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Mobility increases localizability: A survey on wireless indoor localization using inertial sensors

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Mobility Increases Localizability: A Survey on Wireless Indoor Localization using Inertial Sensors

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Wireless indoor positioning has been extensively studied for the past two decades and continuously attracted growing research efforts in mobile computing context. As the integration of multiple inertial sensors (e.g., accelerometer, gyroscope, and magnetometer) to nowadays smartphones in recent years, human-centric mobility sensing is emerging and coming into vogue. Mobility information, as a new dimension in addition to wireless signals, can benefit localization in a number of ways, since location and mobility are by nature related in physical world. In this article, we survey this new trend of mobility enhancing smartphone-based indoor localization. Specifically, we first study how to measure human mobility: what types of sensors we can use and what types of mobility information we can acquire. Next, we discuss how mobility assists localization with respect to enhancing location accuracy, decreasing deployment cost, and enriching location context. Moreover, considering the quality and cost of smartphone built-in sensors, handling measurement errors is essential and accordingly investigated. Combining existing work and our own working experiences, we emphasize the principles and conduct comparative study of the mainstream technologies. Finally, we conclude this survey by addressing future research directions and opportunities in this new and largely open area.

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1. INTRODUCTION

Modern smartphones have been equipped with a number of sensors, which make smartphones not only a communication tool, but also a sensing device. After several years of this trend since iPhone's birth, in addition to point-to-point phone calls, smart-

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phones are rapidly becoming an important interface that bridges the physical and digital worlds.

Taking the case of an iPhone, it includes various types of sensors (including microphone, camera, proximity sensor, GPS, accelerometer, gyroscope, compass, etc.), through which sound, image, video, location, and mobility information can be measured by phones. Thus, human-centric environmental sensing is brought forward. Based on smartphones, we are able to know and record user movements (standing, sitting, walking, running) [Park et al. 2012] [Brajdic and Harle 2013] [Wu et al. 2013b], user environments (indoor/outdoor, office/home, on board) [Rachuri et al. 2010] [Zhou et al. 2012b] [Yang et al. pear], and user activities (driving, cycling, sleeping, having a meeting or class) [Yang et al. 2011] [Zhou et al. 2012a] [You et al. 2013].

The richness of sensors reinvents the smartphone as a magic box, in which many novel mobile applications are given birth and developed. One simple but interesting application is to help users judge the taste of a watermelon without cutting it. The way is that users first press a phone closely against a watermelon and then knock the watermelon from outside. The application then provides a suggestion according to the sound of knocking, which is automatically recorded by microphones. A more complicated application is to monitor the quality of all-night sleeping. When a user go to bed, he puts a phone on the bed as well, with the built-in sensors detecting the body and limb movements. The phone offers a sum-up report of sleeping based on some professional medical knowledge when the user gets up in the morning. The inertial sensors play a key role in this application.

In retrospect, before the prevalence of smartphones, whereas laptops, PDAs, and ordinary phones are all truly mobile devices, they have seldom been involved in human-centric sensing for lack of sensors.

Although smartphone-based sensors can facilitate a wide range of services, this article focuses on positioning; that is, how mobility (measured by inertial sensors) increases localizability of nowadays indoor localization systems.

Accurate, reliable and ubiquitous indoor localization systems are the key enabler for a wide range of personal, commercial, medical and public services and applications. Different from outdoor positioning where GPS almost dominates the market, indoor localization embraces a technology flourish. Many techniques and systems are designed and come into service, providing various levels of accuracy, cost, and applicability. For example, optical positioning mainly targets at sub-millimeter application domains, yet involves privacy concerns and intensive computing complexity [Mautz and Tilch 2011]. Ultrasonic signals generally offer an accuracy of centimeters [Priyantha et al. 2000] [Ubisense 2013] at the cost of extra ultrasound infrastructure. With the astonishing growth of wireless devices and networks, wireless indoor localization has attracted extensive research efforts in the past two decades [Bahl and Padmanabhan 2000] [Youssef and Agrawala 2005] [Ni et al. 2003] [Azizyan et al. 2009] [Sen et al. 2012] [Lim et al. 2006] [Constandache et al. 2010b] [Liu et al. 2012] [Yoon et al. 2013] [Sen et al. 2013] [Liu et al. 2013].

The diversity of application requirements results in the concurrent progresses of different wireless-based positioning techniques. Among all techniques, WiFi-based positioning is one of the most popular one, mainly due to the world-wide availability of WiFi technology. The rationale behind WiFi positioning is straight-forward. A mobile device, at somewhere covered by WiFi signal, records the hearable WiFi Access Points (APs) and their corresponding signal strength as the radio signal characteristics (a.k.a. signal fingerprint) for this specific position. Such a fingerprint, as a location query, is further sent to a location service provider who has a WiFi fingerprint database of a great amount of fingerprints collected at every position within an area of interest. The location service provider then retrieves the database for the most similar fingerprint with respect to the location query, and returns its corresponding recorded location as the location estimation. The uniqueness of WiFi APs (in terms of the MAC addresses) and the signal attenuation across space account for the principle of WiFi positioning. From the systematic aspect, the process of localization is composed of two stages: training and operating [Yang et al. 2012]. During the training phase, traditional methods involve a site survey process (a.k.a. calibration), in which professional engineers record the signal characteristics (known as fingerprints) at every location of an interested area. The collected fingerprints and their corresponding locations are then associated with each other to build up a fingerprint database. When a new user tries to locate himself during the operating phase, he queries his location by uploading his signal fingerprint to the server. The server retrieves the database by comparing fingerprints, and returns the location with the best matched fingerprint to the user.

WiFi positioning is booming recently. In late 2011, Google Map 6.0 announced new services of indoor positioning and navigation [McClendon 2011]. Other followers include Microsoft's Bing Maps, Baidu's Interior Maps, Nokia's Here (formerly Ovi Maps), etc. In addition, Skyhook Wireless [Skyhook 2013] manages a global location database with more than a billion Wi-Fi access points and millions of venues and serves a variety of customers from individual application developers to industry giants including Apple, Google, and Sony.

Despite of its success, WiFi positioning faces several challenges on its fast track of development.

— **Location error.** The indoor attenuation of wireless signals is extraordinarily unpredictable because of complex environmental factors, leading to decreased performance of widely used signal models. For instance, multi-path fading brings about strenuous fluctuation on signal amplitudes in small scale of only several centimeters [Sen et al. 2013] [Wu et al. 2012]. Besides, environmental dynamics (such as human movements, door opening and closing, and furniture rearrangement) can also change the signal strength distribution across an area [Fet et al. 2013]. To make things worse, some researchers observe experimentally that two far-away locations in an open indoor space may have similar signal fingerprints, which, according to the scheme of WiFi positioning, may induce incorrect location estimation [Liu et al. 2012] [Sun et al. 2013a].
— **Deployment cost.** The procedure of site survey is time-consuming, labor-intensive, and vulnerable to environmental dynamics [Chintalapudi et al. 2010][Yang et al. 2012]. However, it is inevitable for fingerprinting-based approaches, since the fingerprint database relies on locationally labeled fingerprints from on-site records [Chintalapudi et al. 2010] [Yang et al. 2012] [Wang et al. 2012]. Even the indoor mapping services of Google Map 6.0 was available only at selected airports and shopping malls in several districts (e.g. the US and Japan) at its release [McClendon 2011]. Its applicability to broader areas is strangled by the limited quantity and granularity of fingerprint data of building interiors. The world-wide usage of indoor positioning calls for low deployment cost.
— **Absence of location context.** Locations, in indoor environments, are strongly related to human activities, which motivates people to discover the semantic context of locations. Location context refers to the name, usage, function, and activity of a specific location that users can understand and feel intuitively [Schmidt et al. 1999] [Kim et al. 2009] [Azizyan et al. 2009] [Ye et al. 2011]. In many cases, the context of a location is equally valuable to or even more valuable than location itself. For example, comparing with the absolute X-Y coordinates, it is more meaningful for users inside buildings to know room numbers or room usages such as office rooms, meeting rooms, or corridors. Furthermore, a route in a floor plan towards the nearest printer is more

convenient than the printer's location coordinates. Nevertheless, WiFi positioning is powerless on distinguishing rooms, identifying room usage, generating indoor maps, and characterizing user activities. So far, the acquisition of location contexts mostly relies on human inputs.

Recently, an increasing number of researchers realize that mobility information, as a new dimension in addition to wireless signals, can be employed to deal with the 3 above-mentioned challenges and consequently upgrade indoor positioning to a higher level [Constandache et al. 2010b] [Wang et al. 2012] [Yang et al. 2012] [Rai et al. 2012] [Sun et al. 2013a] [Wu et al. 2013a]. It is easy to understand that being aware of mobility could benefit localization, since location and mobility are by nature related in physical world. The current location of a moving object depends on both its past location and its movements.

In this article, we survey this new trend of mobility enhancing smartphone-based indoor localization. Specifically, we first study how to measure human mobility: what types of sensors we can use and what types of mobility information we can acquire. Next, we discuss how mobility assists localization with respect to enhancing location accuracy, decreasing deployment cost, and enriching location context. The enhancement of location accuracy can be seen as a direct result of the add-on of mobility, while the latter two require more complicated mechanisms. Moreover, considering the quality and cost of smartphone built-in sensors, handling measurement errors is essential and accordingly investigated. Combining existing work and our own working experiences, we emphasize the principles and conduct comparative study of the mainstream technologies. Finally, we conclude this survey by addressing future research directions and opportunities in this new and largely open area.

2. WHAT TYPES OF SENSORS

Among various sensors, *inertial measurement units (IMUs)* are one of the most widely adopted to measure mobility. An IMU is "an electronic device that measures velocity, orientation, and gravitational forces", and often constitutes of accelerometers and gyroscopes, and magnetometers [Wikipedia 2014a]. IMUs are primarily designed for "inertial navigation systems of aircraft, spacecraft, watercraft, and guided missiles" [Wikipedia 2014a] by means of *dead reckoning*, which refers to "the process of calculating one's current position by using a previously determined position, or fix, and advancing that position based upon known or estimated speeds over elapsed time and course" [Wikipedia 2014b]. Modern smartphones also possess various types of inertial sensors, making them an integrated platform for communication, sensing and computing. Constrained by cost, size, and power consumption of sensors, however, smartphone IMUs have their own unique characteristics. In this section, we review the principles, current development, and future trends of typical inertial sensors on smartphones.

2.1. Smartphone IMU: Principles

Modern smartphones are equipped with various inertial sensors. They compose a simple but workable unit of inertial sensing and are therefore considered an IMU of smartphones. Smartphone IMUs typically include three major types of sensors: accelerometer, gyroscope, and magnetometer.

2.1.1. Accelerometers. An accelerometer is an infrastructure to measure acceleration, which works as "a damped mass on a spring" [Wikipedia 2014c] leveraging Newton's laws of motion. Modern accelerometers are usually micro electro-mechanical systems (MEMS), and in fact "the simplest MEMS devices possible" [Wikipedia 2014c]. The SI unit of acceleration is meters per second squared (m/s^2), or popularly in terms of g-force (g). In practice, it also requires local gravity to calculate the actual acceleration

Table I. Smartphone IMUs.

Host Smartphone	Sensor Type	Axis	Package Size (mm^3)	Measurement Range	Sensitivity	Temperature Range (°C)	Manufacturer	Year
				Accelerometer				
iPhone5s	BMA220	3	2*2*0.98	±2/±4/±8/±16g	2/4/8/16 LSB/g	-40∼85	Bosch	2013
iPhone4	LIS331DLh	3	3*3*1	±2/±4/±8g	250/500/1000 LSB/g	-40∼85	ST	2010
iPhone 3G	LIS331DL	3	3*3*1	±2/±8g	14/56 LSB/g	-40∼85	ST	2008
Samsung Galaxy SII	LIS3DH	3	3*3*1	±2/±4/±8/±16g	83/250/500/1000 LSB/g	-40∼85	ST	2011
Google Nexus 5	MPU-6500	6	3*3*0.9	±2/±4/±8/±16g	$2^{11}/2^{12}/2^{13}/2^{14}$ LSB/g	-40∼85	InvenSense	2013
Motorola Droid	BMA150	3	3*3*0.9	±2/±4/±8g	64/128/256 LSB/g	-40∼85	Bosch	N/A
				Gyroscopes				
iPhone5s	L3G4200D	3	4*4*1.1	±250/±500/±2000	8.75∼70 mdps/digit	-40∼85	ST	2013
iPhone4	L3G4200D	3	4*4*1.1	±250/±500/±2000	8.75∼70 mdps/digit	-40∼85	ST	2010
iPhone 3G	N/A	N/A	N/A	N/A	N/A	N/A	N/A	2008
Samsung Galaxy SII	L3G4200D	3	4*4*1.1	±250/±500/±2000	8.75∼70 mdps/digit	-40∼85	ST	2011
Google Nexus 5	MPU-6500	6	3*3*0.9	±250/±500/±1000/±2000	7.60∼61 mdps/digit	-40∼85	InvenSense	2013
Motorola Droid	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
				Magnetometers				
iPhone5s	AK8963	3	3*3*0.75	N/A	0.15∼0.6 μT/LSB	-30∼85	AKM	2013
iPad2	AK8975	3	4*4*0.75	N/A	0.3 μT/LSB	-30∼85	AKM	2011
Samsung Galaxy SII	AK8975	3	4*4*0.75	N/A	0.3 μT/LSB	-30∼85	AKM	2011
Google Nexus 5	AK8963	3	3*3*0.75	N/A	0.6 μT/LSB	-30∼85	AKM	2013
Motorola Droid	AK8973	3	4*4*0.7	N/A	1.6 μT/LSB	-30∼85	AKM	N/A

value w.r.t. the Earth. The value of local gravity can be obtained by device calibration at rest or gravity modeling given the current position [Wikipedia 2014c].

2.1.2. Gyroscopes. A gyroscope is an instrument to measure or maintain orientation in principle of angular momentum [Wikipedia 2014d]. It is mechanically “a spinning wheel or disc in which the axle is free to assume any orientation” [Wikipedia 2014d]. Besides applications in general navigation, gyroscopes are often exploited in conjunction with accelerometers to derive robust direction information (e.g. X-, Y-, Z-axis acceleration with the extent and rate of rotation in roll, pitch, and yaw, [Wikipedia 2014d]).

2.1.3. Magnetometers. A magnetometer (or magnetic field sensor), is a device that measures the strength and the direction of magnetic fields [Wikipedia 2014e]. The types of magnetometers vary. Magnetoresistive sensors and Hall effect devices are the most popular, yet there is also a huge dispute, both technically and commercially, on the use of the two for consumer devices.

2.2. Smartphone IMU: Typical Performance

Table I lists the parameters of IMUs of several fashionable consumer electronic devices ranging from smartphones to tablets. IMU has demonstrated its wide popularity in the smartphone market. In addition to the latest consumer devices listed in Table I, almost every smartphone today has a motion sensor embedded inside.

In terms of performance, IMUs are qualified to a large number of services, such as linking movements of the user's wrist, arm, and hand to applications, navigation with and between pages, the movements of characters in a game, etc. However, researchers and application developers complain that the accuracy of smarpthone IMUs is insufficient for dead reckoning and other location-based services. In fact, compared with the generally believed accurate IMUs used in Micro Unmanned Aerial Vehicle (MUAV) and other industrial application, the smartphone IMUs possess the same or similar core sensing component, but differ in sensor screening, installation error calibration, cross axis error calibration, zero point correction, temperature drift compensation, etc. For instance, ADI's ADIS16405 and ADIS16400 are based on the same ADI's low cost sensing elements, but the former is more expensive than the latter. The only two major differences are the bias temperature coefficient and sensitivity temperature coefficient. ADIS16405 is carefully calibrated in various temperatures ranging from -40 to 85 °C, resulting in an increased cost on testing.

The reduced factory-calibration efforts contribute to the low cost of smartphone IMUs. As gyroscopes have experienced a dramatic drop in cost, the cost of IMUs is basically acceptable by mainstream smartphones. Yet researchers have to avoid the direct use of dead reckoning with low cost sensors, and resort to pedestrian motion modeling for accurate mobility measurements (Section 3).

2.3. Smartphone IMU: Future Potentials

With advances in sensor design and manufacturing, increasingly powerful sensors of various types are now available in smartphones at low costs, depending on which novel applications are rising in response. Accelerometers today can pick up the sound of key strikes on an alphanumeric keyboard with such precision that a computer program can determine what keys are being struck; magnetometers can detect the 50/60 Hz magnetic field emanating from a power cord; barometers can notice the atmospheric change between floors of a building.

Another future trend of IMU is to combine multi-sensor modules and deploy dedicated sensor fusion algorithms, thus advancing the quadruple convergence of high accuracy, small size, efficient energy, and low cost. Motion sensors in consumer and mobile applications will be dominated by combo sensors, with their revenue hitting $1.4 billion by 2016, or 71% of the overall market, while that of discrete instruments tends to shrink gradually [Dixon 2012]. In fact, the 6-axis combo sensor has dominated as a ready substitute for the 3-axis design. For instance, the recent MPU-6500 chip integrates a 3-axis accelerometer, a 3-axis gyroscope, and an on-board digital motion processor [InvenSense 2013]. And manufacturers have joined the combo sensor race and other pioneer examples include ST's iNEMO, InvenSense's MPU-9150, Bosch Sensortec's BNO055, Kionix's KMX61G, Maxim Integrated's MAX21100, Freescale's FRDM-FXS-MULTI-B, MiraMEMS's DC210, mCube, etc.

Combo sensor IMUs enable in-chip data fusion for accurate motion tracking. Early industry efforts using rudimentary sample codes available from some sensor manufacturers have been unsatisfactory and some codes of sensor usage are proved to be vulnerable even in the Android specification. Today, major sensor suppliers have realized that algorithms and software are essential elements of their product offerings. Independent middleware developers have created sensor libraries that not only provide accurate headings by keeping the sensors in proper calibration, but also mitigate against the distorting effects of internal magnetic interferences.

Current sensors present metrological measurements of their physical environment but, without proper perspectives and interpretation, those sensor readings are often under utilized. Even extracted mobility information can be further refined to infer high level knowledge such as locations, activities and behaviors of users, spawning many applications of context-aware computing in which mobility, as well as user locations, is considered as key context [Abowd et al. 2002] [Yang et al. pear]. This expands the role of mobile devices beyond a sensor of physical environments, to an actuator that adapts its behaviors accordingly.

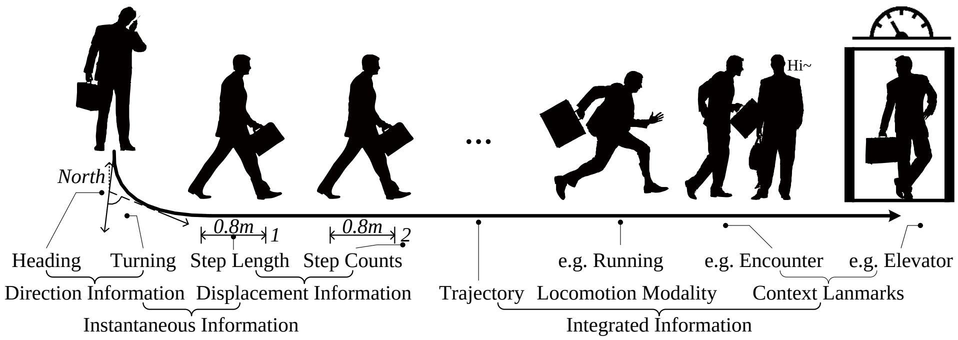


Fig. 1. An illustration of human mobility information derivable from phone sensors.

3. WHAT TYPES OF MOBILITY INFORMATION

The rich inertial sensing modalities on smartphones report numerous instantaneous motion measurements, such as acceleration, angular velocity and absolute direction, via built-in accelerometer, gyroscope and compass, respectively. To assist indoor localization and navigation, these low level *physical* displacement and directional measurements are integrated over time and augmented with location context into more complex *human* mobility information, such as walking steps, trajectories, locomotion modalities (e.g., walking and running), virtual landmarks (e.g., stairs and lifts), etc. Figure 1 illustrates a typical scenario of indoor inertial sensing as well as types of mobility information derivable from phone sensors. However, assembling human mobility information from phone sensory data is an endeavor fraught with obstacles. We briefly summarize them into three aspects:

— **Noisy sensor measurements.** It is inevitable to induce noise in raw sensory measurements. When integrating these physical measurements over time, even small errors may drift dramatically. For instance, errors accumulate quadratically when derive displacement by twice integrating acceleration.
— **Unconstrained phone placement.** Since most inertial sensors measure motion information, these measurements are sensitive to sensor placements [Harle 2013]. For instance, acceleration traces exhibit more distinctive patterns with foot-mounted accelerometer [Angermann and Robertson 2012] than phone accelerometer put in a bag due to random bouncing of phones.
— **Complex human locomotion.** Human body can be in various poses, with at least 244 degrees of freedom [Zatsiorsky 1998]. Individuals of different heights, weights, ages, health states, etc., can exhibit different motion gaits. Furthermore, people may sometimes behave unpredictably. It it therefore challenging to extract consistent and robust locomotion patterns and accurate mobility information leveraging only phone sensors.

Since most indoor localization and navigation systems target at pedestrians, we mainly focus on *step* and *stride (i.e., two steps)* related human mobility information, which is fundamental and specific to pedestrians. In this section, we elaborate the principles to derive displacement and direction information of step vectors, as well as integrated and behavioural human mobility information.

3.1. Displacement Information

Step detection and counting is a basic module in most inertial based pedestrian localization and navigation systems. The physical underpinning is to search for cycles in ac-

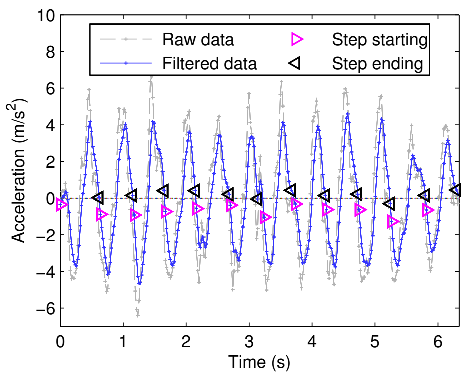


Fig. 2. Acceleration magnitudes during a sample walking demonstrating the repetitive patterns of walking.

celeration traces to capture the repetitive movements during walking. Figure 2 depicts the raw acceleration traces during a sample walking, which exhibits notable repetitive cycles. The subsequent sections summarize algorithms for step detection and counting using phone accelerometers, followed by a brief discussion on the individual-specific stride length.

3.1.1. Step Detection and Counting. When input an acceleration trace, step detection algorithms slice and label the trace into steps exploiting the repetitive patterns of walking, and the labels are then summed into step counts. We roughly group these algorithms as follows:

— **Temporal Analysis.** The cyclic property of walking is directly reflected in the acceleration trace in the time domain. Since heel strikes tend to introduce sharp changes, numerous schemes propose to detect magnitude peaks [Randell et al. 2003] [Wu et al. 2013a], local variance peaks [Jimenez et al. 2009] [Yang et al. 2012], local minima [Wang et al. 2012] [Sen et al. 2013], zero-crossings [Goyal et al. 2011], or level-crossings [Zhu et al. 2013] (levels defined by historical mean and variance) from the low-pass filtered acceleration trace. Auto-correlation is a more robust means to magnify periodicity in the time domain regardless of the absolute amplitude of acceleration [Rai et al. 2012]. Steps can also be recognized by matching with a stride template either linearly (e.g., by cross-correlation [Marschollek et al. 2008]) or non-linearly (e.g., by Dynamic Time Warping [Rong et al. 2007]), yet at a higher cost.
— **Spectral Analysis.** When the acceleration trace contains at least two walking cycles, it is possible to identify the repetitive walking patterns in the frequency domain. The rationale is that walking movements would generate dominant frequencies around 2Hz, a unique spectral characteristic compared with other human activities. Short-Term Fourier Transform (STFT) [Brajdic and Harle 2013] and wavelet transforms [Barralon et al. 2006] [hua Wang et al. 2012] have been employed to extract dominant frequencies, and steps are counted as the sum of the transform coefficients of the walking frequency.
— **Feature Clustering.** Besides the above pattern analysis approaches, research also resorts to machine learning techniques to classify walking steps via features from acceleration traces. Various features have been explored, including statistics [Siirtola and Roning 2012], entropy [Bao and Intille 2004], as well as temporal correlation [Ravi et al. 2005] and Fourier transform coefficients [Kobayashi et al. 2011]. Albeit its high computational cost, feature clustering based schemes are more general and are often applied to classify multiple human activities beyond walking.

Table II. Recent Smartphone based Step Counting Summary.

Citation	Techniques	Cost	Error Rate
[Zhu et al. 2013]	decide levels upon historical statistics detect level crossings	low	N/A
[Yang et al. 2012]	threshold on local variance	low	2%
[Wang et al. 2012][Sen et al. 2013]	detect two consecutive local minima check a significant local maxima	low	2%
[Wu et al. 2013b]	detect step starts and ends by threshold identify steps via finite state machine	low	about 2%
[Rai et al. 2012]	normalized auto-correlation	medium	0.6%
[Rong et al. 2007][Brajdic and Harle 2013]	template matching via DTW	medium	$< 2\%$
[Barralon et al. 2006][Brajdic and Harle 2013]	zero CWT coefficients outside walking frequency inverse transform and count mean crossings	medium	about 1.3%
[Mannini and Sabatini 2011]	two-state HMM clustering	high	about 1.3%

Table II summarizes some recent smartphone based step counting schemes in terms of techniques, cost and performance. We refer interested readers to [Harle 2013] for a review on step counting strategies via non-smartphone IMUs (e.g. foot mounted) and non-inertial sensors (e.g. ultrasonic). Temporal analysis based schemes are the most intuitive in concept, and facilitate physical explanation on the extracted feature metrics. The primary drawback is that the cyclic walking patterns are mixed with other noises in the time domain. Spectral analysis based approaches offer an orthogonal domain to distinguish frequencies of walking and other noises, yet are less intuitive. For example, it is difficult to distinguish fine-grained walking patterns such as heel-up and heel-down directly from the signal spectrum. In addition, the accuracy of spectral analysis improves with the amount of signal periods contained in the input signal. Hence spectral analysis often requires more signals samples than temporal analysis. Feature clustering is agnostic to the underlying physical meanings, yet can provide higher accuracy given sufficient training efforts. As shown in Table II, one recent work exploiting a modified auto-correlation scheme in the time domain [Rai et al. 2012] reports high detection accuracy, since auto-correlation techniques increase signal-to-noise ratio with the increase of input signal length, and the temporal approach facilitates other auxiliary error correction schemes as the signal features have clear physical interpretations.

Although step counting accuracy of above 99% is often reported under laboratory conditions [Harle 2013], unified performance comparison is difficult. A recent study [Brajdic and Harle 2013] conducted a realistic evaluation of 3 categories of step counting algorithms with 27 people and 130 traces. They recommend standard deviation thresholding and windowed peak detection for its simplicity, with reasonable error rate of 3% evaluated with 6 phone placements and 6 user behaviours. However, it remains unsettled whether these algorithms would be robust to varying walking speeds, rough surfaces, etc.

3.1.2. Stride Length Estimation. Knowing stride length is necessary when converting steps into distance traversed. Pedestrians may exhibit different stride lengths due to variety in height, walking speed and style. According to [Weinberg 2002], step length may vary up to 40% at the same walking speed, and 50% with various speeds of the same person. Assuming constant stride length is efficient when frequent landmark calibration is available [Wang et al. 2012] or when only short walking distance is required [Sen et al. 2013]. Nevertheless, with the emerging trend of crowdsoucing based indoor localization and navigation [Wu et al. 2013a] [Rai et al. 2012] [Yang et al. 2012] [Shen et al. 2013] [Purohit et al. 2013] [Jiang et al. 2013a], walking traces of diverse users are expected to be calibrated and integrated. Therefore, it would boost the quality of the crowdsourced mobility information by considering individual-specific stride length. Some pioneer efforts in stride length estimation are summarized as follows.

— **Offline Calibration.** An intuitive way to estimate user-specific stride length is to divide a known walking distance by measured step counts. However, since the walking patterns may not distribute uniformly, this method may induce bias on dominant walking patterns [Cho et al. 2010].
— **Online Estimation.** Some recent systems also propose to simultaneously estimate stride length and user locations via an augmented particle filter [Rai et al. 2012]. The rationale is to iteratively select the optimal stride length that fits user traces and map constraints.
— **Stride Length Modeling.** Originated from human kinematics, other studies correlate stride length with step frequency [Margaria and Margaria 1976] [Ladetto 2000] [Gusenbauer et al. 2010]. The key observation is that stride length tends to be shorter when walking slowly than fast [Bertram and Ruina 2001]. A simple linear relationship suffices [Cho et al. 2010], yet the model parameters, which are trained offline, are specific to walking conditions, such as wearing sport shoes or high heels [Shen et al. 2013].

Accurate stride length improves displacement estimation, yet the accuracy increase is often marginal since heading drift typically dominates the errors [Harle 2013]. Alternatively, when combining wireless and inertial based localization schemes, some novel explorations have partially eliminated the need to estimate user-specific stride length via virtual landmark assisted normalization [Shen et al. 2013] or error-tolerant transforms [Yang et al. 2012].

3.2. Direction Information

The direction of steps during walking is usually obtained by phone gyroscope and compass (magnetometer). The former outputs angular velocities in 3D, which are integrated over time into direction change (turning), while the latter directly measures the absolute orientation (heading) of the phone with respect to the magnetic North. Although compasses alone prove to be feasible for outdoor dead reckoning [Constandache et al. 2010b] [Wang et al. 2013], the two modalities often work synergistically in the literature of indoor localization and navigation [Li et al. 2012a] [Wang et al. 2012] [Rai et al. 2012], due to the unique challenges indoors and their complementary error characteristics:

— The metal and conducting material indoors can significantly disturb compass readings and lead to short-term heading estimation errors of up to 100° [Afzal et al. 2001].
— Gyroscopes remain unaffected by magnetic fields, yet suffer from bias caused by initial direction [Wang et al. 2012], and the estimated orientation drifts substantially with time [Sen et al. 2013].

In this subsection, we first review turning estimation via gyroscope, and then summarize how to combine compass with additional sensory modalities to enhance heading estimation.

3.2.1. Turning. The layout of many indoor environments consists of perpendicular corridors and corners, where pedestrians tend to walk in straight lines and take turns. Turning information benefits indoor localization systems in a range of aspects. For instance, being aware of left or right turns resolves side ambiguity in wireless angle of arrival estimation using linear antenna arrays [Sen et al. 2013]. Turning information also facilitates stride length estimation [Rai et al. 2012] and serves as landmarks to

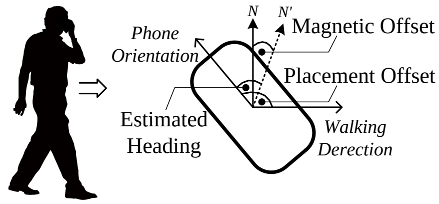


Fig. 3. An illustration of magnetic offset and placement offset when estimating heading via phone compass.

assist drift calibration in pedestrian dead reckoning [Wang et al. 2012] [Park et al. 2013].

A turn is detected when the relative orientation measured by gyroscopes experiences an abrupt change. To differentiate changes corresponding to turns from those caused by noise, only heading changes exceeding a pre-defined threshold are determined as turns. In addition, heading changes within only a short time interval are also discarded. [Park et al. 2013] reports precision of about 85% and recall of 100% for turn detection considering phone placement diversity (messing, calling, swing and in pockets), device type (3 types of phones) and user difference (8 volunteers). According to [Park et al. 2013], phone placement that introduces back and forth movements deteriorates the performance of turn detection most.

3.2.2. Heading. The main hurdle for accurate heading estimation via phone compass lies in two fold:

— **Magnetic Offset.** Metal and conducting material nearby can disturb the perceived north of phone compass, thus leading to offset in heading estimation. Magnetic offset is location specific, and thus unpredictable beforehand [Rai et al. 2012].
— **Placement Offset.** The compass measures the orientation of the phone, while the phone's heading may not be aligned with the moving direction of the user. Thus placement offset refers to the difference between the phone's orientation and the moving direction of the user.

Figure 3 illustrates the magnetic and placement offset when estimating heading of user motion via phone compass indoors.

Table III summarizes some representative proposals to enhance heading estimation. While some efforts attempt to filter magnetic offset on consecutive compass readings [Youssef et al. 2010], others fuse multiple sensors to improve estimation accuracy [Wang et al. 2012] [Li et al. 2012a] [Rai et al. 2012] [Shen et al. 2013] [Sun et al. 2013b]. The rationale is to exploit additional sensors (e.g. gyroscopes) to evaluate the compass readings [Wang et al. 2012] [Li et al. 2012a], and rectify heading estimation iteratively during walking (e.g. particle filter)[Li et al. 2012a] [Rai et al. 2012]. According to the additional sensory modalities utilized, we categorize these schemes as follows:

— **Inertial Verification.** Since multiple inertial sensors are integrated on a single smartphone, they tend to perceive similar movements during walking. For example, compass value is probably valid if the readings of phone compass and gyroscope experience correlated trend [Wang et al. 2012], which assists to discard compass values containing severe magnetic offset. Acceleration traces, on the other hand, can be utilized to identify the time when the phone placement is the same to that when the phone is first put into a pocket, which helps to accurately infer the moving direction of the user, given the initial phone placement offset[Li et al. 2012a].
— **Visual Reference.** Since modern buildings are mostly rectangular [Steadman 2006], the straight ceiling edges offer an orthogonal reference to determine heading

Table III. Representative Heading Estimation Approaches.

Citation	Sensors	Techniques	Errors	Limitation
[Youssef et al. 2010]	CP	Time domain averaging	N/A	Effective only for temporary magnetic interference
[Wang et al. 2012]	CP+G	Gyroscope verification Magnetic landmark calibration	within 20° for 90% cases	Initial heading estimation errors Dependence on landmarks
[Li et al. 2012a]	CP+G+A	Identify inference points Particle filter	23° for 95% cases	Initial heading estimation errors Converge time
[Rai et al. 2012]	CP+G+A	Estimate offset range via spectral analysis Augmented particle filter	N/A	Extra spectral processing Converge time
[Roy et al. 2014]	CP+G+A	Human walking pattern analysis Localize, quantify, and isolate magnetic interference	$<6°$	Require several steps of walk
[Sun et al. 2013b]	CP+CA+A	Detect visual patterns on ceilings and integrate with compass readings	1° on average	High computation overhead Fail if unable to take photos

CP - compass, G - gyroscope, A - accelerometer, CA - camera

information. In [Sun et al. 2013b], the ceiling edges are extracted from images taken by phone camera using computer vision techniques. The orientation of the detected edges relative to the phone is also computed. Together with the absolute orientation of the rectangular building (and thus the ceiling edges), they achieve average heading precision of 1° with arbitrary phone holding poses. Although its heading estimation accuracy improves by dozens than inertial schemes, the computational overhead, energy consumption, as well as the perquisite to take photos, impede its viability.

In summary, while compass directly provides the absolute directions of phones, magnetic offset and placement offset considerably deviate compass readings from the actual moving direction. Recent advances fuse extra sensors with compasses to provide robust heading estimation, yet accuracy still remains a bottleneck for inertial based indoor localization and navigation systems. One recent work [Roy et al. 2014] reduces heading estimation error to less than 6° by in-depth video-based human walking pattern analysis and magnetic interference localization and isolation, which is approaching the accuracy of visual reference based methods. The primary hurdle for this bottleneck is that inertial based heading estimation schemes exploit sensors to perceive the relatively unconstrained human behaviours, making precise walking direction a micro-motion that requires subtle identification [Roy et al. 2014]. In contrast, visual reference based approaches [Sun et al. 2013b] leverage static landmarks such as ceiling edges, yet improve estimation accuracy at the cost of computation and energy consumption.

3.3. Integrated Information

Previous subsections mainly elaborate the principles and methods to derive short-term displacement and direction information (e.g. steps and turns) from sensory data. In this subsection, we demonstrate how the instantaneous displacement and direction information is integrated into more complex human mobility information.

3.3.1. Trajectory. A pedestrian trajectory consists of a sequence of step vectors. While inertial based indoor localization and navigation systems require accurate trajectories to track pedestrians, some recent work [Wu et al. 2013a] [Yang et al. 2012] also exploit comparatively coarse-grained trajectory information to assist wireless localization. In [Wu et al. 2013a], trajectories are utilized to infer whether the wireless fingerprints from different locations are reachable with each other. Yang et al. [Yang et al. 2012] utilize stress-free walking distances, rather than rigid trajectories, to transform the localization problem from two-dimension floor plan space to a high dimension wireless fingerprint space.

Accurate trajectory estimation still lies in the core of various indoor localization and navigation systems. Besides traditional challenges in *calibrating* trajectories of a single user, the emerging trend of crowdsoucing based localization also poses new challenges in *clustering* trajectories from diverse users [Rai et al. 2012] [Shen et al. 2013].

3.3.2. Locomotion Modality. Awareness of locomotion modalities (e.g. walking or running) and usage behaviours (e.g. text messaging or making a phone call) assists to construct more elaborated motion models (e.g. adjust stride length estimation or step counting according to varying speeds and phone placements), thus holding potential for improving localization and navigation algorithms.

Identifying these behaviours belongs to a subset of the enormous research on activity recognition [Ravi et al. 2005]. Some recent work has already explored to utilize phone accelerometers to distinguish different motion modalities (walking or running) [Iso and Yamazaki 2006] [Miluzzo et al. 2008], transportation modes (bus or metro) [Hemminki et al. 2013], and phone poses (in hand or at ear) [Park et al. 2012].

Though promising, it is inevitable to involve relatively complex machine learning techniques to differentiate locomotion modalities and phone placements, which incurs considerable computation and energy overhead. It still lacks comparative studies on the tradeoff between the overhead of distinguishing fine-grained locomotion modalities and the performance gain on indoor localization.

3.3.3. Context Landmarks. The mobility information measured by sensors, when combined with location context, can provide unique virtual landmarks, which facilitates re-calibration and thus improves localization accuracy. The key observation is that certain building structures would demonstrate distinctive sensor signatures. For instance, the acceleration readings on an elevator experience a sharp surge and drop at the start and the stop of the elevator. Wang et al. [Wang et al. 2012] investigate such unique acceleration patterns of stairs, elevators, escalators, walking and standing, and achieve an overall false positive of 0.2% and false negative of 1.1%, respectively. If the locations of these structures are known as prior, they would serve as landmarks to rectify dead reckoning drifts.

In case of multiple users, mobility information (e.g. trajectories) of different users can be associated via encounters. These opportunistic encounters (e.g., Alice happened to meet Bob) can also act as virtual landmarks to calibrate dead reckoning drifts [Constandache et al. 2010a] (e.g., We can adjust the trajectory of Alice to make her current location consistent with Bob's location, since Bob just walked out of an elevator whose location is known as prior). Such social encounters also help to refine the plausible locations of users [Jun et al. 2013] (e.g., if Alice met Bob, then we may safely restrain the potential locations of Alice to the intersection between the potential locations of Alice and those of Bob).

These novel context landmarks stem from user mobility, and are complementary to static landmarks (or fingerprints) such as ambient sound, light and color [Azizyan et al. 2009]. While some pioneer work has explored to incorporate the two, (e.g., inertial patterns + WiFi RSSI [Wang et al. 2012], directions + WiFi trend [Shen et al. 2013], its full potential still remains an open issue.

4. HOW MOBILITY ASSISTS LOCALIZATION

WiFi fingerprinting prevails among various wireless indoor localization techniques due to its wide availability. The general framework can be divided into two phases: training and operating. The former involves a site survey process (a.k.a. calibration), in which RSSs from multiple APs at every location of interest are measured and recorded as WiFi fingerprints. Accordingly a fingerprint database (a.k.a. radio map) is built, where

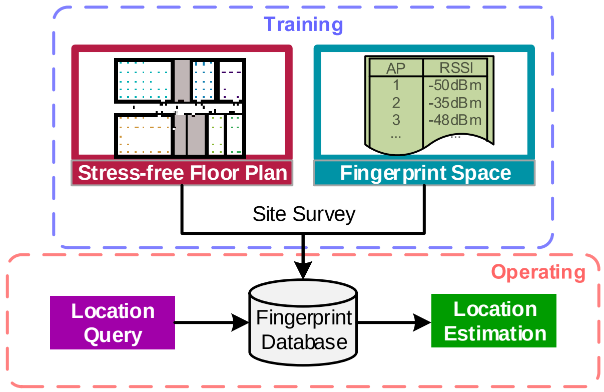


Fig. 4. Typical architecture of WiFi fingerprint-based localization systems.

each location is labelled with its corresponding fingerprints. In the operating stage, to locate a user sends a query with his current fingerprint, localization server retrieves the fingerprint database and return the location of the best-matched fingerprints as the user's location estimation. A typical architecture of fingerprint-based localization is portrayed in Figure 4. Ever since its birth, WiFi fingerprinting is considered static. Human mobility information extends conventional wireless indoor localization to an orthogonal dimension. In what follows, we will discuss in detail how mobility enhances wireless localization in terms of accuracy, cost, and location context.

4.1. Mobility Enhances Localization Accuracy

Despite extensive efforts from both academics and industries in the past decade, localization accuracy remains a primary challenge, especially in mobile environments. While proof-of-concept innovations report high accuracy under controlled settings [Youssef and Agrawala 2005] [Lim et al. 2006], they can experience sharp performance degradation in practice, with median error consistently above 5m [Turner et al. 2011] and unacceptable tail errors of 12m to even 40m [Liu et al. 2012].

The root cause of such large errors in WiFi fingerprinting lies in *fingerprint ambiguity* [Sun et al. 2013a] [Liu et al. 2012]. More specifically, a fundamental hypothesis of fingerprint-based localization is that wireless signal features (e.g. RSS values) vary at different locations. Each location exhibits exclusive and distinctive signal characteristics, which are analogous to biometric fingerprints and are thus referred as WiFi fingerprints of the locations. The ever-increasing number of APs deployed indoors offers high-dimensional WiFi fingerprints and the potential for more accurate localization performance. One common pre-processing procedure, for example, is to compare the sets of detectable APs to distinguish WiFi fingerprints from distant locations. However, this approach is often coarse-grained, since locations within room ranges can share the same detectable AP set due to the relatively large coverage of WiFi signals. In addition, since not all APs are equally sensitive to location changes, their ability of discerning locations varies. Therefore some pioneer efforts [Chen et al. 2006][Fang and Lin 2012] have explored to select a subset or transform of more distinctive APs for higher localization accuracy and energy efficiency. (Note that although AP selection schemes indeed can improve the accuracy of WiFi fingerprinting based indoor localization systems, such schemes are less relevant to the theme of harnessing mobility

Table IV. Recent works on improving accuracy by leveraging mobility.

Citation	Space	Reported Accuracy			Sensor Type	Mobility Info
		Mean	Max	Room		
MoLoc [Sun et al. 2013a]	Indoor	$<$1m	$\sim$7m	N/A	C+A	Direction / Displacement
ACMI [Yoon et al. 2013]	Indoor	6m	N/A	89%	N/A	Trajectory
GloCal [Wu et al. 2013b]	Outdoor	$\sim$4m	$\sim$25m	N/A	A+G	Trajectory
WheelLoc [Wang et al. 2013]	Outdoor	$\sim$40m	$\sim$60m	N/A	A+M	Distance / Turns
Hilsenbeck el al. [Hilsenbeck et al. 2014]	Indoor	1.52m	12m	N/A	C+A	Trajectory
Li et al. [Li et al. 2012a]	Indoor	2m	$\sim$8m	N/A	C+A+G	Trajectory
Naguib et al. [Naguib et al. 2013]	Indoor	$\sim$1m	$\sim$5m	N/A	C+A+G	Trajectory
Zampella et al. [Zampella et al. 2013]	Indoor	$\sim$1m	$<$5m	N/A	A+G	Trajectory
Ubicarse [Kumar et al. 2014]	Indoor	39cm	$<$3m	N/A	G	Orientation

C - compass, A - accelerometer, G - gyroscope, M - magnetometer

to enhance wireless localization. We thus omit the details and refer interested readers to [Chen et al. 2006][Fang and Lin 2012] for more details.) Since distant locations may share similar fingerprints, they may become indistinguishable. To make matters worse, such ambiguity is intractable as it is scarcely possible to eliminate the uncertainty and instability of signal propagation in the air, given that the multipath effects are inevitable indoors.

Towards higher accuracy, recent pioneer work exploits physical layer information [Sen et al. 2012] or incorporate acoustic ranging [Liu et al. 2012] [Liu et al. 2013], among others. However, these methods either rely on information unavailable on commodity smartphones, or resort to unrealistic cooperation among a dense crowd of peers, thus degrading the ubiquity or increasing the costs.

A promising alternative, is to leverage human mobility information acquired from built-in inertial sensors. Table IV lists some recent works on improving wireless localization accuracy leveraging mobility. We demonstrate how they combat fingerprint ambiguity as follows:

4.1.1. Extending fingerprint diversity. User motions captured by inertial sensors add to the diversity of fingerprints generated from RSS observations. Specifically, user mobility indicates the physical relationships between pairs of adjacent locations and extends the dimension of constraints for location estimation, which helps to distinguish multiple locations with similar RSS fingerprints.

Applying such thoughts, Sun et al. proposed MoLoc [Sun et al. 2013a], a system that notably reduces the large errors caused by fingerprint ambiguity. MoLoc employs accelerometer and digital compass to determine relative location reachability and accordingly construct a motion database, which is then attached to the traditional fingerprint database. When a user sends a location query with his/her current fingerprints, MoLoc calculates the most similar candidates, according to the joint probability returned by the RSS fingerprints together with the motion database. MoLoc is an early attempt to integrate user mobility into localization and proves promising for practical applications, at the cost of an extra motion database.

4.1.2. Continuous path matching. Trajectories of mobile users can also mitigate fingerprint ambiguity. Displacement and/or direction information obtained by dead-reckoning impose relative geometrical constraints between consecutive location queries along a trajectory. With these restrictions, fingerprint matching in localization algorithms shifts from point matching to line fitting by embedding the entire trajectory into the radio map, thus contributing to more accurate location estimates.

GloCal [Wu et al. 2013b] is an early attempt to embrace trajectories to enhance outdoor GPS localization. Noting the trajectories maintained by dead-reckoning hold precise structures, (i.e., trajectory shapes), GloCal proposes to align the discretely erroneous GPS readings to the accurate locally monitored traces by coordinate transformation between the global and local coordinate systems. The integration of the local yet accurate trajectory with the global but erroneous GPS samples significantly decreases the GPS biases by 30% in average. Although prototyped for outdoor GPS applications, GloCal can easily be extended to indoor scenarios, by replacing GPS readings with initial fingerprint-matching results.

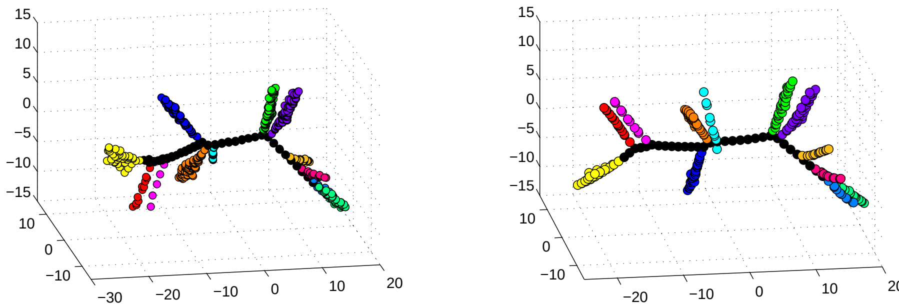
A similar idea is adopted in ACMI [Yoon et al. 2013], which employs FM broadcast signals for localization. ACMI performs path matching to improve localization accuracy, which clusters multiple indoor spots along a mobile user's trajectory. The key insight is that, even though the RSS estimation at each individual location may be ambiguous, the RSS changing pattern over a broader area may be unique with a higher probability. To reduce computational complexity of path matching, a walk detector is designed to monitor the topology of indoor spots, which regulates the distance between two successive spots to relate only neighboring spots that satisfy the distance constraints. Experimental results demonstrate that localization errors decrease from 10m$\sim$18mto 6m, along with the room identification accuracy from 59% to 89%.

A graph-based data fusion technique based on the well-known particle filter is proposed in [Hilsenbeck et al. 2014] to process measurements from multiple sources of sensor information as well as the knowledge of indoor maps. Experiments on a dataset that spans about 20 kilometers in distance walked within four hours demonstrate excellent accuracy of 1.52m 50% of the time and 4.53m 90% of the time. Naguib et al. [Naguib et al. 2013] also combined information of WiFi signals inertial sensor data and indoor maps to achieve reliable and accurate location estimation with reported median accuracy of less than one meter. Li et al. [Li et al. 2012a] devised algorithms for reliable steps and heading direction detection, and accuracy step length estimation and personalization and reports mean accuracy of 1.5m for the phone-in-hand case and 2m for the phone-in-pocket case while integrated these modules with an indoor floor map. The availability of mobility information, even with mere orientation, has enabled accurate WiFi-based SAR (Synthesis Aperture Radar) on commodity mobile devices, achieving tens of centimeter localization accuracy [Kumar et al. 2014]. Besides WiFi-based positioning, inertial sensor data is also combined with other radio signals like RFID and UWB [Zampella et al. 2013], using similar data fusing techniques. In a nutshell, we conclude that embracing inertial sensed mobility information in indoor localization appears to be an irresistible trend and inertial sensing will be an indispensable component in future practical positioning system for smartphones.

Despite dramatic accuracy improvement, it is not all chocolates and flowers to leverage user mobility in the form of trajectory matching. The main drawback is that it may incur higher energy consumption as well as longer time delay, which to some extent limits the efficiency in energy-sensitive and real-time applications.

4.2. Mobility Decreases Deployment Cost

A primary bottleneck of fingerprint-based localization is the process of site survey (a.k.a, calibration or war-driving) due to its expensive manpower and time overhead. With the assistance of mobility, this site survey procedure can be liberated from specialists to ordinary users, from dedicated hardware to commodity devices, and most critically, from conscious labour efforts to unconscious user participation. In essence, mobility benefits localization by two aspects of power: 1) the potential to associate previously independent fingerprints or locations and 2) the ability to monitor user moving trajectories. The former makes it possible to construct the reachability relationship between fingerprints in the fingerprint space, which can then be mapped to the physical space to obtain the targeted radio map. The latter lays the foundation of progressive ra-



(a) 3D fingerprint space

(b) 3D stress-free floor plan

Fig. 5. Fingerprint and physical space generated by LiFS. Regarding the high dimension fingerprint space, the *walking distances* among fingerprints, measured by footsteps, are preserved [Yang et al. 2012].

dio map construction from localized trajectories. Inspired by these new opportunities, many researchers scramble to put forward a number of site-survey-free solutions to decrease the deployment costs of wireless localization. We roughly summarize them into three categories: fingerprint space transformation, trajectory embedding with floorplan and with landmarks.

4.2.1. Fingerprint Space Transformation. In previous literature, wireless fingerprints of different locations were considered independent from each other. Such independence serves as an implicit hypothesis for location distinction via fingerprinting [Patwari and Kasera 2007]. Although these fingerprints may be independent in the wireless signal space, they can still be associated under certain semantics. Early attempts consider the relationship between end-locations such as connectivity or reachability between adjacent locations, usually in the form of transition probability matrix and thus typically modelled by HMM [Liu et al. 2010] [Zheng et al. 2008]. Nevertheless, most of them simply assume the availability of the transition matrix, yet seldom provide details on the feasibility or how to acquire the transition probabilities.

Breakthrough emerges with the availability of smartphone based inertial sensing, where various human mobility information, including step counts, orientation, trajectory, etc., can now be obtained in an automatic, harmonious way without extra hardware deployment or even user attention. LiFS [Yang et al. 2012] pioneers to construct a connected fingerprint space using inertial sensor hints, which is further transformed to the physical floor plan to bridge the fingerprints with the corresponding locations. WILL [Wu et al. 2013a] adopts a similar idea, yet at the resolution of room level fingerprints. Since WILL can be treated as a special case of LiFS, we briefly discuss the principles of LiFS in the following.

To construct the fingerprint space, LiFS automatically collects continuous acceleration readings and the accompanying RSS observations, from ordinary smartphone users during their routine work and living in the buildings. Footsteps are then detected and counted as in Section 3.1.1 and used as the inter-fingerprints distance measurements. Feeding the inter-fingerprint distances to the multi-dimensional scaling (MDS) algorithm, a high dimension space named *fingerprint space* [Yang et al. 2012] is generated, where the mutual distances between points (which represent fingerprints) are preserved (Figure 5). The fingerprint space is then mapped to the floor plan to associate the fingerprints with their corresponding locations.The mapping is achieved by exploring the spatial similarity between the fingerprint space and a transformed floor plan, called *stress-free floor plan* [Yang et al. 2012]. The stress-free floor plan is a space which transforms a normal floor plan into a high dimension space by MDS, such that the geometrical distances between the points in the new space reflect their walking distances instead of the straight distances. The rationale behind such transformation is that, due to the presence of obstacles such as walls, the walking distance between two locations does not necessarily equal the geographical distance between them. Both indicating the walking distance constraints of the same building, the stress-free floor plan and fingerprint space are highly similar in spatial topology, which finally enables fingerprints labeled with real locations.

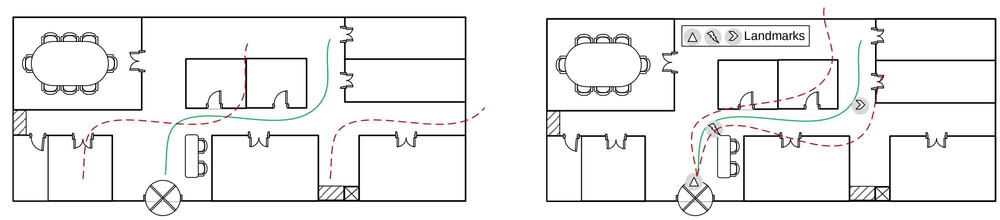
Two key insights motivates the design of LiFS: 1) With user mobility, originally separated fingerprints can be geographically connected by mobile trajectories, resulting in the so called fingerprint space. 2) Although the data of any individual user may be inappreciable, fusing a large amount of sensor hints from numerous participators can make a big difference.

Focusing on fingerprint database construction, LiFS achieves remarkable performance with the 95th percentile mapping error being lower than 4m and the average error of 1.33m. The radio map generated by LiFS is sufficient for use in numerous fingerprint-based localization schemes, including classical ones like RADAR [Bahl and Padmanabhan 2000] and Horus [Youssef and Agrawala 2005] and more recent ones like [Liu et al. 2012]. Among all approaches we surveyed which aim to reduce deployment cost, LiFS is probably the most backward compatible to classical RSS fingerprint-based localization systems and thus can be easily integrated and serve for many existing and emerging localization techniques.

4.2.2. Trajectory Embedding with Floorplan. Considering indoor space, as a user continues to walk and navigate through hallways and and turning around corners, his/her trajectory grows distinguished especially in shape and thus the similarities for his/her trajectory shrink progressively. Some researchers exploit this insight and propose novel techniques for constructing fingerprint database and estimating user location. Among these efforts, Zee [Rai et al. 2012] is a most representative system, which simultaneously estimates user locomotion and location.

Zee enables crowdsourced radio map construction by inferring a user's location from his moving trajectory, without any a prior about his initial location. Zee estimates a user's current location as follows. It initializes the user's location as a uniformly distributed probability over all locations within the entire floor. Accounting for the structure imposed by the floor plan, Zee continuously updates the probability distribution when the user moves on by eliminating all impossible paths that would require the user to violate the physical walls or other obstacles. If the user walks for sufficient length and, particularly, takes enough turns, the location probability is promising to converge to the correct location since there may be probably only one path that can be accommodated to the shape of the trajectory measured from user motion. This procedure is similar to embed a trajectory with specific shape into a 2D floor plan considering the physical constraints imposed by the floor plan. To do this, an augmented particle filter is proposed to track the probability distribution of a user location during his walk. In particular, to simultaneously estimate location, stride length, and heading offset, Zee maintains a four-dimensional joint probability distribution function in a particle filter, and learns all these values as the user walks.

Note that only mobility information is employed but no WiFi measurements are required during this trajectory embedding process. To eventually generate a fingerprint database, however, Zee still expects users to record WiFi measurements during their moving paths, which will then be annotated with the locations estimated from trajectory embedding. Fusing abundant localized walking trajectories from numerous users, Zee is finally capable of building a radio map for WiFi fingerprint-based localization.



(a) Zee: Embedding a trajectory by constraints imposed by the floor plan

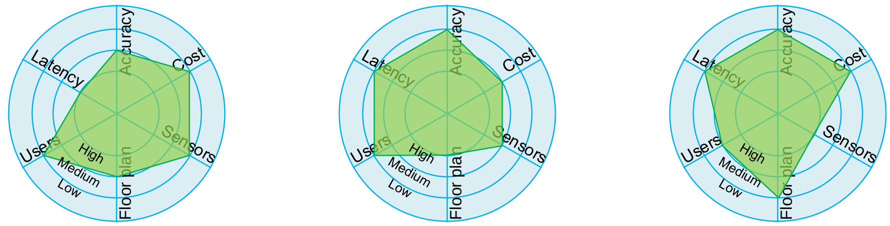
(b) Unloc: Calibrate the dead-reckoned locations with reference locations

Fig. 6. Trajectories are utilized in different ways.

4.2.3. Trajectory Pinning with Landmarks. Given that inertial sensors can capture and maintain user trajectories in an automatic and non-invasive way, it is possible to infer user location using only these trajectories as inputs, as long as an initial start point is known. The idea, typically known as dead-reckoning, is not fundamentally different from ancient transportation and modern robotic navigation systems. However, it is non-trivial to implement this idea for mobile applications due to error drifts caused by noisy phone sensors and complicated human behaviours. In consequence, in addition to notable efforts in reckoning user trajectories as accurately as possible (as in Section 3), researchers also strive to take advantage of reference landmarks both in outdoor and indoor environments.

CompAcc [Constandache et al. 2010b] is an early exploration of infrastructure-independent localization for outdoor scenarios. It leverages electronic compass and accelerometer to measure the walking displacement and orientation of a mobile user, based on which a trajectory is produced and further matched against walkable path segments imposed by a digital map tile. Note a trajectory is a directional trail while the digital map tile is a local area map downloaded based on the rough location of the phone. With infrequent GPS samples, the phone can re-calibrate its location and uses it as a reference for subsequent estimations. By doing this, the accumulative errors arising from the inaccurate sensor readings can be successively resisted.

Translating a similar idea into indoor services encounters remarkable difficulties because of the unavailability of GPS. And researchers have investigated indoor context landmarks as a substitution. These context landmarks vary from dedicated installed reference anchors, to automatically discovered spots (i.e., spots with certain distinctive signatures). As a seminal endeavor, Unloc [Wang et al. 2012] comprehensively explores and exploits environment landmarks for location estimation. In Unloc, inertial sensing of human behavior and ambient sensing of environment contexts are simultaneously conducted to discover underlying landmarks, which are further utilized as reference points, analogous to GPS samples in outdoor scenarios, to re-calibrate the dead-reckoned locations. Unloc looks into a floor plan and identifies seed landmarks from essential structures in the building. The rationale is that users will be forced to behave in predictable ways at certain places such as elevators, stairs, building entrances, escalators. 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. Translating these predictable behaviors into sensor signatures, Unloc manages to identify intrinsic landmarks from smartphone sensor readings. Since the landmarks are spots with known locations in the floor plan, they can be used to calibrate a user's location when he passes through one landmark. On this basis, Unloc can localize a user at any time by incorporating the established dead reckoning on smartphones, without building a fingerprint database or injecting extra reference anchors.



(a) Overall score of LiFS (b) Overall score of Zee (c) Overall score of Unloc

Fig. 7. Comparison of recent systems that decrease the deployment costs of WiFi based localization.

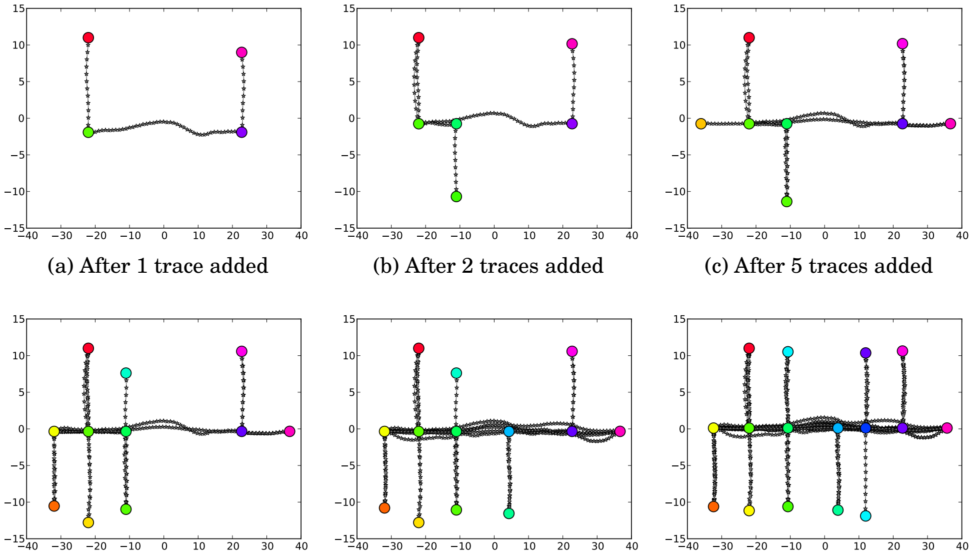
In addition to seed landmarks, Unloc also explores more organic yet unknown landmarks by ambient sensing. These landmarks are postulated to be spots that exhibit distinct ambient signatures across one or more sensing dimensions, which can be magnetism, acceleration, or WiFi domain. Taking magnetic hints as example, metals in a specific location may produce unique and reproducible fluctuations on the magnetometer near that location, rendering a possible landmark. Since accurate locations of such landmarks cannot be known a prior, Unloc employs unsupervised clustering algorithms to identify individual landmarks from a large amount of sensor data gathered from all phone users. Given a set of seed landmarks available, the incrementally recognized landmarks can then be associated with relative locations via dead reckoning, which in turn will benefit dead reckoning itself (by providing denser reference points for calibration). In summary, inertial sensing and ambient sensing hold complementary advantages: the precise trajectory structure preserved by inertial sensing lays the important foundations to connect individual landmarks, while it is the accurate location references from landmarks recognized by ambient sensing that put relative trajectories into a floor plan.

Although both exploring user trajectories, Zee and Unloc exploits them in quite different ways, as illustrated in Figure 6. Finally, we present an overall comparison of LiFS, Zee, and Unloc in terms of localization accuracy, deployment cost, bootstrap latency, the extent of user participation, and the dependence of floor plan and sensors in Figure 7.

4.3. Mobility Enriches Location Contexts

Location, although generally appears in the form of numerical coordinates, should never be monotonous digits. Luxuriant contexts always accompany with physical locations, such as location labels, region functionality, surrounding circumstances, social information, etc. In brief, location, as the most essential element of our physical space, is abundant in its denotation yet rather simple in its basic connotation. Among various location context information, floor plan is the most essential one that provides users with a clear and useful view of the indoor space. As for all the localization approaches mentioned above, floor plan is either a necessary input or a basic requirement for providing positioning services.

Unfortunately, it is never easy to acquire the rich accompanying contexts of locations. Even powerful companies such as Google also have to spend hefty costs of manpower, financial resources and time to obtain, however, rather limited location contexts in the indoor map service project. Requirements of specialized engineers and dedicated



(a) After 1 trace added (b) After 2 traces added (c) After 5 traces added

(d) After 10 traces added (e) After 15 traces added (f) After 23 traces added

Fig. 8. A trace map evolves as traces being merged into it. Circles represent extracted reference points (which correspond to rooms in reality), and stars represent user trajectories.

equipment, and the massive amount of buildings, increase both the difficulties and expenses of generating semantically meaningful indoor maps.

Inertial sensor hints, which act as an efficient interface to obtain user mobility through smartphones, make it possible to construct indoor floor plan automatically and dynamically. A floor plan is a graph that provides the region layout and space partition of a building. In other words, floor plan is one way of presenting the indoor space connections and obstructions. Hence, human mobility, which is constrained to the indoor space reachability, can in turn reveals the structure of building layouts and thus is possible to sketch the floor plan. Generally, the task of portraying a floor plan is twofold: 1) Space regionalization: partition the entire space into pieces of areas, which are usually separated by walls or other obstacles; 2) Functionality recognition: label each partitioned area with a specific category of indoor space function, such as rooms, halls, stairs, corridors, etc.

4.3.1. Space Regionalization. To partition the entire space, trajectories collected from different users are fused and joined together to form the basic topology of the floor plan. One trajectory is spliced with another by exploring the common landmarks they have both passed through. For instance, if two trajectories both start from the same building entrance, they can be joined at the start point. Figure 8 illustrates an example of the incremental generation of the floor plan skeleton, where trajectories are gradually added and fitted. When embracing sufficient trajectories that cover the entire space, a drafted floor plan shows up.

Walkie-Markie [Shen et al. 2013] is a recent, successful system that implements the idea to produce a hallway map. Without floor plan available a prior, Walkie-Markie could not search the "seed landmarks" for location estimation even at the very initial stage. Instead, Walkie-Markie explores the novel WiFi-Marks as landmarks for location reference and calibration. WiFi-Marks are defined as locations where the RSS trend of a certain AP changes, which prove to be excellent landmarks due to their stability and robustness. In addition to using the WiFi-defined landmarks to constrain drifting in dead reckoning, Walkie-Markie further exploits them to align and join different user trajectories, and eventually produces a hallway map.

While the hallway map can be treated as the side product of Walkie-Markie, CrowdInside [Alzantot and Youssef 2012] and [Jiang et al. 2013a] completely target at indoor floor plan generation. In CrowdInside, the procedure is detailed as follows:

(1) Trajectory segmentation. Segments are straight parts of the trajectory that are separated by either turns or pauses, which are supposed to be inside the same area (room/corridor) .
(2) Segment classification. The module is performed to distinguish segments in the corridors from those inside rooms. A decision tree based classifier, using average time spent per step, segment length, and trace density as inputs, is carried out for classification.
(3) Segment clustering. A density-based clustering algorithm, DBSCAN, is put on all segments that are classified as rooms to find the number, boundaries, and center locations of the unknown rooms.
(4) Shaping. Finally, to estimate the shapes of a room (or the corridors), the $\alpha-$shape is calculated based on the corresponding point set, i.e., points that are associated with the room.

Similarly, in [Jiang et al. 2013a], an automatic floor plan construction system based on room WiFi fingerprints and user motion information, the floor plan is constructed via three steps: (1) room adjacency graph construction to identify the adjacency of rooms and construct a room adjacency graph; (2) hallway layout learning to estimate room sizes and order rooms along each hallway, using crowd-based motion sensing on smartphones, and (3) force directed dilation to adjust room sizes and optimize the overall floorplan accuracy.

4.3.2. Functionality Recognition. Once the space is partitioned and identified as individual regions, i.e., rooms, halls, or corridors, higher level of semantic can be attached to each region to extend the contexts of the generated floor plan. These semantics include region functionality and room types, shop brands in a mall or room doorplate information, user counts in a specific room, social events, etc. Particularly, user mobility is closely related to region functionality and room types since user and crowd behaviors are constrained by specific patterns at certain regions, which is also the underpinning insight for the feasibility of mining global landmarks for localization as what Unloc has done. Considering modern office buildings, four types of functional ares are involved in:

— **Rooms.** User behaviors in office rooms also exhibit particular patterns. Users in rooms stay stationary most of the time. Even when users move inside the room, their trajectories incline to be short and contain more turns. Moreover, detecting colocation of people can also further differentiate semantic functions, such as meeting room, classroom, or normal office room.
— **Corridors.** Corridors. Despite a few users may stop for a while in corridors, most of users are always walking. Consequently, users do not spend long time in the corridor. In addition, user trajectories generated in the corridor are dense, mostly straight and long, and with fewer turns.
— **Elevators.** Elevators are distinctive landmarks in a building because RF signals are blocked and the acceleration patterns are unique in the elevators. The acceleration variance sequence of elevator-taking is defined as follows: a normal walking period, a short dwell time for waiting, walking into the elevator, a weight-loss (or over-weight) period, standing statically inside, followed by another over-weight (or

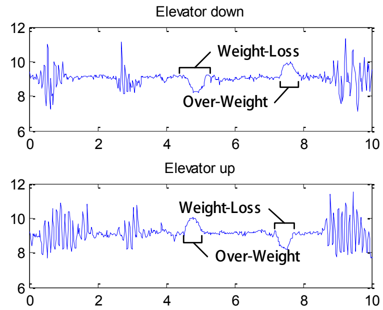


Fig. 9. Distinctive accelerometer signature of using the elevator.

weight-loss), and walking out of the elevator. Figure 9 shows examples of such elevator motion traces.

— **Stairs.** At first sight, it is difficult to differentiate between stairs and corridors. Nevertheless, acceleration patterns provide clues to tell the two apart. For stairs, the variance of acceleration is much larger, which usually varies from $4m/s^2$ to $10m/s^2$ as observed from real user traces.

As can be seen, Unloc and CrowdInside both explore these basic properties of different functional regions in terms of mobility to identify certain spots for landmarks (or anchors in CrowdInside). CrowdInside further exploits the mobile trajectories to differentiate between rooms and corridors. Regarding those higher level location contexts, extensive sensing information, beyond mobility, must be incorporated and advanced pattern recognition or machine learning techniques should be employed. In brief, we review and envision the solutions to perceive rich contexts for locations.

— Incorporate ambient sensing with various types of sensors built on the phone, including inertial sensors as well as other ones like camera and microphone, to investigate richer sensing hints, which can be used to fingerprint some locations. SurroundSense combines such ambient sensing scheme together with inertial sensing to fingerprint logical locations across multiple dimensions and achieves an average accuracy of 87% when all sensing modalities are employed. Map service products such as Google Maps and Baidu Maps have employed high-resolution cameras to scan and construct live indoor station view, which is analogous to the street view for outdoor maps and thus creates expensive costs.
— Integration with social networks and user visiting patterns. With growing interests in location-based social networks such as Foursqure, Facebook Places, Whrrl and location-based mobile games like Google Ingress, users who explore places, write reviews, and share their locations would generate plenty of semantic labels. Fusing and mining these user-generated location tags, it is possible to annotate indoor locations with rich contexts automatically and precisely [Chon et al. 2012] [Lian and Xie 2011] [Ye et al. 2011].

Location contexts are as significant as the location itself, by making location coordinates meaningful, understandable, and eventually attractive as places with distinctive semantics, visual views, specific people, and/or events of interests, etc. While user mobility sheds light on extending the location contexts with low costs in an automatic way, it, as an open issue, still requires adequate research attention and explorations.

5. HOW TO HANDLE MEASUREMENT ERRORS

In the context of smartphone-based indoor localization with inertial sensors, diverse user-phone states constitute the main obstacles that prevent accurate measurement estimates. For example, unconstrained smartphone placements on users may lower step detection accuracy with a generic detection model, while stride length deviations among users make displacement estimation challenging. Therefore, we review existing works that strive to alleviate these measurement errors from two aspects in this section: generate estimates by user modeling and statistics; and combine constraints from external sources.

5.1. Internal Introspection

As discussed in Section 3, basic measurements include step detection, stride length estimation, and heading estimation. Pioneer works have been conducted on making step detection and stride length estimation more robust for users, yet few works have considered the influence of user models for heading estimation. Therefore we focus on methods of handling measurement errors in detecting steps and estimating stride length. Furthermore, as a high level of measurement, user trajectories possess the potential to alleviate errors and will be discussed.

Step detection: Most step detection methods can achieve high accuracy of measurements by analyzing temporal or spectral features of sensor data (Section 3.1.1). These methods are suitable for fixed sensor placement (e.g., waisted-mounted and foot-mounted). However, the interaction between users and smartphones are more complex. Measurement error source points to the diverse smartphone placements as signal patterns change with placements. The study conducted in [Brajdic and Harle 2013] compared various step detection algorithms for different smartphone placements and showed that weakness exists for each method. A direction of handling such errors is to model each placement and apply detection method accordingly. The placements can be categorized according the usual manners of users [Ayub et al. 2012] [Susi et al. 2013] [Renaudin et al. 2012]:

— Static. The user's location does not change during the detection phase. For example, the user may step in the spot when answering the phone.
— Quasi stable. The user is walking, while the phone is relatively fixed to the user. For instance, the user may be texting, playing phone games, or the phone is placed in the trousers.
— Swinging. The user holds her phone in the normally swinging hand while walking.
— Irregular. All irregular motions not belonging to the above cases. For instance, the user is searching in her handbag for the phone.

With the placement modes defined, simple pattern recognition scheme [Ayub et al. 2012] or machine learning method [Susi et al. 2013] can be adopted to detect placements automatically. Thereafter, suitable step detection schemes can be selected for specific placement modes.

Stride length estimation: The difficulty of stride length estimation originates from the diversity of users (such as gender, height, walking speed, etc). Different models have been proposed to depict important factors to estimate stride length. A Gaussian model is adopted in [Constandache et al. 2010a], where the mean of the stride length needs to be measured by users manually, and the deviation of the length is set empirically. The stride length (s) and frequency (f) with body fixed sensors are shown to be linearly related [Margaria and Margaria 1976], which enables a linear model for stride length estimation [Cho et al. 2010]: $s = a \cdot f + b$, where a and b are user dependant parameters. A more complex model adds a random walk parameter w to estimate step length: $s = a \cdot f + b + w$, where w describes the step length asymmetry of both legs [Ladetto 2000] and is modeled using a Gaussian distribution with deviation proportional to the step frequency [Gusenbauer et al. 2010]. Biomechanical studies show that the user's step length and height are directly proportional in general [Rose and Gamble 2006]. Therefore, a linear model explicitly incorporating user's step frequency f and height h is proposed: $s = h \cdot (a \cdot f + b) + c$, where a, b and c are parameters [Renaudin et al. 2012].

These models all depend on user calibration and thus are more accurate than general estimation methods, though the calibration phase may be of high cost. While phone placement modes have been shown to influence step detection accuracy, how they impact stride length estimation need further investigation [Ayub et al. 2012].

Trajectory estimation: User trajectories constitute high level abstraction of sensor readings and user mobilities. By collecting and merging multiple user trajectories, it is possible to reveal the spatial characteristics of indoor environment and hence facilitate localization [Yang et al. 2012] [Rai et al. 2012], navigation [Purohit et al. 2013], and floor plan construction [Shen et al. 2013] [Jiang et al. 2013a]. Different from the outdoor trajectories, which are mostly GPS and time stamp series, indoor user trajectories are more challenging due to the complex user-phone interaction and diverse sensor readings. Therefore, outdoor trajectory estimation and error control methods [Zheng and Zhou 2011] cannot be directly adopted.

The redundancy of user trajectories brings a new opportunity of measurement error control. Note that error control discussed above mainly resort to finer user modeling. However, sensor malfunctioning and abnormal user behavior renders these methods invalid. Numerous user trajectories enable statistical models, especially robust statistical tools, to filter out abnormal data that may jeopardize the trajectory merging results [Zhang et al. pear].

Specifically, given a physical route, each user walking along the route may collect a trajectory. The goal is to estimate the distance between two sample locations along the route. A common method is to use the step counts of a user, which is transformed from the accelerometer readings of a smartphone, to reflect the distance. Yet different users have different strides, and users may collect outlier data due to multiple reasons (e.g., a user may cheat the smartphone sensor by abnormal movement). Therefore, it is necessary to make use of the redundancy of user data to obtain an accurate estimate.

A family of robust statistical estimators are effective in alleviating the influence of outlier data when acquiring an estimate between sample points. Furthermore, a multidimensional estimator, termed minimum covariance determinant, is adopted in [Zhang et al. pear] to estimate the distances among sample points along a physical route. Interestingly, a unique ID is associated with each user, which is revealed to be normal or abnormal by the estimation result. The abnormal users are hence can be excluded when estimating trajectories in other routes. This is very essential in the area where few users step into, as even robust statistical tools may fail in this scenario. For example, if a route has received 3 trajectories, among which 2 trajectories are abnormal and 1 is normal. It is obvious that no statistical estimator can make accurate estimation. However, if we have the ID of these 3 users and have tracked their performance in other areas where user redundancy exists, we can still obtain a satisfiable estimate by eliminating the 2 outlier users.

Robust statistical methods are promising as more and more mobile trajectory-based applications are based on crowdsourcing [Wang et al. 2012] [Yang et al. 2012] [Shen et al. 2013], yet in large open environments where user movements are difficult to characterize, it is still hard to obtain accurate estimates. Further efforts are needed to resolve this issue.

Table V. Typical landmarks as mobility references for error control.

Citation	Landmark	Type	Signature
[Constandache et al. 2010a]	beacon node deployed manually	primary	audio tone
[Wang et al. 2012]	elevator, escalator, stair	primary	accelerometer pattern
[Shen et al. 2013]	pathway tipping point	primary	RSS trend
[Li et al. 2012b]	beacon node deployed manually	primary	TDOA of radio and audio signal
[Alzantot and Youssef 2012]	entrance, elevator, escalator, stair	primary	GPS signal, inertial sensor pattern
[Constandache et al. 2010a]	encountered user	secondary	audio tone
[Wang et al. 2012]	organic landmark	secondary	sensor feature cluster

5.2. External Facilitation

Other than handling errors by solely inspecting the sensor data, the measurements can be further improved by user mobility references, i.e., landmarks and floor plans.

5.2.1. Landmarks. The landmarks can be detected from the unique patterns reflected through smartphone sensor readings. For example, an elevator imposes a distinct patterns on the smartphone's accelerometer; while a corridor-corner may only receive a unique set of WiFi access points [Wang et al. 2012]. These landmarks (or more accurately, unique signal patterns of landmarks) exist in various places of a typical indoor environment, making them valuable to assist rectifying a smartphone user's positions under motion. The rationale of using landmarks lies in that, the locations of these landmarks serve as restarting locations for pedestrians, hence dividing a user's long trajectories into multiple short trajectories and significantly reducing the accumulative measurement errors from inertial sensors [Li et al. 2012b] [Alzantot and Youssef 2012] [Shen et al. 2013]. Table V gives a brief summarization of these landmarks.

As the landmarks themselves are reflected from received patterns of sensors, they are possibly erroneous. However, the uniqueness and large distances from other non-landmark patterns make landmarks more robust and accurate than simply using inertial sensor readings. In fact, recent studies even adopted secondary landmarks, which are summarized directly from user trajectories, to help recalibrate other users' locations. In [Constandache et al. 2010a], beacon nodes deployed in the environment play the role of primary landmarks and reset users' positions within the range. And these users with fresh restarting positions in turn, being secondary landmarks, correct locations of other encountered users. In [Wang et al. 2012], primary landmarks are certain recognizable structures in the building (e.g. stairs, elevators, entrances, escalators), where sensor signatures are stored in advance; while ambient signatures across one or many sensing dimensions, which constitute secondary landmarks (e.g. a spot not covered by WiFi, a water-fountain), are learnt dynamically by clustering more and more users' sensing data.

5.2.2. Floor Plans. Similar to the idea of applying electronic maps to rectify users' positions in outdoor localization schemes [Constandache et al. 2010b] [Zhu et al. 2013], integrating the constraints of floor plans alleviates the inertial sensor errors in indoor localization. There are roughly two means to use a floor plan:

Geometry mapping. Mapping user trajectories to floor plans is effective in weakening sensor drift errors. The rationale is that, though user trajectories may be distorted due to sensor drift, their overall geometric shape should be similar to that of the floor plan. Different geometric abstraction models can be adopted for mapping. For example, a link-node model is applied in [Lan and Shih 2013], while a stress-free floor plan is proposed in [Yang et al. 2012].

Position filtering. The other way of using a floor plan is to exclude unlikely positions for walking users, such as obstacles and walls. A commonly used technique is Particle Filter, which has been successfully applied in locating mobile robots [Fox et al. 2001] and pedestrian tracking with foot-mounted sensors [Klepal et al. 2008] [Woodman and Harle 2008]. Table VI summarizes Particle Filters used in pedestrian localization with smartphones.

Particle Filtering is a non-parametric form of Bayesian estimation, which consists of many particles. In the context of user localization, a typical particle may represent the user's possible physical position and heading. Positions and heading values possess different likelihood. Hence a weight value is assigned to each particle, which reflects the probability of the particle being correct according to the accumulated information. Generally, there are three steps to run an iteration of particle filtering:

— Particle propagation. Particles update their values according to certain motion models. For example, a constant velocity with a Gaussian noise can be used to update the position of a particle.
— Particle correction. Particles update their weights according to their fitness to the environment. For example, if a particle crosses a wall during propagation, the weight of that particle should be set to 0.
— Particle resampling. A new particle set is generated in proportion to the weights of particles in the current set.

The particle correction step is of great concern in the literature, as external constraints can be added in this step to eliminate inappropriate particles. The basic constraint is the floor plan, which defines the accessible area for particles. Another common constraint is WiFi fingerprint, which is helpful for differentiating similar particle trajectories [Thiagarajan 2011] [Kothari et al. 2012]. A recent study attempted to replace the requirement for a detailed knowledge of floor plan by using distances to known reference points (corner, stairs, elevators and WiFi estimation) to restrain particles [Radu and Marina 2013].

The influences of particle propagation are twofold: Firstly, the choice of motion models (e.g. direction error distribution and stride length distribution) is important to ensure particle survival rate. Specifically, as the number of particles that can be simulated is finite due to computational constraints, if all particles end up violating a floor plan constraint, the filter may end up producing no output at all. Towards this issue, mixture models [Thiagarajan 2011], other than simple Gaussian models [Kothari et al. 2012] [Radu and Marina 2013], are investigated and shown to have better survival rate. Secondly, as users have different stride lengths, using a generic model (e.g. Gaussian model) is inappropriate. In fact, the stride lengths vary even for the same user from time to time. A direct approach for this problem is to incorporate the stride length, or the parameters of a personalized step model, as a component of a particle [Rai et al. 2012] [Li et al. 2012a].

6. CONCLUSIONS

In this survey, we reviewed the principles of measuring human mobility via smartphones, and the emerging trend in mobility assisted wireless indoor localization. Back to decades ago, such mobility information is accessible only in the military or robotics communities leveraging dedicated sensors. Modern smartphones have reshaped the landscape of human-centric computing and we have identified numerous types of mobility information derivable via built-in sensors. We demonstrated how to incorporate mobility to improve localization accuracy, decrease deployment cost, and enrich location context. Due to noisy sensor data, unconstrained phone placement and complicated human activities, we also discussed prevalent error control mechanisms for mobility measurement and localization.

Table VI. Types of particle filter designs for smartphone-based pedestrian localization.

Citation	Sensor	Particle Model	Feature	Accuracy
[Thiagarajan 2011]	A+G+W	{position, direction}	incorporate initial position and WiFi information in particles	3 feet
[Rai et al. 2012]	A+C+G	{position, stride length, heading offset}	incorporate stride length estimation in particles	80%ile $2.3m$
[Li et al. 2012a]	A+C+G	{position, step length coefficients}	incorporate personalized step model in particles	$1.5-2m$
[Kothari et al. 2012]	A+C+G+W	{position, direction}	impose constraints of robot map and WiFi fingerprint	$5m$
[Kim et al. 2012]	A+C+W	{position}	assist WiFi fingerprinting	$< 2.4m$
[Radu and Marina 2013]	A+C	{activity, distance, direction}	combine location tracking and activity recognition	$2-3m$

C - compass, A - accelerometer, G - gyroscope, W - WiFi

Despite pioneer efforts in mobility measurements and mobility assisted wireless localization, the realm is still in its infancy and continues to develop from diverse perspectives:

Orthogonal to inertial sensors, wireless signals can also hint mobility. Seminal work exploited the ubiquitous WiFi signals to recognize gestures via micro-Doppler effects [Pu et al. 2013] and estimate walking speed by PHY layer information [Jiang et al. 2013b]. Future research is envisioned to incorporate inertial sensors and wireless modules on smartphones synergically to derive mobility information pervasively and non-intrusively.

Previous smartphone based inertial sensing often abstracts pedestrian mobility as steps, and ignores that human body is non-rigid. A notable shift nowadays is to model detailed locomotion properties based on human kinematics. However, most of these models are valid only with particular sensor placement (e.g. foot-mounted). It remains open how to refine them for unconstrained phone placement to capture precise mobility information and reduce modeling errors.

Another development trend is the finer-grained mobility measurement by smart wearable devices, such as wristbands, watches, necklaces, glasses, etc. Pioneer products like Samsung's Galaxy Gear and Google Glass have attracted numerous enthusiasts all over the world. Interworking with smartphones, these smart wearables, attached firmly to human body, are holding great expectations of highly accurate mobility sensing.

Finally, mobility increases more than localizability. The paradigm of localization has evolved from yielding accurate location coordinates to mining diverse location context. With mobile users round-the-clock, discrete surrounding information such as ambient lights, sounds, temperature, air conditions, etc., is now connected via human activities, social behaviors and even moods. This in turn extends the connotation of location context, and brings deeper insight on individuals, societies, and the nature. Upon this promising frontier though, reside significant challenges in integrating complementary sensing modalities and advancing spatial-temporal analysis with noisy, crowdsourced data, and these leave largely open and attractive research opportunities.

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