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A Crowdsourcing Approach

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Chenshu Wu
University of Maryland
College Park, Maryland, USA

Zheng Yang
School of Software
Tsinghua University
Beijing, China

Yunhao Liu
School of Software
Tsinghua University
Beijing, China

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Preface

Location-based technology surely ranks as one of the most important breakthrough for modern life. Localization techniques underlie the foundation of Internet of Things, while location information contributes one type of the most critical big data nowadays. With the proliferation of mobile computing, location-based services have shaped and enabled a wide range of applications from vehicle navigation to logistical supply chain management and to personal location sharing. While GPS dominates outdoor localization and becomes an essential element of the global information infrastructure like the Internet, indoor localization also attracts people's attention. Indoor location holds important values for various applications, including resource and infrastructure management, smart home and smart building monitoring, retails and sports analytics, mall navigation, virtual reality, etc.

The past decades have witnessed the fast conceptualization and development of wireless indoor localization. Among numerous technologies, WiFi fingerprint-based approach has become one of the most popular solutions that attracts immense efforts from both academic and industrial communities. Not only a number of start-ups, but also grand corporations including Google, Apple, Cisco, QualComm, Huawei, etc., have invested in and have been developing indoor localization products.

This book aims to provide a comprehensive and in-depth understanding of wireless indoor localization for ubiquitous applications. Specifically, focusing on WiFi fingerprint based localization via crowdsourcing, the book follows a top-down view and involves the three most important issues of indoor localization: deployment, maintenance, and accuracy. Through extensively reviewing the state-of-the-art literatures, it presents the latest advances in crowdsourcing-enabled WiFi localization.

Crowdsourcing is a recently invented and increasingly hot topic in not only research areas but also enterprise business. It has been widely applied in indoor localization to address several critical bottlenecks. As to WiFi fingerprint based localization, crowdsourcing helps with the issues including significant deployment costs, lack of indoor floorplans, and limited location accuracy. Despite a large number of research outputs, it lacks a representative book that provides an extensive view of crowdsourcing-based indoor localization. This book turns out to be the first of its kind, as far as we are aware of, which introduces WiFi fingerprint based localization from a perspective of crowdsourcing. Hence, we hope the reported latest advances can promote the development of this research area and contribute to the interdisciplinary research areas as well.

Organization of the Book

The book begins with an introductory Part I. We firstly present the background of location-aware applications, current wireless localization problems, and representative localization systems in Chap. 1. The preliminary introduction in Chap. 2 to the concepts and techniques of crowdsourcing, mobile sensing, etc., would guide the readers to understand. The subsequent parts focus on tackling the critical challenges of WiFi-based localization for ubiquitous applications, each from a distinctive aspect of deployment costs, maintenance overhead, and location errors. In these parts, we present the ideas, methods, and systems for implementing the crowdsourcing approach in localization. Specifically, rapid deployment is the first step to make indoor localization available, which is extensively investigated in Part II. In addition, it is also important to maintain consistent quality of service over long-term running, which is carefully addressed in Part III. Moreover, accuracy acts as the most critical metric to reliable and usable indoor localization, which worths in-depth exploration in Part IV. Finally, we make a summary of this book and discuss several future directions in Part V.

Part II to Part IV consist of the main content of this book, and are further elaborated into seven chapters as follows:

Part II *Boosting deployment: making it available*

In this part, we consider two deployment issues of WiFi-based localization: radio map construction (Chap. 3) and digital floorplan generation (Chap. 4). Harnessing the power of mobile crowdsourcing, we present techniques that automate these two procedures, which can only be completed by manual efforts previously, and therefore rapidly boost the deployment for WiFi-based location systems in practice.

Part III *Facilitating maintenance: making it sustainable*

WiFi fingerprints are sensitive to temporal environmental dynamics and vary over time. To tackle this problem, in Chap. 5, we seek for adaptive fingerprint updating techniques to adapt collected fingerprints to environmental changes and to guarantee the performance of deployed location services over time. Furthermore, we introduce a self-deployable approach for indoor navigation, which can work in a peer-to-peer manner with no prior installed location services.

Part IV *Enhancing accuracy: making it reliable*

Traditional WiFi-based localization suffers from large location errors. Based on in-depth understanding of root causes of its location errors, we present novel approaches to improve accuracy by embracing spatial awareness in the form of fingerprint spatial gradient in Chap. 7. We further present image-assisted WiFi fingerprinting in Chap. 8 and address several practical causes of location errors in Chap. 9.

Anticipated Audience

The book considers the state-of-the-art research results in many academic journals and conferences during its preparation. Thus, readers can track trends and hot topics in the field. With the detailed introduced techniques for practical localization systems, it would draw attention of scientists and researchers in mobile and ubiquitous computing area and other related areas. The provided techniques would also systematically contribute to the practical applications and well guide the readers. Thus, it can serve as a guide book for the technicians and practitioners in the industry of location-based service and mobile sensing. Moreover, we wish this book can genuinely benefit all levels of readers.

The book intends to fit the audience's different technical backgrounds and career objectives and provides a balance of localization technology and location-aware applications. It does not require very specific knowledge of location-awareness technology. We kindly suggest the readers should have some basic knowledge of computer algorithms and wireless networks.

Should the readers have any questions or suggestions, please contact the authors by email via wucs32@gmail.com.

College Park, USA — Chenshu Wu
Beijing, China — Zheng Yang
Beijing, China — Yunhao Liu
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Chenshu Wu

Contents

Acronyms

AoA	Angle of Arrival
AP	Access Point
BLE	Bluetooth Low Energy
CSI	Channel State Information
FSG	Fingerprint Spatial Gradient
FSM	Finite State Machine
GPS	Global Positioning System
IMU	Inertial Measurement Unit
LOS	Line of Sight
LDPL	Log-Distance Path Loss
MDS	Multi-dimensional Scaling
MEMS	Micro Electro-Mechanical Systems
mmWave	Millimeter Wave
MST	Minimum Spanning Tree
PDR	Pedestrian Dead Reckoning
PLSR	Partial Least Squares Regression
RM	Radio Map
RSG	RSS Spatial Gradient
RSS	Received Signal Strength
SLAM	Simultaneous Localization and Mapping
ToA	Time of Arrival
TDoA	Time Difference of Arrival

Part I
Getting Started

Part I consists of two chapters presenting the basis of crowdsourcing-based wireless indoor localization systems. The first chapter introduces location-awareness applications, typical indoor localization systems and the state-of-the-art techniques and summaries the challenges of WiFi-based localization for ubiquitous applications. The second chapter includes the concepts of crowdsourcing and presents basis of mobility monitoring via smartphone sensing, which help readers understand the techniques before going over the subsequent chapters.

TO INDOOR LOCALIZATION SYSTEMS:

> *The biggest thing I've learned is location.*
>
> *– Roy Halladay*

Chapter 1
Background and Overview

Abstract Location acts as the most important information that bridges the physical world and the cyber space and thus a key enabler for Cyber-Physical Systems (CPS). In this chapter, we first introduce why indoor localization technology is particularly needed and then review the state-of-the-art approaches. In the end, we outline the book structure.

1.1 Wireless Indoor Localization

The word "smart" becomes ubiquitous in the era of Internet of Things and big data. If you believe the hype, smart homes will analyze user behaviors in kitchen and bedrooms to improve in-home experience. Smart buildings will collect user trajectories for intelligent analytics to understand user behavior in buildings. Smart cities will monitor the realtime traffics on every street corner. Smart factories will track every robot and object in the facility and further every product they deliver in the coming Industry 4.0. Getting all these to work, however, necessities resolving locations of devices, sensors, machines, and people in the space.

Thanks to the Global Positioning System (GPS), and digital maps freely available online, a smartphone (or any GPS-equipped end devices) is the only thing one needs to pinpoint his/her own location anywhere on the Earth. GPS works by broadcasting precise time and position data using on-board synchronized atomic clocks, allowing a receiver to calculate its location by measuring signals from four or more satellites. Nowadays, GPS dominates the market of outdoor positioning and, together with the proliferation of mobile computing, has enabled a splendiferous paradigm of mobile Internet that profoundly revolutionized people's life styles.

Unfortunately, GPS doesn't work indoors. GPS satellite signals cannot penetrate modern building walls. And even in outdoor areas of metropolises like Manhattan and Hong Kong, GPS may not work properly due to the lack of clear Line-of-Sight (LOS) propagation since the satellite signals are also easily blocked by nearby buildings. To enable wireless localization indoors, where modern people spend more than 80% of their time, alternative technologies are needed.

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1.2 State-of-the-Art Approaches

The past decades have witnessed the conceptualization and development of wireless indoor localization, with research and engineer efforts from both academy side and industry side. Various technologies have been proposed to enable a ubiquitous indoor positioning system.

1.2.1 Infrastructure

By now, different signals have been utilized, including WiFi, RFID, UWB, laser, visible light, acoustic signals, and magnetic, etc. We first briefly introduce some of the representative technology as follows.

WiFi-based WiFi-based solutions utilize existing WiFi infrastructure and have been studied since RADAR initialized a very early system [3]. After that, numerous efforts have been devoted to WiFi-based localization in the past decades, both from academic side [6, 7, 20, 40, 42, 49, 60, 62, 66, 70] and from industrial side [5, 9, 12, 19, 32, 58]. Thanks to the ubiquity in deployment of WiFi infrastructure and accessibility on off-the-shelf smartphone, WiFi-based approaches are treated as *infrastructure-free* and thus turn out to be the most attractive solution for ubiquitous indoor localization. This book mainly focuses on WiFi-based pervasive localization and we will detail its methodology, framework, advantages, and challenges in next section.

RFID-based RFID is an as popular solution to indoor location tracking. Early back to 2004, commercial active RFID tags (powered by a small battery) have been exploited for localization [34]. Recently, passive RFID tags that are battery-free and cheaper draw more attentions [1, 35, 43, 44, 50–52, 55, 67, 68]. With precise phase information available from commercial RFID reader, centimeter-level accuracy can be achieved for tracking [51, 67]. Although passive RFID tags are pretty cheap, the indispensable counterpart readers are quite expensive. And they are not likely to be available on smartphones. Furthermore, the tracking coverage is very limited due to weak backscatter signals from the tags and not suitable for ubiquitous scenarios.

Bluetooth-based Bluetooth, especially the recently released Bluetooth Low Energy (BLE) standard, has also been adopted as a promising approach for practical localization. Bluetooth-based approaches are particularly useful for logical localization, which identifies the room or retail store, rather than the absolute location a user presents. Cheap and energy-efficient BLE beacons are available to be deployed widely, each beacon covering a modest indoor area. By examining the detected beacon ID, one can figure out the location by a beacon or simply a smartphone. Beacons can also be deployed densely for accuracy and robustness gains. Due to limited accuracy, Bluetooth-based methods usually don't appear as independent solutions, but are combined with other technology like WiFi.

mmWave-based Recently, the progress of millimeter wave (mmWave) communications also promotes its application in wireless tracking and sensing. Working on an ultra-high frequency baseband with ultra-wide bandwidth, mmWave provides the feasibility of an indoor radar with millimeter-level resolution in location tracking and motion sensing [25, 28, 36, 57, 78, 79]. Albeit promising, mmWave technology is still in its early phase and not yet widely available on commercial devices.

Sound-based The Bat [15] and Cricket [38] systems, developed more than 15 years ago, both employed ultrasound for localization with specialized transmitter and receiver devices. With higher computation resources on mobile devices like smartphones, sound-based localization becomes feasible on them. BeepBeep [37] and Guoguo [27] both use microphones and speakers equipped on smartphones for localization. ABS [47] enables room localization by extracting background sound as fingerprints. Recent innovations further enable ultrasonic signal transmission on commercial smartphones and achieve precise tracking, such as AAMouse[71], CAT [31], FingerIO [33], Strata [72], LLAP [54], etc. While audible sound based approaches are intrusive to humans, ultrasound-based methods mainly suits near-field sensing.

Image-based There has been an increasing research interest in image-based localization with mobile phones, especially when computer vision technologies are more and more mature today. Camera-taken images are used for image matching or structure reconstruction or to extract Place-of-Interests (POIs, e.g., physical features or indoor landmarks like shop logos, statues, and billboards) [11, 30, 48, 64, 65, 74]. The major limitation, however, is that image-based methods usually rely on user cooperation to locate, thus not suitable for continuous back-end localization services.

Visible light positioning Another approach works with existing smartphones is to use visible light of light-emitting diodes (LEDs) that provide normal illumination but also invisible flicker in a unique pattern [22, 24, 41, 61, 69, 73]. Localization is achieved by identifying lamps using smartphone cameras. However most of previous proposals focus on using modulated LEDs as location landmarks and their real life deployment are largely prohibited by high deployment overhead and performance degradation in dynamic environments. A recent work [77] achieves high-precision visible light positioning using conventional LEDs and fluorescent lamps inside today's buildings, shedding light on practical adoption of this kind of approaches.

Smartphone dead-reckoning Dead-reckoning is a well-known technology used in robot and drone navigation. It becomes applicable to modern smartphones as more and more motion-sensitive sensors including accelerometers and gyroscopes are equipped on today's mobile phones. By tracking the distinctive motions of human walking, one is able to derive the direction and distance travelled, a common branch of dead-reckoning approaches named as Pedestrian Dead Reckoning (PDR) [4, 10, 13, 13, 14, 18, 23, 76]. Yet due to low resolutions of smartphones sensors, smartphone PDR usually suffer from large drifts and significant accumulative errors over long trajectories. As a result, smartphone dead-reckoning is often integrated with other approaches to improve performance.

Magnetism-based Magnetometer is another sensor on smartphones that is exploited for positioning purpose. The rationale is that modern steel-and-concrete buildings and various steely furnitures inside them disrupt Earth's magnetic fields that vary subtly over different locations. These distorted magnetism may be measured by magnetometers on smartphones to determine their own locations [8, 17, 45, 46, 75]. Magnetism is a good indicator as it is easily scalable all over the world and is capable of providing location accuracy of less than two meters, as reported by IndoorAtlas [17], a start-up on geomagnetic hybrid indoor positioning technology, once a venue has been surveyed.

There are also many other signals used for localization, including FM signals, ultra-wide band signals, infrared, etc. In practice, a more common case is that multiple technologies are integrated into one system. For example, dead-reckoning almost always comes with other techniques [16, 40, 49]. BLE is often used as a supplementation to WiFi-based solutions, especially in real world systems. Image-based and sound-based approaches can be combined with WiFi-based methods for better accuracy [26, 64]. While the independent research of each category continuous, a trend for practical systems will be systematic integration of orthogonal and supplementary technologies.

1.2.2 General Architecture

Whatever the infrastructure is used, a typical indoor positioning system usually follows the architecture as shown in Fig. 1.1, which consists of *infrastructure* installed in building, *mobile clients*, and a *position engine*. Depending on the

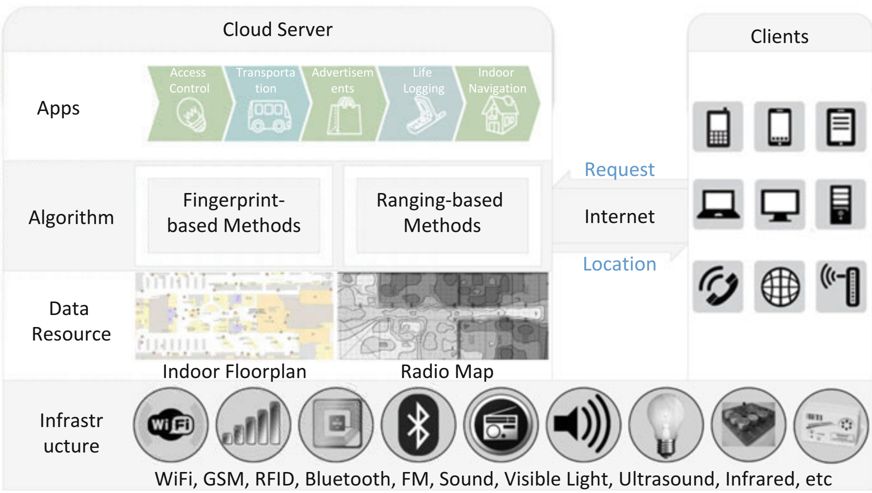

Fig. 1.1 A typical architecture of an indoor positioning system

specific infrastructure used, the localization clients could be either specialized or commodity hardware. The position engine is usually a cloud service, yet could also be a local server for certain local areas, or even directly the mobile device itself. The core localization algorithm is running on the position engine, which responses user requests and outputs user location, typically together with a digital map. The digital floor plan is not inelastic requirement of an indoor localization system, but has the added benefits of accuracy gain and semantic gain that transforms location coordinates into location contexts.

Generally, localization methodologies are divided into two categories: *ranging* and *fingerprinting*. (1) Ranging-based algorithms follow the same principle as GPS. Location is determined by the well-known *muiltilateration*, i.e., calculating the distances (or directions) from the target to multiple anchors (at least three for 2D locations and four for 3D locations). Anchors are also called reference points, which are, e.g., satellites in GPS and Access Point (AP) in WiFi-based approaches. Distances and directions are usually estimated by Time-of-Arrival (ToA) [27, 63], Time-Difference-of-Arrival (TDoA) [37], Angle-of-Arrival (AoA) [20, 21, 62], and Doppler frequency shifts [39, 71], etc. It is also common, although inaccurate, to derive distances from Received Signal Strength (RSS), which is readily accessible on almost all RF radios such as WiFi, Bluetooth, GSM, etc. [7, 42]. Recent advances have exploited physical layer Channel State Information (CSI) for better resolution [20, 21, 62]. Nonetheless, ranging-based approach is more commonly used in acoustic signals and UWB signals that yield precise ranging estimates, yet less frequently in RF signals like WiFi because ranging will be vulnerable and erroneous due to low channel resolution and light speed propagation. (2) Alternatively, fingerprint-based approach is popular for RF signals. Instead of modeling signals and analyzing signal properties to derive distances and directions, fingerprint-based approach explores spatial diversity of signals over different locations and utilizes these distinctive signal patterns as *location fingerprints*. Such fingerprints are collected for each specific location and then location is determined through pattern matching. Here the fingerprint is not limited to features of RF signals like WiFi and Bluetooth [3, 40, 51, 66, 70], but can also be acoustic signals, images, magnetic fields, etc.

1.2.3 Historical Stages

From a historical view, the development of indoor localization roughly undergoes three themes, depending on what device a target user needs to carry on.

1. **Sensor-based** In its early stage, dedicated sensors are used for localization. Examples include Active Badge [56] and Bat [15], which were proposed around 1990s, using infrared and ultrasonic respectively. The Cricket location system [38] is another pioneering example based on ultrasound sensors. Not only sensors need to be installed in the building, users are required to carry these specialized

devices in order to be located. These added ingredients prevent their wide adoption in ubiquitous applications. Yet thanks to their reliable and precise performance, they are valuable in special scenarios, especially critical industrial applications.

2. **Smartphone-based** The proliferation of mobile computing has promoted mobile phones as the most convenient handsets for ubiquitous localization. With powerful computation capability and various sensors equipped, modern smartphones are capable of running various localization approaches, e.g, WiFi-based, sound-based, image-based, dead-reckoning, etc. [23, 27, 65, 66]. In fact, smartphone-based indoor localization has been the most important theme during the past 10 years and, with smartphone ownership continuously rising, will stand to be the most promising solution in the future.
3. **Sensorless** Recently, the progresses of wireless communications enable a new paradigm of *passive* (a.k.a, sensorless, or device-free) localization, where no additional devices are attached to or carried by a user. The key idea is to capture RF or acoustic signals reflected by human motions and derive the information of interests therein [2, 39, 52, 53]. Different from device-based approaches, sensorless localization is especially useful to scenarios like security monitoring, elder care, and in-air interaction, where users are not likely to carry any device for localization.

Each of the three themes has its own advantages and is suitable to different scenarios. For example, industry-level products would prefer sensor-based approaches while ubiquitous applications demand smartphone-based solutions. And indeed the research community is witnessing a concurrent progress of three themes. Different from GPS that dominates outdoor positioning, there will always be multiple competitive technologies in the community of indoor localization, each serving different applications with diverse requirements. In this book, we mainly focus on WiFi fingerprint-based approaches for smartphones.

1.3 WiFi Fingerprint-Based Approach

The ideal indoor-location technology for ubiquitous applications would be one that requires no additional hardware to be installed in buildings or added to mobile phones. A promising approach towards this goal is to use widely existing WiFi signals. WiFi-based approach is known to be free of extra infrastructure and specialized hardware. On one hand, WiFi hotspots have been deployed in modern buildings all over the worlds, not only homes and office buildings but also the most common places where people get lost: airports, malls and city centers. On the other hand, smartphones already have the WiFi radio to receive the wireless signals and can readily be used as the localization devices. In addition to a large number of research papers, great companies including Google, Apple, Cisco, Huawei, and Baidu etc. have all built or invested and are still developing related products, using WiFi as infrastructure and smartphones as clients.

As aforementioned, there are also ranging-based and fingerprint-based methods in WiFi-based solutions. However, RSS-based ranging is erroneous, usually producing location error of 5 m to >10 m [7, 26, 29]. Better precision could be achieved by resorting to physical layer CSI, which is however, currently not accessible on most commercial WiFi devices, not to mention smartphones [20, 59, 62]. In the contrast, WiFi fingerprint-based approach has become the mainstream, drawing a lot of attention from both research community and industries.

1.3.1 General Frameworks

The rationale behind WiFi fingerprint-based positioning is straight-forward. A mobile device, at somewhere covered by WiFi signal, records the hearable WiFi APs and their corresponding signal strength as the radio signal characteristics (i.e. 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 underlie the principle of WiFi positioning.

From the systematic aspect, WiFi fingerprint-based systems typically consist of two phases: a *training phase* and a *localization phase* as illustrated in Fig. 1.2. In the first training phase, fingerprints are collected with known location labels to form a *fingerprint database* (a.k.a *radio map*). Conventionally, the training procedure is also known as *site survey*, which is labour-intensive and time-consuming. Then during the localization stage, user location is determined by matching fingerprint observation against those stored in the fingerprint database.

Formally, the area of interests is sampled as a discrete location space $L = \{\boldsymbol{l}_1, \boldsymbol{l}_2, \cdots, \boldsymbol{l}_n\}$ where n is the amount of sample locations. For each location

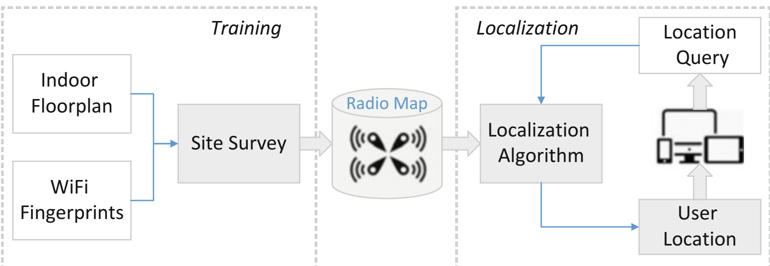

Fig. 1.2 A common framework of WiFi fingerprint-based localization