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On Analyzing User Location Discovery Methods in Smart Homes: A Taxonomy and Survey

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Abstract

User Location Discovery (ULD) is a key issue in smart home ecosystems, as it plays a critical role in many applications. If a smart home management system cannot detect the actual location of the users, the desired applications may not be able to work successfully. This article proposes a new taxonomy with a broad coverage of ULD methods in terms of user satisfaction and technical features. In addition, we provide a state-of-the-art survey of ULD methods and apply our taxonomy to map these methods. Mapping contributes to gap analysis for existing ULDs and also validates the applicability and accuracy of the taxonomy. Using this systematic approach, the features and characteristics of the current ULD methods are identified (i.e., equipment and algorithms). Next, the weaknesses and advantages of these methods are analyzed utilizing ten important evaluation metrics. Although we mainly focus on smart homes, the results of this article can be generalized to other spaces such as smart offices and eHealth environments.

Keywords:
User location discovery, smart home, localization, survey.

1. Introduction

Smart home has been considered as a topic of interest for both academic researchers and industries. The term *smart home* refers to homes equipped with intelligence-based technologies that can supply an added value for users [1]. We have recently seen a remarkable advance in smart home technology. It is moving rapidly from programmable thermostats to an era where all of a home's systems are integrated into a centralized control unit, accessible from multiple entry points such as touch pads, computer screens and other wireless mobile devices (e.g., smart phones and tablets). The result is a highly personalized environment, a home that reacts to individual needs and demands, and even anticipates actions and events [2, 3].

The purpose of the smart home is to create an environment where the inhabitants can live in comfort with a minimal effort to maintain their preferred home environment. In order to provide a variety of services to the inhabitants, smart homes need to process as much context as possible. The context is defined as the information that can be used to characterize the environment of an inhabitants. Context information can include the location of humans and objects within the particular environment, inhabitant's action and behavior (e.g., at what time the inhabitant is moving), interaction history between inhabitant and objects, etc [4, 5].

The inhabitant's location is a crucial factor and is usually the first step for context-aware service provisioning [6] [7]. An inhabitant's location information is required for many in-home applications like home entertainment (e.g., [8, 9, 10]) and automatic device control (e.g., [11]). In addition, healthcare systems have recently attracted enormous attention worldwide in this field (e.g., [13, 14, 15, 16]), and many localization methods have been proposed in this area for medical tele-monitoring (e.g., [17, 18, 19, 20, 21]), Activity of Daily Life (ADL) measurements (e.g., [22, 23]), elderly monitoring (e.g., [24]), and child monitoring (e.g., [25]).

Contrary to outdoor User Location Discovery, where Global Position Systems (GPS) provide accurate location information, indoor ULD requires the use of other mechanisms to provide an accurate measurement of the target's (e.g., human, object) location. Knowing the location of humans and objects is the key to the operation of intelligent environments. Recent research in this area has already presented impressive opportunities [26, 27], but the available systems are neither cheap nor robust or easy to integrate.

This article focuses on user localization in smart homes rather than the general subject of indoor localization. Although smart homes and other public spaces (e.g., offices, hospitals, shopping malls) have some features in common with each other, the current body of work specializing in smart homes and some of the unique characteristics and requirements of the smart home environment (e.g., the number of users, user profile and identification, security and even individual applications) inspired us to focus on this particular aspect. While we mainly focus on smart homes, the results of this work can be generalized to other spaces such as smart offices and hospitals.

In general, an appropriate ULD system for smart homes should have two main characteristics: ease of use (from the user viewpoint) and appropriate performance (from the expert viewpoint). Based on these two characteristics this article intends to answer two main questions addressed by ULD designers. We put ourselves in the shoes of the ULD designer and question the effectiveness of the various indoor ULDs at achieving user satisfaction, such as user comfort and privacy. By technically evaluating the current ULD methods, we also identify the most appropriate technologies for ULD methods, especially regarding accuracy, the required equipment, installation and cost. To achieve these complementary goals, we first propose a new taxonomy to categorize ULDs based on joint user-expert viewpoints. Since the role of ULD users has a significant effect on their satisfaction, we first categorize ULD methods based on their user role policy (i.e., users carrying or wearing a device). Then, in each subcategory, we classify ULD methods according to the various technical issues. We believe (and common sense dictates) that cost is an important concern for both consumers and producers. Many consumers consider cost as the most important metric in their decision to buy and install a ULD system. On the other hand, producers are willing to offer acceptable costs to their consumers to increase their overall returns. To offer a complete and useful reference, we estimate and compare the market costs of several different ULD methods. Our key contributions are to: (i) Develop a taxonomy of ULD methods that provides an extensive coverage of this field in terms of technical-technological features and user satisfaction. The main aim of our proposed taxonomy is therefore to explore the unique features of ULD methods from similar paradigms and also to provide a basis for categorizing present and future developments in this field. (ii) Present a state-of-the-art survey of the existing ULD methods that provides a basis for an in-depth analysis and clear understanding of the current ULD landscape. In addition, this survey offers an insight into the underlying technologies that are currently deployed user localization. (iii) Map the proposed taxonomy to the available ULD methods to demonstrate its ability to categorize and analyze the existing ULD methods. This mapping makes it possible to perform gap analysis in this area. In addition, it can help to interpret the related essential concepts of this field and it validates the accuracy of our proposed taxonomy. (iv) Identify the strong points and weaknesses of existing ULD methods, to find opportunities in this area through our state-of-the-art investigation, and to suggest possible future directions (a roadmap) as growth advances in related areas through the rapid deployment of new user localization-based services.

The rest of the article is organized as follows: Section 2 presents the taxonomy of ULDs in terms of two issues/viewpoints–user and technical-technological features. Section 3 then conducts a detailed survey of the existing ULD methods. Section 4 classifies the existing ULDs by performing a mapping of the taxonomy to each ULD method, analyzes them by mentioning the strong points and weaknesses of each method based on ten important metrics, and outlines the future directions in the ULD domain for smart homes. Finally, Section 5 offers a roadmap of future directions and presents the concluding remarks.

2. Taxonomy

This section introduces a detailed taxonomy of ULDs with respect to two different viewpoints/issues: user-focused and technical-technological features. The issues considered for our taxonomy provide a reflection of the properties of available ULD methods. Unlike other survey papers (e.g., [28], [29], [30]) that mainly have done a review on available work in this domain only based on a technical-technological viewpoint and without considering or offering a taxonomy, we first present a taxonomy considering both user and technical-technological perspectives. The proposed taxonomy (see Fig. 1), defining two main groups (i.e., Device Based Localization (DBL) and Device Free Localization (DFL), which are described in Section 2.1), can easily cover all of the ULD methods. This claim is confirmed in Section 5, in which a state-of-the-art survey of current ULD methods is classified according to this taxonomy.

The first issue in this section covers several aspects of ULD methods related to user satisfaction as well as the user's role in ULD systems. The second topic deals with the localization technologies in ULD and classifies the ULD methods with respect to their physical and technical attributes.

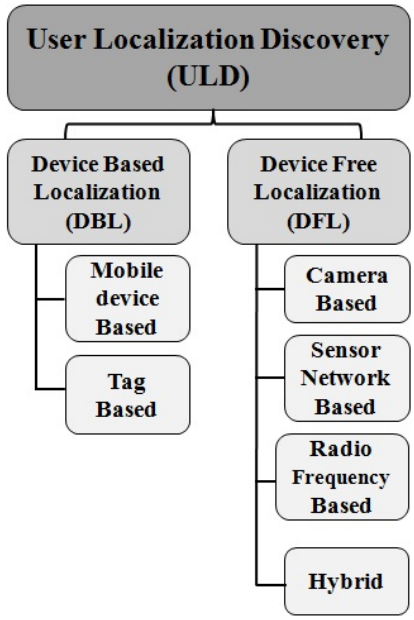

Figure 1: Proposed ULD taxonomy.

Based on the proposed taxonomy for ULD, the following provides a detailed description of the different ULD methods.

2.1. User aspect

User satisfaction is a major issue for ULD systems. One of the most important metrics that affects user satisfaction is user comfort (e.g., must be easy to use). Users are not usually willing to be limited or coerced by ULD systems (e.g., to wearing or carry a device). Therefore, how users are involved in ULD systems has an important effect on their satisfaction. Generally, ULD methods in smart homes can be classified into two groups based on user's role: (i) *Cooperative user* and (ii) *Non-cooperative user* [2, 3].

In the *cooperative user* method, an end user actively interacts with the system components by using wireless devices such as mobile devices (e.g., a smartphone) or wearable devices such as Radio Frequency IDentification (RFID) tags to allow direct communication with the smart home infrastructure. In such a configuration, the user can be considered as a mobile node of the network, recognized by the system through the identification of the associated devices. The location discovery and the behavior interpretation are based on the processing of the data exchanged between the wireless network devices. Since the users of the *cooperative user* group usually have to carry a mobile handheld or wearable device to communicate with the smart home infrastructure, from a technical-technological viewpoint we call this Device Based Localization (DBL).

In contrast, in the *non-cooperative user* method users do not utilize devices and no direct communication with the system is established. The user is part of the environment instead of being part of the wireless network infrastructure. Therefore, behavior monitoring depends on the ability of the system to sense environmental changes and, in particular, the perturbation caused by the user's presence and movements. The *non-cooperative user* approach encompasses the practice of locating humans or objects where no tag or device is attached to the entity being tracked [32]. As the users of the *non-cooperative user* group do not need to carry any device to communicate with the smart home infrastructure, we call it Device Free Localization (DFL).

Both DBL and DFL have their benefits and drawbacks. DFL methods are usually more comfortable and fail-safe (in terms of forgetting their device) than DBL methods, as users do not need to carry any special tag or device. However, user privacy is a serious problem with DFL methods that use cameras. In addition, DBL methods can often detect more than one user in the same space, while DFL methods are usually designed for single-user smart homes.

2.2. Technical-technological aspect

The technical-technological aspect is strategically vital in a ULD for efficient user localization and for overall performance. We conducted an extensive study to identify and extract the most important technical-technological characteristics of ULD systems. These include the technology used (physical phenomenon), detection level, application type, required equipment, the localization technique(s) and the algorithm. We believe that the physical phenomenon plays a central role in a ULD system and that the physical phenomenon type can directly or indirectly affect the other characteristics. For this reason, we consider the physical phenomenon in our taxonomy as the most important component and the base of the technical-technological aspect. However, for each type of physical phenomenon we will present other technical-technological characteristics individually.

Physical phenomenon (technology used)– An initial survey of the ULD field showed that a diverse collection of candidate user localization technologies exists across many different disciplines. This diversity makes it difficult to categorize the various technologies. Even if we can categorize the current technologies, it is completely possible that in the near future other different technologies may arise that are not compatible with the current classification. We classify the available technologies used in ULD systems based on an intensive study of the current methods and two simple but important questions, each tailored to a type of ULD.

For DBL, what types of technology (devices) can be supported on the user side? These devices can be categorized into two main groups: mobile-based and tag-based. Mobile-based refers to any small computing device, typically one small enough to be handheld (e.g., a smartphone) and that can be equipped with capabilities such as WiFi and Bluetooth to establish connections to the Internet and other devices to provide location-based services. Tag-based devices are usually wearable chips that can communicate with other parts of the ULD system through any current and near-future communication technology such as radio frequency (e.g., RFID tags).

For DFL, what types of technology can be used to detect users? Users can be detected in three main ways. By any type of camera (e.g., optical), any type of sensor network (e.g., using pressure sensors) and any type of radio frequency (e.g., ultra-wide band or UWB). However, sometimes a combination of these mechanisms is also possible (hybrid). Fig.1 shows our classification.

Detection Level– A ULD system can provide two types of information: symbolic (i.e., the presence/absence of a user in a room) or physical (i.e., the accurate detection of the users' position and location inside a room).

Application– In general, ULD methods can support three type of applications. Some methods only support ULD applications to find and return the users' current location (physical or symbolic). Other methods that support tracking applications can continuously track and even save a users' behavior (based on location). Usually these tracking applications (considering users' behavior history) can also be used to predict users' future locations. In addition, some methods have the ability of user identification.

Equipment– Equipment and technology have a close relationship. The required equipment for each ULD method is normally defined based on its technology. This equipment has a direct effect on the ULD cost and on user satisfaction.

Technique and Algorithm used– After selecting the appropriate technology and equipment, the technique of detecting users (e.g., fingerprinting) and the localization algorithm (e.g., K-shortest path) are the other important players in a ULD system. Both the technique and the algorithm can directly affect the performance of a ULD system. For example, an appropriate technique can improve accuracy and an effective algorithm can guarantee a good service response time.

3. Exiting ULDs: A survey

This section provides a state-of-the-art survey of the current ULD methods. As a large number of ULD methods are introduced in this section, to have a better organization and presentation, we simply categorize them based on their utilized techniques. However, accurate categorizing the ULD methods based on our proposed taxonomy is presented in Section 4.

3.1. Fingerprinting

Wu et al. proposed a Wireless Indoor Logical Localization (WILL) approach in [33]. By exploiting user motions from mobile phones, they successfully remove the site survey process of traditional approaches, while achieving competitive localization accuracy. The rationale behind WILL is that human motions can be applied to connect previously independent radio signatures under certain semantics. WILL requires no prior knowledge of access point locations, and users are not required to label measured data with corresponding locations for explicit participation, even in the training phase. Such features introduce new prospective techniques for indoor ULD.

In [31], the authors discussed in detail how RF signal strength is affected by obstacles (i.e., materials such as glass, wood, and walls, as well as humans) that are generally found in indoor environments. They endeavored to determine if signal strength alone can be used to locate users in indoor environment like smart homes and buildings. They concluded that in indoor environments, the Received Signal Strength Indications (RSSI) alone cannot be used for precise location sensing in the presence of obstacles.

Tanzeena Haque [56] proposed a flexible infrastructure-based ULD without having any constraints on the number and the position of the infrastructure nodes. To this end, low-cost and low-power small sensor devices are utilized as pegs and tags. In brief, when a server receives a user location estimation request, it searches through the database of the stored fingerprints and selects a small set of best matching ones. Then the server orders them based on their discrepancy and chooses K neighbors in the signal space that are closest to the query. Finally, the coordinates of the K selected fingerprints are averaged to generate the estimated location.

3.2. Filtering

We also can see some ULD methods which use different filtering techniques.

Moreno et al. [55] proposed a low-cost and non-intrusive ULD system for energy efficient smart buildings. The proposed mechanism is based on radio frequency identification and infrared data. They also use two computational techniques: (i) a radial basis function (RBF) network to estimate the person location. For that, users should wear an RFID monitoring tag. (ii) a particle filter to estimate the next location of the person based on the previous locations estimated by the RBF. The particle filter, after the location estimation, is used as a tracking technique, which considers previous user location data to estimate future states according to the current system model.

Ballardini et al. [54] proposed a ULD system based on a probabilistic filtering technique (Bayes filter) to estimate and localize a single person within a home. They divide home in macro-zones and fixed passive motion sensors are installed to detect a person. Their proposed ULD method can localize a person with sub-room accuracy without forcing him to carry any mobile device. One important point which is considered in this paper is related to handling the sensors inherent noisiness. Their ULD method, using Bayes lter, is able to deal with sensors providing realistic data (i.e., noisy data). They showed that their proposed ULD system is robust against sensor noise and misplacement.

Yang et al. [57] presented a combined ULD method using Passive InfraRed (PIR) sensors and an accessibility map of the indoor environment. They proposed using the accessibility map to reduce the uncertainty of localization discovery, where the typical PIR-based ULD solutions suffer. The accessibility map represents user habits in home environment, which also includes geometric and furniture layout information. The accessibility map is first created based on the user's visiting habits as the prior knowledge and, to estimate the user location, the PIR sensor data is then utilized. They used particle filtering to improve the location accuracy. The proposed method needs a fine map based on long-term monitoring.

Another example that uses filtering technique can be found in [6], where the Condensation algorithm is used to locate residents' positions via multiple cameras and a sensory floor. This system performs indoor ULD by fusing the data from the sensory floor and four video cameras, tracking the locations of multiple users through multiple sensors.

Sousa et al. [58] have demonstrated the use of a textile-based sensor system placed under the floor for ULD systems to localize and track users. In this work, they analyzed the way a foot can be located on the floor. They utilized Kalman filtering for multi-object tracking and proposed a probability based data fusion method for user identification.

Rahal et al. proposed a ULD solution employing Bayesian filtering and a set of anonymous sensors disseminated throughout a smart home [43]. Their goal was to build a robust and accurate ULD system using the available set of sensors already installed in smart homes. They found that the reliability of the ULD system depends on the ability to analyze the sensor data. According to their study, sensor fusion is an efficient method to reinforce the validity of location data. They demonstrated how using probabilistic methods such as Bayesian filtering is a worthwhile method for indoor ULD as well as for robotics.

3.3. Other techniques

In addition to filtering and fingerprinting techniques that are used in a significant number of ULD methods, we can see some researchers use other techniques as well (details of using techniques are described in Section 4).

In [7], Salah et al. analyzed several methods of monitoring a room for the purpose of locating and identifying a set of individuals. They worked with different modalities using multiple sensors to observe a single environment and to supply multimodal data streams. These streams are processed with the assistance of a client-server middleware called SmartFlow and signal processing modules. Their system works in a completely automatic fashion; there is no manual segmentation or user intervention.

The work in [11] uses 3D cameras, microphones and PIR sensors to perform ULD in smart home environments. A controller interprets the information about the users' position as a command issued to a list of UPnP/DLNA rendering devices (e.g., PC, TV, or audio system).

Zetik et al. [9] mainly focused on passive UWB-based localization systems for home-entertainment applications such as smart audio systems, which can set the sound based on the user's location to provide an optimum listening experience. They also present an example of the passive localization of a person in motion (walking) according to the measured data, as a way to demonstrate the main challenges that arise in passive localization. They show that without a proper background subtraction, data validation and tracking algorithm, the precision of the location estimation is usually very inaccurate.

Despite the satisfactory results obtained in some studies, Li et al. [34] explored the problems of wireless ULD, considering the interferences associated with the human body. They have proposed the use of video cameras to help estimate human body interference on mobile device signals. Their process combines human orientation detection and human/phone/access point relative position inference estimation to better measure how the human body blocks or rejects wireless signals. They have also developed a signal distortion compensation model to amend RSSI measurements and thereby give the relative position. Based on these technologies, they implemented a new ULD system, EV-Human (EV means to associate electronic (E) objects with visual (V) objects), and their experiments show that it can accurately and robustly localize humans, as it efficiently manages human body interference.

The use of tags, usually based on RFID technology, leads to benefits for ULD in smart home environments. Their low hardware costs, together with the comfort brought by the tags' small size and their easy transport, makes this technology appropriate for special groups of users such as the elderly, children, and disabled people. Using active and passive RFID technology, the work in [4] presents a low-cost ULD system with great scalability, oriented to track human location, mobile service robots, and everyday objects. It is based on a grid of artificial landmarks consisting of passive RFID tags, while wireless reader units can be mounted on top of a human foot. They also present a discussion about the trade-off between technical effort and costs, and level of data accuracy is required for the final application.

A new method to track the spatial location and movement of a human using wearable inertia sensors without additional external global positioning devices was introduced in [35]. This work combines two approaches to detect human motion and to localize individuals. The first method is a common skin detection methodology; the second is a classical gradient-based motion detector. The combination of these two methods produces a new proposal for ULD and motion detection. Starting from human lower limb kinematics, the method uses multiple wearable inertia sensors to determine the orientation of the body segments and the lower limb joint motions. At the same time, based on human kinematics and locomotion phase detection, it can determine the spatial position and the trajectory of a reference point on the body. An experimental study showed that the position error can be controlled within

1-2% of the total distance in both indoor and outdoor environments. Since the sensors can be worn by individuals at any time and in any place, this method has no restrictions in indoor and outdoor applications.

Machine learning techniques are used in [36] for location discovery and tracking. This study considers environments such as smart homes, assisted living facilities, and medical recovery units equipped with tiny wireless devices that interact with a device carried by the user/care receiver. Both the decision tree and instance-based learning methods performed similarly on the data sets. Machine learning is considered as an important technique that makes it possible for several other components to operate properly, and in this context it is even more important because the use of range-based ULD systems is prohibited by the barriers of multi-room environments.

An example of methods that use cameras for ULD can be found in [37], wherein a real-time human tracking system to detect human location and motion is presented. They proposed an algorithm that captures an effective area in which an individual can be detected and his/her position estimated utilizing four network cameras. Three kinds of images are used to detect human motion: IMAGE1: empty room images, IMAGE2: images of the furniture and home appliances in the home, and IMAGE3: the images of IMAGE2 and the individual. The system decides if specific furniture items or home appliances are associated with the human by analyzing these three images, and then estimates human motion using a Support Vector Machine (SVM). Human motion is recognized as having four types: *lie down*, *sit*, *stand-up*, and *walk*. The human motion recognition is decided from the pixel number by the array line of the moving object using SVM.

Omnidirectional vision can be considered as a generalization of camera-based ULD methods. In the work presented in [38], omnidirectional vision equipment composed of a camera and a hyperbolic lens can obtain full 360-degree scene information, and has been widely used in various realms such as video surveillance, micro-robot vision, and virtual reality. This study used the background subtraction technique to detect the foreground areas of the human body. First, the background model of the image is established through a statistic method, and then the different foreground areas of an individual are extracted by a background subtraction technique. The human position, size, the number of connecting areas, and other information can then be obtained from the foreground region of the human body, which is segmented by a connected component-labeling algorithm of its binary image. The labeling algorithm is described in [39].

An interesting option is to reuse the hardware that is already deployed in a smart home to perform ULD tasks. A method to localize and detect individuals from a Kinect[1]-captured sequence of images is presented in [40]. Their method takes a sequence of the gray-scale images and the corresponding depth images as input. The gray-scale image and the depth information are captured using two different sensors within the same device, a Kinect, and the processing is performed by the processor attached to the Kinect. This method localizes an individual by using their motion along the x, y direction and then considering all the pixels connected to those pixels over a 3D plane. It accomplishes this segmentation with an accuracy of 77%.

To avoid the disadvantages, in terms of users privacy protection, of traditional ULD and tracking methods, system configuration and maintenance, Shen et al. present a new method based on radial distance modulation to detect and locate moving objects from a top view angle [41]. This method has the advantage of directly extracting the information from the moving object's characteristics and spatial position. Their experiments demonstrate that although the output of Passive InfraRed (PIR) detectors only has two values, 0 and 1, they can locate a moving object with simple information after modulating and encoding the sensors' perception area.

In [42], Noury et al. presented a decision algorithm, encapsulated in the Health Integrated Smart home information System (HIS^2), to locate patients in smart home environments based on the triggering of human detectors. This system was designed to allow the remote follow up of patients when they return home. ULD is achieved by using the door contacts and volumetric sensors installed in each room of the HIS^2. Their concept achieves two detection levels: (i) major incidents (falls, long periods of inactivity) and (ii) any long term deviation of a patient's behavior (a slowdown of their displacements over months, or a drop in their rate). Noury et al. project that their HIS^2 will increase the security of elderly people remotely followed up at home, and above all it will expand tele-care solutions to more people who until now must receive their care at hospitals or rehabilitation centers. In [24], Obo et al. apply a spiking neural network to localize human positions by using sensor networks. They also propose a learning method for determining temporal relationships between sensors based on the output of the spiking neural network.

[1]http://www.xbox.com/en-US/kinect

A ULD method that does not utilize any wireless IC tags or target nodes is investigated in [44], which considers the case where the person is walking in a room. The ULD is achieved using a Multiple-Input Multiple-Output Ultra-Wide Band (MIMO-UWB) radar system that measures the propagation channels between the antennas and the human body. The waves reflected by the human body are extracted by using the differences between consecutive snapshots of the impulse response, eliminating the need for any pre-measured room response characteristics. In addition, by using this MIMO radar system, many pairs of propagation channels between the antennas can be measured, leading to a reduction in the effects of clutter, a major cause of errors in radar systems. The Root Mean Square Error (RMSE) of the experimental location accuracy was found to be 20 cm or less. When considering the thickness of the human body, this measurement error should be acceptable for medical and healthcare applications.

Some ULD approaches combine several methods in order to increase the localization accuracy, including using different equipment under the same technological framework (i.e., diverse sensors), or a combination of different technologies, such as sensors, cameras, and electronic tags.

An example of using a combination of different sensors for ULD in home environments can be found in [21]. The proposed platform is based on a combination of commercially available movement sensors (infra-red) and sound sensors (microphones). This multimodal combination relies on an expert system which allows the efficient use of these sensors and a palliation of the possible failings of the single modalities. To improve the localization accuracy, they developed a scalable platform where they can add any other modality to help in making better decisions; for instance, additional modalities based on vision and on using accelerometers.

A combination of different technologies is presented in [50], where an indoor tracking model using the IEEE 802.15.4 compliant radio frequency is set up to work with a video monitoring system for target monitoring. The concept is that the erratic or unstable RSSI signals can be manipulated to deliver stable and precise position information in the indoor environment. They propose a ULD method based on statistical uncorrelated vectors, and develop a smoothing algorithm to minimize the noise in RSSI values. They also present a solution combining the wireless sensor network (WSN) with Ethernet technology to decrease the RSSI interference caused by buildings. The developed system can complete the functions of multi-target detection and tracking, as well as specific target inquiries, alarm systems, and monitoring.

The use of robots to help us in our daily lives is gaining popularity thanks to their increasing functionality. In order for a robot to serve humans, it must be able to autonomously detect and recognize users. Sound plays an important role in locating a speaker in a wide target range, and thus sound ULD systems with a microphone array have been developed in various forms. However, a robot usually has space restrictions when mounting a microphone array on its head; this increases the time delay of arrival (TDOA) error and decreases the resolution of sound ULD [45]. Vision, on the contrary, has directional limitation, i.e., vision can only detect users inside the visible range. To solve these problems, several attempts have been made to integrate sound and vision ULD [47, 48, 46, 51].

Kim et al. [52] propose a method for accurate ULD using a sequential fusion of sound and vision. Although sound ULD on its own works well in most cases, there are situations, such as noisy environments and small inter-microphone distance, which may produce erroneous or poor results. However, the vision system also presents some drawbacks linked to a limited visual field. To solve these issues, their proposed method combines sound ULD and vision in real time, wherein a robot first determines a rough location of the speaker via sound source ULD, and then uses vision to increase the location accuracy.

Guettari et al. [49] proposed a ULD method using thermopile sensors. The method considers two states of occupied and unoccupied for each room and detects person presence in a room using the two time series generated by a thermopile sensor (First time series corresponds to temperature measured and the second one representing the sensor's temperature). In other words, the authors goal is to distinguish between a signal generated in presence of a person in a room and a signal produced in his absence. In this case, they used median filter to avoid abnormal measures (signal cleaning) and have utilized k-means method to discriminate between signals generated in presence of the person and signals produced in his absence. After using k-means method to separate these two sets of observations, they used k-Nearest Neighbors (KNN) classifier model to distinguish between these two classes.

Ahvar et al. [12] recently proposed a sensor network-based and user-friendly ULD system that utilizes different types of inexpensive (mostly already installed) sensing nodes combined with a context broker that uses a fuzzy-based decision-maker. The proposed idea can provide a simple, but effective method that meets users' demands for privacy and comfort. A user does not need to carry a device, and system does not use sensors (e.g., cameras, microphones) that impose on users privacy. Sensors detect the presence of a user and send the context information to a fuzzy-based decision-maker. The decision-maker processes the context information based on fuzzy set theory and makes a decision about the user' s location. However, the method does not force users to carry a device, it can only be used for applications where a single user is present in the environment (e.g., a single elderly person who lives alone in his or her home).

4. Performance evaluation

4.1. Mapping of the proposed taxonomy to existing ULDs

This sub-section provides the classification and mapping of our taxonomy to the current ULDs surveyed in Section 3.

The important technical-technological features of each ULD method, including the technology used, detection level, application, required equipment, techniques and algorithms are presented.

Because of the large number of ULD methods we categorize them into two tables. Table 1 summarizes DBL methods and Table 2 represents different DFL methods.

The source field in the tables refers to the reference number for each method.

Table 1: Technical-technological features-DBL methods

Source	Technology	Detection Level	Application	Equipment(s)	Technique(s)	Algorithm(s)
[34]	Mobile-Based	Physical	Localization and tracking	Video cameras, access points, Mobile Phone	Visual estimation, signal-based technique	Hungarain, K-Shortest Path(KSP) , Viola-Joues face detection
[35]	Tag-Based	Physical	Localization and tracking	wearable tags, camera, wireless receiver	3-D localization (body kinematics and locomotion phase detection)	joint motion calculation
[33]	Mobile-Based	Symbolic	Localization	Mobile phone and Access Point(s)	Logical localization (WiFi Fingerprints and user movement)	skeleton mapping and branchknot (Kuhn-Munkras) mapping
[50]	Tag-Based	Physical	Localization and tracking	Tag, camera, Tag reader	tag broadcasting	Localization algorithm based on statistical uncorrelated vector, smoothing and nearest neighbor algorithms
[4]	Tag-Based	Physical	Localization, tracking and identification	Passive-active RFID tags and readers	Passive-active UHF-HF RFID localization	position calculation based on RFIDs information in range of each reader and history of calculated positions

[58]	Tag-Based	Physical	Localization, tracking and identification	SensFloor (a textile-based large-area sensor system), pedometer (a device able to detect human footsteps including accelerometer and transceiver), a central receiver	footstep detection	Kalman filtering, data fusion
[55]	Tag-Based	Physical	Localization, tracking and identification	Reference RFID tag, monitored RFID tag, RFID reader, IR transmitter	Radial Basis Functions (RBF), particle filter	position estimation based on RBF and particle filter
[56]	Tag-Based	Physical	Localization	Sensors, tags	Fingerprint	Location Estimation by Mining Oversampled Neighborhoods

Table 2: Technical-technological features-DFL methods

Source	Technology	Detection Level	Application	Equipment(s)	Technique(s)	Algorithm(s)
[52]	Camera-Based	Physical	Localization	humanoid robot(camera, microphone)	Sequential fusion of vision and sound with assistant of robots	Voice Activity Detection (VAD)
[21]	Hybrid	Physical	Localization and tracking	Infrared sensors and microphones	acoustic person tracking, movement detection	Making a combined decision targeting
[9]	RF-Based	Physical	Localization and tracking	UWB Rx-Tx antennas	Reflection of Electro-Magnetic waves	Background substraction
[38]	Camera-Based	Physical	Localization and tracking	Cameras	Omnidirectional vision, background subtraction	Algorithm of connected area labeling in binary image
[37]	Camera-Based	Physical	Localization and tracking	Cameras	Analyzing three kinds of images (the image difference pixel)	Support Vector Machine(SVM)
[11]	Hybrid	Physical	Localization, tracking and identification	3D cameras, microphones and PIR sensors	Motion and voice detection	Generalized Cross Correlation (GCC) with PHase Transform (GCC-PHAT) & GCC
[40]	Camera-Based	Physical	Localization, tracking	Kinect cameras	2D motion estimation	a simplified version of Adaboost algorithm
[6]	Hybrid	Physical	Localization and tracking	Cameras, sensory floor (pressure sensors)	Motion detection (video and floor), Bayesian filtering	Condensation, roulette wheel selection
[7]	Hybrid	Physical	Localization, tracking and identification	Cameras and microphone array	Motion and speech detection, face recognition	probabilistic occupancy map (POM), OpenCV(Viola-Jones algorithm), Global Coherence Field, Hidden Markov Models (HMMs), SVM
[41]	Sensor Network-Based	Physical	Localization and tracking	Wireless PIR sensors	Motion detection	Distributed localization
[42]	Sensor Network-Based	Symbolic	Localization and tracking	Magnetic contact switches, IR sensors	Motion and contact detection	Boolean equations
[24]	Sensor Network-Based	Physical	Localization and tracking	Database management server, sensor network (accelerometer, illuminance, laser range finder)	Measuring 2-dimensional distance by using lasers, spiking neural network	Learning-based algorithm
[44]	RF-Based	Physical	Localization	Multiple antennas (MIMO-UWB system)	measuring the propagation channels between the antennas and the human body	distance estimator (time difference between sending the pulse and reception of the echo)

[31]	RF-Based	Physical	Localization and tracking	Crossbow's Zigbeemotes (Micaz and IRIS)	considering the received signal strength values	Fingerprinting and signal processing
[43]	Sensor Network-Based	Physical	Localization and identification	IR sensors, Tactile carpets, light switches, door contacts, pressure detectors	Particle filters	Bayesian filtering
[49]	Sensor network-based	Symbolic	Localization	Thermopile sensors	variance estimation (temperature difference, median filter, frequency analysis, Wavelets decomposition)	K-means and K-nearest neighbors
[54]	Sensor network-based	Symbolic	Localization and tracking	ZigBee devices equipped with PIRs, Routers	probabilistic lter-ing, motion detection	Bayes-based algorithm
[57]	Sensor network-based	Physical	Localization	PIR sensors	Map-based localization, Bayesian and particle filtering	Data fusion by particle filters
[12]	Sensor network-based	Symbolic	Localization	Various sensors	Using various sensors with different detection methods	Fuzzy set-based algorithm

As Tables 1 and 2 show, the proposed taxonomy could cover all mentioned methods in Section 3.

4.2. Important metrics

Based on the information extracted and gathered from the mapping subsection, we proceed to analyze the ULD methods. We consider ten important metrics for evaluation: accuracy, privacy, cost, user comfort, user health, support of multiple-users, latency, security, fault tolerance and interaction with other smart home systems. The metrics were selected based on both user and technical viewpoints.

4.2.1. Accuracy

Localization accuracy is always a basic consideration for smart home applications. Depending on the type of application, the level of localization accuracy may vary. For example, for a heating/cooling application, it would be sufficient to know if the users are present, and in which room they are located. On the contrary, for elderly care and monitoring applications it is desirable to know the precise location (and sometimes the situation in terms of activity and health) of users at all times, which requires much more accurate mechanisms and more complicated methods.

4.2.2. Privacy and trust

The preservation of user privacy is crucial for any ULD system. Location information is very sensitive, and the identity of users should only be accessed under special authorization and within the purposes described in the application agreement that should have been previously accepted by the users.

Efficient privacy preservation techniques should be implemented and offered to users in order to keep sensitive data out of the reach of fraudulent stakeholders, thereby offering users a trustworthy environment. The use of open policies and the possibility of totally customizing the privacy options will be a plus in the path to ULD system adoption.

4.2.3. Cost

Another important metric for users is cost of ULD system. Many users do not have the means and/or are not willing to invest a large amount in a ULD system.

4.2.4. User comfort (ease of use) and simplicity

With the aim of generalizing the use of ULD systems, one of the most important aspects that will definitely encourage their adoption is simplicity, ease of use and level of comfort.

4.2.5. User health

User health is one of the most crucial aspects when deciding to acquire and use any technological system. Thus, the technology that ULD systems use (e.g., radio waves) should not have any negative effect on the human body, including accounting for the continuous exposure, as these systems will work 24/7.

4.2.6. Multiple Users

In most cases, multiple users will simultaneously utilize the ULD system.

4.2.7. Latency

Aligned with the accuracy issue, latency or speed is another major challenge that can be very critical for some applications. For example, for home entertainment applications, the use of low-latency (real-time) ULD systems will be required, while for other applications such as heating/cooling management, a few seconds of delay will not be decisive. Again, depending on the application, it will be necessary to use different types of hardware as well as different ULD systems to offer the performance level required to ensure the correct operation of the application and produce the desired user satisfaction.

4.2.8. Security

The development of a secure, private and trustworthy ULD system is a challenging task that is also decisive for the adoption of these systems by the public. Security requirements are somewhat aligned with privacy and trust issues. Apart from privacy and trust preservation, the use of secure ULD approaches will avoid undesirable situations such as theft. Encrypted communications are one of the techniques to provide secure ULD.

4.2.9. Fault tolerance, reliability and robustness

Some problems such as reflection, data loss and data duplicity may occur during the operation of ULD systems; therefore they should be able to deal with these situations while continuing to operate properly, even in the event of the failure of some of their components. Alarm situations or the detection of anomalous readings should be recorded for further analysis and sent to the users or managers to ensure the continuous correct operation of the system.

4.2.10. Interaction with other systems (adaptability)

Since ULD systems are meant to be integrated with other technologies in a smart home, and eventually with the Internet of Things, the interaction with other deployed components should be transparent to users. For those incompatible devices, hardware, or software that may make use of the ULD data, interfaces and/or translation mechanisms should be developed to ensure the correct operation of all the systems deployed in a smart home.

4.3. Analysis

This sub-section evaluates the ULD methods based on the ten described metrics. The advantages and weaknesses of the ULD methods are summarized in two tables. Table 3 summarizes DBL methods and Table 4 represents advantages and weaknesses of the different DFL methods. The tables include three different fields:

- *Source:* Contains the reference number of each method.
- *Advantage(s):* Describes the strong points of each method.
- *Weakness(es):* Highlights the main drawbacks of each method.

In addition, as we have already discussed, cost is an important concern for both ULD consumers and producers. However, a few researchers consider cost in their work. We therefore conducted an individual study to estimate the cost of different ULD methods.

We considered a smart home (around 60 m^2) with one kitchen/dining room (30 m^2) and one bedroom (20 m^2). Based on this home architecture, we prepared a list of the required equipment for each ULD method according to information extracted from the references.

To estimate cost we had following challenges and limitations: (i) there were a variety of products and brands for one device (e.g., cameras) with quite different prices. (ii) as this work is a technical guideline for researchers of this domain (rather than a marketing guideline for consumers), we could not mention any special marketing brand. However, we needed to prepare a real or close to real cost list. (iii) many of the papers do not present a systematic and accurate model (e.g., the size of a smart home, the number of devices needed and their chrematistics, such as minimum resolution or the extent of the radio range).

To address these problems, we sometimes had to make some assumptions for their proposed models to prepare a list of the required equipment (e.g., to find number of needed sensors in a room). We, then, found the market price of each piece of equipment by searching on Amazon[2], Ebay[3], Alibaba[4] and Aliexpress[5] websites and, to get a close to reality price estimation, we tried to consider the prices of the most popular equipment items (rather than a randomly selection of prices).

After finding the prices of the most popular equipment items, we estimated cost of each ULD method. We then used a normalization of all estimated costs to see only relative differences among different ULD methods. In other words, we considered the maximum cost among all ULD methods as our reference cost. We then divided estimated cost of each ULD method to the reference cost (i.e., [ULD cost/reference cost]) to get a normalization value for each ULD method. By the normalization method, we could estimate how much different ULD methods are cost efficient. The methods with normalization value under 0.1 were considered as very high cost efficient, between 0.1 and 0.4 as high, between 0.4 and 0.7 as medium, between 0.7 and 0.9 as low and, finally, above 0.9 were considered as very low cost efficient

[2]www.amazon.com
[3]www.ebay.com
[4]www.alibaba.com
[5]www.aliexpress.com

methods.

Table 5 shows the results of our efforts to determine the costs of these different methods. Considering the above-mentioned difficulties and our solutions, Table 5 is a good basic reference for researchers of this domain to make a general comparison between ULD methods in terms of their equipment costs. However, we would like to stress this point that it only presents an estimation to give a general view of cost differences between various ULD methods and technologies to researchers and can be modified according to the brands used and the abilities of the equipment items (e.g., radio range). In Table 5, we have not considered software and maintaining prices as well as price of a central home controller (e.g., coordinator or home gateway).

In a first and general view, DBL methods would be considered to be more accurate than DFL methods. A quick evaluation would see that with DBL methods, a user (attached to a tag or phone) is a part of the ULD system and so detecting that user is easier and more accurate than with DFL methods where the user is not involved in the ULD system. However, Tables 1 and 2 indicate that there are some highly accurate DFL methods. After further analyzing the characteristics of the highly accurate DFL-based references in the tables, we found that they are all equipped with cameras (in addition to image processing techniques) or with other types of sensors in the floor or on the walls, with which their systems can easily detect any user movement, and do so with a high rate of accuracy. On the other hand, in DBL methods, which work based on mobile devices, wave interference, noise, jitter and even the human body can affect their accuracy. As a result, there is no general rule that DBL methods are more accurate than DFL ones and vice versa.

According to Tables 3 and 4, some ULD methods suffer from privacy issues. These include DFL methods that use cameras, as well as hybrid DFL methods that obtain information from cameras to detect users, situations where sensitive data would be handled by the system. These tables also make it possible to highlight some of the main differences between the DFL and DBL methods. In DBL methods, where users need to carry some type of device, electromagnetic waves could have an effect on users' health. Wearable tags often fail quickly due to the users' mobility. Electromagnetic wave interference is another problem for DBL methods, a problem that can lead to erroneous readings and localization failures. Meanwhile, DFL methods usually suffer from accuracy issues, since their methods cannot precisely detect a users' location and position (except for those methods that work in combination with other types of sensors, as explained above).

Table 3: Advantages and weaknesses-DBL methods

Source	Advantage(s)	Weakness(es)
[34]	Accuracy, robustness	User privacy and comfort, cost
[35]	Applicable for many moving patterns, multiple user, good accuracy, repeatability	User privacy and comfort (wearing many sensors)
[33]	Simple, easily scalable, low cost, average room-level accuracy of 86%, no need to access point location information	complicated localization algorithm and latency
[50]	real time (latency), multi-target detection (multiple users)	User privacy
[4]	accuracy and privacy	Cost, installation (4000 tags for $60m^2$), scalability
[58]	Multiple users, anticipate the step-to-step location of a given human,	Scalability, installation, cost
[55]	Accuracy, easily congurable, energy efficiency, privacy, cheap sensors	Complexity (defining different region of interests), user comfort problem(carrying a tag)
[56]	Low cost and low power infrastructures	User comfort problem (carrying tag), accuracy depends on the number of pegs

The acquisition and maintenance costs of ULD systems are still very high for the public. Technology tends to reduce its cost with the passage of time, so it is expected that the cost of indoor ULD systems will come down as long as the popularity of this technology continues to grow. An interesting possibility would be to make use of already-deployed or otherwise utilized hardware, such as wireless signals, smartphones, or Kinect-based systems to reduce the implementation and deployment costs.

Looking at Tables 3 and 4 we can find, in general, that covering multiple users is not a problem for DBL methods, since the system focuses on recognizing the different devices carried by users. However, for DFL methods, the detection and localization of multiple users represents a challenging task, because apart from detecting the position of several users, the system must also be able to differentiate among them, significantly complicating the algorithms involved by having to add identification techniques to accurately localize the different users.

In general, DBL methods have the problem of a single point of failure, which means if the mobile (handheld or wearable) device carried by user does not work, the ULD system cannot localize the user. DFL methods, by

Table 4: Advantages and weaknesses-DFL methods

Source	Advantage(s)	Weakness(es)
[52]	Accuracy, reliable (both vision and sound)	User privacy
[21]	reliability (both infrared and microphone), low delay, good adaption in environments (adaptability)	Influenced by echoes and reflections
[9]	multiple users, privacy, ease of use and simplicity	localization quality strongly depends on the number of persons to be detected, their activity and environmental conditions
[38]	Accuracy, ease of use	User privacy, low precision at the edge of the image
[37]	predicting human motion, average accuracy 85.3%	User privacy, installation (networked cameras, needs photos of empty rooms, furniture and appliances to save in database)
[11]	Reliability (integrating cameras, microphones and PIR sensors), accuracy, multiple users (3D camera)	User privacy, installation
[40]	Simplicity, easy to use	needing to have data set, user privacy, error prone (noise in depth image information, camera motion estimation inaccuracy)
[6]	Multiple users, reliability (cameras and sensory floor)	User privacy, installation
[7]	reliability (cameras, microphones), accuracy, multiple users	User privacy, complexity, installation
[41]	scalability, user privacy, low complexity, robustness, fault tolerance	accuracy depends on number of sensors, installation
[42]	Simplicity, easy to use, user privacy	low accuracy, limitation to only one person
[24]	User privacy, multiple users	installation, scalability
[44]	easy to use and simplicity, user privacy	effected by the clutter (multiple-input multiple-output radar system reduced this effect)
[31]	User privacy, easy to use	relative accuracy (Increasing the number of reference nodes can improve accuracy), signal strength is effected by environmental parameters such as humidity or by interference from other RF sources
[43]	User privacy, easy to use and comfortable	Scalability, only one user
[49]	Cost, comfortable, privacy	Complexity, accuracy, need to have recorded observations
[54]	Cheap, easy to use, energy efficient, dealing with noise, recovery from the failure	Accuracy depends on number of sensors, limited to single person
[57]	Based on cheap and low cost PIR sensors, privacy, user comfort	Limited to single person, needs to build the accessibility map
[12]	Based on cheap and low cost or already installed sensors, privacy, user comfort	Limited to single person

definition, are robust in this sense.

4.4. Future directions

To reduce the limitations and challenges of the current ULD systems, the traditional approach is to develop new ULD algorithms. Another effective solution would be to identify and utilize emerging technologies for ULD. For example, white light-emitting diodes (LEDs) are widely used for illumination in smart homes. They can provide energy-efficient lighting. This widespread using of white LEDs creates the opportunity to create a flexible, accurate, and ubiquitous ULD system. Signals transmitted by the LEDs can be used to determine user's location in a smart home.

Table 5: Estimated cost of equipment for different ULD methods

Source	Equipment	Deployment	Cost efficiency
[9]	Vivaldi antenna, Bi-conical antenna	2 Tx antennas, 8 Rx anntenas	Medium
[11]	Kinect Camera, Microphone array , PIR sensor, 802.15.4 TelosB mote	2 Kinect Cameras, 2 Microphone array series, 2 PIR Sensors, 2 TelosB motes	Very high
[21]	Infrared sensors, CMT microphone, 802.15.4 TelosB mote	8 Gradient Microphone, 4 IR sensors, 4 TelosB motes	High
[24]	Accelerometer sensor, illuminance sensor, laser range finder (LRF)	4 laser range finders, 4 accelerometer sensors, 2 illuminance sensors	Very high
[33]	smartPhone, access point	1 smart home, 1 access point	Very high
[34]	Video camera, access Point, mobile phone	2 video cameras , 6 access points	High
[35]	Inertial measurement unit (IMU) sensors, insole devices, wireless receiver	8 IMU sensors ,cameras ,Insole Devices, 1 Wireless Reciver	Very high
[37]	Server camera (32 bit RISC CPU), client camera	2 Server cameras, 6 client cameras	High
[38]	Camera	2 Ceiling security camera	Very high
[40]	Kinect camera	2 Kinect camers	Very high
[41]	wireless pyroelectric infrared sensors, 802.15.4 TelosB mote	24 pyroelectric infrared sensors , 24 Tmotes	High
[42]	magnetic contact switch, volumetric lens sensor, Linear lens	1 magnetic contact switch, 5 volumetric lens sensor, 1 Linear lens	Very high
[43]	IR sensors, Tactile carpets, light switches, door contact, pressure detectors	10 IR sensors, 18 Tactile carpets, 8 light switches, 32 door contact , 1 pressure detectors	Very high
[6]	Web camera, pressure sensors	4 CCD-cameras with the resolution of 352 X 340 pixels in the four corners of ceiling, forty pressure sensors under the wooden floor	High
[44]	Double ridged guided horn antennas	6 double ridged guided horn antennas	Medium
[50]	Tracking tag, RFID tag, reader, dome camera	2 Dome cameras, 2 reader, 16 reference tag, 1 tracking tag	Very high
[52]	Kinect sensor, Tiepin microphones, PreSonus, humanoid robot	2 Kinect sensors with RGB and IR cameras, microphone (Tiepin Microphones (TCM) and PreSonus DigiMax FS preamplifier),1 humanoid robot	High
[4]	FEIG UHF antenna, handheld with RFID reader, FEIG UHF module for passive RFID, active RFID	1 FEIG UHF antenna, 1 handheld with RFID reader, 1 FEIG UHF module for passive RFID, 1 active RF	High
[58]	Sensitive floor, accelerometer Sensor, wireless sensor receiver, pedometer	Sensitive floor (whole apartment floor), 1 accelerometer Sensor, 1 wireless sensor receiver, 1 pedometer	Very low
[7]	Fix camera, zenithal fish eye, active camera (PTZ), omnidirectional Microphone, Directional microphone	12 cameras :8 fix cameras, 2 zenithal fish eye, 2 active camera (PTZ), 40 Microphone (24+8 omidirectional, 8 directional)	Low
[31]	Crossbows Zigbee motes (Micaz and IRIS	4 Micaz motes, 2 IRIS mote as base station	Very high
[49]	Wireless thermopile PIR	8 wireless PIRs	Very high
[54]	ZigBee devices equipped with PIRs, Router	4 ZigBee devices,1 Router	Very high
[57]	PIR sensors	50 PIR sensors	Very high

A major advantage of a lighting-based ULD system is that the available bandwidth is not restricted by concerns about interference with multiple users in other locations. Installing the system can be almost as simple as changing a lightbulb. It may also be possible to use power line communication (PLC) to achieve relatively high-speed data connectivity to devices without rewiring. This could be an important complement to a lighting-based ULD system [59].

In a nutshell, the use of appropriate technologies that are commonly used for other applications is an opportunity to both enhance the accuracy and reduce the cost of ULD systems.

5. Conclusions

Indoor ULD, knowledge that is the basis of many services and applications, is becoming a challenging task due to the complexity of the required mechanisms. In contrast to outdoor ULD, where GPS does all the work, indoor ULD requires the use of specific techniques and technologies in order to accurately detect a users' position.

This article has provided a deep analysis on the existing indoor ULD mechanisms. An overview of the applications requiring ULD mechanisms was presented to illustrate the heterogeneous environments that require indoor ULD. A complete taxonomy was then presented, differentiating between hardware-based and hardware-free methods. All the approaches represented in the taxonomy were analyzed, detailing their main characteristics, as well as their advantages and drawbacks. Finally, a detailed list of challenges and open issues were presented, with the aim of serving as a starting point for future research and development.

Similarly to other technologies, the varying features of indoor ULD mechanisms makes them appropriate for one or several applications, but we consider that there is not yet a definitive indoor ULD approach. Until now, there has not been any appropriate solution to support multiple users for DFL methods. Utilizing emerging technologies, designing more flexible, accurate and ubiquitous ULD methods are another important issue that should be considered for future smart homes.

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