Analysis and Status Quo of Smartphone-based Indoor Localization Systems

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***Abstract*—Over the past decade, indoor localization has been a topic of interest for both the academic and industrial communities. The need for location estimation, fueled mainly by inaccuracies of GPS indoors, has been addressed by specifically designed systems achieving a high localization accuracy but with a high deployment cost. Lately, dedicated systems are being replaced by smartphones through intelligent use of the built-in sensors. For instance, an accelerometer that can detect user activity can be combined with a wireless radio that captures wireless signal strength information to locate a user. With the advent of such technology, a myriad of systems have been proposed in the literature presenting an indefinite picture to a reader as to which systems actually work and which do not given practical considerations. This article takes up the goal of surveying state-of-the-art smartphone based indoor localization systems with critical analysis on their properties such as accuracies across various sensor designs, energy consumption and computational cost, user satisfaction etc., thereby providing a status quo of such systems.**

Keywords*—*Indoor Localization, Smartphones, Fingerprinting, Dead Reckoning.

I. Introduction

INDOOR localization despite being a well studied problem with innovative solutions proposed by researchers, still presents a daunting task for users while finding their way inside indoor spaces, such as campus buildings, shopping malls, underground subways, and airports. The reasons could be unconstrained user mobility, non-uniformity in building structures/plans and many others. This has led to the dependence on static you-are-here (YAH) maps which are not periodically updated and hence force users to resort to human help for locating and navigating themselves.

Driven by the mobile computing impetus, several solutions have been proposed. Hightower *et al.* [1] discuss the functionalities of most available technologies in the pre-smartphone era, including infrared badges, ultrasound tags, laser rangers, as well as wireless modules (e.g., RFID) All the referenced proposals in [1] require additional equipments to be carried by users, making them seminal solutions to begin with but not necessarily practical for real-life deployments. A recent survey by Harle [2] focuses on indoor positioning systems facilitated by wearable inertial sensors such as accelerometer, gyroscope and magnetometer. While being a valuable source for understanding inertial positioning (e.g., techniques for computing displacement and direction from user movements), the survey barely touches the area of using smartphones as platforms for indoor localization.

Over the past few years smartphones have been penetrating the market at an exponential rate. Built-in sensors such as accelerometer, gyroscope, magnetometer, microphone and camera have extended beyond the boundaries of entertainment and user interaction to give us the benefit of encapsulating communicating, sensing and computing capabilities into one device. A survey by Lane *et al.* [3] provides a concise discussion on all novel application developments using smartphones including indoor localization. In a nutshell, [1], [2], [3] provide readers either a general understanding of indoor location systems or and the sensing capabilities of smartphones, but they never delve particularly into smartphone-based location systems, whereas our goal is to bridge this gap.

We aim to provide a performance comparison of systems developed across a diverse range of smartphone platforms. The metrics we take into account for the analysis are energy consumption, built-in sensor variation, computational cost, user diversity, and user intervention. Due to the lack of uniform evaluation methodologies, we do not re-implement the existing work but provide a discussion based analysis on how the aforementioned metrics affect the accuracy of the localization systems. To reiterate, our contributions lie in providing an analysis of smartphone based localization systems, their capabilities and drawbacks and finally proposing a working principle of our infrastructure-less localization system.

We lay down the road map of this paper. Section II provides an introduction to the different location inferencing techniques. Section III provides a comparative analysis on the systems discussed using the metrics mentioned. Section IV first presents the need for an indoor navigation system on a portable smartphone, followed by an evaluation of a publicly available localization system. The final part in this section, consists of a working idea of our infrastructure-less system and how it caters to satisfying certain key design factors for an indoor localization and navigation system. Finally, we conclude our survey in Section V.

*This work is done when the first author, Kalyan P. Subbu, was working as a post-doctoral researcher at NTU.

Fig. 1. Location inference using smartphone sensors: fingerprinting (FP) is performed through built-in sensors indicated on the left side, whereas dead reckoning (DR) is performed through sensors on the right.

II. Overview of Location Inference

Locations can be estimated intermittently (i.e., locating a user from time to time when he/she is stationary) or continuously (e.g., tracking a user who keeps moving). Usually, intermittent localization relies on fingerprinting where observed signal strengths are matched with stored signal strength maps to find a best match. Continuous localization is facilitated through dead reckoning algorithms which track and update the position of the user continuously using inertial data collected at every time instant. Fig. 1 illustrates the various built-in sensors utilized by each of the techniques.

Fingerprinting (FP) is performed with various signal sources such as cellular [4], wireless [5] ambient sound [6], light [7], and magnetic fields [8]. Fingerprinting systems need extensive human effort and time in mapping locations with corresponding signal strengths. However, the idea of crowdsensing has been utilized by some works [9], [10] for reducing the efforts. Crowdsensing essentially involves the general user in data collection through the smartphones they carry. As users move indoors, they either participate in the sensing process or their smartphones opportunistically collect data for further analysis.

Dead reckoning systems [11], [12] typically use the accelerometer data for computing the displacement [2], the compass (through the magnetic field sensor) to obtain the direction or heading information and perform tracking using probabilistic algorithms. However, indoor spaces induce magnetic field variations due to the presence of ferromagnetic building structures like pillars. These variations cause the compass to fluctuate leading to inaccurate heading. To overcome this issue, compasses are used in conjunction with gyroscopes which are immune to magnetic field variations and they measure the angular rotation of the device [13]. As the inertial sensors used by a DR system are often measuring differential quantities, their inherent drift can cause large errors in the final estimation (drift is the increase of error in displacement due to the double integration of noisy acceleration data). Therefore, a typical drawback of DR systems is the need for complicated algorithms to cope with such errors.

III. A Critical Analysis

For any comparative analysis, it is a norm to re-implement the proposed systems. However, Harle [2] correctly pointed out that this is hindered due to the lack of uniform testing methodologies particularly for DR systems. Similar statement can be made for FP systems. Hence it may not make much sense to re-implement and compare all existing systems because of the differences in infrastructure, device and deployment effort requirement. Instead, we resort to analyzing whether prior work has addressed critical factors in smartphone based localization namely accuracy metric, energy consumption, sensor variation, computation power, and user intervention. Table I lists all the work discussed in this survey along with the results obtained comprising of relative accuracy and average estimation error. Relative accuracy is the number of test fingerprints correctly classified to their corresponding locations and average error is calculated as average distance between estimated location and ground truth. FP systems are evaluated based on the former metric whereas DR systems are evaluated based on the latter.

A. Energy Consumption

We define energy consumption as the amount of battery drain caused by various components such as the screen, cellular and WiFi radios, built-in sensors and the algorithmic or computational cost. In conjunction with indoor localization, we point out that the constant usage of built-in sensors and data transfer over wireless network are two of the potential energy consumers.

All multi-sensor fusion based localization systems [7], [9], [12], [13], [15], [16] involve continuous sensing of data which could burden the smartphone battery. For instance, UnLoc [13] constantly detects WiFi, magnetic and accelerometer landmarks to improve dead reckoning estimates, whereas Redpin [9] uses all three radios namely WiFi, Cellular and Bluetooth for fingerprinting and classifying locations. Although magnetometer, accelerometer and cellular radio are continuously running, the added energy consumption is marginal when compared to continuous usage of wireless and Bluetooth radios.

TABLE I. SYSTEM LEVEL RESULTS OF DISCUSSED WORKS. THE TRACKING CAPABILITY (OR CONTINUOUS LOCALIZATION) IS ALSO SHOWN INDICATING THE POSSIBILITY OF BUILDING AN INDOOR NAVIGATION SERVICE ON TOP.

Author	System	Sensors Used	Relative Accuracy (%)	Average Error (m)	Tracking	Reference
Varshavsky *et al.*	SkyLoc	Cellular	73	N/A	×	[4]
Jiang *et al.*	ARIEL	Acc, WiFi	95	N/A	×	[5]
Tarzia *et al.*	Batphone	Microphone	69	N/A	×	[6]
Azizyan *et al.*	SurroundSense	Acc,Microphone,Camera,WiFi	87	N/A	×	[7]
Subbu *et al.*	LocateMe	Magnetometer	90	4.5	×	[8]
Wang *et al.*	UnLoc	Acc,Compass,Gyro,WiFi	N/A	1.69	✓	[13]
Li *et al.*		Acc,Compass	N/A	3	✓	[11]
Rai *et al.*	Zee	Acc,Compass,Gyro,WiFi	N/A	1	✓	[12]
Bolliger *et al.*	Redpin	WiFi,Cellular,Bluetooth	90	3	×	[9]
Park *et al.*	OIL	WiFi	N/A	5	×	[10]
Ravi *et al.*		Camera	80	N/A	×	[14]
Park *et al.*		Acc, Magnetometer	N/A	7	✓	[15]
Zhang *et al.*	MaWi	WiFi, Magnetometer	90	3	✓	[16]

Therefore, MaWi [16] proposes to use only WiFi and magnetic sensing to achieve a satisfactory location accuracy.

Work in [7], [14] have exploited the camera for fingerprinting locations based on the images captured. Locations are further classified using different image processing techniques. Although [14] accounts for the energy spent to transmit low resolution images, it does not include the energy consumed by the camera application running. Also, data transfer over WiFi or 3G affects the battery usage. In [17], Vallina *et al.* show that approximately 12.5J and 7.6J of energy are consumed to transfer just 50KB of data over WiFi and 3G respectively on a Nokia handset. Since high resolution images have large file sizes, they could incur in much higher energy consumptions.

B. Sensor Variation

Differences in the built-in sensor models over a wide range of smartphones may also affect both FP and DR based systems. In order to validate the scalability of proposed FP systems, it is crucial to perform training and testing over diverse phone models, but most systems surveyed here do not tackle this challenge. The SkyLoc system [4] fingerprints cellular signals and classifies locations, particularly floors in multi-storied buildings. They use different instances of Nokia AudioVox phones which may not necessarily mean that the radio chipsets are different. Since different radios have different signal reception rates, they could potentially affect the cellular signal collection and classification. Next, Redpin [9] despite being a collaborative system uses only Nokia N95 phones across multiple users for validation. Batphone [6] uses the built-in microphone of an iPhone to fingerprint and classify locations based on the ambient acoustic information. Although encouraging accuracies are obtained, testing could have been performed across multiple phones since microphone sensitivity varies across different devices. On the contrary, LocateMe [8], implemented and discussed the effect of device diversity on their proposed magnetic field based location classification and distance estimation system.

As mentioned earlier, DR systems compute displacement and direction using inertial sensors such as the accelerometer, gyroscope and magnetometer. These sensors have different sensitivity and sampling rates across different vendors. Particularly, peak detection algorithms extract peaks which represent user steps. Variation in the sampling rates can have a significant impact on the algorithms resulting in false positives. For instance, [11] and [12] propose heuristic algorithms for step detection by sampling the accelerometer at 50Hz while ARIEL [5] samples at 5Hz. For faster computation, it might be advantageous to use lesser number of samples however it is not clear whether the algorithms in each of the proposals will work if the sampling rates are interchanged. Zee [12] crowdsources WiFi data as users are tracked using inertial sensors, but the proposed scheme was evaluated using only one user and one smartphone. Authors in [11] propose a personalized stride estimation and step detection algorithm. Although the system was evaluated across multiple users with different physical profiles, only a Windows 7 based HTC Mazza (specifications are not available) was used. On the other hand, [15] evaluate its tracking system using accelerometer and magnetometer from different Android based smartphones such as HTC Desire, HTC Nexus One, and Samsung Galaxy S.

C. Computational Cost

Complex computations by algorithms could cost the processor to devote entirely to one application. This could in turn burden the battery. We shall see how existing works address this problem. Most of the works follow a client-server approach. In other words, they offload processor intensive operations such as particle filter computation [11], [12], [15], supervised and unsupervised classification [13] and image processing [14], to a powerful server for reducing the burden on the smartphone's processor. Albeit a good strategy, we feel this could have direct implications on accuracy and user satisfaction. Depending on the network connectivity, the amount of test data transferred to a server could in turn affect the accuracy. In other words, due to network constraints, if only 100 WiFi samples are uploaded instead of an entire data set of 1000 samples to characterize a particular location, the accuracy of location estimation might reduce.

An ideal system should be capable of either computing locations locally on the phone with minimal or no requirement of a server. The alternative is to facilitate buildings with fast network connections for reducing data transfer and location computation delays. Both delays directly affect user satisfaction of a localization application i.e., a user may not be willing to wait for several minutes until the required data is transferred, location queried and the estimated location is sent back. For instance, the system in [8] downloads the respective magnetic maps (unique magnetic signatures of various locations) of buildings or hallways through a user input of the building name. Location is estimated locally using the downloaded maps, eliminating the need for any server computation. Since the delays mentioned above are reduced, this greatly increases user satisfaction.

D. User Intervention

Indoor localization systems should be designed in a way so as to minimize or avoid user intervention. In other words, the system should be adaptive to the ambient environment rather than expecting user inputs. Redpin [9] and OIL [10] propose collaborative systems for populating fingerprint databases. Both employ only a few users to build fingerprint maps of a building and perform localization. Although this validates the usefulness of crowdsensing systems, user intervention is involved to some extent in both proposals to correct wrongly classified locations (e.g., the system may ask a user to point their locations on the floor map). On one hand this could affect the accuracy if the user is not sure about his/her particular location due to building complexities and on the other hand, it may not be desirable for a first hand user who has no knowledge of his/her surroundings to provide valuable inputs about the location.

E. Accuracy

All the above discussed metrics affect the accuracy in one way or the other. Consider the accuracies obtained by Ariel [5] and SurroundSense [7] from Table I. They both utilize WiFi for localization but end up obtaining different accuracies. Factors such as sensor variation and environmental test beds may as well be attributed to this variation. Similarly, SkyLoc [4] and Redpin [9] utilize cellular fingerprints. However, Redpin obtains increased accuracy which can be attributed to the combined use of WiFi and Bluetooth fingerprints at the cost of battery drains thereby resulting in an accuracy Vs energy trade-off.

To conclude, we summarize two critical points. First, all the performance indices in Table I are taken from individual references obtained by individual testing platforms (e.g., certain smartphones) and fields (e.g., the office building occupied by the concerned research group). Therefore, these performance indices are not good indicators to comprehend which system performs better than another. Second, none of the works support navigation or implement indoor navigation on the smartphone which is the next step in getting closer to a GPS like system for indoors.

In the next section we discuss the need for an indoor navigation system, validate some of these requirements on a publicly available indoor maps service and finally introduce the design of our indoor localization and navigation system.

IV. What does the Future Hold?

To understand the general need for an easy to use indoor navigation service, a survey was conducted through a questionnaire raised toward navigating in a local shopping mall. Questions included the number of times people visited a particular shopping mall over the past year, their familiarity with the indoor space, common landmarks that they recall when visiting the mall and finally their need for a smartphone based indoor navigation system (INS). 120 participants male and female between ages 23-50 and belonging to Singapore participated in the survey. Table II shows the responses to the questionnaire. The statistics column indicates the average and standard deviation of participants' answers.

S/N	Question	Statistics
1	Num of visits to mall within the last year	10.61 ± 8.74
2	Familiarity with the indoor space (1-10)	5.11 ± 2.8
3	Ease of navigation using you-are-here maps (1-10)	5.00 ± 1.43
4	Need for smartphone-based INS (1-4)	3.5 ± 0.67
5	Cognitive landmarks recalled	5.00 ± 2.66

TABLE II. User perceptions on indoor navigation solutions (average ± standard deviation).

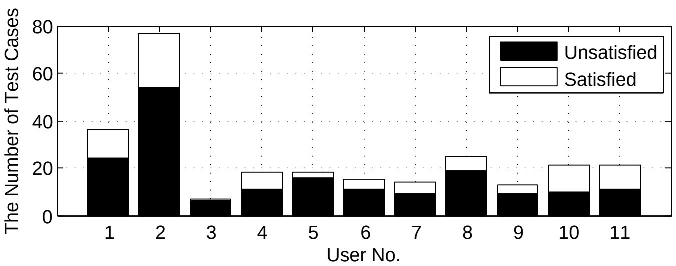
Table II lists the quantitative answers to all questions averaged over 120 users. For instance, for question I the responses indicate the maximum and minimum number of times users visited a mall. The maximum was close to 19 times and minimum was 2 times. Similarly for the next question, the highest familiarity was close to 8 and lowest was 2.

From the responses it is interesting to see that people on one hand, have low confidence in finding ways and remembering landmarks (confirming the importance of indoor localization), while they on the other hand, do not generally trust a smartphone-based system (demonstrating the need for better developments of such systems). To better interpret user satisfaction with an indoor localization service, we requested users to install the publicly available Google Maps Indoors (GMI) service which has been made available across various indoor facilities particularly shopping malls. Through this evaluation, we also aim to understand the actual working principle behind GMI.

A. Evaluating GMI

One key requirement of GMI is that facility owners release floor maps. Also, according to anonymous online sources, GMI is an FP system based on WiFi and GSM signals. To confirm this, we let 11 users use the service in eight shopping malls and evaluate GMI. The accuracy of GMI was evaluated through user feedbacks, which involved labeling actual locations for comparison with GMI marked locations. Fig. 2(a) illustrates the observed accuracy. Next, user satisfaction was rated based on how close they were located, in other words, GMI's accuracy directly affected user satisfaction. Fig. 2(b) shows the user satisfaction rates after using GMI. As can be seen, users tend to be dissatisfied with the service.

(a) Screenshots for GMI. The blue arrows indicate locations estimated by GMI and the labels show the actual location. Though without actual measurements, the differences between the estimated and actual locations are clearly very significant.



(b) The number of satisfied and dissatisfied cases from 11 users.

Fig. 2. GMI performance evaluation

All the tests had three common observations: i) The smartphone's WiFi and 3G needed to be turned on, ii) GMI provided a coarse location of 20m based on cellular base stations in locations with weak or no WiFi networks, and 3) GMI delivered satisfactory accuracy only when there is a very high density of WiFi access points. All these observations tend to indicate the strong dependence of GMI on wireless and cellular networks whose accuracy depends on ubiquitous infrastructure availability even in basements and car parking areas. The drawback or a concern among users of this service may also be the continuous running of WiFi radio which tends to cause faster battery drains.

GMI actually makes the first step toward a common platform for comparing various system designs: if Google provides application programming interfaces (APIs) to access GMI, most of the systems discussed so far can be ported to GMI, which in turn allows for a fair comparison among them. Unfortunately, the reliance on the availability of digitized floor maps still poses an obstacle. Crowdsensing systems such as Redpin [9] and OIL [10] only "paste" fingerprints on known floor maps, whereas Zee [12] utilizes floor maps to assist its particle filter. A common factor in all these proposals including GMI is *the dependence on known floor maps*. The availability of floor maps for every possible building cannot be assumed and WiFi is not ubiquitous.

B. Towards Zero Infrastructure Reliance

To this end, we propose an idea using crowdsensing and fingerprinting to potentially eliminate both the infrastructure requirements namely dependence on floor maps and wireless networks [18]. We combine the power of crowdsensing to construct floor maps and perform localization through fingerprinting. The general idea is to join user trajectories that are confined to the same indoor locations and form a simple floor map which resembles a graph representing an indoor road network. Ambient magnetic fields have shown promising results [8], similar to those obtained with multi-modal data [7]. Therefore, using magnetic fields as source for location identification, long user trajectories are segmented based on the turns detected from gyroscope data. Fig. 3 illustrates this. The data in Fig. 3 was collected by one of the authors who used a smartphone and walked along a corridor taking three turns. The magnetic field data captured along the corridor was used for location identification and the gyroscope data was used for identifying the turns. Using the gyroscope data, every section of the hallway is segmented with each segment comprising of a unique magnetic signature.

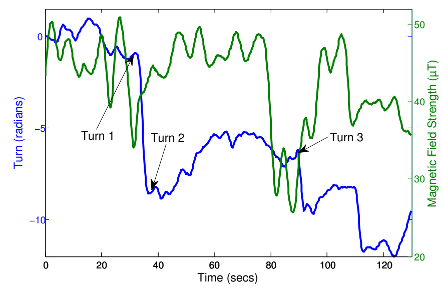
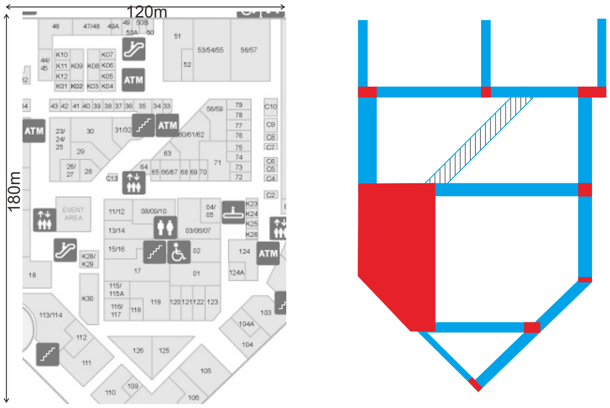


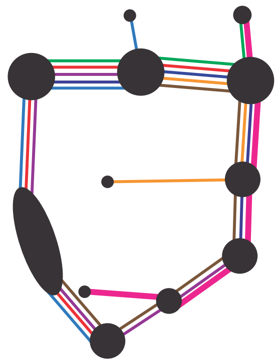
Fig. 3. Location segmentation: magnetic signatures at different locations are segmented at Turns 1, 2 and 3. These segmented signatures from multiple users are appended with start and end points and later joined to form a floor map with a graph topology.

Consequently, multiple long trajectories can be merged based on the similarities (in terms of magnetic fingerprints) among the segments, which in turn assembles a floor map. Using this map, localization can be performed based on magnetic field fingerprinting. Fig. 4 illustrates a constructed floor map. In Fig. 4(a), the original floor map and its line segment version are shown. As users walk along the same location or different locations, the magnetic signatures corresponding to each of the location are combined and hence a crowdsensed floor map is constructed as shown in Fig. 4(b). With this procedure, the requirement for requesting store or building owners to upload floor maps can be completely eliminated.

Any user new to the building can download the constructed floor map and request either localization or navigation service. Our system further enhances the localization by adding a navigation element. We incorporate Bayesian approach to probabilistically estimate the user's location in real time and use the constructed floor map as a graph network to calculate routes to the required destination. We are in the process of evaluating the navigation system in large scale shopping malls across a number of users.



(a) Original floor map and its line segment version



(b) Re-constructed floor map

Fig. 4. Crowdsensing floor map construction: magnetic signatures collected from user trajectories are segmented and combined as per the conjunction points (marked in red), then a floor map shown in 4(a) (the hatched area is temporarily unavailable at the moment) can be reconstructed as shown in 4(b), with the segments and conjunction points aligned.

To summarize, we briefly throw light on how our proposed system caters to satisfying some of the metrics discussed in the earlier sections.

1) Energy Efficiency: By depending only on the light weight magnetic field sensor, we ensure that the energy consumed is much lesser than WiFi based approach.

2) User and Device Diversity: As mentioned, we are planning to evaluate our system across varied kinds of smartphones with different magnetic field and gyroscope sensors and also across different users.

3) One Missing Piece: Through our proposed navigation system, we aim to fill in the void of an indoor smartphone based navigation system that works anywhere and does not require any form of infrastructure installation, yet addressing the basic need for users lost indoors.

V. Conclusion

Smartphones have become the defacto medium for mobile sensing applications. To give a clear view of how smartphones have been used for indoor localization, this paper has surveyed a variety of indoor localization systems developed over different smartphone platforms. Specifically, we discussed how existing works have addressed the important design factors namely energy consumption, built-in sensor variation, computational cost and user diversity. Due to the lack of common grounds to re-implement and evaluate all systems, we have evaluated Google's indoor localization service and also identified its drawbacks. Finally, we have briefly introduced a novel crowdsensing based localization and navigation system and presented how the new system caters to the design requirements which were not accounted by existing works.

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