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Indoor location based services challenges, requirements and usability of current solutions

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ABSTRACT

Indoor Location Based Services (LBS), such as indoor navigation and tracking, still have to deal with both technical and non-technical challenges. For this reason, they have not yet found a prominent position in people's everyday lives. Reliability and availability of indoor positioning technologies, the availability of up-to-date indoor maps, and privacy concerns associated with location data are some of the biggest challenges to their development. If these challenges were solved, or at least minimized, there would be more penetration into the user market. This paper studies the requirements of LBS applications, through a survey conducted by the authors, identifies the current challenges of indoor LBS, and reviews the available solutions that address the most important challenge, that of providing seamless indoor/outdoor positioning. The paper also looks at the potential of emerging solutions and the technologies that may help to handle this challenge.

1. Introduction

Location Based Services (LBS), such as navigation, Location Based Social Networking (LBSN), asset finding and tracking, are used by many people widely around the world [1,2]. About three quarters (74%) of smartphone device owners are active users of LBS [3] (Pew Research 2013). However, when used indoors, applications have difficulty providing the same level of positioning accuracy, continuity and reliability as outdoors [4]. Global Navigation Satellite Systems (GNSS) are the most widely used positioning technology for outdoor use [5]. However their signals can be easily blocked, attenuated or reflected [6]. This makes them unreliable indoors, making it impossible to seamlessly use them for positioning across outdoor and indoor environments. Many life-saving services, such as for emergencies and security, could be improved hugely if indoor LBS could address this challenge. In addition, although people spend most of their time inside, indoor LBS generates less than 25% of total revenue (ABI research 2015). If LBS could overcome these challenges, its market will develop and more users will be attracted. This paper identifies these challenges using a survey of the latest research and the results of a survey conducted by the authors. The paper also evaluates current solutions and uses this analysis to identify the most suitable solution among those currently available.

Research into the challenges presented by LBS is on-going [4,7–9]. This paper considers their findings, in addition to a comprehensive survey targeting ordinary LBS users, application developers, component providers and companies, market analysts and content providers. This synthesizes both the technical and non-technical challenges in one study. The most important challenge identified by this paper is providing Quality of Positioning Services (QoPS) — the functional and non-functional parameters that include accuracy, availability, and cost (both to the user and for infrastructure deployment) including the availability, continuity, and accuracy of positioning services for indoor use. Other major

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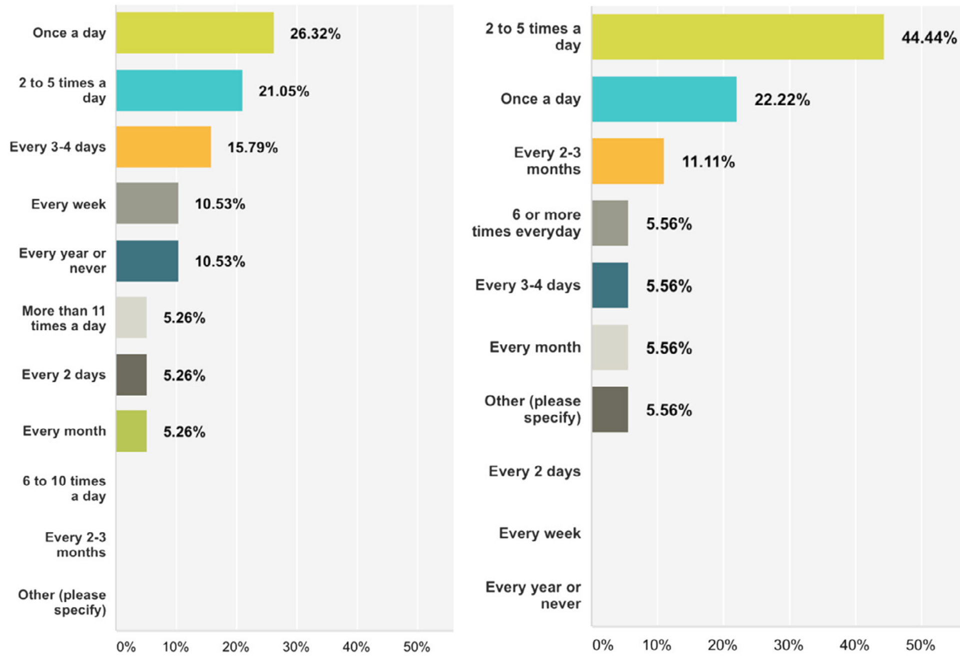

Fig. 1. The frequency of use of the location-enabled devices (left) and applications (right) by ordinary users of LBS.

challenges are identified as concerns over privacy associated with location data and the overall cost of services.

Some of these challenges, including accuracy and reliability, are directly linked to the effectiveness of positioning technologies while others, such as cost and privacy, are closely related to them. However, there are some issues that are independent, such as the business model used and the social acceptability of an application. The latter have been reviewed elsewhere [10].

This paper reviews the technologies which are currently being used as solutions to these challenges. Also, based on the results of a survey, a literature review and analysis on the available systems, this paper compiles the requirements of current LBS applications. By comparing the technological requirements of LBS applications and the available solutions, the paper assesses the usability of the current technologies for five application categories.

In addition, an analytical tool is described to evaluate the usability and fitness-to-purpose of each positioning technology for specific applications. The application requirements might differ slightly from the general category it falls into. This tool uses the Analytic Hierarchy Process (AHP) [11] to select the most appropriate technology among those currently available according to the positional requirements for the application. AHP is a powerful tool for systematic multi-criteria decision-making. The developed tool is sufficiently flexible that it can assess new LBS applications, which are currently emerging very frequently.

In section two, the structure of the survey and the process of the identification of LBS challenges and requirements are explained. Section three studies the current solutions to the identified challenges and a usability analysis tool is introduced and used.

2. Identification of indoor LBS requirements and challenges

Although some of the challenges in the development of LBS are shared by a wide range of applications, their impact can vary from one application to another. For example, the availability and the accuracy of indoor positioning services is one of the major obstacles for indoor applications. The main positioning technology, Global Navigation Satellite Systems (GNSS) such as GPS, is not usually available. A lack of accurate positioning is a major issue for tracking and navigation services. However, in advertising and social networking applications, a hundred-meter locational error might be satisfactory. Therefore, if we separate LBS applications into categories, we can identify the shared issues within each. This section describes the process of identifying each application's requirements, its categorization based on this, and the implementation challenges. This is based on a literature review and the results of a survey.

2.1. Survey structure and participants

The web-based survey, conducted in May 2015 for three months, had 245 participants (212 valid responses), aged between 18 and 73 years, with 164 male and 48 female respondents. The distribution of 212 participants and their level of expertise in LBS are shown in Table 1.

The frequency of using LBS applications and the number of devices owned with positioning capabilities varied among the different participant groups. However, across all a minimum of 52.63% of the users have three or four devices with positioning capabilities, such as mobile phones, vehicle satellite navigation, fitness devices, iWatch, iPod, iPad), and a minimum of 44.44% on average use their location-based devices at least twice a day. The frequency of using LBS applications by the largest participant group (LBS ordinary users) is shown in Fig. 1.

2.2. LBS application segmentation

The participants were asked about the frequency of use of several applications, including navigation, tracking, emergency and safety, local news, location-based social networking, travel guidance, elderly assisted living, and pet/asset finding. The participants were asked about the important features of these that they would consider when buying, downloading or in use. For each application, the participants were asked to rank the features by importance to them, including the cost of first purchase, update fees, battery consumption, user-friendliness of the interface, size and weight (of the device), location accuracy, continuity of service (seamlessly indoor/outdoor), delay in providing service, and privacy features. The participants were also asked about their

Table 1
The categories of the participants in the survey.

Participants group	Percentage
LBS ordinary users (use LBS applications, devices and/or services in daily life)	54.72%
LBS application developers (design, develop, or deploy LBS applications and services)	9.43%
LBS content providers (provide content and/or information, such as map, points of interest and advertisements, to be delivered through LBS applications and/or services) *and components companies* (produce LBS components, such as antennas, receivers and transmitters)	1.89%
LBS researcher and LBS market analyst (study LBS and related technologies, applications and markets)	26.42%
Other	7.55%

minimum (and maximum) requirements for each of these features that would provide an "acceptable" quality of service.

The Random Forest method [12] was used to cluster applications based on the answers from the various groups and identify the requirements of each category (Table 2). Random Forest method classifies (or provide with a regression trees) each node (input data). Each node is split using the best split among all variables/parameters, here such as privacy, power consumption, etc. In a random forest, each node is split using the best among a subset of predictors randomly chosen at that node. Random Forest is very user friendly in the sense that it has only two parameters (the number of variables in the random subset at each node and the number of trees in the forest), and is usually not very sensitive to their values. Based on this method, the five application categories of indoor LBS were classified as:

- Indoor navigation and tracking (such as pedestrian navigation, indoor tracking),
- Marketing (shopping advertisements, proximity-based voucher sharing),
- Entertainment (location-based social networking and fun sharing, location-based gaming),
- Location-based information retrieval (such as in-gallery tours, underground real-time information),
- Emergency and security applications (such as ambient assisted living, E112 response).

These results were within two STD when measured for significance and compatibility in responses. This satisfies the required Quality of Service (QoS) identified by other studies [13–17]. They mainly identify positional accuracy and availability, privacy, cost, power consumption, reliability and continuity of service, plus the response time.

In addition to having a better understanding of the requirements of each application category, the results give the pairwise comparison ratio for the AHP analysis to find the best positioning technology, among those currently available.

2.3. Identification of current LBS challenges

The answers to these questions also indicate one of the most important challenges of the development of LBS markets — a lack of mutual understanding among the value chain. One of the best examples of this is the underestimation of the users' concerns regarding privacy by developers [10]. Ordinary users prioritized privacy as one the most important features, except in emergency, safety and security-related services, while developers believe that privacy is less important than cost and a well-designed user interface. There is also a need for technological development to bridge the gap between what developers need and what content and technology providers can deliver.

In another question, participants were asked to name and rank the important criteria for LBS applications to become successful. Predictably, the answers to this question vary between different participant groups. For example, availability of an API for developers was voted as one of the most important features (Fig. 2) while it was not even mentioned by ordinary users or technology providers.

Based on this analysis, weighted by the number and the role of participants, and clustered using the Random Forest method, the top three biggest challenges for LBS applications were identified as (1) Quality of positioning service, (2) Privacy concerns, (3) Availability of the content.

Privacy concerns refer to the (perception of) issues concerning the mis/re-use and/or inference of positional data by the service provider or a third party. Availability of content refers to the possibility of having access to the data, services and information essentially required to provide the service. This includes up-to-date maps, APIs, contextual data, and so on. These three challenges to the development of LBS have been identified in market reports and literature reviews. Knowing these requirements, the current solutions can be explored and evaluated to see if they are being addressed and, if not, where are the deficiencies and how they can be bridged.

3. Indoor LBS challenges and the potential solutions

3.1. Positioning requirements and solutions

Reliable, inexpensive indoor positioning is needed for many LBS applications. It needs to be able to localize users accurately and work seamlessly with outdoor positioning technologies [18]. In this subsection we review positioning technologies from a quality-of-service point of view to give a clearer picture of what is the biggest challenge to achieving this.

In general, localization technologies can be categorized into three main groups: Beacon-based positioning technologies, Dead-Reckoning (DR), and Device Free. Some technologies blend more than one of these, so can be classified into a fourth group Multisensory positioning. Each will now be described.

3.1.1. Beacon-based positioning systems

GNSS, the most widely used outdoor positioning technology, uses Radio-Frequency (RF) signals. However, the signals can be easily attenuated, reflected and/or blocked by buildings, walls and roofs [6]. There have been attempts to use GNSS signals inside buildings using ground-based PseudoLites (PL) [19] mimicking satellite signals or high-sensitivity GNSS (HSGNSS) receivers. However, despite being technologically possible, neither could become a ubiquitous solution for "indoor GNSS" due to the high costs involved.

PL requires installation of many stations, thus it is not a low-cost solution and must be carefully planned so as not to interfere with GNSS. Effective HSGNSS receivers can be expensive, up to hundred euros depending on the features the module offers [20]. Moreover, the signals indoors are so weak that it is very difficult to acquire a dynamic position easily. Television broadcast and cellular signals penetrate buildings better than GNSS [16]. The positioning accuracy that can be achieved with these signals is not accurate, often greater than 50 m [21–24].

In addition to these technologies, there are some other methods that can be applied for GNSS-based positioning in partially denied areas. These include shadow matching [25]. Digital Video

Table 2
LBS application segments and the identified required features using the Random Forest method.

LBS category	Applications examples	Quality of service requirement
Navigation and tracking	• Pedestrian Navigation • Path Finding And Routing • Tracking • Asset Finding	– Response in near-real-time – Accuracy within a few meters – Seamless availability (indoors and outdoors) – Good reliability and continuity of service – Low–medium power consumption – Reasonable or cheap price – Strong privacy preservation
Marketing	• LB (Social) Marketing • Advertisement • Proximity-Based Voucher/ Offers/ Rewards • LB Social Reward Sharing • Location Based Dealing	– Medium to low availability – Response in few minutes – Accuracy in the order of hundreds of meters – Medium reliability and continuity – Very low power consumption – Free or very inexpensive – Medium to strong privacy preservation
Entertainment	• LB Social Networking • LB Gaming • LB Fun Sharing • Find Your Friend • LB Chatting • LB Dating	– Medium to high availability (seamless indoors and outdoors) – Response in real-time or a few seconds – Accuracy in the order of tens of meters – High reliability and continuity – Low power consumption – Reasonable or cheap price – Medium privacy preservation
Location-Based Information Retrieval	• Location-Based Q&A (Query) • Proximity Searching • Tourist Guide •Transportation Info.	– Medium availability – Response in real-time or a few seconds – Accuracy from a few meters (e.g. for tourist guide and proximity search) to hundreds of meters – High reliability and continuity – Low power consumption – Reasonable or cheap price – Medium privacy preservation (depending on the application)
Safety and Security	• Emergency Services • Emergency Alert Services • Ambient Assisted Living • Security Surveillance	– Very high availability (seamless indoors and outdoors) – Response in real-time or few seconds – Accuracy of tens of meters or lower –Very high reliability and continuity – Low power consumption – Reasonable or cheap price – Medium or low privacy preservation

	Minimum	Maximum	Median	Mean
Novelty of the idea behind the app	7.00	13.00	8.00	9.00
Availability of required APIs	3.00	13.00	9.50	8.75
Scalability (request/user number)	5.00	11.00	7.50	7.75
Loyalty to previous versions of applications and/or OS	1.00	12.00	8.50	7.50
User-friendly interface	5.00	9.00	8.00	7.50
Monetisation approach	3.00	11.00	7.50	7.25
Positioning services availability	4.00	11.00	7.00	7.25
Privacy concerns	2.00	13.00	7.00	7.25

Fig. 2. The ranking of the features contributing to the success of an LBS application from the developers' perspective.

Broadcasting — Terrestrial (DVB-T) relies on orthogonal frequency-division multiplexing (OFDM), which can provide fine information regarding the channel state. Besides that, the emitters' locations are usually known, which also offers a great advantage over the other technologies. However, one of the main challenges is the low number of emitters. In addition, the receiver has to identify and match the incoming signal to a specific emitter. This poses a question on how accurate and reliable this can be done, increasing the risk of errors in the position estimation.

Wireless Local Area Networks (WLAN) technologies are certainly one the most popular positioning technologies provided based on the RF-based technologies, which had not been developed initially for positioning purpose. IEEE 802.11 is one of the most popular standards for WLAN. This protocol has made its way to almost every electronic device. Since most recent IEEE 802.11 protocols rely on OFDM signals, these signals pose a new opportunity for positioning. Due to its ubiquitous availability in urban environments, residential and commercial, it can be used for indoor positioning with an acceptable availability. For positioning these networks have been used mostly under fingerprinting solutions, offering a relatively good performance, 5 to 10 m, in densely covered areas [26,27].

These signals report on the channel state, which can be exploited in a positioning context to obtain range measurements. This metric is more reliable than the Received Signal Strength Indicator (RSSI) but it also requires accurate environment models. However, these models are difficult to build, since most channel effects are difficult to model or understand how to properly model them. Therefore a training phase could also be necessary [28].

There are many existing Wi-Fi access points. Signal strength and flight time are usually the wanted attributes. 802.11v consists also of positioning protocol. [29] assesses the 802.11v standard for Time of Arrival (ToA) positioning. Furthermore [30] compares the coverage and interference of the different protocols in the 802.11 families. In [31] Wi-Fi access point signal strengths were collected for fingerprinting. The strength was represented according to the Wi-Fi Access Point MAC addresses. Hejc et al. [32] used Wi-Fi with GNSS receiver and IMU. Moving from indoor to outdoor environment is challenging because the GNSS requires time to achieve the first fix. Thus it is necessary to identify these transition region characteristics between the technologies used. There is also work going on with the next-generation 802.11az amendment, which is designed for new positioning applications designed to run on wireless networks.

Ultra-wideband (UWB) characteristics offer advantages for coping with multipath. Particularly its impulse radio short pulses make it easier to detect the multipath components. Repeatability is a strong advantage for the ultra-wideband approach. This means that the positioning result stays consistent over a time period [33]. UWB tag was placed on shoe and helmet in [34]. The tag measurements on the shoe had much more outliers due to non-line-of-sight conditions. Although high time resolution of UWB signals makes it easier to distinguish between original and multipath signals, the non-line-of-sight condition is still a challenge.

Bluetooth is another wireless technology standard for exchanging data over short distances [35], which has increasingly become popular since the release of the standard Bluetooth 4.0 protocol. Bluetooth low energy (BLE) is a version of Bluetooth meant for low power applications, which allows some of applications to operate in a continuous manner for extended periods of several months. Due to its power efficiency and low cost, BLE can be deployed in several tags or beacons throughout the environment, in order to offer a more accurate indoor positioning solution [36]. A shorter operation range allows for the proximity based positioning, providing a better performance regarding the estimated position error. The specification does not set an upper limit for the BLE range of operation, but experiments show that over 20 m the RSS become very low, making the positioning practically impossible.

RFID system consists of RFID readers and transceivers or tags. In the active approach, the user carries the reader and scans the tags in the environment. In the passive approach, the user carries the tag and the environment has readers set up for positioning. The passive RFID detection range is very short (2 m) and in practice, a stand-alone passive system would be costly to set up. Privacy is of concern especially in passive RFID tag systems where the computation capability of the tag cannot support necessary cryptographic data protection. RFID is implemented generally as a proximity positioning system [37–40].

Cameras can also be used for positioning in several ways. The user can carry the camera and the images can be matched against available geo-referenced photos [41]. Basiri et al. [42] used markers/codes placed at landmarks and a mobile phone camera was used to identify unique markers and look up the corresponding position in a database. Kivimäki et al. [43] lists infrared sensor technologies. However, micro-bolometer and Golay cell-based infrared cameras are very expensive and may not be applicable for many indoor LBS applications. Thermopiles and pyroelectric sensors, although less accurate, are very affordable. These can be effective in low lighting conditions where conventional image processing is impossible.

Compressible media, such as sound and ultrasonic signals travel through a medium like air and the received strength or the time of travel can help to calculate the position of the receivers. Signal strength, form recognition and travel time are the common methods used to derive the location. Hoflinger et al. [44] used signal amplitude envelope detection on received chirp-form signals. Rishabh et al. [45] used time of arrival (ToA) to calculate the position. The timing was based on detecting specific sound signals by comparing them with the reference signals at base stations. The recorded signal detection was carried out by cross-correlation with the reference signals. The sound source can be carried by the user or multiple sound sources can be located within the environment as base stations. Multipath, echoes and ambient noise in the environment make sound-based localization system design challenging.

3.1.2. Dead-reckoning (DR) positioning systems

Dead-reckoning positioning systems can be classified into two groups; plain Inertial Navigation Systems (pINS) and Step and Heading Systems (SHS). With arrival of Microelectro Mechanical System (MEMS) INS found wide use. Smartphones with inertial sensors, such as accelerometers and gyroscopes, allow us to use them as input devices for Pedestrian Dead Reckoning (PDR). The increased interest in the MEMS sensor utilization is related to their small size (in cm order) and low cost due to the silicon fabrication process. In the most common configurations, MEMS inertial units comprise accelerometers that provide the user position by double integrating the specific force along its sensitive axis; MEMS gyroscopes, measuring the body rotational motion across each sensitive axis, with respect to the body sensor frame and 2- or 3-axes accelerometers and gyroscopes along with the magnetometers measuring the heading of the vehicle. In many cases only horizontal positioning is of great interest, a standalone position from the dead-reckoning MEMS sensor can be provided from the use of two gyroscopes and one accelerometer. Racko et al. [46] used smartphone sensors, including low-cost Inertial Measurement Unit (IMU), for PDR and compared with more precise and expensive Xsens IMU. The accuracy of inertial sensors has increased in the past few years, but they still cannot alone provide proper accuracy because of many negative effects, such as heading drift due to gyroscope bias [46]. Among the pINSs, the tactical grade IMU have a drift of a few meters in a minute (Boll et al., 2011), but they are quite expensive and bulky for many LBS applications. On the other hand, the low-cost MEMS inertial measurement units require additional external features, such as zero velocity updates, map matching or external sensor aid, to achieve similar accuracy [14,47–49]. Skog et al. [50] evaluated zero-velocity detectors for foot-mounted INS. Gait style, step size estimation and attitude determination are the key parameters in Step and Heading Systems. Map matching techniques aided inertial navigation [20], bring the low-cost MEMS INS accuracy closer to that required for indoor LBS. Also, cold atom interferometry and chip-scale atomic clocks are still under development [25]. Dead reckoning systems are not generally considered as stand-alone positioning systems as they have to rely on the calibration of external positioning technologies such as GNSS and Wi-Fi due to their drift. Drift of position is the challenge in inertial dead reckoning, and the double integration of acceleration data into positional information is hard to stabilize. Another challenge is the initialization of the IMU parameters. If the starting position and heading are slightly wrong these errors will accumulate over time. Pinchin et al. [51] uses the cardinal directions of the built environments as a map-matching technique to adjust the user track and position. A comprehensive literature review on inertial positioning systems has been published by Harle [14]. Step and Heading Systems (SHS) use estimates of step length and heading. Peak-detection, zero crossing, template matching and spectral frequency analysis are some of the approaches to detect steps. Skog et al. [50] compared four step detection algorithms: acceleration moving variance, magnitude, angular energy rate detection and a likelihood method that combined all three. Slippery ground, shuffling and use of elevators are all challenges for estimating the next step position. These make it difficult to detect zero velocity thresholds or zero angular velocity. Alternative and even more complex ways for getting the inertial navigation solution are for example by using learning methods like statistical model comparisons of learnt IMU records, artificial neural networks and regression forests [52]. In summary, the inertial systems as dead reckoning systems are not sufficiently accurate for indoor positioning by themselves.

3.1.3. Device-free positioning

Tactile sensors, such as piezoelectric, capacitive touch surfaces, levers and buttons can recognize the presence of a user at a certain location. Tactile localization is based on the deployment of sensors or probes being in direct physical contact with a surface or an obstruction. Similarly, an odometer is direct and continuous [43,53]. Localization using tactile sensors is relatively straightforward and accurate. However, identification in public environments may need additional information, such as a camera image, to identify and deliver the correct location for the targeted user. Identity for odometry, on the other hand, is easier to implement but it requires the user to carry the sensor.

Cameras, such as CCTVs, also can be used for positioning; the user (feature or marker) can be detected by a camera network covering the environment [16]. Using visual odometry, location can be tracked using image flow by comparing patterns in sequential images. A stereovision setup can also be applied for more accurate camera movement estimation or three-dimensional positioning.

Barometers are relatively easy to use for measuring air pressure, particularly indoors, and this makes it feasible to use it for detecting changes in height or altitude. Floor level was successfully distinguished by Bai et al. [54]. As weather conditions can change, affecting the reference pressure, measured pressure and the temperature, calculating the correct height is challenging in a real time application.

As mentioned before, magnetic-based positioning technologies determine location based on the magnetic field value assigned to each point. However, the existences of the metallic objects or radio devices often make this very difficult with magnetometers. Zampella et al. [34] measured the stable magnetic field while stationary. If there was any angular rate detected during the stance this was used to correct the yaw drift and gyroscope bias. Fuzzy Inference System (FIZ) [55] uses four magnetic field parameters to detect whether the magnetic field was disturbed inside a building [56]. As practical experiments and requirements analysis have shown, a single positioning technology cannot be the answer to the requirements of many applications of indoor LBS. Multi-sensor positioning can solve some problems for some applications. Improvements in the sensitivity and accuracy of current sensors, upcoming technologies such as BLE, Galileo with its higher signal penetration, a change in policy and legislation regarding the use of some technologies such as pseudolites can help to improve the quality of indoor positioning services.

Table 3 summarizes the important characteristics of the reviewed positioning technologies (including surveillance positioning systems). They include the possibility of being used stand-alone, the achievable accuracy, cost of the sensor and components on the user's device, cost of implementations and the deployment of the infrastructure for a citywide application, privacy (system security measures against location information hacking categorized into three categories of (a) high (the positioning signal is broadcasted from the terminal and device receive and calculated location with a minimum communication over network, e.g. GNSS is highly privacy preserving), (b) medium (device can receive and calculate the location but it needs communications over network and the device is potentially identifiable by the transmitter, e.g. Wi-Fi based positioning), and (c) low (where the location are not calculated on the device and a third party can only send back the location to the user, e.g. positioning using CCTV cameras)), power consumption (on the user device), coverage of the positional signals, and required data rate.

This paper applies a usability analysis to select the most suitable positioning technology, among those already available, for each LBS application segment. To do so, AHP methodology [11] is used to make the comparisons of objectives and alternatives in a pairwise manner. Analytic Hierarchy Process (AHP) is one of the Multi-Criteria Decision Making (MCDM) processes, which derives ratio scales from paired comparisons between criteria and factors [11]. AHP can systematically help decision makers to select between choices based on criteria and factors, which can represent priorities and preferences. One of the most valuable aspects of AHP is the flexibility to consider both quantitative and qualitative parameters and factors to prioritize the choices [11]. This enables decision makers to include almost any kind of criterion, from wide range of natures, allowing AHP to be practically applied in many real-world decision-making problems. In addition, AHP can accept human inconsistencies in judgments. AHP is based on pairwise comparisons, ideally done by experts.

The AHP has been applied to a wide range of problem situations, however, one of the most widely used applications of AHP is selecting among competing alternatives in a multi-objective environment. It is based on the well-defined mathematical structure of consistent matrices and their associated right-Eigenvector's ability to generate true or approximate weights [11]. To do so, AHP methodology includes comparisons of objectives and alternatives in a pairwise manner. The AHP converts individual preferences into ratio-scale weights that are combined into linear additive weights for the associated alternatives. These resultant weights are used to rank the alternatives and, thus, assist the decision maker (DM) in making a choice or forecasting an outcome. In order to select the most suitable positioning technology, the selection criteria are first set. As discussed in Section 2.2, the participants of the survey gave a score to each feature of LBS

Table 3
Positioning technologies specifications and features.

Positioning technology	Stand-aloneness	Data (output) rate	Accuracy	Coverage (range of the positioning signals)	Cost for users	Cost of the Infrastructure	Computational load/Battery consumption	Privacy
GNSS	Stand-alone	~1 Hz	4–7 m	Generally available outdoors	£1–£100 (e.g. u-blox LEA5H ~£50)	Billions of Pounds (but already existing)	150 mW–1.5 W	High
Pseudolite	Stand-alone	~1 Hz	3–7 m	~50 km	Locata receiver ~£5000/ IFEN NavX	~£100,000 per transmitter	~1 W transmit power	High
Mobile networks	Stand-alone	1 Hz — a few Hz	1 m — a few hundreds of meters	~A few km	>£10(OMAP)	Millions of Pounds (but already existing)	~1 W(TI OMAP)	Medium
WiFi RSS	Stand-alone	0.25 Hz, 3 Hz, 0.2 Hz	2–4 m	10 cm–50 m	HP Ipaq £77	20£–(more than £50) per Access Point	>1 W, 700 mW (for WSN802GX), >500 mW for transmit and 200 mW for receivers	Medium
WiFi ToF/AoA	Stand-alone	1–10 Hz	1.7–10 m	~25 m	>£5	>£50 (AP Prices)	>1 W/ 100 mW	Medium
UWB ToF	Stand-alone	~25 Hz, >10 Hz	15 cm–1 m 1.5–3 m (for UWB RSS Proximity/Scene Analysis	~5–175 m	£60 (for ubisense tag IP63 slim)–£1000 (laboratory equipment)	Expensive laboratory equipment	>1 W/(500 mW transceiver)/~300 mW receiver and 600 mW transmitter)	Medium
RFID active	Stand-alone	0.5 Hz, 0.2 Hz	1–3 m/	30–100 m	~£300 (I-Card III interrogator), >£500 M220 reader	>£10 per tag	~250 mW	Medium
RFID passive	Stand-alone	20 Hz, 80 Hz	15–50 cm	~2 m	>£10 per tag	~£200 >£1000 per reader	<50 mW for tag and 300 mW for reader	Low
Bluetooth RSS	Stand-alone	0.2 Hz, 2 Hz, 1 Hz, 30 Hz	2–5 m	Modifiable (1–25 m, 150 m in open fields)	~£5 receiver	£5–£30 per tag	25–50 mW	High
Barometer	Assistive	~2 Hz	33 cm–0.2 m	Ubiquitously	~£10	Not applicable	~5 mW	High
Sound	Stand-alone	1 Hz — tens of Hz	1 cm–1 m	~3–10 m/	£10–~£300	£10–£100 per node	20–100 mW	Medium
Infrared (IR) marker or reflective element	Stand-alone	~50 Hz	10 cm–6 m (for active Badges)	~6 m (depends on tag placement)	~£1 (marker)–~£10(camera)	£1 (marker)–£10 (camera)	<50 mW (for markers)–165 mW (for camera) + processing consumption	Low (for environment)/high (for user with the camera)
Infrared (IR) Light Image feature matching	Stand-alone	~20 Hz	0.2–0.8 m	~6–10 m	~£1 (thermopile)	~£1 per thermopile–€8000 microbolometer camera	<50 mW (thermopile)	Low (for environment)/ high (for user with the camera)
Magnetometer	Stand-alone (needs magnetic maps)	5–75 Hz	1 mm for permanent magnet–20 cm for fingerprinting	1 m magnetic fingerprint map	£2–£10	>£2 ∗ *n*	<50 mW	High for sensor but low for user if carrying a magnet
Electromagnetic system	Stand-alone	1 Hz	1% of the range	~5–20 m	>£1000	~£16 per mmˆ2	>1 W	Low
Light Image marker	Stand-alone and Assistive (for snapshots or odometry)	5–30 Hz	1 mm–30 cm	~6 m (resolution dependent)	~£10–£500	>£10 for marker amount	200 mW–~2 W	High (if user carries the camera)
Light Image feature matching	Stand-alone	5–30 Hz	~10 cm (1% drift for odometer)	~6 m (resolution dependent)	~£1 for odometer–£100 for camera modules	~£10–£100 per camera	50 mW for odometer and up to 1 W for cameras	High (odometry and user carrying)
Tactile on user device	Assistive	50–500 Hz		Ubiquitously			Very low	High
Tactile Environment	Stand-alone	22–60 Hz	4–40 cm	Ubiquitously	Low	~£100 (per 3 × 2 mˆ2 area)		Low
Tactile Odometer	Assistive	4 pulse per rotation		Ubiquitously	Low		~150 mW	High

applications. These scores are used for the pair-wisely comparison of features, that is finding the ratio/value showing which feature has priority over the others [57]. For example, for the group covering navigation and tracking, according to the criteria pairwise comparison matrix (with consistency ratio of 1.5% and eigenvalue of 5.067) the weight of quality features of sorted as follow: coverage/range (38.3%), cost to the user (20.1%), power consumption (15.8%), accuracy (14.5%) privacy (5.9%), and cost of the infrastructure (5.4%).

As a second level comparison, the pair-wise comparison from the criteria point of view, the results of the experiments and literature review summarized in Tables 3 and 4, are used. This means, for example, regarding accuracy, the priority of GNSS over WLAN is determined based on the ratio of the accuracy of GNSS positioning (4–7 m) with respect to the WLAN's (2–4 m). For qualitative parameters some values are assigned to the scores. For example, for privacy, technologies are weighted as GNSS (and HSGNSS, Pseudolite, barometer+GNSS, INS+GNSS) (33.8%), UWB (12.5%), BLE (12.5%), Ultrasound (11.2%), WLAN (11.3%), RFID active (8.4%), tactile floor (5.1%) and RFID passive (4.2%), and camera (1.1%). The results have a consistency ratio of 1.5% and principal eigenvalue of 8.142.

At this stage, the positioning technologies, which cannot be used as a stand-alone technology, such as a barometer, are either excluded or the combination of them with another technology is considered as one single alternative. Based on the calculated priority and weights of positioning technologies and also quality features of each LBS application group, it is possible to prioritize each technology for each application.

$$\begin{aligned}&\text{Priority of each technology}\\&\quad=\text{summation of (importance of each quality feature}\\&\qquad*\text{priority of the technology from quality feature perspective)}.\end{aligned}$$

For example for the application group of information retrieval, the GNSS and WLAN are the most suitable positioning technologies with values of 16.2% and 16.5%, respectively. This can be done for all the application groups and the most suitable positioning technology for each application group is shown in Table 4.

3.2. Privacy concerns

Personalization is one of the key features of intelligent, context-aware, adaptive LBS. However, this requires the storage of personal preferences, activity history, current location and previous movements [58]. The threats associated with the violation of location privacy can dramatically limit the development, adoption and growth of LBS applications. LBS require the user to disclose their location to enable personalization. Service providers can potentially store, use (or misuse, reuse), and sell location data. Such potential threats can discourage users [59]. Unrestricted access to information about an individual's location could potentially lead to harmful encounters.

In addition, an individual's location history can potentially disclose activities, preferences, health, background and history and other (even more) private aspects of life. In particular, if the locations are accompanied by temporal information, the trajectory of movement, then more can be revealed [60]. De Montjoye et al. [61] understood that only four anonymous spatio-temporal points are enough to uniquely identify 95% of the individuals within the crowd.

In addition to these potential threats, lack of awareness regarding issues of location privacy among ordinary users may introduce an even big threat to LBS markets: the public may overestimate the threat [62,59]. This might be partially due to the fact that the necessary guards to protect location privacy do not need to be the same for all applications and services. The level of accuracy, the potential of unauthorized access and/or inference of higher-level private information, and the impact of any privacy violation in each application can be different [63]. The level of privacy for each application category identified within the survey is illustrated in Table 1.

In order to access location-based services, mobile users have to disclose their location to the service providers. However, such information can be simply reused by the same or other sectors without the user's permission. In order to protect the privacy of the LBS users, there are several approaches and mechanisms which we can categorize into four groups; regulatory, privacy policies, anonymity, and obfuscation.

Regulatory approaches to privacy develop and define rules to manage the privacy of individuals and the public. Although these are being developed by governments and legislative sectors and are, in general, strictly enforceable, they have faced several challenges. In addition, due to the time-consuming and complicated process involved, the number of privacy regulations is still relatively small for this fast-growing technology and they are far behind the needs and demands.

While regulatory approaches target global or group-based safeguards, privacy policies provide more flexible and adaptive protection mechanisms for individuals [64,65]. Location privacy policies, such as the Internet Engineering Task Force (IETF) GeoPrive, the World Wide Web Consortium's privacy preferences project (P3P) and Personal Digital Rights Management (PDRM) are current protection approaches. The nature of LBS applications introduces a big challenge to these privacy policies. The rapidly changing, highly innovative and fast growing ecosystem of LBS makes it difficult to update, issue or adapt the policies to protect emerging applications and technologies.

Anonymity-based approaches, such as K-Anonymity [66], disassociate location information from the user's identity and minimizes the possibility of inference and traceability the other information. Although they are technically easy to implement, they can be a barrier to the personalization of LBS, which are becoming more common and for many applications essential [67]. A possible solution for this can be pseudonym-based approaches as they allow partially some levels of personalization by keeping the individual anonymous while giving a persistent identity (an alias or pseudonym). The pseudonym can be linked to their actual identity when using higher safeguards. However, location patterns may lead to identification if this data is combined with other data as well. Sweeney [66] shows that 87% of people can be uniquely identified by combining otherwise anonymous attributes, such as their postcode, age and gender.

Obfuscation lowers the positional quality of the recorded user location to protect it from misuse by degrading the quality of locational information through the addition of inaccuracy, imprecision and vagueness [68]. As it mainly deals with the quality of positional data, Table 2 summarizes aspects of quality-of-service provided by the common LBS positioning technologies.

It can be the case that for many scenarios more than one privacy protection approach is required. Table 5 summarizes the challenges and disadvantages of each four categories identified. Despite the need for these multiple approaches to protect user privacy, in many situations (location) data does not need protection. Due to their spatial and/or temporal inaccuracy, there are some datasets that may not be worth attacking and therefore (extra) protection may no longer be required. However, one application's public data can be considered private for another, and vice versa. Also, social trends and public perception of the concept of privacy is fluid.

Table 4
Positioning technologies suitability for each LBS application category.

Indoor LBS Category	The Top3 Most Suitable Positioning Technology already available
Indoor Navigation and Tracking	1. Bluetooth Low Energy (BLE) — 17.27% 2. Wireless Local Area Networks (WLAN)— 13.75% 3. (GNSS+INS) — 13.3%
Marketing	1. Wireless Local Area Networks (WLAN) — 12.65% 2. Bluetooth Low Energy (BLE) — 10.25% 3. Mobile Network — 8.47%
Entertainment	1. Wireless Local Area Networks (WLAN) — 17.45% 2. Camera — 16.98% 3. Mobile Network — 10.43%
Location-Based Information Retrieval	1. RFID — 10.43% 2. Bluetooth Low Energy (BLE) — 9.67% 3. Wireless Local Area Networks (WLAN) — 9.65%
Safety and Security	1. (GNSS+INS) — 10.43% 2. Wireless Local Area Networks (WLAN) — 8.74% 3. The rest are almost equally unsuitable (suitability less than 5%)

Table 5
Privacy protection approaches.

Privacy Protection Category	Disadvantages And Challenges
Regulatory	• The possibility of having different interpretations and implementations of the very same rule and regulation. • The small number of rules and regulations due to the time-consuming and complicated process of their development, particularly for fast-growing, innovative and rapidly changing technologies and applications. • The regulations, on their own, cannot guarantee or even prevent the invasion of privacy and they only act after the privacy violation has happened.
Policy	• The rapidly changing, highly innovative and fast growing ecosystem of LBS makes it difficult to update, issue or adapt privacy policies • The privacy policies need to rely on the available regulation to be practically applicable and the liability relies on supporting regulations and rules.
Anonymity	• Anonymity can be viewed as a barrier to the personalization features of LBS, which are becoming more and more popular and, for many applications, essential. • The pattern of anonymized data may lead to identification of the individual if combined with other data.
Obfuscation	• Obfuscation can compromise the quality of LBS responses that depend on the quality of positional data. • It needs user authentication. • Obfuscation assumes that users are able to choose what information to reveal to a service provider, which may not always be the case.

3.3. Availability of content

LBS is supposed to provide tailored information to users with satisfy their requests, needs, situations and preferences. This requires the availability of relevant information to be filtered based on the query and contextual information. Among all the relevant data sources, maps and other spatial datasets are essential for the functionality of many LBS applications. These include transport networks for routing and navigation and locational maps of points-of-interest. However this content, particularly for indoors, raises issues of privacy and legal concerns. In addition, the often limited access makes it is difficult to assure the quality of indoor data such as its reliability and its spatial, temporal and thematic accuracy [69].

Google is one of the major providers of indoor LBS. Their product tells customers what floor they are on in a building. Google's indoor mapping concentrates mainly on important well-frequented buildings such as major airports. Detailed floor plans automatically appear when the user is viewing the map and the map is zoomed to buildings where indoor map data is available. But even for this newest release, many indoor areas are not available and, even when present, does not provide full navigational instructions. For example, stairs between floors are not included. Overall, indoor map coverage and resolution is not comparable with that for outdoors.

The poor coverage of indoor maps is not mainly a technical issue [70]. It is more due to the privacy issues associated with privately-owned properties and also the lack of suitable policies and technical standards for privacy protection this data.

One of the solutions, which has already shown its practicality and growing popularity, is crowd-sourcing and volunteer-based mapping [71]. Collaborative mapping through crowd-sourcing is one method of generating spatial content. It involves contributions from a large, disparate group of individuals. These methods, part of Web 2.0, use applications that allow people to upload information easily and allow many others to view and react to this information [72].

There are several tools available which allow users to create and edit web content, including tagging tools, wiki software and web-based spatial data editors. This method of data collection and generation uses citizens in large-scale data collection, sometimes also with the participation of companies and is referred to as volunteered geographic information (VGI). This approach could be very suitable for indoor mapping. The popularity of VGI is growing. Table 6 shows that the number of contributors in 2016 has been six times that in 2011 and more than 3.5 billion nodes and 450 million ways (links) have been stored, a three-times increase.

These approaches can be partially used by mapping agencies and data gathering institutions. Despite the popularity and the involvement of citizens with the collection of geospatial data,

Table 6
Statistics for the number of registered contributors and the stored ways and nodes in the OSM database.

Year	Percentage of active contributors	Number of Registered Contributors	Number of ways	Number of nodes
2011	3.5%	501,465	116,196,873	1,280,961,903
2012	2.8%	1,100,215	159,811,148	1,680,385,760
2013	1.50%	1,824,599	207,118,018	2,108,992,829
2014	1.20%	1,882,817	262,569,075	2,629,122,837
2015	1.00%	2,371,829	318,959,062	3,126,436,219
2016	0.85%	3,106,987	445,110,741	3,551,080,106

there is still only poor mapping coverage for indoor spaces. VGI projects, such as OpenStreetMap (OSM), are contributing to the increasing interest in indoor mapping but there is still a long way to go. Standardization of data formats, scale, metadata and privacy policies are still needed. Global coverage of indoor mapping is likely to find obstacles in the form of cultural and political opposition. Many of those who openly contribute to VGI projects for outdoor public environments will not want to publish maps of private indoor property. In addition, if they do contribute this data to a VGI project, these maps cannot be edited by other contributors since they may not have access. This simple example highlights accuracy, reliability, and precision as some of the key criticisms regarding VGI data.

The best option to improve coverage of indoor maps might be changing policies and legislation where necessary to encourage more contributions to crowd-sourced data. Privacy is an on-going issue that needs to be included in these. However, there are many public places, such as shopping malls, airports and universities, which already provide their map online via their own web pages. These types of locations can be good targets to start the expansion of indoor maps.

Considering these issues (positioning, map coverage and privacy) it appears that indoor applications comprise quite a challenging segment of LBS. In addition, there are some other challenges such as their complexity for modeling and analysis, contextual information inference, data storage and streaming, which need a further level of customization for current LBS services.

4. Discussion

Indoor LBS has not yet found its position in the market, despite the fact that people spend most of their time inside buildings, e.g. offices and apartments. Indoor LBS faces several technical and non-technical challenges and this paper has studied the three most important ones, according to a survey conducted, including indoor positioning, availability of indoor maps, and location privacy.

In terms of positioning technologies, the usability analysis of current solutions for different segments of indoor LBS market shows that there is a gap between the quality of positioning services and the requirements of indoor LBS applications. This becomes particularly concerning when it comes to safety and security applications, which are potentially life-saving such as emergency services. Multi-sensor positioning could provide a solution for indoor positioning but it is subject to miniaturization of more devices to be embedded in a size of a mobile phone, as the most widely used device for using indoor LBS. There are also some promising results based on new technologies, such as quantum technologies, which requires more tests and more importantly mass market (with lower cost) productions.

For indoor content, particularly maps as the essential type of contents for indoor LBS, there are still some long ways to go. Storing indoor maps are somehow associated with the third biggest challenge of indoor LBS, i.e. privacy. What this paper finds a relatively smoother start to improve the coverage of indoor maps, is crowd-sourcing the indoor maps of public places. Crowd-sourced maps can hugely improve the coverage of indoor places, as the biggest issue for indoor maps unavailability rather than quality. Also, it seems that in the era of social media networking, particularly new generation can have milder privacy concerns and so this can help the development of indoor LBS. In addition, new/updated legislations and policies regarding location privacy can make a big difference.

5. Conclusion

Indoor LBS is not commonly implemented in mobile services due to the many technical challenges that remain. This paper has analyzed the requirements and challenges of providing indoor LBS by reviewing the available literature and conducting a survey. The main requirements of indoor LBS applications were determined and challenges were identified. Aspects related to quality of service (including availability, accuracy, and cost) were identified as the major challenges. The development of multi-sensor positioning services and new technologies such as BLE give potential solutions. The paper also highlighted the most suitable existing solutions using an Analytic Hierarchy Process on the LBS application categories. The results of this analysis shows that in some applications, such as emergency and security, there is actually no good option for indoor positioning. WLAN is the technology that comes as the most suitable over all application categories. However, its relatively low suitability value in specific areas indicates the need for improvement or the development of something superior.

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