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Crowdsourced Indoor Mapping

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1 Introduction

While global positioning system (GPS) solved the outdoor localization problem quite successfully, it is not as successful indoors. This is due to the fact that GPS signals generally require an unobstructed line-of-sight (LOS) view from receiver to satellite, but cannot penetrate most construction materials. Also, indoor location-based service (LBS) applications require finer granularity and precision of localization accuracy that GPS is unable to offer under such constraints (Hossain and Soh, 2015). Besides the usual applications of resource tracking to finding the nearest store or distribution of electronic coupons within close proximity, LBSs have tremendous prospects in terms of business intelligence (BI) applications. Brickstream, an in-store analytics-related software company, published a survey result in 2014 collating the transcripts of interviews of 124 retail executives across the United States, Europe, Asia, and South America who emphasized the benefits of using data collected from in-store consumers for their businesses (Harkins, 2014). The executives identified operations, merchandizing, and profits as functions of being aware of what is happening in the store, for example, counting the customers (71% agreed), the value of adopted technology (68% preferred Wi-Fi), mobile/contact-less payment (of interest to 58% respondents), etc. Around 88% of retailers acknowledged the necessity to deploy technologies in-store, and the importance of various mobile device-driven applications to attract customers. Indoor positioning based on a customer's carried mobile device's sensor readings is a prerequisite to perform such consumer-driven data analysis. On top of it, availability of indoor maps has been treated as a natural assumption of such indoor localization research (Bahl and Padmanabhan, 2000; Youssef and Agrawala, 2005; Hossain and Soh, 2015). Only recently, it has been realized that the access to these maps especially for public or commercial buildings requires lengthy negotiations with the owners or operators. This is identified as a major hindrance toward ubiquitous availability of LBSs' indoors.

The newer emerging calibration-free indoor localization techniques succeed the labor intensive indoor fingerprinting solutions eliminating its pre-deployment site survey component of radio-map creation. Just like the calibration-free techniques, indoor floor

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layout conceptualization research also aims for automated, and implicit user participation by collecting their traces through the carried smartphone sensor measurements. Most of the commercial products based on calibration-free indoor localization use and process the crowdsourced inertial sensor measurements from their smartphones. For example, Navigine (2017) uses Wi-Fi signals together with the smartphone's inertial sensors for navigation with a claimed accuracy of 1–2 m whereas Navisens (2017) only uses the inertial sensor measurements. indoo.rs (2017) follows similar techniques as Simultaneous Localization and Mapping (SLAM) (Durrant-Whyte and Bailey, 2006) that relies on dead-reckoning (Constandache et al., 2010), sensor fusion, and filtering algorithm for indoor navigation purpose. They utilize crowdsourced data, and provide software as a service (SaaS) for incorporating their location service inside the various location-based applications.

Google Maps, Apple Maps, Bing Maps, etc., can provide street maps, and navigation direction outdoors with the help of GPS. However, the indoor counterparts were not as successful. Manual adding/editing to maintain up-to-date indoor floor maps undertaken by Google Maps did not offer a feasible and scalable solution. Only major airports, museums, and other business locations that are partnered with Google have been addressed (Google, 2017a). On the contrary, the crowdsourced approach's basic idea is to automate the modeling of floor plans by collating the pedestrian traces perceived from their smartphone sensors. Although these approaches are promising utilizing the already existing infrastructure, for example, Wi-Fi networks, and off-the-shelf hardware existing inside user smartphones, they either require a large number of motion traces or warrant the active collaboration of users collecting traces, or help of a number of sensor fusion (e.g., camera) in order to refine the traces. Considering the fact that the crowdsourced data acquired are from different sensors, and even coming from different persons' devices, they may be noisy, uncertain, and incomplete. The challenges of processing these data and the subsequent adoption of algorithms to come up with a realistic indoor map are investigated in this chapter. Subsequently, a comparative discussion based on the findings is provided by pointing out a few future research directions.

This chapter is organized as follows. We explain the existing popular outdoor Web map systems and its apparent shortcomings when applied indoors in Section 2. Next, we discuss a few emerging crowdsourced indoor map construction techniques, and some relevant calibration-free indoor localization methods in Section 3. In Section 4, we point out some crowdsourced indoor floor layout construction-related challenges, and a future research directions. Finally, we conclude in Section 5.

2 Some Existing Crowdsourced Outdoor Map Systems

An accurate Web map system is necessary to bridge the gap between the real world (i.e., what we see) and the online world (i.e., the interpretation of our surroundings). While majority of the map systems are dedicated to provide accurate location and navigation information outdoors, very few have ventured into the domain of indoor map dynamics. This is fundamental to enable location-based BI applications for various consumer-centric industry like retail store marketing and management. The ubiquity of smartphone, and its equipped sensors' rich technology, and cost effectiveness opened the door for harnessing the crowd's intelligence into such map systems. The popular Web map systems, such as Google Maps and Apple Maps to some extent acknowledge this opportunity. They had laid out certain projects, for example, Tango (2017) and TryRating (2017), respectively, to incorporate crowdsourcing for conceptualization of accurate map systems. In this section, some popular Web map systems that incorporate crowdsourcing to some extent are discussed, and a comparative analysis is provided based on the discussion.

2.1 Google Maps

Google Maps operates by means of a request/response protocol for providing various LBSs. The request from a client device (e.g., smartphone) contains its current location (if the device is equipped with a GPS receiver), Wi-Fi access points (APs), and cellular tower profile information. The response from Google servers includes the current geographical position of the client device, together with the locations of the Wi-Fi APs, and cellular towers—the profile of which were included inside the request message. This facilitates subsequent faster determination of the client device's position to enable LBSs. In addition to providing visualization of real-time traffic information, Google Maps also offers other services such as point of interest (POI) search, route planning, street view, geocoding, mass transit system's status and navigation information, etc. (Google, 2017b).

Crowdsourcing was initially considered unimportant by Google Maps during the build of US proprietary database, which was constructed by acquisition of maps from the authoritative or trusted state, regional and city sources. However, crowdsensing is then used as the main agent for the revision of the map database worldwide, which has recently been discontinued (Neis et al., 2012). Google also encourages public building owners to submit their indoor maps in order to bring them under their services. Even though Google Maps APIs are free for a number of use cases, its full functionality access requires a licensed version. Google's Tango envisioned crowdsensing to enable indoor navigation, conceptualization of indoor 3D maps, and interesting "Augmented Reality" (AR) applications (Tango, 2017). The ubiquity of mobile devices where over 1.4 billion new smartphones were sold in 2016 alone, and the advancement, and cost-effectiveness of its equipped sensor technologies motivated Google to invest heavily in such research (Lee, 2017). Google launched Tango hardware and software that equips mobile phone carried by a user with motion tracking, depth sensing, and area learning capabilities.

2.2 OpenStreetMap

OpenStreetMap (OSM) is one of the most utilized and analyzed Volunteered Geographic Information (VGI) platforms that generated keen interests among researchers and practitioners (Arsanjani et al., 2015). The OSM project was conceptualized in 2004 with the vision of creating an editable map of the whole world through crowd participation. Volunteers collect the map data via performing systematic surveys using inexpensive portable satellite navigation devices such as a GPS receiver equipped hand-held or a digital camera, which is then uploaded into the OSM database. The registered diverse set of trusted volunteers contribute to the overall data collection procedure, and editing of the uploaded maps by taking advantage of their local area knowledge. The crowdsourced map data is made available to the general public under the Open Database license (ODbL). As a result, researchers have attempted to adopt OSM tools more compared to their commercial alternatives over the years in order to create indoor maps of railway stations, hospitals, public library, etc., via volunteer participation (OpenStreetMap, 2017).

2.3 MapQuest

MapQuest uses a standard client-server architecture where the user's client requests for a particular map, and the MapQuest servers respond with the resultant map within a web page. Introduced in 1996, it quickly became the premier online map provider before ultimately falling behind Google Maps around 2009 (Peterson, 2014). Today, MapQuest provides street-level details, and navigation planning only for some selected countries. MapQuest-based iOS and Android mobile app also provide other features such as POI search, voice-guided navigation, real-time traffic information, etc. (MapQuest, 2017). In 2010, MapQuest tried to venture into crowdsourced mechanism of creating or manipulating maps by using OSM of Section 2.2 for few of its services but with limited success (Peterson, 2014).

2.4 Waze

The largest community-based free traffic and navigation application (Waze, 2017) utilizes floating car data (FCD) obtained from the driver's or passenger's smartphones in order to generate real-time traffic information similar to Google Maps. Even though the main purpose of the Waze application is to facilitate user's vehicle navigation, it also gives users the provisions for manipulating maps (e.g., adding new roads, reporting hazards and potholes). Just like Google Maps, Waze works upon the simple request/response protocol principle where the smartphone client application sends periodic messages to the Waze server with its current position acquired through the phone's GPS receiver. Subsequently, the Waze server returns the navigation plan together with the traffic information along the planned route in a response message. Since Waze is a community-driven approach, it generally requires the user to register before using the app. Once the user logs into the system, an appropriate Waze server ID is returned with a cookie, which is used to differentiate the individual user session for subsequent request messages. Waze incorporates crowdsourced sensor data in a limited manner for outdoor navigation map manipulation purpose only, but does not address the indoor map construction-related challenges.

2.5 Others

Not all the existing map services try to incorporate crowdsourcing as part of their operating principles. The four popular map systems discussed earlier try to include crowdsourcing aspects of map building in some ways. However, there are a few other alternatives as well such as Apple Maps, Microsoft's Bing Maps, HERE, etc., which have treated users only as consumers so far; they do not include them in building or refining the maps.

Apple Maps (Apple, 2017)—the default map system of iOS offers similar services like Google Maps such as navigation, POI search, route planning, mass transit system's status, navigation information, etc. TomTom Maps is the primary provider of Apple's map data. Apple is reportedly trying to involve freelance users to refine its map data through a program called "TryRating," where they are paid a nominal incentive for verifying POI or other searches made with Apple Maps.

HERE, formerly known as "Nokia Here," concentrates on collecting road map data to offer navigation, traffic information, and location solutions (HERE, 2017). It is the primary provider of LBSs to Microsoft Bing, and Facebook. HERE also works in the autonomous vehicle industry by providing its HD map data to manufacturers such as Alpine, Mercedes, Garmin, Hyundai, Pioneer, Volkswagen, and Toyota for testing their driverless vehicles. HERE recently partnered with Mobileye that harnesses crowdsourcing by collecting geometry and landmarks around the user's driving path through camera-equipped vehicles in order to maintain real-time map information.

The API of Microsoft's Bing Maps enables a wide range of applications to include its functionality like navigation, real-time traffic, POI search, geocoding, etc., through a variety of licenses (Bing, 2017). Some of the Microsoft products such as SharePoint, Excel, and Office 365 Pro Plus offer them out of the box. Bing Maps collects its road data from HERE, and various country-specific partners, and its imagery data generally comes from their own team.

2.6 Discussions

The popular Web map systems' knowledge base is dependent upon the service provider's associated commercial partners—not necessarily on its users, for example, Google Maps (in most cases) and Apple Maps as can be seen from Table 1. OSM is the only exception where its operating principle is completely based upon user participation and trusted volunteers' local knowledge. Another community-driven system, Waze is a traffic and navigation application that is targeted toward a niche area (i.e., vehicles only). In general, the crowdsourced data-set arising from the smartphone sensors carried by the people are still largely unexplored by such map systems. If they are used effectively, it will not only enhance their existing system's performance, but also can give rise to new interesting business cases. The big players such as Google Maps, and Apple Maps realized its importance, and announced innovative crowdsensing-based projects such as Tango (2017) and TryRating (2017), respectively. Another important observation is that—the attempts to bring indoor environments under these map systems were largely unsuccessful.

Table 1 Comparison of Some Existing Popular Web Map Systems

	Map Data Providers	**Map Environment**	**Signals and Sensors**	**Crowdsourcing**	**License**	**Supported Apps**
Google Maps	Federal, state, regional, user contributions, and other partners	Indoor and outdoor	Satellite (GPS), Cell-based, Wi-Fi, Tango: Inertial sensors, Camera	Yes; Google's Tango, device: user smartphones, apps: indoor 3D maps, AR applications, etc.	Proprietary	Google Earth, BMW, and Tesla navigation
OpenStreetMap	Users, open data	Indoor and outdoor	Satellite (GPS), Wi-Fi, Camera	Yes; add, edit, and refinement of maps by users	ODbL	Foursquare, Craiglist, Wikipedia, World Bank
MapQuest	TomTom, OpenStreetMap, and other partners	Outdoor	Satellite (GPS)	Attempted in the past by incorporating OSM	Proprietary	N/A
Waze	Users	Outdoor (for vehicles)	Satellite (GPS)	Yes; seamless integration of user smartphone's position data	Free	Waze Carpool
Apple Maps	TomTom and other partners	Outdoor	Satellite (GPS), Wi-Fi	Reported to venture into it recently through paid freelancers	Proprietary	iOS LBS apps
HERE	Naviteq (Nokia)	Outdoor	Satellite (GPS), Cell-based, Wi-Fi	Yes; via camera-equipped vehicles	Proprietary	Mercedes-Benz, Alpine car systems
Bing Maps	HERE, country-specific partners	Outdoor	Satellite (GPS), Cell-based, Wi-Fi	No	Proprietary	Windows OS LBS apps

One of the prerequisite of incorporating user participation data into such map systems is the availability of their position information. Using this position data as a reference, services such as traffic and navigation information can be correctly correlated with it. While position in an outdoor environment can be successfully resolved by GPS; it could not be the overwhelming solution indoors since GPS signals are blocked by most buildings. As a result, conceptualizing indoor maps through crowdsourcing is likely to pose additional challenges compared to its outdoor map systems counterpart in terms of unavailability of GPS signals, indoor environment complexity, lack of intelligent incorporation of crowdsourced rich sensor data, development of efficient mapping algorithms and architecture, etc.

3 Indoor Map Systems' Research

Indoor localization refers to the technique of obtaining location/position information of a device (or of a person carrying the device) indoors with the help of a set of reference nodes within a predefined space (Hossain and Soh, 2015). This space is characterized by indoor environment maps that are generally assumed to be available by the localization researchers. However, this assumption may not hold for many scenarios, especially for public buildings such as shopping malls, airports, museums, hospitals, etc. Furthermore, it is common for such environments to go through frequent changes or rearrangements, therefore, a up-to-date mechanism of ensuring the correct detailed indoor maps is also necessary.

GPS enables a user carrying a GPS receiver to pinpoint its location using the signals from the GPS satellites (i.e., reference nodes). A well-known observation is that GPS performs poorly in urban environments where buildings block GPS signals (especially indoor) (Hossain and Soh, 2015). An alternative cost-effective solution compared to GPS could well be through the possible use of the available resources (e.g., user smartphone sensors) and infrastructure (e.g., Wi-Fi networks) existing in an indoor environment. Traditionally, the fingerprinting approach is deemed appropriate in such scenarios where the surveyor laboriously collects signal signatures over the localization area that are annotated with the locations where they are captured. They are then stored inside the database as a ⟨location, signal fingerprint⟩ tuple. Subsequently, some well-known machine learning algorithms such as Maximum Likelihood Estimator (MLE) or Nearest Neighbor (NN) are applied in order to locate a user.

There is a newer family of emerging calibration-free techniques that try to relieve the pre-deployment woes of the laborious signal signatures collection phase of the fingerprinting solutions discussed earlier. Many work of this family just assume the availability of a floor-plan of an indoor environment. They feel the map knowledge is required to consume any LBSs (Rai et al., 2012); so it is only natural to assume its availability. A few map construction tools can also be accessed from the robotics literature (Shin et al., 2012). However, the inherent assumption of indoor map availability may have resulted in skewed optimistic conclusions for such indoor localization research. The conceptualization of the indoor maps rather than having it as a precondition for offering LBSs is therefore drawing attention from the indoor localization research community. In this section, we discuss both the robotics, and calibration-free indoor localization perspective of map construction, and the associated challenges. The relevant sensor technologies are also identified together with the well-known algorithms that are adopted.

3.1 Simultaneous Localization and Mapping

SLAM is the computational problem in robotics navigation and mapping where it constructs and updates the map of an unknown environment, and simultaneously locates the robot's position within it (Durrant-Whyte and Bailey, 2006). Various filtering algorithms, for example, Kalman filter, Particle filter, etc. (Welch and Bishop, 1995; Montemerlo et al., 2002), and odometry or dead-reckoning (Constandache et al., 2010) techniques utilizing the inertial sensor measurements are adopted in order to build the map, and for localization purpose. The filtering techniques generally consist of two different phases—the prediction step (i.e., the state transition model through odometry) and the update step, which takes into account the sensor measurements for correction of the prediction step. Odometry navigation method's fundamental idea is the integration of incremental motion (i.e., wheel revolution information over time). Inertial sensors' purpose is to explore the properties of inertia, for example, sense the change in angular motion (gyroscope), and change in linear motion (accelerometer). GPS, landmark, magnetic compass, active beacons (Wi-Fi, sonar, etc.), and computer vision (e.g., camera) sensor measurements can be considered during the update step of the filtering techniques to refine or correctly estimate the state.

Traditional SLAMs generally require custom-made inertial measurement units (IMUs), for example, FootSLAM (Robertson et al., 2009) and ActionSLAM (Hardegger et al., 2012) use foot-mounted and body-mounted IMUs, respectively, to track a user's motion. PlaceSLAM (Robertson et al., 2010) is an improvement over FootSLAM by explicitly involving user participation for refining the interpretation of the physical surroundings. Unlike traditional SLAMs, SmartSLAM (Shin et al., 2012) uses smartphone's inertial sensors, and Wi-Fi modules to observe the device's movement and environment, and thereby construct the indoor map. The on-going incorporation of computer vision technologies enriched the SLAM approaches, which largely concentrated on robot navigation via changing direction when faced with an obstacle. The application of drone or micro aerial robot facilitates the creation of indoor 3D maps through the use of IMU, camera, laser scanner with deflective mirrors (Shen et al., 2012; Intel, 2017). SLAM has also been used as a viable commercial tool especially in autonomous vehicle industry, major Web map systems such as Google and Apple navigation, etc. iRobot which is MIT institution's brainchild already developed SLAM-based product in the form of a vacuuming robot—so did a few other industries such as Samsung, Dyson 360 Eye, Robo.com, etc. Wi-Fi SLAM (Ferris et al., 2007), which was later acquired by Apple, and SmartSLAM (Shin et al., 2012) attempted to utilize the sensor readings that are normally available inside the user carried smartphones or mobile devices. Hence, crowdsensing can potentially be part of such SLAM variants for indoor map construction, while most of the other SLAM techniques or even commercial solutions require additional customized sensors such as sonar or laser sensors, mechanical parts (wheels or wings) of robots or drone, etc.

3.2 Calibration-Free Indoor Positioning System

SurroundSense (Azizyan et al., 2009) opened the door for various ambient sensors (e.g., sound, light, color), and Wi-Fi, accelerometer, to be collectively used for localization through user participation, and subsequently, others followed suit (Chintalapudi et al., 2010; Rai et al., 2012; Wang et al., 2012). Most of them assume these sensors' availability in the mobile phones carried by the crowdsourcing users which might be unreasonable. However, modern smartphones are equipped with a few inertial sensors, for example, accelerometer, gyroscope, and other additional sensors such as Wi-Fi, compass, camera, etc. In this section, we first briefly discuss a few calibration-free localization techniques which can be used for indoor map conceptualization, and then also explain a few crowdsensing-based indoor map construction research.

TIX

Crowdsourced Wi-Fi received signal strength (RSS) measurements are utilized for Triangular Interpolation and eXtrapolation (TIX)'s localization purpose (Gwon and Jain, 2004). TIX does not require the indoor floor plan map to operate; however, it needs the Wi-Fi APs' location information with respect to the indoor map. The distance of the client device to each AP is approximated via its perceived RSS from them, and also through the inter-AP RSS measurements. Then the TIX algorithm is applied (Gwon and Jain, 2004). Any other lateration-based algorithms (e.g., Trilateration) could work as well. Assuming RSS (log-scale) decays linearly with distance, the Wi-Fi RSS measurements are enough to localize the client device without the need of a map when the APs' location information are known. TIX's reported localization accuracy was not great though; it was only 5.4 m inside an office setting of size 1020 m^2 with zero calibration effort.

SDM

Just like TIX, signal-distance map technique, SDM (Lim et al., 2010) also utilizes only the online RSS measurements for localization. Periodic inter-AP RSS measurements facilitate to calibrate RSSs in the spatiotemporal domain. To map the relationship between these RSSs and the inter-AP distances, a truncated singular value decomposition technique is applied. No floor plan map is necessary for its operation but the locations of the APs with respect to the indoor map are required. Its reported localization accuracy is within 3 m inside a small building, and it claims to perform better than TIX.

EZ

The Wi-Fi RSS measurements are implicitly reported by EZ clients that typically run inside a user's hand-held device. The log-distance path loss is used to model the RSS measurements where its unknown parameters are resolved using Genetic Algorithm (Chintalapudi et al., 2010). EZ does not require the knowledge of indoor map layout or even the AP's location and its transmit power information. The only assumption is the availability of occasional location fix, for example, GPS lock at entrance, or other uncluttered places.

UNLOC

UnLoc (Wang et al., 2012), an unsupervised indoor localization scheme, follows similar principle as the SLAM techniques discussed previously. It utilizes dead reckoning (Constandache et al., 2010) for tracking a user while recalibrating its estimate whenever it encounters a landmark—the location of which is known. The landmarks can be identified through the equipped inertial sensor measurements of the client device where they exhibit distinct signatures indoors (e.g., elevators, escalators, entrances, etc.). UnLoc is purely a crowdsensing-based technique since these landmarks are also identified in an automated manner through the user device sensor measurements (i.e., no a priori knowledge is necessary).

WALKIE-MARKIE

Walkie-Markie (Shen et al., 2013) leverages crowdsourced user traces to generate indoor pathway maps without any a priori knowledge of the propagation characteristics, and floor plan map. It uses Wi-Fi RSS trend (increasing or decreasing) as a location fingerprint in an indoor environment. These fingerprints (i.e., landmarks where the RSS trend tripping point occur) are then placed inside the 2D plane by a graph embedding algorithm incorporating user trajectories. Subsequently, a user is colocated with a landmark when he/she passes it, and dead reckoning (Constandache et al., 2010) is utilized in order to localize him/her in between two such landmarks.

The global indoor location market has seen a rapid growth over the years, and is expected to grow even more. To enable these LBSs, the availability of an indoor floor plan is mandatory. While the outdoor Web map systems discussed in Section 2 gather map/street data from various sources such as federal database or even volunteer participation, indoor floor plan acquisition is deemed to be more challenging. There are multiple challenges, which pose an obstacle to acquire an indoor floor plan: (i) in an multi-tenant public/commercial buildings, different sections might be managed by different entities; therefore, no central authority may be liable for the whole area's map, (ii) it requires effort to maintain an up-to-date map since it is quite common for indoor premises to go through frequent changes or rearrangements, and (iii) manual adding/editing of indoor floor plans is not a scalable solution which was attempted in the past (e.g., Google Maps) but with limited success. The indoor floor plan construction through crowdsensing has drawn attention recently mainly due to: (i) the ubiquity of smartphones and (ii) the rich technology and cost-effective sensor technologies equipped inside the modern smartphones. In the following, we discuss a few such research that are targeted toward conceptualizing indoor floor plan through user participation utilizing their smartphone sensor measurements.

CROWDINSIDE

CrowdInside (Alzantot and Youssef, 2012) pioneers the indoor map conceptualization research utilizing only user smartphone sensor measurements. It operates following client/server architecture where the smartphone client records sensor measurements, and periodically sends them to the server which in turn collates and processes them to come up with the floor plan layout. The user motion traces take the form of ⟨time-stamp, location, Wi-Fi measurements⟩ tuple where dead-reckoning approach is followed for their generation together with error resitting fix through known absolute landmarks. CrowdInside can provide both overall and detailed floor plan layout where the overall floor plan only shows the occupancy map based on the user motion traces. The detailed one can identify rooms/corridors, and define the boundaries among them. To provide such details, the motion traces are divided into segments by taking into account the events such as sharp turn, inactivity tracking identified through the smartphone inertial sensor measurements. These segments are classified as rooms and corridors, and then a density-based clustering algorithm is used to merge "similar" segments together, and define boundaries/connectivity between them.

MAPGENIE

MapGenie (Philipp et al., 2014) infers indoor floor plan layout of a building from user smartphone's inertial sensor measurements, and its exterior structural information which can be obtained via OSM of Section 2.2. From the user motion traces, first, the hallways are detected, and their skeletons are approximated under certain constraints inferred from the exterior structural information of the building. Thereafter, the room geometry is estimated where room segments correspond to the maximum-length continuous sequences of motion traces without overlapping the hallway skeleton. Finally, the grammar-based room-layout generation corrects the trace-based indoor model's inaccuracies.

JIGSAW

Jigsaw combines mobile computing with computer vision technologies, and uses probabilistic and optimization methods to conceptualize indoor floor layout (Gao et al., 2014). Computer vision enables to obtain rich features and detailed information of a user's surroundings, while inertial sensors of mobile devices provide coarser information of the indoor environment but at lower computational complexity. First, some absolute landmarks' (entrance, elevators, etc.) placement and orientation information are inferred from crowdsourced photos and smartphone inertial sensor measurements. Subsequently, this map is augmented by including walls for external hallways, its structure, and room shapes.

IMOON

iMoon's operation is based on client/server architecture where the smartphone client collects imagery (i.e., photos), inertial sensor (i.e., accelerometer, gyroscope), and Wi-Fi RSS measurements, and then sends them to the server (Dong et al., 2015). The iMoon server builds the 3D floor plan utilizing the crowdsourced photos applying Structure from Motion (SfM) techniques (Stockman and Shapiro, 2001), and incorporating user trajectories perceived via the inertial sensor measurements, and application of dead-reckoning method. The Wi-Fi measurements serve the purpose of geolocation through a typical location fingerprinting technique (Bahl and Padmanabhan, 2000; Youssef and Agrawala, 2005). Localizing a client device is resolved via a two-step process where a query photo together with the Wi-Fi measurements are submitted. First, k-nearest neighbor (k-NN) algorithm is applied to acquire a set of approximate locations based on Wi-Fi fingerprinting. Second, iMoon server selects the partitions corresponding to these coarse locations, and searches the photos within the partition space to find the query photo's best match. This two-step process improves the computational complexity of iMoon localization. The features of this client query are added to the overall knowledge base under certain constraints to facilitate crowdsensing approach of constructing and maintaining an up-to-date database.

3.3 Discussions

It is apparent from Table 2 that the earlier calibration-free indoor localization research (TIX, SDM, or even EZ) required occasional fix from known locations for their operation while the more recent ones (UnLoc, Walkie-Markie) tend to focus on crowdsourcing approach of inferring such fixes. They also tend to incorporate modern smartphone's equipped inertial sensor such as accelerometer, gyroscope measurements more effectively. Although none of the discussed calibration-free localization research requires floor plan knowledge; the crowdsensing operating principle of UnLoc and Walkie-Markie will put them in a better position for adaptation for constructing such maps if required.

Table 2's list of crowdsourced indoor map conceptualization techniques make use of inertial sensors. Their sole usage was not as successful as the ones where they are used in conjunction with vision sensors (e.g., camera) (Gao et al., 2014; Dong et al., 2015). However, the photo captures require explicit participation on the users' parts, which arguably undermine the true spirit of crowdsourcing approach. All the listed crowdsourcing based floor plan construction approaches such as CrowdInside, MapGenie, Jigsaw, iMoon, follow client/server architecture where a data acquisition client runs inside a user's smartphone. The main floor plan construction-related computing intensive tasks are performed at the server. While this division of tasks between a client and the server is practical from energy efficiency perspective, early calibration-free localization methods attempted pure client-based approach ensuring security/privacy but they could only provide coarser accuracy (e.g., TIX/SDM). On the contrary, EZ, UnLoc, Walkie-Markie ensured better localization accuracy but at the expense of client being tracked transparently at the server.

Table 2 Comparison of Some Map-Free Indoor Localization, and Crowdsourced Indoor Map Conceptualization Research

	Need Location Fix	User Participation	Sensors	Accuracy and Precision	Security and Privacy	Architecture
TIX/SDM	Yes; from APs with known locations	N/A	Wi-Fi	Average error ∼5.4 m (TIX) and ∼3 m (SDM)	Yes	Client-based
EZ	Yes; occasional fix, e.g., GPS lock near entrance	Implicit	Wi-Fi	2 m inside a building of size 486 m^2; 7 m inside a large building (12,600 m^2)	No	Location computed at server
UnLoc	No; only one landmark's location needed during bootstrapping	Implicit	Inertial, Wi-Fi	Median error ∼1.69 m across three different indoor setups (largest being 4000 m^2)	No	Location computed at server
Walkie-Markie	No; only one landmark's location needed during bootstrapping	Implicit	Inertial, Wi-Fi	Average error ∼1.65 m inside a medium-sized office floor (3600 m^2)	No	Location computed at server
SmartSLAM	No	Implicit	Inertial, Wi-Fi	Average error 10 ± 5.73 m using raw mobility traces	N/A	Client/server
Wi-Fi SLAM	No; but Isomap without finer resolution required	Implicit	Wi-Fi	Average error 3.97 ± 0.59 m along $250 \sim 500$ m traces	N/A	Client/server
CrowdInside	No	Implicit	Inertial, Wi-Fi	Not reported	No	Client/server
MapGenie	No	Implicit	Inertial	72% rooms are found with at most 0.37 m average error	No	Client/server
Jigsaw	No	Explicit	Inertial, Wi-Fi, Camera	Average error 0.61−1.80 m; 80% of the hallway size is correctly identified	No	Client/server
iMoon	No	Explicit	Inertial, Wi-Fi, Camera	More than 90% measurements points are correctly localized	No	Client/server

4 Research Challenges of Crowdsourced Indoor Floor Plan Construction

4.1 Quality of Crowdsourced Data

The volume of user smartphone originated crowdsensed data has increased significantly over the years as a result of its widespread availability and affordability. There is a surge in utilizing the smartphone equipped technology in order to understand consumer behavior from a retailer perspective as well. Gathering such information would facilitate interesting BI applications such as devising personalized marketing strategy, and ensuring efficient store management functions. For example, becoming aware of the route a customer has taken can play a significant role in arranging product displays, thereby enhancing a customer's shopping experience on one hand, and also helping to maximize sales, on the other.

One of the challenges for the incorporation of crowdsourced data for indoor floor layout conceptualization is to ensure the localization algorithm's accuracy and precision since the more accurate and precise the indoor location information is; the more meaningfully the position annotated crowdsourced data can be used. Consequently, the challenges associated with the calibration-free indoor localization techniques, for example, acquiring location fix, additional sensors requirement, available infrastructure, algorithmic complexity, etc., which are discussed in Hossain and Soh (2015), have impact in this family of research as well. The crowdsourced mechanism of conceptualizing indoor floor layout mandates implicit user participation as can be seen from Table 2. Therefore, their challenges are quite different that are identified for explicit user feedback-related research, for example, sentiment analysis of social media, quantifying trust-worthiness of an individual user, etc. The main challenge here is to correctly model the user surroundings through the usage of their devices' sensor measurements of *good* quality, and adopted localization and mapping algorithm's efficiency.

4.2 Implications of Internet of Things (IoT) Devices' Equipped Sensors

The inertial sensor (accelerometer, gyroscope, compass) measurements are incorporated in all the crowdsourced indoor floor plan construction-related research discussed in Section 3, such as CrowdInside, MapGenie, Jigsaw, iMoon. Additionally, Jigsaw and iMoon utilize camera sensor measurements, and apply computer vision technology in conjunction with them. The adopted inertial sensor measurements traditionally constitute a fundamental component of dead-reckoning techniques commonly seen in SLAMs. Through the use of camera sensors, the geometric features of the surroundings are captured which in turn refine the inertial sensors' motion traces by identifying the known landmarks. Both Jigsaw and iMoon reported finer accuracy and precision compared to CrowdInside and MapGenie which were purely inertial sensor-oriented research. This outlines the importance of combining computer vision technologies with mobile technologies.

Alternatively, it also necessitates more sophisticated algorithms compared to the ones that have been used so far regarding inertial sensors-based solutions. All the user IoT devices, for example, smartphones are generally equipped with the inertial sensors and camera that are utilized in such research. However, the quality of the sensor measurements (e.g., camera resolution) may have impact on the outcomes of the algorithms which need to consider these factors in more detail.

4.3 Dimension of the Floor Plan Layout

By definition, a 2D map is two-dimensional, which is the flat representation of the surroundings, whereas a 3D map is three-dimensional, which depicts the surroundings' length, width, and height. Depending on the applications, both variants can be useful, for example, a 2D map is commonly used for navigation using only street names and numbers, whereas a 3D map may be needed when the depth information is also required such as Google Map's street view. The inertial sensor-based research can only construct a 2D map, whereas iMoon's output is a 3D model, which is only possible because of the use of camera sensor and computer vision techniques. This may come at the expense of higher computational complexity, and additional latency incurred for accessing the LBSs. All these factors should be weighed carefully against the provided LBSs' needs, for example, whether they can be met by a 2D or 3D map which subsequently have impact on the technologies adopted, and the algorithm choices.

4.4 Type of Architecture

The crowdsourced indoor floor layout construction technique generally operates upon client/server architecture as can be from Table 2. The data acquisition component resides inside the smartphone client which delivers the collected sensor data to the server, which then conceptualize the indoor map using them. To reduce the communication overhead, the smartphone client might include additional component for preprocessing the data in order to ensure its quality before sending it to the server. However, this may have adverse impact on the resource constrained IoT devices in terms of energy efficiency. Therefore, a balance between certain performance metrics should be explored in designing the architecture, and the delegation of various tasks between the smartphone client and the server. In addition to that, the number of sensor data that needs to be communicated may increase the communication overhead again, and also add to the server's computational complexity. An ideal solution would be to use as little sensor data as possible but still able to model the surroundings correctly. This warrants more sophisticated algorithms to be adopted which leaves a plenty of research opportunity in terms of the architecture chosen, and the division of client and server functionalities.

4.5 Privacy and Security

Security corresponds to system resilience toward attacks from adversaries, and privacy ensures the confidentiality of system data. Traditionally, the client-based indoor localization where the client computes its location itself by using the available infrastructure beacons was preferred in terms of privacy. This is due to the fact that the client's location information will then be private. It may not need to be communicated with the localization infrastructure to access the available LBSs. There are alternative measures to ensure anonymity of a client device, for example, MAC randomization for the infrastructure-based solutions as well. Accessing location-based data at the server or infrastructure is a prerequisite for the crowdsourced approach of indoor map construction as can be seen from Table 2. Ensuring client anonymity at the server is more relevant compared to opting for a client-based solution for such systems. Furthermore, the research that strive to combine computer vision techniques with mobile computing such as iMoon, Jigsaw would require photos to be taken inside the areas of interest. This not only poses a question mark whether they are truly a crowdsourced approach but also gives rise to various privacy- or security-related issues especially for a commercial or public building setting.

5 Conclusion

In this chapter, we reviewed the existing popular outdoor Web map systems, and discussed the degree to which crowdsourcing was incorporated inside them. Their inapplicability inside an indoor environment was outlined with rationale. Subsequently, a few crowdsourced indoor map construction techniques, and their characteristics were discussed. The similarity of their working principle with some calibration-free indoor localization techniques was pointed out, and a comparative discussion is provided based on a few performance metrics. Finally, the challenges associated with the crowdsourced approach of indoor floor layout conceptualization were discussed, and a few future research directions have been identified.

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