario with constant speed is separated,

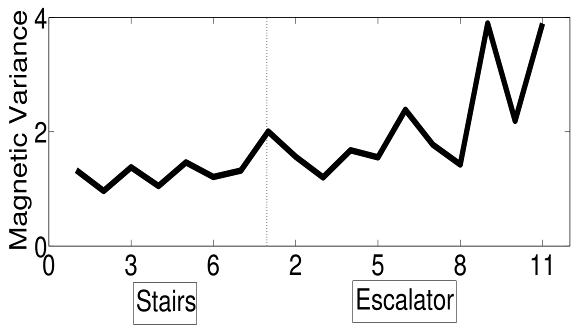

Figure 9: Magnetic variance when a user is climbing stairs versus escalator.

we need to differentiate between the stair and walking case. The main observation here is that when the user is using the stairs, her speed increases or decreases based on whether the gravity is helping her or not. This creates a higher correlation between the acceleration in the direction of motion and direction of gravity as compared to walking. As reported later, staircases can sometimes lead to false negatives (1.8%).

3.2 Dead Reckoning

The two sub-tasks in dead reckoning are (1) computing the user's displacement from accelerometer and (2) continuously tracking the direction of movement.

Displacement from accelerometer:
One possible solution is to double-integrate the accelerometer readings. Figure 10(b) shows the unacceptable results – the difference between the estimated and actual displacement reaches more than $100m$ only after $30m$ of actual displacement. This is an attribute of a noisy accelerometer, low sampling rate (24Hz), as well as jerky movements of the phone when carried by the user. A better approach [2,20] is to identify a human-walking signature as in Figure 10(a). This signature arises from the natural up/down bounce of the human body for each step taken. To capture this, we pass the signal through a low pass filter, and identify two consecutive local minima. Between these local minima, we search for a local maxima, and check whether the difference between the maxima and minima is greater than a threshold. If so, we increment the step count.

The physical displacement can be computed by multiplying step count with the user's *step size*, a function of the user's weight and height [21][5]. Employing a fixed step size across all users can clearly be erroneous. However, UnLoc has the opportunity to infer the step size by counting the number of steps for a known displacement (i.e., between two landmarks). Figure 10(c) shows the error accumulated by UnLoc using these techniques in place – the results are encouraging. The step count accuracy (verified with 10 users) was also 98%.

Orientation using compass/gyroscope:
Past work has demonstrated the feasibility of dead-reckoning using the smartphone compass. However, to the best of our knowledge, all these results are for outdoor environments. Indoors, the magnetic field due to ferromagnetic material and electrical objects in the vicinity, completely derailed our dead

[5]A more accurate approach is to estimate the user step size based on her gait [22].

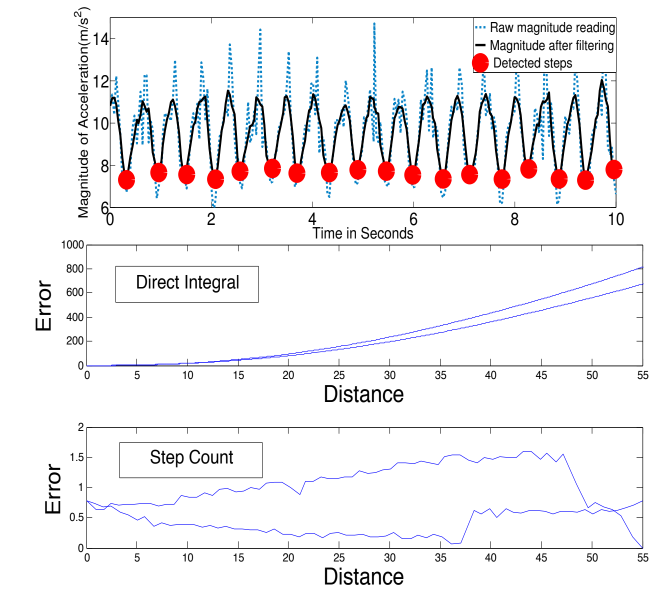

Figure 10: (a) Accelerometer readings (smoothened) from a walking user. (b) Displacement error with double integration for two users. (c) Error with step count method.

reckoning attempts[6]. In response to this, we explored the feasibility of using gyroscope to *infer* the user's movement directions. Our intuition was that the gyroscope is decoupled from the magnetometer sensor, and hence, could be insensitive to ambient magnetic fields.

While this insensitivity proved true, i.e., the gyroscope indeed remained unaffected by changing magnetic fields, the trade-off was that the gyroscope offered *relative angular velocity*. This is in the form of a 3D rotation matrix which when multiplied by a time interval, yields the relative angular displacement (RAD) of the device. Unfortunately, the RAD is with respect to a direction that is not necessarily the absolute direction. Thus, while we could track the structure of the user's motion path using the gyroscope, these paths were biased by the error in their initial direction. Thus all the estimated paths appeared as rotated versions of the true path, shown in Figure 11(a).

We observe that encountering landmarks can help infer this bias. Figure 11(b) explains the opportunity. Consider a user encountering a known landmark L_1 at time t_1, and later another landmark L_2 at time t_2. UnLoc identifies that the user encountered these two landmarks because the signatures matched, and hence, regardless of the dead-reckoned estimates, UnLoc "pins down" the user's path at these locations. Now, let θ denote the angle between the line joining L_1, L_2 and the line joining L_1, X_2, where X_2 is the dead-reckoned estimate at time t_2. We observe that θ is the initial bias, and therefore, UnLoc rotates the entire motion segment by θ. Importantly, the same θ can be used to track the user for the subsequent motion segment – say until the user encounters landmark L_3 – at which point the bias can again be updated. This process of learning and updating the bias at every landmark leads to stable and consistent results. The only remaining problem lies in tracking the user until she has encountered the second

[6]We attempted at least 5 different techniques to learn and correct for these fluctuations.

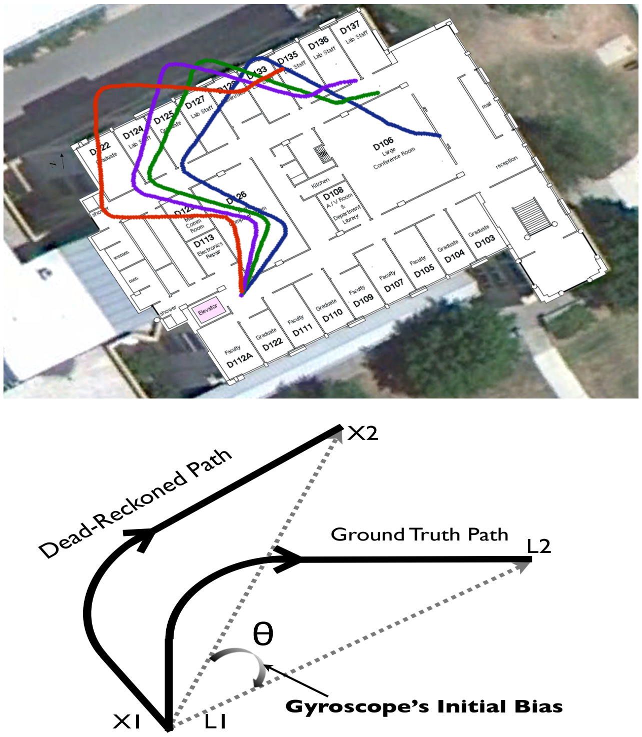

Figure 11: (a) Rotated walking trail due to gyroscope's initial bias. (b) Correcting gyroscope's bias using landmarks.

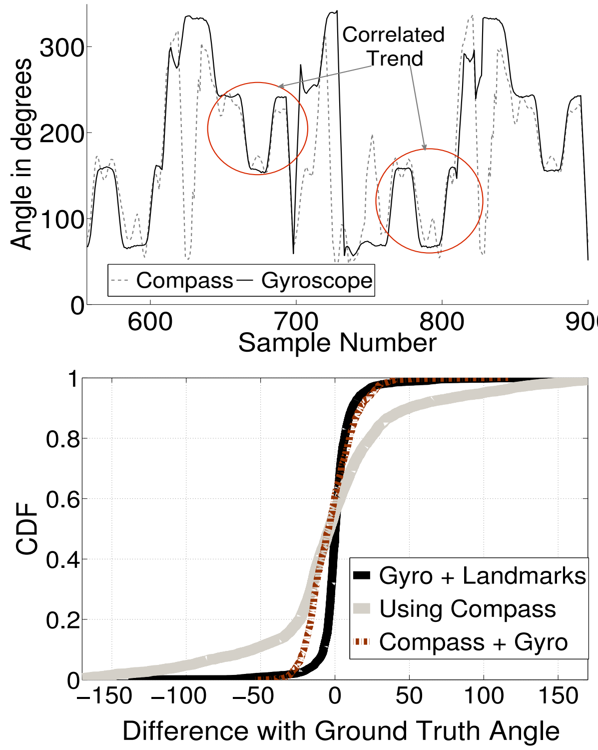

Figure 12: (a) Compass orientation is more reliable when it is correlated with the gyroscope. (b) CDF of orientation estimation error.

landmark – during this phase, her dead reckoning error can be arbitrarily high.

UnLoc turns to the compass during the initial phase when the gyroscope bias is still unknown. Clearly, the compass value cannot be used blindly – ambient magnetic field fluctuations can actually degrade the results. Thus, UnLoc juxtaposes the gyroscope and compass readings – Figure 12(a) – and whenever the trends are correlated, the compass value is selected as the direction of motion. The gyroscope's bias is now inferred, and used thereafter. The intuition here is that correlated trends in compass and gyroscope is an indicator of proper compass readings; and if the compass is not reflecting the gyroscope's trend, it is probably affected by other factors. Figure 12(b) shows the eventual outcomes in angular direction estimation. The compass helps with the initial phase, while gyroscope based dead reckoning proves to be effective. In fact, to the best of our knowledge, UnLoc is the first to leverage smartphone gyroscopes for indoor dead reckoning.

3.3 Organic Landmarks

The task of discovering organic landmarks (OLMs) is rooted in (1) recognizing distinct patterns from many sensed signals, (2) and testing whether a given pattern is spatially confined to a small area. Recall that Figure 2 illustrates the flow of operations. All the sensor readings are gathered in a matrix: element <i,j> of the matrix contains sensor readings from phone i at time j. These sensor readings are essentially *features* of the raw sensed values (from the accelerometer, compass, gyroscope, magnetometer, and WiFi). Features for the magnetic and inertial sensors include *mean, max, min, variance, mean-crossings*, while for WiFi, they are *MAC ID, RSSI*.

UnLoc normalizes these features between $[-1, 1]$ and feeds them to a $K - means$ clustering algorithm. (we tested with *Expectation Maximization* (EM) clustering as well, but it was not consistently better than K-means). The clustering is executed for each individual sensing dimensions, as well as their combinations (such as accelerometer and compass together). Figure 13, for example, shows the clusters from the magnetometer readings for $K = 3$. We varied the value of K and recorded the clusters in each case. Our goal is to identify clusters that have *low similarity* with all other clusters; this will suggest a good signature. For this, we compute the correlation between a given cluster and all other clusters – if the maximum correlation is less than a *similarity threshold*, we consider this cluster as a candidate for landmark.

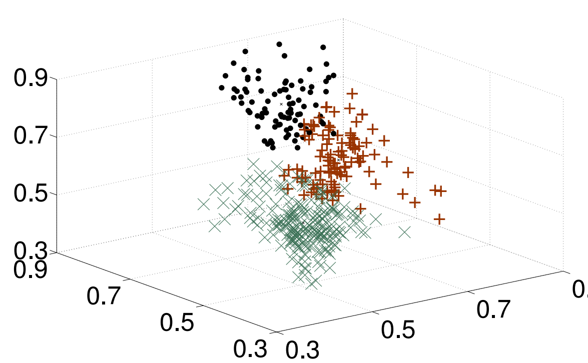

Figure 13: Clusters identified by kmeans algorithm

To qualify as an OLM, the candidate cluster must also be confined to a small geographical area. For this, we first test whether the members of a cluster are within the same WiFi area (i.e., they overhear the same WiFi APs). While this is necessary, it is not sufficient because many WiFi areas are large. Therefore, for clusters within a WiFi area, we compute the dead-reckoned locations for each of their members. If locations of all cluster-members are indeed within a small area – we use $4m^2$ – then we recruit this cluster as an OLM. As an anecdote, we found that using accelerometer, one of the sensor clusters were scattered all over the indoor space; upon investigation, we detected that this cluster roughly captured walking patterns. On the other hand, another cluster that proved to be within the $4m^2$ area was from a magnetic signature near an electrical service room in the building. UnLoc announces the centroid of the cluster as the OLM's location.

While the above describes the generalized version of the OLM detection algorithm, the different sensing dimensions require some customization, discussed next.

3.3.1 WiFi Landmarks

We use MAC addresses of WiFi APs and their corresponding RSSI values as features. To remain robust to signal variations (which alters the set of overheard APs), we only consider APs that are stronger than a threshold RSSI. Now, applying K-means clustering, we identify small areas ($4m^2$) that have low similarity with all locations outside that area. We compute similarity of two locations, l_1 and l_2, as follows. Let us denote the sets of WiFi APs overheard at locations l_1 and l_2 as A_1 and A_2, respectively. Also, let $A = A_1 U A_2$. Let $f_i(a)$ denote the RSSI of AP a, $a \in A$, overheard at location l_i; if a is not overheard at l_i, then $f_i(a) = 0$. We now define similarity $S \in [0, 1]$, between locations l_1 and l_2 as:

$$S = \frac{1}{|A|} \sum_{\forall a \in A} \frac{min(f_1(a), f_2(a))}{max(f_1(a), f_2(a))}$$

The rationale for this equation is to add proportionally large weights to S when an AP's signals are similarly strong at both locations, and vice versa. We threshold on S to define a WiFi landmark. We choose a threshold of 0.4 in our system, indicating that all locations within the WiFi landmark needs to exhibit less than 0.4 similarity with any other location outside the landmark. Of course, this rather strict threshold ensures that landmarks are quite distinct, but also reduces the number of possible landmarks. Figure 14 shows this tradeoff using traces from two Duke University buildings. We observed that 0.4 was a reasonable cut-off point, balancing quality and quantity of WiFi OLMs.

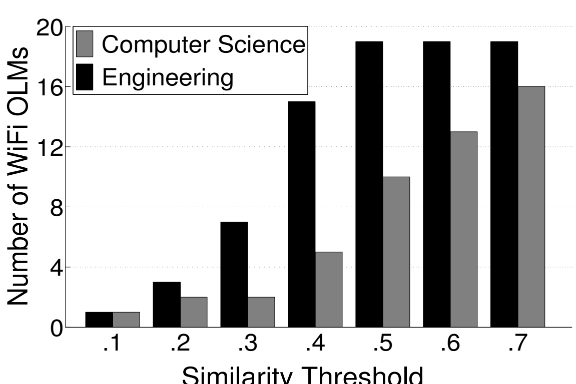

Figure 14: Tradeoff between similarity threshold and number of WiFi landmarks.

3.3.2 Magnetic and Inertial Sensor Landmarks

Indoor environments are characterized by at least a few turns (at the end of corridors, into offices, classrooms, stairs, etc.). Since the gyroscope offers reliable angular displacements, we recognize the opportunity to use them as organic landmarks. We design a special feature called the *bending coefficient*. Essentially, the coefficient captures the notion of path curvature, computed as the length of the perpendicular from the center of a walking segment to the straight line joining the endpoints of the segment. We compute the bending coefficient over a sliding window on the user's walking path, and use them as a separate feature. Later, when we cluster on bending coefficient and WiFi together as features, similar turns within a WiFi area gather in the same cluster. The turns in the cluster could still be doors of adjacent classrooms in a corridor – these turns may very well lie within the same WiFi area. To avoid coalescing all these turns into the same landmark, UnLoc checks if the cluster is confined to within a $4m^2$ area; only then is the cluster declared a landmark.

Magnetic landmarks are also derived through similar techniques. So long as the magnetic signature is unique within one WiFi area, and the sensed locations are spatially confined within $4m^2$, we deem it as a magnetic OLM. Figure 15 shows an anecdotal example where the magnetic field near our networking lab demonstrates a unique distortion.

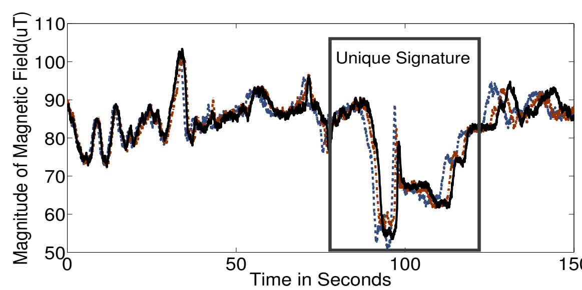

Figure 15: Magnetic signature near networking lab.

3.4 Simultaneous Localization and Mapping

UnLoc uses the SLMs and OLMs to reset dead reckoning error and track the user. The improved dead-reckoned paths help in refining the landmark locations because different paths offer *independently* erroneous estimates of a specific landmark. Combining these independent errors produces the refinement (the intuition derived from law of large numbers, where the sampled mean converges to the true mean for a large number of samples). We combine the estimates of a landmark, say L_i, as follows. While the obvious approach would be to compute the centroid, we actually take advantage of the observation that all estimated locations may not be equally incorrect. Consider 2 users who arrive at L_i from landmarks L_j and L_k, respectively. If L_j is closer to L_i than L_k, then the user that walks from L_j is likely to have incurred less error. This is because pure dead reckoning is known to accumulate error over time. Thus, accounting for this confidence in landmark estimates, UnLoc computes a weighted centroid. The result is declared as the location of the landmark.

3.5 Points of Discussion

• **While we assumed the knowledge of a floorplan, we can relax that assumption now.** Observe that in reality, we need just one ground truth location of any seed landmark. This could be the location of the building's entrance, staircase, elevator. Once we know the GPS coordinate of one SLM, the rest of the SLMs and OLMs can be organically grown, using this known coordinate as the origin. Importantly, the location of this origin SLM – say the building's entrance – needs to be learnt *only once* when UnLoc bootstraps for the first time. In the steady state, even if users do not know when they are passing through the entrance, their locations will become known once they encounter a landmark. The same is true when a user enters through a different entrance of the building, or turns on her phone at some time after she is inside the building. The localization service will activate once they pass through the first landmark.

In this paper's implementation, we extracted the GPS location of the building entrance from Google Satellite View. During bootstrap, a user activated UnLoc when entering through this entrance. Alternatively, the entrance location could have been collected by other means, or even estimated from locations where GPS fixes are lost (after entering a building). We firmly believe that obtaining the GPS coordinate of one SLM, just one time, will not be difficult in real life.

• **Activity based landmarks are feasible too – a busy cafe may invariably have a queue, or visiting a restroom may have a unique signature.** These activities can very well be landmarks as long as their patterns surface upon clustering. Even temporary landmarks can be learnt (i.e., queue exists between noon and 2:00pm only), and even unlearnt if the queueing behavior disappears during, say, winter vacations. Our current implementation has not explored these opportunities – we have only used signatures that are stable over time.

• **The early adopters of UnLoc will help with localizing the OLMs and bring the system to convergence – is this not war-driving?** We argue that this is certainly not war-driving because the early adopters behave naturally and do not collect ground truth (since they do not need GPS). In fact, they collect exactly the same sensor readings as all other users. The only difference is that the early users may experience less localization accuracy (Figure 19). The process of war-driving, on the contrary, is associated with the notion of (ground truth) calibration, which naturally requires additional equipment.

The next section discusses the implementation, experiment methodology, and performance of UnLoc.

4. EVALUATION

Prototype Implementation

UnLoc is implemented on Google NexusS phones using JAVA as the programming platform. The phone samples the 4 sensors (magnetometer, compass, and accelerometer at $24Hz$; gyroscope at highest permissible rate) and WiFi at $1Hz$. Various features derived from these measurements are sent to the UnLoc server.[7] The server side code is written using C# and MATLAB, and implements the dead reckoning, clustering, and landmark signature-matching algorithms. Whenever a new landmark is detected from clustering, the server updates the OLM list.

[7]In a real-life deployment of UnLoc, communication to the server may not be necessary. The landmarks of a building can be downloaded *a priori*; clustering and landmark matching algorithms can be executed locally on the phone.

Methodology

We design real-life experiments with 3 different users in 3 different university buildings – (1) Computer Science (2) Engineering, and (3) North Gate shopping mall. Approximately, we covered $1750m^2$, $3000m^2$, and $4000m^2$ respectively, in these buildings. Each user walked around arbitrarily in the building for 1.5 hours, covering multiple floors; they carried 2 phones, one in the pocket and another in the hand with the screen facing up. We made separate arrangements to collect ground truth (recall that GPS is not available inside any of these buildings). Briefly, we pasted markers on the grounds at precisely known locations, such as the center of a classroom door, the first step in a staircase, the entry-point to the elevator, in front of a window, etc. Each of these markers had a number on them; as a user walked through a marker, she spoke out the number on the marker, and the phone recorded it. By superimposing the map of the building on Google Earth, and identifying the corresponding locations of the markers, we extracted their GPS locations. This offered us ground truth at these markers. Between two markers (separate by $5m$ on average), we interpolated using step-count. Of course, UnLoc did not rely on any of the ground truth markers to compute its location. Thus, at any given time, the difference between ground truth and the UnLoc-estimated location, is UnLoc's instantaneous localization error.

4.1 Evaluation Results

We intend to concentrate on the following questions:

- How many landmarks are detected in different buildings? Are they well scattered? (Figure 16))
- Do real users encounter these landmarks (i.e., is the matching between the sensor reading and established landmark signatures, reliable)? (Figure 17)
- What is the localization accuracy of a user, in real-time, and offline? (Figure 18, 19, 20)

SLM Detection Performance

Table 1 shows the confusion matrix for the detection of all SLMs (using traces from 2 malls in Egypt). The matrix shows that some SLMs are easier to detect than others due to their unique patterns. This leads to zero false positive and negative rates for the elevators and walking cases. However, even with the difficult SLMs, the UnLoc's template signatures can still achieve a high accuracy, with an overall 0.2% false positive and 1.1% false negative rates.

Detecting Organic Landmarks (OLMs)

Figure 16(a) shows the number of landmarks detected inside different buildings. For the engineering building, the breakup of the landmarks is: 9 magnetic, 8 turns, and 15 WiFi OLMs. For the computer science building, the breakup is: 9 magnetic, 10 turns, and 10 WiFi OLMs. Perhaps more importantly, Figure 16(b) shows how these landmarks are quite homogeneously scattered inside the buildings. We observe that with these numbers of well-scattered landmarks, a user's dead reckoning error is not likely to grow excessively, in turn

Table 1: Confusion matrix for classifying different seed landmarks

	Elevator	Stationary	Escalator	Walking	Stairs	FP	FN	Traces
Elevator	24	0	0	0	0	0%	0%	24
Stationary	0	31	1	0	0	0%	3.1%	32
Escalator	0	0	22	0	0	0.6%	0%	22
Walking	0	0	0	39	0	0%	0%	39
Stairs	0	0	0	1	52	0%	1.8%	53
Overall						0.2%	1.1%	170

helping landmark localization. This well matches our core intuition and expectation.

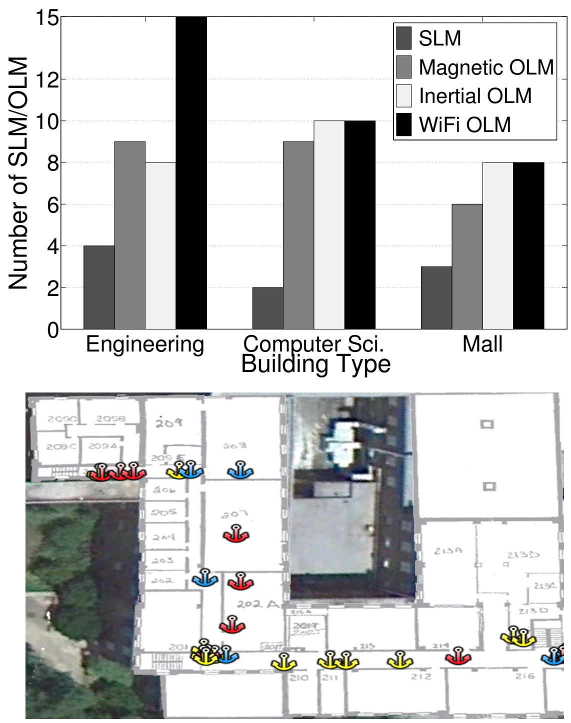

Figure 16: (a) Number of SLMs and OLMs located in different buildings (b)Location of different types of OLMs in the engineering building

Figure 17(a) reports the accuracy of the landmark locations, as computed by UnLoc. Observe that aligned with our intuition, the number of landmarks increase over time, as more users explore the space (Figure 17(b)). Moreover, the accuracy of these landmarks also increase, since different paths bring different independent estimates. In fact, our data sets are limited in diversity of paths since volunteers could not walk around into any rooms or auditoriums in these buildings – many were research offices, faculty offices, or classrooms. In reality, the diversity of different independent paths may be expected to augment the accuracy.

Landmark Signature Matching

If landmark signatures fluctuate quickly over time, then OLMs will be unstable. Thus, users may never encounter the established OLMs because their signatures are changing faster than they can be learnt. Furthermore, it is entirely possible that users at a different location sense a signature that matches a far-away landmark. In such a case, the user's location will be repositioned to the (highly erroneous) landmark. To verify if such variations occur in our buildings, we collected sensor readings on multiple days. We found sound consistency in the signatures. This is not surprising because all our signatures are designed to be stable, particularly WiFi and accelerometer/gyroscope based turns. While the magnetic signatures can change, in our cases we did not observe anything appreciable.

Nonetheless, recall that UnLoc embraces a conservative approach by using a low "similarity threshold" while declaring a landmark. In other words, the signature of the landmark should be very dissimilar with other signatures to qualify as a landmark. This ensures that when a test user matches her sensed readings with existing OLMs, the false positive (FP) rate is low. Figure 17(c) quantifies false positives – evidently FP is less than 1%. As a tradeoff for choosing very distinct signatures, it is possible that a test user may not match it well. Figure 17(c) shows that the matching accuracy is reasonably high, although not perfect. We believe that this is an acceptable tradeoff – given that the number of landmarks are high, missing a few will affect performance much less than matching to an incorrect landmark. In other words, UnLoc is in favor of trading off matching accuracy to maintain low false positives.

Of course, changes in the ambience – say relocation of major electrical equipment to a different room, or deactivated WiFi APs – will affect existing landmarks, and UnLoc will not be able to match them. However, UnLoc will learn these changes changes over time, both the disappearance of the landmark from its original location, as well as the emergence of a landmark at a different location. So long as these changes are not all at the same time, UnLoc should be able to remain resilient to landmark churn. We leave the quantification of this claim to future work.

Localization Performance

In offline localization, whenever a user encounters a landmark, UnLoc learns her errors, and therefore can track back and partly correct her past trail. Online, real-time localization does not offer this benefit. Figure 18(a) shows the comparison of these two forms of localization – evidently, the advantage of offline is appreciable. This implies that for applications which do not need online tracking, localization error can be within $1.15m$ on average, even with a few landmarks.

Beyond the bootstrapping phase, as UnLoc identifies several organic landmarks, error correction opportunities will increase. How much accuracy can we expect in steady state when many OLMs have already been recognized? Figure 18(b) demon-

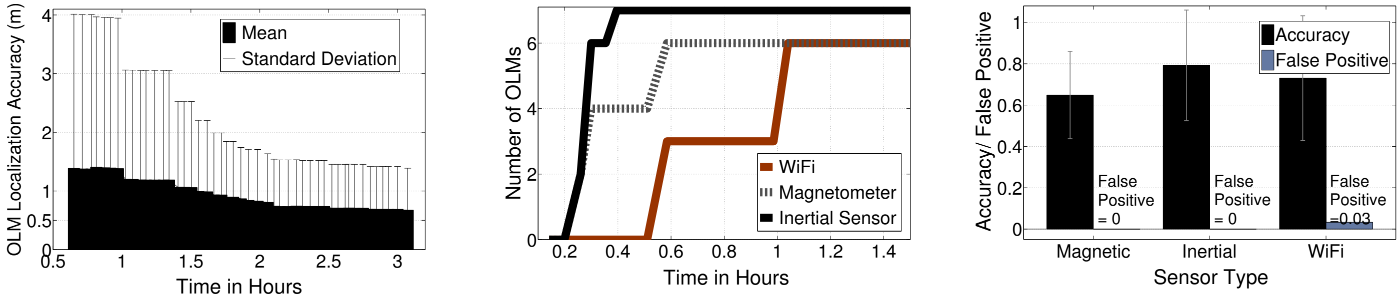

Figure 17: (a) OLM localization accuracy improves over time. (b) Also more number of OLMs are detected as more users walk around the building. (c) OLM matching accuracy and false positives

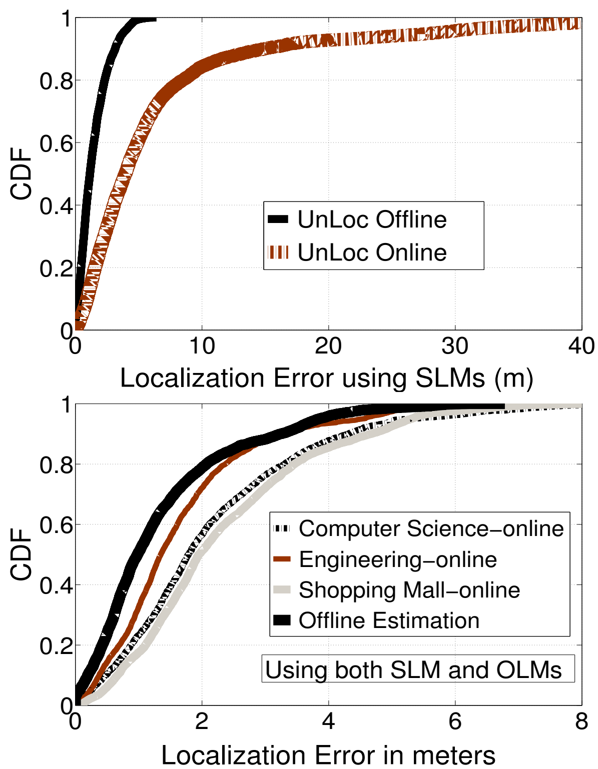

Figure 18: CDF of localization accuracy using (a) only SLMs (b) both SLMs and OLMs

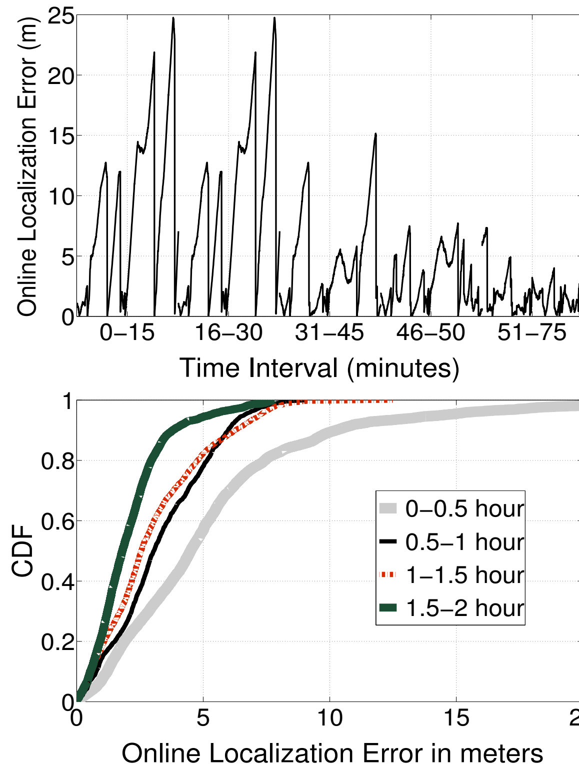

Figure 19: Localization error over time for (a) a single user. (b) averaged over all users.

strates the result; mean instantaneous localization error is within $1.69m$. However, the performance will only improve over time as more OLMs are detected. Figure 19(a) quantifies the intuition. As a user moves away from a landmark, her location error grows and eventually gets reset at the next landmark. Initially, UnLoc only has a few landmarks and hence the error between two landmarks is high. As more landmarks are identified and added to the system, the error growth is curbed frequently. We aggregate the error over time across all the users walking on multiple routes, and present in Figure 19(b). The benefits of additional OLMs are evident.

The above results are from experiments across 3 different buildings using several landmarks. It is difficult to predict how many such landmarks exist in other buildings. Thus, it is natural to ask if *localization performance will get derailed if only a few landmarks exist?* Figure 20 presents location error for varying landmarks. Even with 10 out of the 28 landmarks, average instantaneous location error is within $1.9m$. We expect a few landmarks to be available in most buildings – when in doubt, UnLoc could even turn on the microphone to expand to ambient acoustic signatures. While far more rigorous experimentation is necessary (across more buildings, people, phone platforms, and time), we believe the results from these small scale tests are promising to justify moving forward.

Note on Performance Comparison

Table 2 shows a qualitative comparison of UnLoc with a number of other indoor localization schemes. The most relevant scheme for comparison is EZ [23], which to the best of our knowledge, was among the first to attempt calibration-free localization. However, we believe that EZ's reliance on "occasional GPS fixes" in indoor environments could be problematic. We believe UnLoc's requirement of only a door location is more dependable/scalable. Also, UnLoc is far less sensitive to RF signal fluctuations; the data volume needed to bootstrap is also less. Other schemes in Table 2 require war-driving or special infrastructure; UnLoc is free of both.

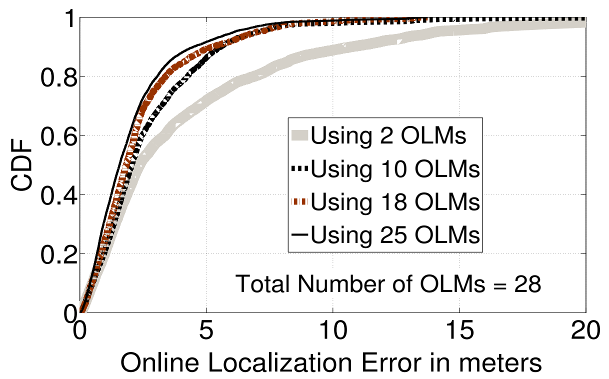

Figure 20: Tradeoff between number of landmarks and localization performance.

Table 2: Comparison with other Localization Systems

Name	**EZ**	**SLAM**	**Horus**	**UnLoc**
Accuracy	$2-7m$	$\sim 5m$	$\sim 1m$	$1-2m$
Pitfalls	GPS Lock?	Special Sensors (LIDAR, Odometer.)	RF Sensitivity	Door Location
Overhead	None	None	War-driving	None

5. LIMITATIONS AND FUTURE WORK

• **Heterogeneous Hardware:** It is possible that the landmark signatures will vary across smartphone platforms – UnLoc has not been tested for this. However, if data gathered from smartphones are indexed by the phone's make and model, it should be feasible to detect landmark signatures for each distinct model (as we have, for the Android Nexus series). Thus, in real-life, a phone would download landmark signatures that are specific to its hardware, and run UnLoc for localization. In other words, UnLoc would extend to all platforms from which initial sensor data has been gathered.

• **Phone Orientation Effect:** We have experimented with the phones in realistic orientation (in pocket and in hand). Handling arbitrary phone orientations and their effect on the reported sensor values is an important direction for future research. As gyroscopes are becoming more available on new phones, they can be leveraged to map arbitrary orientation to a specific frame of reference. Meanwhile, orientation-independent features, such as the magnitude of the acceleration, should be investigated.

• **Energy Footprint:** UnLoc avoids using sensors that have a high energy footprint, e.g., light and sound. This is expected to limit the energy consumed from sensing. Moreover, UnLoc can incrementally turn on sensors, perhaps depending on the density of landmarks available in the environment. For example, if a wing of a building has numerous landmarks, UnLoc could turn off the magnetometer, and use only the accelerometer and compass based landmarks for localization. This paper has not addressed such optimizations – these are part of our ongoing work.

• **Scalability Testing:** A complete UnLoc system needs to be tested over larger scale, in terms of the number of users and data size. However, as with other crowd-sourcing based systems, it is difficult for us to deploy a large scale testbed. This includes in part providing incentive systems for users to deploy the system and experiment with it.

6. RELATED WORK

Our goal and vision intersect with a number of projects in literature. In particular, the indoor localization literature is vast, ranging from theoretical models to simulations to implemented systems [1–9, 9–16]. In the interest of space, we heavily sub-sample this literature, focussing on systems related to UnLoc.

Calibration-free Localization: A recent work called *EZ* [23] was among the first to attempt indoor localization without war-driving. Their key intuition is that overheard WiFi APs and RSSI can together offer the user's location (via a genetic algorithm), provided that a mobile device occasionally gets a GPS fix. While EZ demonstrates accuracies between 2 to $7m$, the GPS locks inside a building can be erratic. Moreover, the precise RF signal propagation may vary over time due to environmental dynamism. UnLoc eliminates this reliance on periodic GPS fixes, and only relies on a one-time global truth information – e.g., the location of a door, or staircase, or elevator. The entire system can bootstrap from this.

WiFi based techniques: Other RF based techniques [1, 3, 5] also inspire UnLoc. Place Lab [5] is a highly successful project where signals from different WiFi and GSM base stations are utilized for localization. A wireless map is created by war-driving a region; the mobile device localizes itself by comparing overheard APs/cell towers against the wireless map. UCSD's Active Campus project [6] adopts similar techniques of localization, but assumes that the location of the WiFi access points are known *a priori*. RADAR [1] also operates on WiFi fingerprinting, and is capable of achieving up to $5m$ accuracy in indoor settings. As a tradeoff to accuracy, RADAR needs to carefully calibrate WiFi signal strengths at many physical locations in the building. High resolution calibration is time-consuming and may not scale over wide areas. Some techniques have bypasses the calibration effort through deployment of additional infrastructure, e.g., Cricket [10], Lease [4], PAL [8], Pinpoint [15]. UnLoc is designed to be an infrastructure-independent, calibration-free, system.

Dead-reckoning: Dead reckoning using inertial sensors is a well-studied research area. However, typical sensors used in such domains are expensive and high-quality ones – coping with noisy smartphone sensors in indoor environments is far less explored. The key problem is that dead-reckoning suffers from the accumulation of error, and can grow cubically even with foot mounted accelerometers [24]. To reduce such error, periodic recalibration with the GPS has been used in outdoor environments [2, 25]. However, GPS is not available indoors. UnLoc presents an option to replace GPS with indoor landmarks; the ability to identify these landmarks in an unsupervised way enables zero-calibration indoor localization.

Simultaneous Localization and Mapping (SLAM): A highly popular and successful technique in robotics, called SLAM, allows a robot to simultaneously discover landmarks and build a map-representation of an indoor environment [26]. However, SLAM typically depends on using explicit environment sensors, such as laser range finders and cameras. Moreover, the rotation of the robot wheels offer a precise computation of displacement. Recently, WiFi-SLAM [27] proposed the usage of the WiFi signal strength for SLAM based on a Gaussian Process Latent Variable Model (GP-LVM). However, the multipath propagation affects the accuracy of the model that captures the relation between the WiFi signal and distance. The paper also assumes that motion between multiple WiFi samples can be accurately determined. UnLoc is certainly reminiscent of SLAM, even inspired – however, it is completely different. Unlike SLAM, UnLoc uses smartphone sensors to compute the displacement and direction of users; the landmarks are essentially ambient signatures or user-activities. While ambient signatures and activity recognition have been utilized in the past [14, 28], its applicability towards dead-reckoning is, to the best of our knowledge, novel.

Sensor fusion: Multi-modal sensing has received strong interests – [29] uses a body worn sensory board (MSB) for human activity recognition. UnLoc, however, is an early attempt to apply activity recognition to indoor location tracking, using cheap mobile phone sensors.

7. CONCLUSION

We observe that inherent properties of indoor environments offer unique opportunities to perform localization. The core approach draws from existing ideas in literature, and combines them in an unconventional way. Essentially, mobile devices are dead-reckoned using their sensor measurements, but these same measurements are leveraged to detect unique environmental signatures within the building. These signatures are used to correct the dead-reckoning error, which in turn improves the location accuracy of these signatures – a recursive procedure. Performance results suggest promise, motivating us to pursue UnLoc to the point of real deployment.

8. ACKNOWLEDGMENT

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9. REFERENCES

[1] V. Bahl et al. RADAR: An in-building rf-based user location and tracking system. In *INFOCOM*, 2000.

[2] I. Constandache, R.R. Choudhury, and I. Rhee. Towards mobile phone localization without war-driving. In *INFOCOM*. IEEE, 2010.

[3] M. Youssef and A. Agrawala. The horus WLAN location determination system. In *MobiSys*, 2005.

[4] P. Krishnan and others. A system for LEASE: Location estimation assisted by stationary emitters for indoor rf wireless networks. In *IEEE Infocom*, March 2004.

[5] Yu-Chung Cheng et al. Accuracy characterization for metropolitan-scale wi-fi localization. In *MobiSys*, 2005.

[6] William G. Griswold et al. Activecampus: Experiments in community-oriented ubiquitous computing. *Computer*, 2004.

[7] M. Youssef et al. Pinpoint: An asynchronous time-based location determination system. In *ACM Mobisys*, 2006.

[8] S.J. Fontana, R.J.and Gunderson. Ultra-wideband precision asset location system. In *IEEE Conference on Ultra Wideband Systems and Technologies*, May 2002.

[9] D. Niculescu and others. VOR base stations for indoor 802.11 positioning. In *ACM MobiCom*, 2004.

[10] N. B. Priyantha. *The cricket indoor location system*. PhD thesis, MIT, 2005.

[11] A. Savvides and M. Han, C.C. Srivastava. Dynamic fine-grained localization in ad-hoc networks of sensors. In *ACM MobiCom*, 2001.

[12] J. Xiong and K. Jamieson. SecureAngle: improving wireless security using angle-of-arrival information. In *ACM HotNets*, 2010.

[13] S. Sen et al. Precise Indoor Localization using PHY Layer Information. In *ACM HotNets*, 2011.

[14] M. Azizyan et al. SurroundSense: Mobile phone localization via ambience fingerprinting. In *MOBICOM*, 2009.

[15] M. Youssef, A. Youssef, C. Rieger, U. Shankar, and A. Agrawala. Pinpoint: An asynchronous time-based location determination system. In *ACM MobiSys*, 2006.

[16] S. Kumar and D. Shepherd. Sensit: Sensor information technology for the warfighter. In *Proc. 4th Int. Conf. on Information Fusion*, 2001.

[17] I. Constandache et al. Did you see bob?: human localization using mobile phones. In *ACM MobiCom*, 2010.

[18] L. Bao and S. Intille. Activity recognition from user-annotated acceleration data. *Pervasive Computing*, pages 1–17, 2004.

[19] J. Chung et al. Indoor location sensing using geo-magnetism. In *MobiSys*. ACM, 2011.

[20] F. Evennou and F. Marx. Advanced integration of wifi and inertial navigation systems for indoor mobile positioning. *EURASIP journal on applied signal processing*, 2006:164–164, 2006.

[21] Step size in pedometers. `s.http://walking.about.com/cs/pedometers/a/pedometerset.htm`.

[22] M. Alzantot and M. Youssef. Uptime: Ubiquitous pedestrian tracking using mobile phones. In *IEEE Wireless Communications and Networking Conference (WCNC 2012)*. IEEE.

[23] K. Chintalapudi, A. Iyer, and V. Padmanabhan. Indoor localization without the pain. In *MOBICOM*, 2010.

[24] O. Woodman and R. Harle. Pedestrian localisation for indoor environments. In *UbiComp*. ACM, 2008.

[25] M. Youssef et al. Gac: Energy-efficient hybrid gps-accelerometer-compass gsm localization. In *IEEE GLOBECOM 2010,*.

[26] M. Montemerlo et al. Fastslam: A factored solution to the simultaneous localization and mapping problem. In *Proceedings of the National conference on Artificial Intelligence*, 2002.

[27] B. Ferris, D. Fox, and N. Lawrence. Wifi-slam using gaussian process latent variable models. In *Proceedings of the 20th International Joint Conference on Artificial Intelligence*, pages 2480–2485, 2007.

[28] S.P. Tarzia et al. Indoor localization without infrastructure using the acoustic background spectrum. In *ACM MobiSys*, 2011.

[29] J. Lester, T. Choudhury, and G. Borriello. A practical approach to recognizing physical activities. *Pervasive Computing*, pages 1–16, 2006.