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Survey paper

INDOOR LOCALIZATION AND TRACKING: METHODS, TECHNOLOGIES AND RESEARCH CHALLENGES

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Abstract. *The paper presents a comprehensive survey of contemporary methods, technologies and systems for localization and tracking of moving objects in an indoor environment and gives their comparison according to various criteria, such as accuracy, privacy, scalability and type of location data. Some representative examples of indoor LBS applications available on the market are presented based on the reviewed localization technologies. Prominent research directions in this domain are categorized and discussed.*

Key words: *location sensing, indoor localization, indoor positioning, triangulation, fingerprinting, location-based services, accuracy*

1. INTRODUCTION

The proliferation of wireless communication and mobile devices with sensing capabilities has given rise to mobile and pervasive systems and services that offer novel opportunities for users behaving and acting in the environment. The range of services, often referred as location-based (LBS) and context-aware services, have emerged in many different domains, such as personal navigation, mobile tourist guides, vehicle tracking, traffic monitoring, pervasive healthcare, emergency management, environment protection, analysis of animal behavior, etc. [1][2]. At the heart of these services lies the ability to

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sense and determine in real-time the location of mobile users [3]. In open space (outdoors), mobile devices/users are most commonly and accurately positioned by GPS technology and satellite-based infrastructure that provide location as a point in a geographic reference system. The current satellite positioning systems are: NAVSTAR Global Positioning System[1], GLONASS[2] and Galileo[3], which is expected to be fully operational in 2020. The main disadvantage of GPS-based positioning is its dependency on a direct line-of-sight with the satellites and thus unavailability in indoor spaces, as well as in natural/urban canyons. Also, the accuracy of positioning methods based on cellular networks (e.g. Cell-ID or TOA – *Time of Arrival*) is not sufficient for use indoors.

Nevertheless, people spend most of their time indoors (80-90%), in offices, shopping malls, hospitals, metros, museums, etc., hence the possibility to determine locations and trajectories of people and objects inside buildings and other closed structures becomes increasingly important. For advanced indoor LBSs supporting museum/fair guides, fire rescues, emergency management, or simply ordinary businesses, quality and effectiveness of services demand knowing immediately where people and resources are inside buildings and other complexes and how to navigate to certain locations [4]. It is of great importance to provide seamless integration and handover of different localization technologies while users move from open space to various closed environments and vice-versa, and efficient adaptation of indoor LBSs to changing environments, contexts and situations.

With advances in sensor technologies and wireless communications, various indoor localization methods and systems have been developed over the past years. In indoor environments, positioning is mainly achieved through the use of radio technologies, such as Wireless Local Area Networks (WLAN, Wi-Fi), Bluetooth, Zigbee, Ultra-wideband (UWB), and Radio-frequency identification (RFID), or infrared (IR) and ultrasound technologies [5][6]. In 2011, twenty-two international companies formed the In-Location Alliance [7] to standardize and commercialize the indoor localization technologies and systems. The alliance currently includes large multi-national companies such as Nokia, Samsung, Qualcomm and Sony, and more than a hundred other high tech companies, showing the importance of indoor LBS research and development domain.

This paper presents a survey of the state-of-the-art methods, technologies and systems for indoor localization and tracking and reviews of some advanced indoor LBS applications based on these methods and technologies. The paper is organized as follows. Section 2 describes methods and algorithms for pervasive positioning. Section 3 presents indoor localization systems and technologies, gives their comparative classification, and presents representative examples of indoor LBS applications. The prominent research directions are categorized and discussed in Section 4. Finally, Section 5 gives a conclusion.

2. METHODS AND TECHNIQUES FOR INDOOR LOCALIZATION

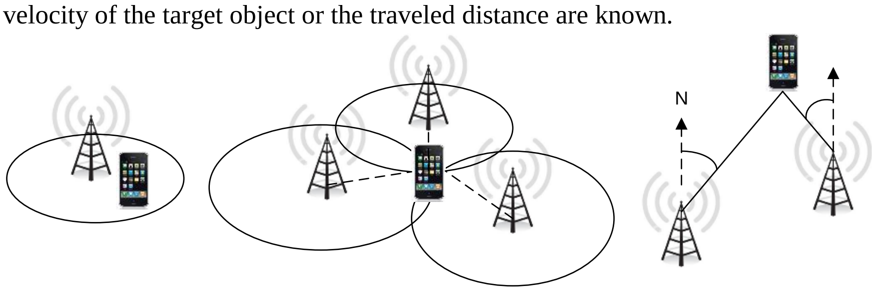
The core of any localization method relies on the real-time measurement of one to several parameters, such as angles, distances, or distance differences [8]. Measurement parameters reflect the location of a target object relative to a single point or several fixed

[1] http://www.gps.gov/
[2] http://www.glonass-ianc.rsa.ru/en/
[3] http://www.esa.int/esaNA/galileo.html

points in the environment with the known locations. Such parameters are measured using physical characteristics of electromagnetic radio and infrared signals, as well as ultrasound signals, such as their travel time, velocity or attenuation. After the determination of the required parameters, the target object's location can be calculated using the measurement results and the known locations of the fixed points.

There are four principal techniques and methods for location calculation and estimation:

- The proximity technique (see Fig. 1a) derives the location of a target object with respect to its vicinity to the location of the known object(s). A target object receives the signal from a given node, so the location of the node or the symbolic cell identification defines the location of a target.
- The triangulation technique uses the triangle geometry to compute locations of a target object. It is applied via lateration (actually trilateration) (see Fig. 1b), that uses distance measurements to points with the known locations, or via angulation (sometimes also referred as triangulation) (see Fig. 1c), which measures angles relative to points with the known arrangement. Since electromagnetic/ultrasound signals move with the known and nearly constant speed, the determination of the time difference between sending and receiving a signal enables computation of the spatial distance between a transmitter and a receiver. Known distances from three or more transmitters provide accurate positioning of the target object. For the angulation technique, antennas with direction capabilities are used. Given two or more directions from fixed locations to the same object, the location of the target object can be computed.
- Scene analysis techniques involve examination and matching a video/image or electromagnetic characteristics viewed/sensed from a target object. The analysis of electromagnetic "scene" sensed by a target object defined by electromagnetic signals and their strengths from different transmitters, provides the determination of location using a pattern matching, radio map technique. Using video cameras, a positioning system can detect significant patterns in a video data stream to determine the user's location. If users wear badges with certain labels, they can be detected in video images and thus localized and tracked in indoor environment covered by a camera. At the other extreme are techniques involving the matching of perspective video images of the environment captured by a camera, worn by a person or mounted on a mobile robot platform, to 3D models stored in an image/video database of the mobile device.
- Dead reckoning techniques provide estimation of the location of a target object based on the last known location, assuming that the direction of motion and either the velocity of the target object or the traveled distance are known.



a) b) c)

Fig. 1 Location sensing techniques a) proximity b) trilateration c) angulation

Indoor localization technologies, based on one or more positioning techniques and methods, possess different characteristics that determine their suitability for specific indoor LBS and context-aware applications.

Indoor localization and tracking technologies can be based on either an existing communication network, or a dedicated network/infrastructure that is solely used to receive/transmit positioning signals. Mobile devices worn by a person or mounted on a robot can be active when transmitting a signal themselves, or passive when just receiving a signal. The location can be determined in the mobile device itself, in the wireless network, or within the dedicated positioning infrastructure.

Indoor localization systems differ in accuracy, precision, scope, the type of determined location: geometric or symbolic, and the cost. An estimated location is considered accurate if it corresponds, as much as possible, to the true location of the target object. Precision refers to the repeatability of the measurement and indicates how sharply a location can be defined for the sequence of location determinations. The accuracy of a localization system could be defined by an uncertainty area, i.e. the location is actually defined as an ellipse (ellipsoid) around the determined location.

An indoor localization system delivers the target object's location with regard to a spatial reference system or to a defined symbolic space. Geometric location is determined in the defined geographic/geometric reference system, such as WGS-84 or a local coordinate system, and can be either absolute or relative to a reference point. The localization and tracking of moving indoor objects can be either in 2-D, 3-D, if the object can be localized in the entire volume of 3-D space, or in 2.5-D, when the object location is tracked at discrete levels, e.g. floors, of the 3^{rd} spatial dimension. For the purpose of indoor navigation and tracking the symbolic location is more appropriate. Thus, indoor localization systems mainly determine symbolic locations in terms of cell identifiers, buildings, room numbers, objects in the room, etc. Indoor localization systems differ also in scope of location determination. Since the majority of localization methods depend on the propagation properties of electromagnetic signals their effectiveness and efficiency depend on the environment. While satellite-based (GPS) and cellular network-based positioning systems are intended for outdoor space with the scope that may be the whole Earth, a certain region or a metropolitan area, indoor localization systems are characterized by a much narrow scope, such as a university campus, a building or a room. There exist a variety of indoor localization technologies and solutions intended for indoor spaces that require some kind of infrastructure that is usually not available in open space. An indoor localization system determines also the cost needed for a system to be fully operative, such as the time and space for installation and maintenance of the required infrastructure, as well as the price of equipment that is required. For example, the need for specialized hardware and/or network installations, leads to higher deployment and maintenance costs and poor scalability.

Indoor localization methods and technologies can be classified according to the scope of infrastructure needed for localization, the type of such infrastructure if any and their suitability for indoor or limited outdoor spaces. Also, according to the part of the system where the location is calculated/estimated, i.e., whether a mobile device locates itself or is tracked, indoor localization systems can be centralized or distributed. All mentioned characteristics significantly determine the usability of particular indoor localization technologies for specific indoor LBS applications.

Thus, according to the wireless communication and sensing technologies employed, indoor localization technologies can be classified as:

- Wireless communication-based localization technologies (Wi-Fi, Bluetooth, UWB, Zigbee, RFID, IR, ultrasound, etc.) are based on wireless communication or stand-alone infrastructure (WLAN and WPAN) constrained to indoor and limited outdoor spaces, providing determination of location either at the mobile device or in the infrastructure.
- Dead reckoning localization technologies use motion sensors (accelerometer, digital compass, gyroscope, etc.) and odometers to determine location at the device without the need for infrastructure, with the scope limited by the accumulated error.
- Video scene analysis represents localization technologies based on the processing of video signals to detect specific tags in the scene (barcodes) or match the scene with prerecorded images/video to determine the location at either the mobile device itself, or to track target objects moving in the scene.

3. Indoor Localization and Tracking Technologies and Systems

Over the last twenty years, many indoor localization technologies have been proposed, developed and experimentally evaluated by both academia and industry that provide appropriate location data to tracking and navigation capabilities of indoor location-based and context-aware services. But there is still a lack of wide acceptance and large scale deployments of indoor localization systems.

The most popular indoor localization systems use Wi-Fi technology, because of wide availability of Wi-Fi network infrastructure [9]. Wi-Fi positioning systems use a radio propagation model to determine the distance to the various access points and then triangulation techniques (TOA, TDOA) to estimate location of a mobile device. Multipath distortion and variability of Wi-Fi signal strength in time limit the accuracy of such techniques. Most currently available Wi-Fi positioning solutions are based on the scene analysis technique, called the fingerprinting technique. The method uses the Received Signal Strength Indication (RSSI) to measure the strength of signals received from the surrounding access points at discrete locations in space. Such a radio map has to be built before the system is operational. The calculation of the location consists of measuring the RSSI from several access points (AP) and then attempting to match these measurements with the RSSI values of the previously calibrated location points stored in a radio map database. Depending on the pre-built radio map and the density of calibration points, the accuracy of the fingerprinting technique is expected to be in the range of 1 to 10 m [6][9]. The major limitation of the Wi-Fi based fingerprinting localization systems is the construction of the RSSI radio map that needs to be generated in advance and updated after furniture reallocation, removal/reallocation of the existing access points and installation of new ones, or algorithmically adapted, as proposed in [10]. The fundamental problem in Wi-Fi fingerprinting is that heterogeneous mobile devices measure radio signal strength differently. In that case, either a calibration for each new wireless device is needed or specialized methods, such as hyperbolic location fingerprinting, presented in [11], need to be implemented.

One of the first Wi-Fi localization systems was RADAR [12]. Recently many Wi-Fi based localization systems emerged. Hensen at al. in [13] describe SmartCampusAAU as a platform that enables indoor positioning and navigation based on Wi-Fi fingerprinting technique and supports both device- and infrastructure-based positioning. The localization platform is available on all major mobile platforms (Android, iPhone and Windows Phone). The work of Laoudias et al. in [14] presents the localization approach based on signal strength differences, that is more robust to device variations and maintains the localization accuracy regardless of the number and type of contributing devices. Besides research works, several commercial localization systems are also available on the market, such as Ekahau Real-Time Location System [15], Skyhook Wireless [16] and Navizon indoor location solutions [17].

On the other hand, UWB communication technology has emerged, providing better positioning accuracy than Wi-Fi. It is suitable for high-precision real-time positioning using TOA, TDOA, AOA and fingerprinting. UWB signals are less sensitive to multipath distortion and environment than conventional RF-based positioning systems, so they can achieve higher accuracy. At bandwidths of at least 500MHz and high time resolution in the order of nanoseconds, it is possible to obtain accuracy of ranging and localization at cm-level [18]. A MUSIC-based method proposed in [19] can achieve high localization accuracy, in the order of 1 cm, by using spatially distributed antennas that transmit the same UWB impulse sequence used for self-localization of IR UWB nodes [20]. However, the high cost of UWB equipment and infrastructure deployment results in its limited availability for positioning [21]. To date, several UWB positioning systems have been implemented and deployed, such as the Ubisense system [22] and PulsON [23] system developed by Time Domain.

Bluetooth is a wireless technology that can be used for localization and tracking, mainly indoors. Bluetooth positioning systems have similar working principles as the self-localization schemes of sensor networks. The operation principle of both types of systems is based on obtaining the range information to anchor devices or access points and exploring unknown device locations using various algorithms. The majority of the available research and commercial systems are based on trilateration using the RSSI for calculating distances between Bluetooth devices, although several reported systems have explored proximity, cell-based approach. A comprehensive evaluation of all Bluetooth signal parameters and their suitability for localization purposes is provided in [24]. Bluetooth localization methods are primarily based on RSSI and Link Quality (LQ) measurements. Cell-based methods rely on the proximity (visibility) of Bluetooth beacons for determining the location of a device and are gaining popularity with the implementation of Bluetooth LE (Low Energy) standard. The localization accuracy of the system is 1 - 5 m (< 0.3 m for Bluetooth LE) and depends on the positioning technique used and the characteristics (density, layout, etc.) of the deployed infrastructure of Bluetooth devices and beacons [6][25]. Current examples of Bluetooth positioning systems are ZONITH Indoor Positioning System [26], TOPAZ [27] and Apple iBeacon [28].

In general, RFID systems are designed so that the reader detects the vicinity of a tag and retrieves the data stored in that tag. Therefore, the absolute location of the tag is not known but the RFID system is aware that a tag is placed at a certain range that depends on the type of the system used, either active or passive RFID [29]. Besides the proximity technique that provides symbolic location of the tag according to a reader location, there are several methods for performing accurate positioning using active RFID technology. These methods employ techniques such as AOA, TDOA and RSSI that achieves accuracy in the range of 1-5 m, or even bellow 1m, depending on the density of tag deployment and RFID reading ranges [30]. The examples of location sensing systems using the RFID technology are SpotON [31] and LANDMARC [32].

The ZigBee technology is an emerging wireless communication standard for PAN/LAN intended for applications which do not need significant data throughput, but require low-power consumption. As such, ZigBee is widely used in smart home environments. The localization is usually performed using proximity and TOA methods based on distances from the surrounding ZigBee nodes calculated using RSSI. Several recent research papers propose and evaluate localization algorithms and systems based on ZigBee achieving the accuracy of 1-10 m [5]. Larranaga et al. in [33] present a flexible indoor localization system based on ZigBee Wireless Sensor Networks based on RSSI level measurements. The localization system consists of two phases: calibration phase, which is performed whenever a blind ZigBee node needs to be located and actual localization phase with accuracy 3m on average. Hu et al. in [34] propose an algorithm based on signal preprocessing and calibration to correct multipath propagation and improve ZigBee based indoor localization. Bras et al. in [35] describe a ZigBee location protocol, implemented by reducing end nodes communication intervals and developing a proper router and coordinator firmware. This protocol provides two localization methods based on proximity and multi-RSSI reference nodes location that provides support for triangulation and fingerprinting.

Dedicated positioning methods, commonly based on infrared and ultrasound technologies, provide a high degree of accuracy, but require expensive equipment limited to a small scale that usually have high installation and maintenance costs [5]. In infrared (IR)-based systems, each tracked person is wearing a small infrared device that emits a unique pulse signal representing its unique identifier. The signals are detected by at least one particular IR sensor in the vicinity. A location server estimates IR device location by aggregating data obtained from fixed IR sensors deployed within the indoor environment. The Active Badge system [36], as the first IR positioning system, works this way and provides symbolic location information at the room or smaller level depending on deployed IR sensor infrastructure. Ultrasound-based systems use an ultrasound time-of-flight lateration technique to provide more accurate physical positioning than by using infrared signals and sensors. The existence of NLoS (Non Line of Sight) conditions and multipath propagation in indoor environments are the main problems in the development of reliable ultrasound-based indoor localization system, achieving accuracy in the range of 1 cm – 1m [37]. The prominent examples are Active Bat system and the Cricket indoor location system [5].

Many existing indoor localization approaches reviewed so far require infrastructure (e.g., Bluetooth beacons) to achieve reliable accuracy. There are also passive positioning systems that do not require specialized infrastructure. Such systems sense naturally occurring signals or physical phenomena and are based on, for example, magnetic compasses sensing the Earth’s magnetic field, inertial sensors measuring acceleration and the heading of an object in motion, and vision systems sensing a scene and its features or recognizing specific visual patterns (barcodes). In order to be functional they require indoor map information. Dead reckoning is the process of estimating the current location of a moving device using the location calculated at some previous time instant, and the velocity, speed or heading estimate till the current time instant. The dead reckoning-based localization systems, also known as Inertial Navigation Systems (INS), can be used for both indoor and outdoor positioning. In indoor environment such systems use accelerometers to obtain human velocity rate information through step detection and step length estimation. Also, digital compass and gyroscope measurements are used for direction and angular rate information. All measured data is processed to continuously calculate the location, direction (bearing), and velocity of a moving object without the need for external references, but taking into account the known indoor map constraints. On the other hand, the velocity of indoor vehicles or robots is calculated by appropriate odometers. However, even very small errors in the rate information provided by inertial sensors cause an unbounded growth in the error of the integrated measurements, usually referred as the “drift error”.

Dead reckoning based systems have been implemented in various indoor tracking domains, such as for pedestrian navigation [38] and mobile robot localization [39] [40]. Hardegger et al. in [41] present Smart ActionSLAM, an Android smartphone application that performs location tracking in home and office environments that uses the integrated motion sensors of the smartphone and an optional foot-mounted inertial measurement unit to perform personal localization and tracking. A mobile robot localization system that combines INS and odometry, and use Kalman filters to estimate the orientation and velocity of mobile robots to calculate their more accurate positions, is presented in [39]. Localization systems that do not require pre-deployed infrastructure, or with which such an infrastructure could be deployed fast by e.g. ultrasound bacons, are particularly suitable for use by emergency responders such as firefighters. The conditions they work in are significantly more demanding, caused by darkness, smoke, fire, power outages, etc., so special efforts have been put to the research and development of appropriate localization and navigation systems based on dead reckoning, but also ultrasound and RFID [42].

Visual positioning systems use low cost 2D tags (e.g., barcodes) with the encoded information that can be recorded and processed by a mobile device with a built-in camera, as in the system proposed in [43]. The symbolic location of a device is estimated by finding the tag’s identifier and associated location in a deployment database, or by decoding the location information embedded in the tag itself [44]. Positioning systems based on video scene analysis are based on computer vision technology to recognize tracked objects in video data. Easy Living by Microsoft Research provides one example of this approach [45] where a video surveillance system tracks moving objects recognized in the video scenes. Also, the mobile device can use video scene analysis to estimate its location by comparing a snapshot of a scene generated by itself with a number of pre-observed simplified images of the scene taken from different positions and perspectives. An improved performance and sub-meter (1 cm – 1 m) accuracy of camera-based localization systems has promoted them as promising positioning solutions for applications in industry, as well as robot and pedestrian localization and navigation [46]. Murillo et al. in [47] present a wearable omnidirectional vision system and a novel two-phase localization approach running on it for personal localization and guidance. It is based on real time visual odometry SLAM (Simultaneous Localization and Mapping) method adapted to catadioptric images augmented with topological-semantic information.

The important characteristics of indoor localization systems and related technologies are reviewed in Table 1.

Indoor LBSs deliver local spatially-referenced information and spatial–processing power to mobile users in accordance with their past, current and predicted location, or to the locations of the moving/stationary objects of their interest. Depending on services' requirements and the context of their usage, different indoor localization technologies and systems are used at the heart of such services. There are a lot of classifications and taxonomies of location-based services presented in the literature so far [1][48], while new services continue to emerge. This is an attempt to make a classification of indoor LBSs, the localization technologies and systems they are based on, and to present some prominent examples of such applications.

Table 1 A review of indoor localization technologies and systems

System	Technique	Methods	Accuracy	Calculated at		Location type		Scalability	Cost
				Mobile device	Infrastr-ucture	Geo metric	Sym bolic		
Wi-Fi	Proximity Trilateration Angulation Scene anal.	Cell-ID TOA TDOA AOA RSSI	10-100 m (Prox.) 1-10 m	√ RSSI	√ TOA TDOA AOA Prox.	√		high	low
UWB	Trilateration Angulation	RSSI TOA,TDOA, AOA	1cm-1 m		√	√		low	high
Bluetooth	Proximity Scene anal. Trilateration	Cell-ID RSSI TOA	1-5 m	√ TOA RSSI	√ Prox.	√	√ Prox.	high	low
RFID	Proximity Trilateration Scene anal.	Cell-ID RSSI	1-5 m	√	√		√	medium	low
Zigbee	Proximity Trilateration	Cell-ID RSSI	1-10 m	√ RSSI	√ Prox.	√	√ Prox.	low	medium
Infrared	Proximity Trilateration	Cell-ID TOA	1cm-5m	√ TOA	√ Prox.		√	low	medium
Ultrasound	Trilateration	TOA, TDOA	1cm-1m		√	√		low	high
Video scene analysis	Scene anal. Angulation	Computer vision	1cm-1m	√	√	√		low	high
Barcodes	Proximity Angulation	Pattern recognitin	1-10 m	√	√	√	√	medium	high
Sensor networks	Proximity Trilateration	Cell-ID RSSI	10 cm-1 m		√	√		medium	medium
INS, PNS	Dead reckoning		1-10 m	√		√		high	low

The location-based service requirements and applications of localization technologies and methods in various indoor LBSs available on the market are reviewed in Table 2 along with the accuracy required by a particular service (Very high, from 0-1m; High, from 1-5m; Medium, from 5-15m; and Low, greater than 15m).

Table 2 Applications of localization technologies and systems in indoor LBSs.

Application domains	Indoor localization technologies	Accuracy	Indoor LBS and system examples
Asset tracking	RFID, Infrared (IR), Barcode Scanning	Very high	MultiLUX http://www.multilux.eu/
Location-based advertising	Bluetooth beacons (iBeacon)	Low	Mobile to Mortar™ - inMarket http://www.inmarket.com/
Shopping assistance system	Bluetooth, WiFi	High	StoreMode - PointInside http://www.pointinside.com/ aisle411 - Walgreen stores http://aisle411.com/
Museum, fairs, airports, guided tours	Wi-Fi fingerprinting, Bluetooth LE	Medium	awiloc® – Fraunhofer IIS http://www.iis.fraunhofer.de/en/bf/ln/technologie/rssi/mf.html
School, university campus	Wi-Fi fingerprinting, Wi-Fi TOA/TDOA	Medium	SmartCampusAUU http://smartcampus.cs.aau.dk/ Campus Guide (MazeMap) https://use.mazemap.com/
Hospitals, healthcare, Ambient Assistant Living (AAL)	Wi-Fi fingerprinting, RFID, IR	High	Radiance skyView http://www.radianse.com/ Versus Advantages www.versustech.com/
Emergency response and rescue management	Ultrasound, dead reckoning	Medium	Pathfinder- SummitSafety http://www.summitsafetyinc.com
Robotics	Dead reckoning, infrared, UWB, vision sensors	Very high	Adept MobileRobots http://www.mobilerobots.com
Indoor sports	Bluetooth LE	Very high	SportIQ - http://www.sportiq.fi/ using HAIP – http://quuppa.com/
Smart home	ZigBee	High	CC2431 - Texas Instruments www.ti.com/corp/docs/landing/cc2431/
Augmented reality	LLA Markers (barcodes), INS	High	Junaio http://www.junaio.com/

5. RESEARCH CHALLENGES

Localization technologies and location data collection systems provide many resources for the development of mobile and pervasive computing and applications. Still, a lot of open issues and future research directions should be explored for the development of the next generation of location-based applications and services.

5.1. Seamless integration of localization methods and systems

When considering the accuracy, availability and scope of a localization system while reducing its power consumption and cost, the integration of several localization technologies and systems is an option that might be relevant in many contexts. The goal of such integration is to improve the accuracy, availability and scale of single indoor localization systems while reducing cost. Moreover, the integration should also provide seamless handover of integrated localization systems that selects the most suitable positioning method with appropriate accuracy, granularity and resource consumption according to the user's context and situation and application requirements. Khider et al. in [49] present the indoor localization system based on Particle Filter approach and sensor fusion that combines GNSS, foot mounted inertial sensors, electronic compasses, baro-altimeters, indoor maps and active RFID tags to improve the accuracy and availability of the determined location. Other examples of integrated indoor localization systems are the integration of GPS and Wi-Fi based positioning [50], Bluetooth-based positioning and IR-based positioning technique in Topaz system [27] and a combination of IR and RFID localization to achieve higher accuracy in healthcare in Versus RTLS [51] .

5.2. Handling massive location data sets

With the rapid advances in mobile positioning technologies, a huge volume of location data is acquired wirelessly transmitted in the form of continuous data streams that need to be processed both off-line and online, so called Big Mobility Data. Such data with high arrival rate must be continuously monitored, processed and analyzed at the server side. Continuous location data streams define trajectories of moving objects that provide unprecedented information to understand their mobility and behavior [52]. Within this research direction, methods and algorithms of mobility data stream management are investigated, as well as application of high-performance and data-intensive computing techniques and systems for handling massive trajectory data collections, both on-line and offline, such as cloud computing techniques (MapReduce), GPGPU (OpenCL, CUDA) and cluster/grid (MPI) [53].

5.3. Participatory location-based sensing

With the proliferation of mobile phones with increasing sensing capabilities in everyday use, an important source of sensor data has become the users with their mobile devices [54]. Thanks to an increasing number of built-in sensors: ambient light, orientation, accelerometer, sound, camera, velocity, GPS, but also user-generated content (video, photo, sound, text, etc.), each mobile device can continuously capture, process, analyze and transmit spatially and temporally referenced data describing the context and the situation of the user [55]. We need efficient methods, techniques, algorithms and systems that provide collection, monitoring, processing and analyzing of large volumes of moving sensor data that define the context and situation in an indoor environment relevant to a particular application domain [56].

5.4. Semantic location and trajectory data

Once the location of an indoor moving object is known, in either geometric or symbolic form, many other pieces of information can be inferred to enrich such location information. The research aims to develop methods and software tools to provide collection, processing and analysis of indoor location and trajectory semantics. Semantic locations and trajectories enable development of advanced indoor LBSs which can provide more intelligent, proactive and valuable services to users navigating in indoor, but also in outdoor environments [57]. Processing, analysis and mining of semantic indoor locations/trajectories provide insights in semantics of movement and recognition of user activities, behavior and prediction of a future movement [52].

5.5. Privacy in indoor location-based services

Although indoor location determination provides many valuable location-based applications and services to mobile users, revealing people's locations to potentially untrusted service providers poses significant privacy concerns. There is a trade-off between the quality of services offered by an indoor LBS provider and the privacy of a user's location. The research in this direction focuses on the protection of sensitive locations against LBS providers and untrusted members of collaborative geo-social networks [58]. As such, it is highly related to all other research directions. Releasing locations and trajectories to the public or a third party could pose serious privacy concerns, so privacy protection in a LBS and location/trajectory data collection has increasingly drawn attention from the research community and industry [59].

6. CONCLUSIONS

This paper gives an overview of the methods, technologies and systems involved in the development of indoor location-based services for mobile users and moving objects navigated and tracked in the indoor environment. As no localization system is equally accessible and available everywhere, compromises between accuracy, scope, latency, privacy and costs may result in a system that seamlessly integrate two or more localization technologies and systems with regard to the corresponding application domain. For example, depending on the application requirements, the indoor LBS can employ Wi-Fi fingerprinting, Bluetooth beacons, and/or dead reckoning technologies to achieve medium/low accuracy, high availability and coverage, as well as minimal costs for indoor installations. If the indoor LBS requires higher accuracy within small coverage, there is a need for extensive node (RFID, infrared, ultrasound, UWB, optical tags, etc.) deployment and maintenance of a costly infrastructure. Thus, depending on indoor LBS application requirements the appropriate trade-off between indoor localization characteristics should be made and integration of localization technologies and systems should be developed.

Research challenges in pervasive localization and tracking cover not only data collection methods which are reaching a relatively mature level, but also semantic and technical research avenues where the objective will be to make the best possible use of the data. This is why location-based and context-aware services and systems are the object of several exciting research efforts, from semantic to participatory sensing and privacy, and where several international projects are performed, such as the EU projects MOVE[4] (Knowledge Discovery from Moving Objects) and MODAP[5] (Mobility, Data Mining, and Privacy) [60]. No doubts that other research projects will soon emerge at the international level as opportunities cover many different location-based application domains that can be successfully applied to indoor and outdoor environments.

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