Indoor location-based services: Challenges and Opportunities

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Abstract

Billions of smartphone users throughout the world have come to expect, and rely upon, intuitive, reliable and accurate maps, directions, turn-by-turn navigation and other location-based services (LBSs). Those same users will over the next few years come to expect and then demand the same experience and services when they enter any large building or facility in the world whether that be a hospital, airport, shopping mall or university campus. Based on various reports and surveys, it is reported that indoor LBSs are expected to have an even bigger impact than outdoor LBSs mainly because indoor is where we spend our time and money, meet friends, and where business happens. Indoor LBSs have numerous applications including navigation, location based social networking, emergency services, location-based marketing, mobile games, asset tracking, and workforce location. In this paper, we describe the challenges that need to be solved in order to make indoor LBSs as ubiquitous as their outdoor counterpart and discuss the opportunity this provides.

1 Introduction

Location-based services (LBSs) are the services that take into account geographical locations of users and other entities. Some applications of LBSs include car navigation systems, emergency services, travel planning, asset management, location-based recommendation, and geosocial networking. LBSs have become ubiquitous because of the surge in adoption of smartphones and the availability of cheap wireless networks. The Australian Communication and Media Authority (ACMA) reported [1] that 72% of Australians accessing the internet via their mobile phone use a LBS at least once a week. ACMA concluded that: *"Location services exhibit their potential in countless situations, which generally fall within the government, business, and consumer domains. The uses encompass emergency management and government applications, business solutions and consumer applications'*.

Although we spend more than 85% of our time indoors (30% at indoor venues other than homes, often in unfamiliar places [29]), nearly all of the existing LBSs focus on outdoor space and ignore indoor space altogether. The indoor LBSs promise huge potential for research organisations, government agencies, technology giants, and enterprising start-ups – to adapt to the indoor applications such emergency services, assisted health-care systems, indoor asset tracking, and event planning. For example, indoor LBSs can be used to help visually impaired people navigate indoor venues, directing people to safe exits during emergency evacuations, tracking staff, patients and equipment in hospitals [2] and providing location-based shopping assistance for customers.

Realising the potential of indoor LBSs, major technology companies, government and research organizations and start-ups are investing heavily in indoor technology. For example, the US Federal Communications Commission is exploring indoor positioning for more timely and effective emergency services [3]. In October

2014, Apple allowed [4] businesses to use its indoor location capabilities – but the service was soon completely overwhelmed by pent-up demand, forcing Apple to limit it to venues with over 1 million visitors a year. Based on such reports of its immense popularity, Forbes reported that indoor venues are the next frontier for LBSs [5] and indoor LBSs are expected to have an even bigger impact than their outdoor counterpart [14].

Despite the huge need of indoor LBSs, they are still not widely available due to some major challenges that hinder its ubiquitous availability. In the next section, we present the details of two such major challenges. Then, in Section 3, we present some important research directions that address the two challenges and pave the way for ubiquitous indoor LBSs. We remark that this paper does not aim to provide a *comprehensive* list of important research directions in this area. Although some of these research directions have already received some research attention [35, 39, 31, 27], we believe that these research areas demand significant more work from the research community. The goal of this paper is to highlight the importance of indoor LBSs and to provide *some* of the important research directions, thus encouraging research in these areas.

2 Challenges

In this paper, we discuss two major challenges that need to be addressed before the indoor LBSs become as ubiquitous as outdoor LBSs: 1) there does not exist any ubiquitous indoor positioning technology to identify a user's location; 2) in order to provide indoor location-based services at a global-scale, efficient and effective data management and analytics techniques are required to handle indoor venues and indoor data. Below, we provide the details.

2.1 Ubiquitous Indoor Positioning System (IPS)

Global positioning system (GPS) is a ubiquitous technology that identifies the location of a user carrying a GPS-enabled device such as a smartphone. Unfortunately, GPS does not work in indoors and we are still far from a ubiquitous technology for indoor environments. Some indoor positioning technologies require installation of special hardware (e.g., RFID readers, bluetooth beacons) in the indoor venue that makes them infeasible for global deployment. WiFi based positioning technologies [18, 30] provide a better option due to the ubiquitous availability of WiFi in indoor venues. However, most existing technologies require *fingerprinting* – manually mapping signal strengths at different indoor locations – which is time consuming and labor intensive. This is a major hurdle in the worldwide deployment of such a technology also because fingerprinting is sensitive to indoor environments and becomes invalid with time due to the changes in indoor environment. Some systems have been proposed to reduce the fingerprinting overhead of WiFi-based localization systems. However, these systems depend on installing special hardware to monitor changes in the signal strength [30], crowd-sourcing [34] which requires active feedback from users, and/or theoretical modelling tools that rely on detailed information of the indoor venues such as material of walls and doors etc. [22, 28]. Due to the manual efforts involved, none of these approaches is suitable for a ubiquitous indoor positioning system that can locate indoor users in *any* WiFi-enabled building with minimum overhead.

2.2 Indoor Data Management and Analytics

Another largely unmet challenge is how to effectively manage and analyze indoor location data. Current indoor indexing and query processing technology is in its infancy and falls short in managing different types of indoor data critical for a variety of location-based services. Some limitations of the existing techniques are: 1) rich textual information associated with indoor locations is not utilized; 2) uncertainty in the data is not adequately handled, leading to poor or incorrect results; 3) indoor trajectory data, which can be very useful in providing insights, have not been exploited; and 4) outdoor space is not integrated with indoor space, ruling out a large class of applications that involve both outdoor and indoor space.

Outdoor techniques [15] cannot address the above limitations due to the specific characteristics of indoor settings. For example, we need to not only represent the spaces (airport, hospital) in proper data model but also manage all the indoor features (lifts, escalators, stairs) and locations of interest (boarding gates, exit doors, counters) such that search can be conducted efficiently. Indoor spaces are characterized by indoor entities such as walls, doors, rooms, hallways, etc. Such entities constrain as well as enable indoor movements, resulting in unique indoor topologies. Therefore, outdoor techniques cannot be directly applied to indoor venues. One possible approach for indoor data management is to first model the indoor space to a graph using existing indoor data modelling techniques [26] and then applying existing graph algorithms to process queries on the indoor graph. However, this approach is inefficient because the techniques fail to exploit the properties specific to indoor space. For example, it was recently shown [36] that the state-of-the-art outdoor algorithm [41] takes over one second to answer a single shortest distance query between two indoor points in the Clayton campus of Monash University. A world-scale indoor service provider using the outdoor techniques would have a low throughput and would be unable to meet the high query workload, e.g., Google Maps is adding indoor venues and may provide spatial queries involving indoor spaces in the near future. The query workload is expected to be quite high and the existing techniques would not be able to meet the demand. In contrast, the techniques that exploit the properties specific to indoor space [36] can answer a shortest distance query in around 0.01 milliseconds on the same dataset, a 10^5 times improvement. To support a large number of indoor queries in real time, there is a need to develop techniques for indoor location data that address the limitations mentioned above and carefully exploit the properties specific to indoor venues to provide efficient query processing capabilities.

3 Research Directions and Opportunities

Indoor LBSs exhibit their potential in countless situations, which generally fall within the government, business and consumer domains. The uses encompass emergency management and government applications, business solutions and consumer applications. Below, we briefly describe some representative applications of indoor LBSs in each of the three domains:

- *Government.* Indoor LBSs are critical in areas such as public safety, emergency services, and healthcare. The U.S. Federal Communications Commission has a strong interest in improving emergency services using indoor positioning technology [3]. LBSs are also used in hospitals for indoor navigation, tracking staff and patients, location-based messaging, asset management, location analytics, and in integrating with other clinical systems. The global LBS market in the healthcare sector was predicted [2] to grow at a compound annual growth rate (CAGR) of 31.23% from 2015 to 2019.
- *Individuals.* Indoor LBSs have many applications for individuals such as navigation, in-store guidance, guided tours, and location-based social networking. For example, Google reported [6] that 84% of the smartphone shoppers use their mobile to help shop while in-store and 1 in 3 shoppers use their smartphones to find information instead of asking store employees. Indoor LBSs will also benefit visually impaired people and autonomous machines such as robots. Analyst firm ABI research estimated that, by 2018, over 800 million mobile devices will be using indoor LBSs [7].
- *Businesses.* Commercial applications of Indoor LBSs include location-based marketing, asset management, and workforce allocation. Indoor location- and place-based marketing is expected to surpass 10 billion dollars by 2018 [8]. Also, Forbes stated that the location-based services are a bonanza for start-ups due to their immense popularity and low entry barrier [9].

Realising the potential of indoor location-based services, major companies and research organizations have started investing heavily in this area. For example, Google offers more than 10,000 indoor maps of U.S. and international facilities in Google Maps [10], Microsoft and Nokia have partnered to provide indoor services on more than 3,000 facilities including U.S. airports and convention centers, and Apple acquired WiFiSLAM, a company providing indoor positioning services [11]. Huge demand of indoor LBSs and increasing availability of indoor maps have created a huge opportunity for research and development in indoor LBSs. In this section, we briefly describe several important and promising research directions and opportunities.

3.1 Developing a Ubiquitous Indoor Positioning System

There is a large body of work on indoor positioning systems (e.g., see [17, 32, 38]). However, almost all existing techniques either require installation of special hardware or require extensive manual calibration that makes them infeasible for global deployment. Although the accuracy of these positioning systems has improved a lot in the past few years, such indoor positioning systems are still far from being as ubiquitous as GPS is for outdoor spaces. This is a major hindrance in the deployment of indoor LBSs at a global scale. Thus, there is a need to develop an indoor positioning system that relies on the ubiquitous availability of existing equipment (e.g., WiFi access points or light sources) and does not rely on manual calibration (e.g., fingerprinting). Some recent research [23] have started working towards addressing this need. However, such efforts must be continued and more work is needed before the vision of global deployment of such systems is realized.

3.2 Indexing and Querying Textual Indoor Location Data

In the present Web 2.0 era, spatial data are increasingly annotated, whether manually or algorithmically. This results in a rich body of information associated with objects. For instance, products in a supermarket may be tagged with price, ingredients, nutritional information and use-by date. Similarly, medical instruments in a hospital are tagged with textual information such as name, category and department.

Despite the popularity of keyword search, the current indoor query processing systems only deal with the spatial dimension of the data and *cannot* support keyword search on spatial data (called *spatial keyword search*). In a spatial keyword query, the objects are returned not only based on their distances from the query location but also based on their keyword similarity to the query keywords. A user may issue a query with the keyword string "low fat milk" to find nearby shops that sell low fat milk. Or a library user may want to navigate to the location of a book, and use its title as keywords. Existing systems that answer spatial keyword queries in outdoor space rely on specialized indexes [19] (e.g., IR-tree, KR*-tree, S2I etc.) that are only applicable for outdoor venues. They do not extend efficiently to ontologies that are typical of indoor domains.

There is a need to develop efficient indexing and query processing techniques for spatial keyword queries that allow to search for indoor objects based not only on their distances from the query location, but also on how well they match query terms. For example, a user may issue a query to find the nearest defibrillator in an emergency situation. Queries may be ambiguous (when several objects match a query), inaccurate (when there are no objects that match all the requested attributes, e.g., "a *cheap* food place *nearby*"); and if spoken, some words may be mis-heard by an Automatic Speech Recognizer. In addition, the data may be dynamic, e.g., locations or terms associated with objects may change, medical instruments may be moved, the user may be walking, or the price of a product may change.

3.3 Handling Uncertainty in Indoor Location Data

Real-world data are noisy, and location-based data are even more so [16]. Reasons include built-in inaccuracy of the positioning technology (for GPS, IPS, etc.), transmission delay, and deliberately added noise to protect privacy [21]. This is worsened by the fact that data are increasingly user-created, or automatically annotated by spatial data-mining algorithms [37]. More and more queries are sent from mobile devices with misspelt or otherwise defective keywords. There could be serious consequences of ignoring such uncertainties in data. Notoriously, there are news reports on how errors in Google Maps have led to unwanted traffic, wrong destinations or itineraries [12], and even international conflicts [13].

Location inaccuracy in indoor space is even more of a concern. A minor discrepancy in reported location may render results worse than useless. A location error of just a metre or two in Euclidean distance may indicate a different room, or even the wrong floor, and a wildly incorrect estimate of indoor walking distance that could be catastrophic in an emergency.

A fundamental challenge is to model the uncertainties for different types of data, and to design efficient techniques for answering probabilistic queries regarding uncertain indoor data, such as probabilistic k nearest neighbors and probabilistic range queries. In general, uncertainty significantly increases the complexity of query processing, e.g.,the complexity of evaluating conjunctive queries over uncertain data is #P-complete [20]. When uncertainty is considered together with the characteristics of indoor settings, the queries are even harder to process.

3.4 Indoor Trajectory Management and Analytics

Just as a user's web browsing history (e.g.,clickstream) in an online world provides insights about the user, a user's trajectory gives insights about him/her in the physical world [33]. For example, the trajectories of indoor users may be used to learn how people flow through an indoor venue. These insights may be valuable for users, government agencies and venue owners, and scenarios such as optimizing the layout of a venue, planning emergency evacuations, flow analysis, and congestion prediction. Due to the different topology (indoor vs outdoor space), different positioning systems used (GPS vs IPS) and different user behaviours (driving vs walking), indoor trajectories have different characteristics from outdoor trajectories [27]. Thus, there is a need to develop new indexing, retrieval and analytics techniques to exploit the potential of the indoor trajectories.

3.5 Integrating Outdoor and Indoor Space

Almost all existing query processing techniques are designed either for outdoor space or for indoor space. However, a lot of real-world applications encompass both − for example, navigation from a multi-level car park to an office on a university campus. Hence, it is important to seamlessly integrate outdoor and indoor space (OI-space, together) and propose a unified indexing scheme to support a wide range of applications in OI-space that are not supported by the current systems. This is non-trivial mainly due to the inherent differences between outdoor and indoor space.

Concern for integrating indoor and outdoor space (OI-space) has prompted research in the past few years. This includes seamless positioning handover between indoor and outdoor [25], data models for OI-space [24], and ontologies for OI-space [40]. However, there is no work on a unified index to allow efficient processing of spatial queries in OI-space. Thus, there is a need to effectively and seamlessly integrate outdoor and indoor space in a unifying index, to support efficient and scalable processing of queries in OI-space. Given inherent differences between the ontologies appropriate to indoor and outdoor space, the techniques and indexing schemes designed for one do not work well for the other.

4 Conclusions

We spend a large part of our lives in indoor environment. However, almost all existing location-based services (LBSs) focus on outdoor spaces. To meet the growing demand and popularity of indoor LBSs, several challenges must be addressed that hinder the ubiquitous availability of indoor LBSs. In this paper, we first present an overview of two major challenges and then provide some important and promising research directions that will support and enhance a wide range of indoor applications, such as emergency services, assisted healthcare systems, indoor asset tracking and event planning, thereby improving the stakeholders' experience.

Acknowledgments

The author is supported by Australian Research Council Future Fellowship FT180100140 and Discovery Project DP180103411.

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