Hindawi
Journal of Sensors
Volume 2017, Article ID 2630413, 21 pages
https://doi.org/10.1155/2017/2630413

Review Article

Evolution of Indoor Positioning Technologies: A Survey

Ramon F. Brena,[1] Juan Pablo García-Vázquez,[2] Carlos E. Galván-Tejada,[3] David Muñoz-Rodriguez,[1] Cesar Vargas-Rosales,[1] and James Fangmeyer Jr.[1]

[1] *Tecnológico de Monterrey, Av. E. Garza Sada 2501, 64849 Monterrey, NL, Mexico*
[2] *Facultad de Ingeniería, MyDCI, Universidad Autónoma de Baja California, Av. Á. Obregón S/N, 21100 Mexicali, BC, Mexico*
[3] *Programa de Ingeniería de Software, Universidad Autónoma de Zacatecas, Av. Begonias 2, 98000 Zacatecas, ZAC, Mexico*

Correspondence should be addressed to Juan Pablo García-Vázquez; pablo.garcia@uabc.edu.mx

Received 13 October 2016; Revised 22 January 2017; Accepted 21 February 2017; Published 29 March 2017

Academic Editor: Alberto J. Palma

Indoor positioning systems (IPS) use sensors and communication technologies to locate objects in indoor environments. IPS are attracting scientific and enterprise interest because there is a big market opportunity for applying these technologies. There are many previous surveys on indoor positioning systems; however, most of them lack a solid classification scheme that would structurally map a wide field such as IPS, or omit several key technologies or have a limited perspective; finally, surveys rapidly become obsolete in an area as dynamic as IPS. The goal of this paper is to provide a technological perspective of indoor positioning systems, comprising a wide range of technologies and approaches. Further, we classify the existing approaches in a structure in order to guide the review and discussion of the different approaches. Finally, we present a comparison of indoor positioning approaches and present the evolution and trends that we foresee.

1. Introduction

Position location of a user or a device in a given space is one of the most important elements of contextual information. The widespread use of sensors has produced an increasing wealth of such information. By itself, location has generated great attention because of its potential to leverage commercial applications such as advertisement and social networks [1]. The user context, constituted by all relevant items surrounding her/him, has been given paramount importance in the design of next-generation information systems and services. The adaptation to a changing context is precisely what makes those next-generation systems flexible and robust [1].

Location detection has been very successfully implemented at outdoor environments using GPS technology [2]. The GPS has made a tremendous impact on our everyday lives by supporting a wealth of applications in guidance, mapping, and so forth [3]. Nevertheless, in indoor environments, the usability of the GPS or equivalent satellite-based location systems is limited, due to the lack of line of sight and attenuation of GPS signals as they cross through walls. Indeed, precision of some 50 meters inside a commercial setting is useless with respect to a task such as locating specific merchandise on a shelf. Thus, the need for specialized methods and technologies for indoor location systems (also called *indoor positioning systems*, IPS) has been widely accepted [4–11].

Many surveys have been written based on various IPS related topics [12–16]. However, most of them omit several relevant technologies, have a limited perspective, or lack a classification structure. For instance, the use of visible light [17–19] or Earth's magnetic field [20, 21] has been overlooked in some reviews (see Table 1). Also, the lack of a classification scheme that would guide the readers in a clean way is a serious flaw of some otherwise good surveys [15]. Furthermore, an updated survey in indoor positioning systems is always welcome as this is a rapidly evolving area and a decade-old review can be considered outdated.

In this survey, we review the field of indoor positioning systems (IPS) because it presents specific features, challenges, and opportunities. Indoor settings are mostly full of obstacles that obstruct the signals between emitters and receivers, and a wide variety of materials, shapes, and sizes affect signal propagation more than in outdoor scenarios. IPS face an interesting technical challenge due to the great variety

Table 1: Previous surveys comparison, including ours. "Passive" means that the infrastructure generates the signal and that the object or person to be located receives it.

Technology or feature	Liu	Gu	Mautz	Deak	Koyuncu	Ours
Infrared mobile reader	No	Yes	No	No	No	Yes
Infrared badge	Mention	Yes	Yes	Yes	Yes	Yes
Laser (passive)	No	No	Yes	No	No	No
Ultrasound passive	No	Yes	Yes	No	Yes	Yes
Ultrasound active	Mention	Yes	Yes	Yes	Yes	Yes
Audible sound active	No	Yes	Yes	No	No	Yes
Audible sound passive	No	No	No	No	No	Yes
Audible sound ambient	No	No	No	No	No	Yes
Magnetic generated	No	Yes	Yes	No	No	Yes
Magnetic ambient	No	No	Yes	No	No	Yes
RFID mobile tag	Yes	Yes	Yes	Yes	Yes	Yes
RFID mobile reader	No	No	Yes	No	No	No
Wi-Fi	Yes	Yes	Yes	Yes	Yes	Yes
Bluetooth	Yes	Yes	Yes	Yes	No	Yes
ZigBee	No	No	Yes	No	No	Yes
UWB	Yes	Yes	Yes	Yes	Yes	Yes
Tomographic (water resonance)	No	No	No	Yes	No	No
Cameras infrastructure	Mention	Yes	Yes	Yes	Yes	Yes
Cameras (portable)	No	No	Yes	No	No	Yes
Floor tiles	No	No	Yes	Yes	No	No
Air pressure	No	No	Yes	Yes	No	No
Inertial	No	No	Yes	Mention	Yes	Yes
Ambient light	No	No	No	No	No	Yes
Artificial light (no encoding)	No	No	No	No	No	Yes
Artificial light (encoded)	No	No	Yes	No	No	Yes
Indoor AGPS, pseudolites	Yes	No	Yes	No	Yes	Yes
Cellular	Yes	No	Yes	Mention	Yes	Yes
TV, FM	No	No	Yes	Yes	No	Yes
Classification-guided	Partial	Partial	No	Yes	Partial	Yes

of possible sensor technologies that can be applied, each one with different strengths and weaknesses. The focus of this particular survey is precisely on reviewing the different technologies that have been used for IPS. We present a comprehensive review of the literature on indoor positioning systems, with the goal of providing a technological perspective of IPS evolution, making the distinction between different technological approaches by using a classification scheme, and presenting the evolution and trends of the field.

We stress that although outdoor positioning techniques could be used in indoor environments, these are left out of our scope because this survey is specialized specifically in indoor technologies.

This paper's structure is as follows: after this introduction, we compare this survey with other ones, to justify its publication; then, in Section 3, we present the methods and issues related to the field itself. Then, in Section 4, we proceed to present the review of indoor positioning technologies, which is the main subject of this report. After that, Section 5 presents a comparison of location technologies. Finally, in Section 6, we present a discussion, forecasting the possible evolution that indoor positioning systems will have in the years to come, and some conclusions.

2. Related Work

Though, as mentioned before, many IPS surveys have been published [12–16, 31–34], we can see that some surveys such as Hightower and Borriello's [32] are just outdated for a rapidly changing area such as IPS. Also, some otherwise good reviews lack a classification scheme that would allow the reader to organize the different works in some conceptual structure more useful than a flat and an unorganized list. The most representative example of this flaw is the otherwise very good review by Mautz [15], where a flat list of 16 technologies is presented in a sequential order, with no classification whatsoever. In our paper, we introduce thorough classification criteria that will partition the set of different works, making it more manageable and providing a conceptual structure for mapping the IPS field. Furthermore, some classification schemes proposed in previous reviews are not sound; for instance, Gu et al. [14] classified IPS systems as network-based, *systems that take advantage of existing network infrastructure*, and non-network-based, *systems using infrastructure solely dedicated to positioning*, but this leaves no space for purely passive systems, like magnetic field fingerprinting or ambient light analysis, as well as other technologies like image analysis.

One can also see that most reviews that strive to be comprehensive omit entire technologies, not to mention individual works. For instance, Gu et al. [14] omitted inertial navigation, ambient magnetic fingerprinting, the use of encoded patterns in artificial light (fluorescent or LED), ambient light analysis, the use of audible sound transmitted by the infrastructure (some with encoded patterns), RFID where the tags are fixed and the reader is mobile, ZigBee, vision analysis with portable cameras, floor tiles, and the indoor use of outdoor technologies (GPS, cellular, TV, and FM signals).

In Table 1, we present the technologies reviewed in several prominent technology-oriented surveys, compared with this survey. In the table, we write "mention" to indicate that the survey does not include a complete discussion of the corresponding technology. As the reader can see in this table, even current, supposedly comprehensive surveys like Deak's omit fifteen different technologies.

We stress the fact that very broad technology names are not fit as organizing principals in an IPS survey because the applications of a broad technology can be very creative and different. For instance, "magnetic" technologies include both those which pick up the irregularities of Earth's natural magnetic field and those which generate a pulsating magnetic field that will be registered by a sensor; these are completely different technologies. Thus, saying that a given survey covers "magnetic fields" is not precise enough. Some reviews intentionally leave out some areas. Liu et al.'s review [12] only considers wireless-based positioning systems, thus leaving out infrared, vision-related systems, sound or ultrasound, inertial systems, ambient light, floor tiles, and magnetism analysis (infrared and ultrasound are briefly mentioned in a section about "Positioning Using Multiple Media").

Finally, some surveys have not focused on the use of technologies as this one does. For example, Sun et al. [31] analyzed location algorithms, not technologies. In the case of the very comprehensive Mautz survey, we stress the fact that it has a slightly different character inherent in the fact that it is primarily a thesis and not a journal publication. Please refer to Table 1 for a detailed comparison.

In Table 1, "passive" means that the infrastructure generates the signal and that the object or person to be located receives it. For instance, "ultrasound passive" means that the device the user is carrying receives sound generated from the infrastructure and calculates the position from that information. Sometimes we write "portable" or "mobile" for "passive," as in "cameras (portable)," to emphasize the fact that the user is carrying the camera. Indeed, the distinction between active and passive is pervasive to many technologies and is one of the classification criteria we used; in the case of RFID, we cannot use the terms "passive" and "active" to indicate which end of the communication is the reader because the terms "active" and "passive" have another very specific meaning in the context of RFID. Another distinction is between signals with embedded encoded information and signals without embedded encoded information, where the former include some method of attaching symbolic information to the carrying signal in such a way that the receiver decodes the signal and recovers that information.

3. Location Methods and IPS

In general terms, a location estimation consists of an algorithm with three stages. The first stage is the *evidence*, where devices involved measure characteristics of a signal. The second stage is the *range estimation*, where devices use the measurements or evidence obtained to estimate distance to/from the object that needs to be located. The third stage is the combination of such range estimates in order to estimate position. This combination could be carried out using optimization methods (see [35]) or matrix equation methods (see [36, 37]), among other techniques. In this section, we present the most common techniques used to locate a user/object in indoor environments.

We will use the term position to emphasize the notion of a point in a coordinate system, whereas place will emphasize a region in a given context, for example, "living room"; location could refer to both. Indoor positioning systems (IPS, also "indoor location systems") thus provide information about the place where a user or object is situated in an indoor environment.

An IPS estimates the target object location from the observation data collected by a set of sensing devices or sensors [33]. An indoor location system can report the estimation as a symbolic reference, for instance, "kitchen," or as a coordinate-based reference [12]. Positions could be given in a number of different coordinate systems, depending on the purpose of the application. For instance, in outdoor navigation systems, the latitude and longitude are associated with a spherical coordinate system, but, for indoor location, generally a flat Cartesian coordinate system is better suited. In any case, a coordinate system transformation is always possible, so this is not one of the most crucial issues.

In this paper, we make the distinction between *techniques* and *technologies*, where the term "technique" refers to some basic abstract tool, not necessarily tied to physical media, which in principle could be used in several "technologies"; technologies are specific ways of using physical signals, registered through sensors, like radio waves or magnetic fields, in order to accomplish the goals of an IPS.

Multilateration basically uses geometry to combine the range estimates from different reference devices [32, 35, 36]. The range estimates could come from different measurements such as RSS (Received Signal Strength), ToA (Time of Arrival), TDoA (Time Difference of Arrival), and AoA (Angle of Arrival). If three reference devices are used in the combination, then it is called trilateration.

Time of Arrival (ToA) is sometimes called Time of Flight (ToF); it is the time taken by the signal to go from the transmitter to the receiver. If the receiver is able to obtain as evidence ToA, say t_0, then it will estimate range d by using the speed of light $c = 3 \times 10^8$ m/s with $d = ct_0$.

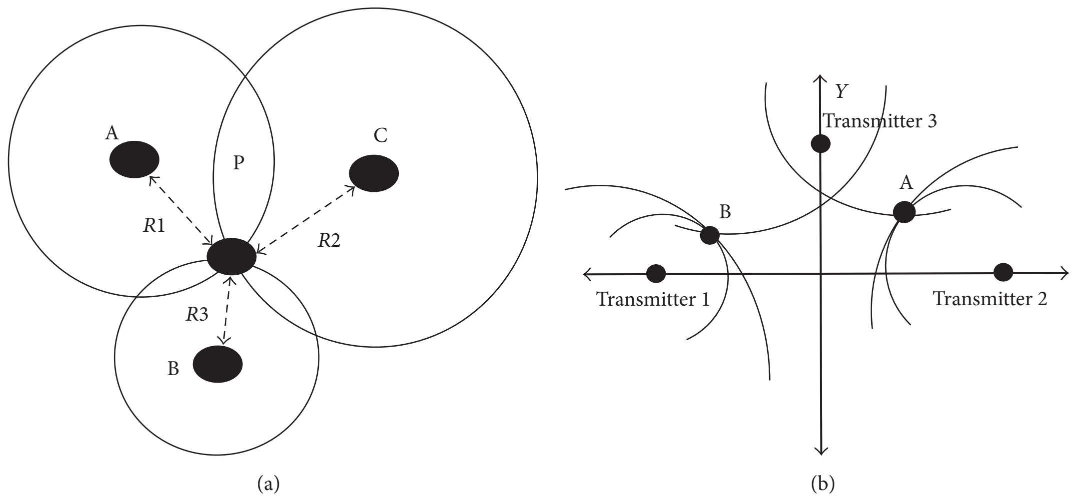


Figure 1: Time measures (a) ToA and (b) DToA.

Then, several reference devices combine their range estimates [36]. From the multilateration point of view, ToA describes circles around the reference devices (see Figure 1(a); this figure, as well as the following three, is similar to the ones in Liu et al.'s survey [12]), and although two circles are sufficient to solve for the coordinates, a third one is needed to get rid of the ambiguity. Normally, for the configuration in Figure 1(a), A, B, and C will be the transmitters and P will be the receiver, as is the case in GPS applications; this setting allows keeping the location of P private. As there could be errors in the ToA measures, either small ones due to noise and measurement precision or large ones due to reflections, multipath, or scattering of the signal, we will not be able to determine a single point as the solution, but a region, of which we normally select the point considered as the best guess. In the context of IPS, some of the problems with ToA will be aggravated: first, while in GPS the satellite positions are known in advance by their orbital parameters, in IPS, this is not the case, because there is not a general agreed reference. Second, for very short distances as are indoor ones, for RF signals, the time differences will be extremely small, so great precision is needed.

Time Difference of Arrival (TDoA) is related to ToA in the sense that it uses the travel time from the transmitter to the receiver in order to estimate distances, but sometimes the emitting time is unknown; thus, the difference in travel times from each receiver is used to estimate the distance to each of them. The calculation of the time difference eliminates the need for the time of transmission to be known [35]. As in ToA or any other time-based method, synchronicity between devices must be achieved to have accurate measurements. However, since TDoA does not use the distance between the transmitter and the receiver, the transmitter is not required to be in sync with the receiver. Synchronicity is only required between all receivers, since the calculation is based on their time/distance difference [38].

Angle of Arrival (AoA) provides a measurement of the angle at which a signal is received in a reference device. The reference device defines a line that departs from its position with such angle measured, where the target object is assumed to be. The combination of several lines from several reference devices places the target object at the intersection of several lines. At least two reference points and two angles are used (θ_1, θ_2) (see Figure 2). The advantage of this measure is that no time synchronization is required between references. The disadvantage is that it requires complex hardware to determine AoA [39].

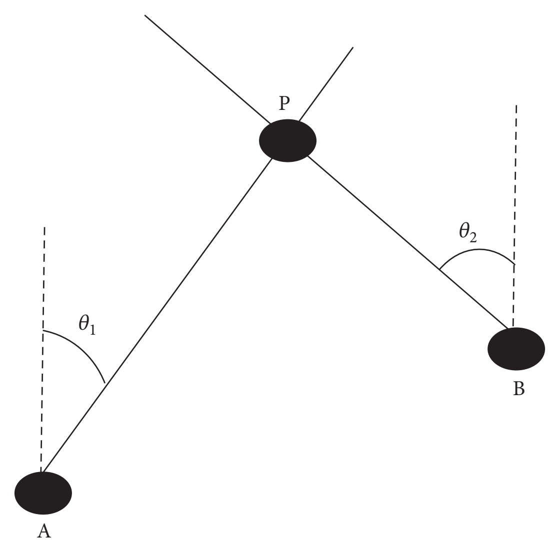


Figure 2: AoA measure.

Received Signal Strength (RSS) is the field intensity of a signal at the receiving point. RSS is measured at the receiver (see Figure 3), and then distance could be estimated by using a signal propagation model [40, 41] or other methods. In particular, the *Friis propagation equation* is often used [42]; at other times, more complex models are considered. The RSS technique requires the use of multilateration.

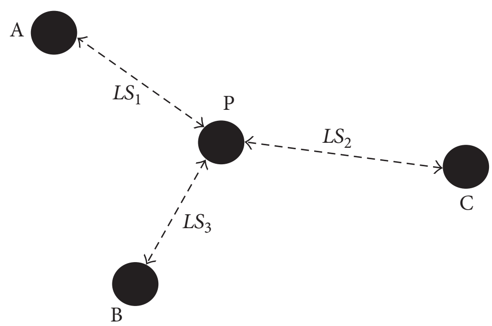


Figure 3: RSS measure.

Proximity techniques consist of determining when an object is "close" to a known location, as registered by a sensor specifically aimed at detecting proximity. There are two main approaches to sensing proximity: (i) detecting an object with a physical contact through touch sensors, capacity sensors, and so forth or (ii) detecting an object in a range area of one or more remote identification systems such as Bluetooth and RFID cards [43].

Fingerprinting is a method used to calculate approximate locations. The term has been used especially as a way to obtain locations from the detection of Wi-Fi signals and the like, as these are registered at a mobile device, but it is a general technique that has been used for Bluetooth and magnetism as well. It is composed of two phases: training and position determination. In the training phase, a radio map of observed signal strength values from different locations is recorded. Then, in the position determination phase, the signal strength values observed at a user device are compared to the radio map values using proximity matching algorithms, such as k-nearest neighbor (k-NN), in order to infer current user location [44], together with interpolation.

Very often, it is necessary to compensate for signal propagation impairments and the presence of noise in the measurements. This can be done using forms of aggregating partially redundant signals over a lapse of time. Some of the most useful smoothing methods are carried out by digital adaptive filter algorithms [45] such as Kalman [46] and particle [47] filters.

The *Kalman filter* [46] is useful for smoothing noisy data by taking a sequence of noisy values and estimating the value of the underlying variables more reliably.

In the context of location systems, *particle filtering* involves creating a "cloud" of estimated position points called *particles*, using some probability distribution around the believed actual position. When a movement takes place, displacement is applied to all particles at each "prediction" step. The relation between the transformation and the new particle positions requires the application of a model, which is application dependent. Then, a *resampling* step evaluates the fitness of each particle with respect to the new observations, so that unfit particles are destroyed and new particles are created near the best fit particles; eventually, the *weights* of particles are updated as well. This process is repeated in an iterative way [47].

Regardless of the specific details, many location technologies face the following challenges; the severity of each challenge varies from one technology to another.

Signal Propagation. Most methods and algorithms used to locate objects are based on signal propagation, as is the case for electromagnetic signals and sound. As they propagate, their power is gradually reduced ("attenuated"), following well-known physical laws [40, 41, 48]; the signal attenuation is normally measured in decibels (dB) logarithmic scale. As the signal gets weaker as the distance from the source increases, the signal-to-noise ratio gets worse. During its travel, the signal could also encounter obstacles and density changes, and so it is affected by propagation impairments such as reflections, scattering, and interference, becoming more difficult to measure with sensing instruments.

Multipath Environment. Signals can become mixed with some of their reflections, causing them to be scrambled and difficult to recognize. Another associated problem is that when a sensor receives a signal, it might not come from a line-of-sight path; hence, the total distance traveled by the signal is greater than the direct path. This can cause an error in the distance estimation and hence an error in the location estimation.

Line of Sight. Some of the location technologies require a nonobstructed path between a transmitter and a receiver, which is called line of sight (LOS). If LOS is required, the transmitter and the receiver must have a clear trajectory that avoids obstructions [49].

Synchronization. For some of the techniques used in IPS, it is required to have several clocks in very precise synchronization: for ToA, the signal travel time is taken from the time difference between the transmitter and the receiver clocks, whereas in TDoA we need to measure with much precision the difference between the clocks of two receivers [38].

4. Indoor Positioning Technologies

Before introducing the technologies, we introduce a classification to provide useful structure to an otherwise tangled mass of references. We classify IPS technologies using several criteria, one of which is the kind of signal used for location. We can have the following kinds of signals:

(i) *Radio Frequency Signals* (RF). A very generic term related to the frequency of radio signals, used in many popular communication protocols such as Wi-Fi and Bluetooth [38]. RF signals for indoor environments considered are in the MF (medium frequency, around 1 MHz) range, particularly between 2 and 5 GHz.

(ii) *Light*. Both visible and infrared light. Although this is an electromagnetic signal just as the RF signals, the associated technologies are quite dissimilar.

(iii) *Sound*. Both audible and ultrasonic.

(iv) *Magnetic Fields*. Both natural Earth's magnetic field, along with its irregularities, and artificially produced magnetic fields.

The second criterion is whether the associated signal is received and analyzed, so that the location is calculated, in the infrastructure or in a portable device carried by the user or some object with mobility. In the first case (infrastructure), we are going to say that the approach is "active," like in Table 1, because the portable device generates the signal instead of receiving it. In the second case, we say that the approach is "passive" because the mobile device receives the signal instead of generating it. Passive approaches have the advantage of privacy because the location calculation is done at the mobile device.

Finally, a third criterion is whether or not the signal used for location contains an intentionally embedded pattern of symbolic information, which is generated in the signal source and then reconstructed at the receiving end. In the affirmative case, we say that the approach uses *embedded information*; in the negative case, we say the opposite. Examples of signals containing embedded information are Wi-Fi signals as well as visible light and sound methods that encode a predefined signal in light or sound that is not perceived by humans (see Sections 4.1.2 and 4.2). Examples of signals not containing embedded information are the magnetic field of Earth as well as ambient noise. As an illustration of our classification scheme, consider one audible sound location approach [50] in which music playing in a public place (like a mall) is modulated in a different way by each speaker using predefined patterns that are not perceived by humans, so that the mobile receiver identifies the relative intensity of music from each speaker and using triangulation calculates the user location. According to our classification scheme, this approach is (i) sound-based, (ii) passive, and (iii) with embedded information.

The three classification criteria (type of signal, active/passive, and with/without embedded information) are orthogonal, so you can visualize the classification space as a cube. We cannot stress enough the importance of structuring the huge set of location approaches, which otherwise would look chaotic and difficult to grasp.

In the following sections, we present a description of these technologies, as well as some representative examples of indoor positioning systems based on these technologies, starting with a pioneering system, then a state-of-the art proposal, and sometimes a commercial system. Later, in Section 5, we will present the strengths and weaknesses of each technology.

4.1. Optical Technologies. Though optical signals are in fact just a form of electromagnetic radiation, we separate them from radio waves, because the specific technologies are different, as well as their advantages and challenges; for instance, optical signals used in location technologies are restricted by line-of-sight constraints.

4.1.1. Infrared Technology. *Infrared technology* (IR) for IPS [5, 51] uses electromagnetic radiation with wavelengths longer than the visible light spectrum [52]. An infrared simple system is composed of an infrared light emitter diode, which emits an infrared signal as bursts of nonvisible light,

Figure 4: Active Badge prototype (http://www.cl.cam.ac.uk/research/dtg/attarchive/ab.html).

and a receiving photodiode to detect and capture the light pulses, which are then processed to retrieve the information [52]. Infrared location can be used in active or passive configurations.

IR system reliability is affected by many characteristics of the emitted optical signal, such as its directivity (to which degree it is unidirectional), as well as its way of reacting to obstacles, such as the reflectivity and scattering (irregularities in direction and when hitting obstacles). Many domestic IR devices, such as remote controls, are intended to have low directivity because the user is not supposed to point exactly to the receiving sensor. Most IR systems require line-of-sight clearance from the emitter to the sensor, though sometimes reflected signals have enough power to activate the sensor. Of course, in the context of IR IPS systems, the requirement of LOS clearance is a great disadvantage, as it suffers from no-detection areas that are occluded from the transmitter or sensor.

A pioneering "active" system was the Active Badge, developed by Want et el. [5]. The system is intended to locate employees, who carry an IR "tag," in an office environment (see Figure 4). The badge emits a unique infrared code every 10 seconds. The codes are picked up by the infrared sensor networks that are placed around the office environment. The information received by the sensor network is then processed by a computer that is also connected to the network. The system makes the location of a user available to portable devices that may display it. The system presents two limitations: it requires LOS between the receivers and the badge and the system performance is affected by sunlight. It has been reported that this system compromised user privacy. During the implementation, some employees declared to be "horrified" to learn that their location was known at all times by the organization [5].

A more modern system is reported by Gorostiza et al. [51] for estimating the location of a mobile robot, using an active configuration. In order to estimate the position of the mobile target, distances are measured from it using phase shifts to predetermined reference points and introduced into a hyperbolic trilateration nonlinear equation system, to obtain the mobile target location. They claim a precision below 10 cm.

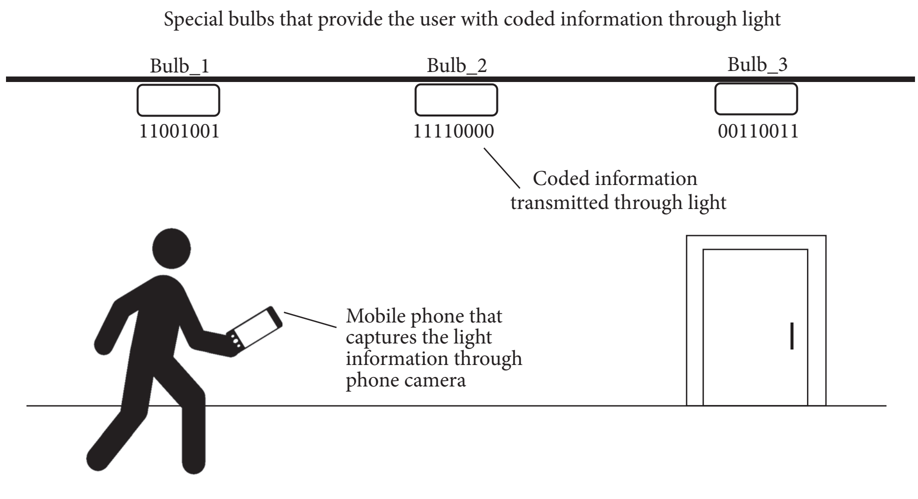


Figure 5: VLC approach.

4.1.2. Visible Light Communication. Visible Light Communication (VLC) is a technology that uses visible light to transmit data. Any type of lamp can be used, but LED lights have been found to be the most appropriate [18]. The transmission of data using visible light is possible due to the ability of the light source to be switched on and off again in very short intervals. This flicker can be so fast that it cannot be perceived by human eyes and can use a variety of modulation methods. VLC for IPS has been considered due to the fact that it allows the reuse of already available artificial light infrastructure, so the cost of implementation could be low [53].

The principle for VLC is that each of the fixed lamps has different flicker encoding, so the sensor, which could be carried by the user, receives the light and compares the modulation against the known encoding schemes and eventually determines which is the dominant one, thus associating the sensor location with the vicinity of the corresponding lamp (see Figure 5).

One advantage of such an arrangement is that it is not intrusive at all, because the human users see just ordinary lamps fixed at standard places such as the ceiling. The receiver could be a photodiode or an optoelectronic device capable of capturing light intensity (e.g., photocell), or an image sensor (e.g., camera) for registering the light pulses from the transmitter. The advantage of an image sensor is that it can register simultaneously several lamps with their positions, thus achieving a more precise location estimate.

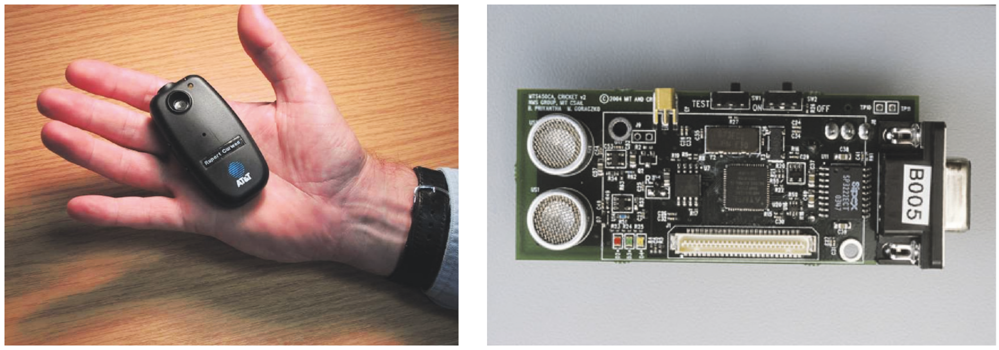
All VLC projects, as [18, 19] and Zhang et al. [8], use passive configurations because obviously lamps are heavy and need connection to the electricity network. The latter reports an accuracy below 20 cm.

There are as well some commercial systems, like the Philips proposal [17] (http://www.lighting.philips.com/main/systems/themes/led-based-indoor-positioning.html) (http://www.gelighting.com/LightingWeb/na/solutions/control-systems/indoor-positioning-system.jsp), as well as ByteLight [17]. The ByteLight Company claims that the system provides submeter accuracy and that it is easy to extend the coverage by adding more ByteLight bulbs. The disadvantage of the system is that it requires specialized devices (ByteLight bulbs).

4.2. Sound-Based Technologies. Sound signals, consisting of pressure waves propagating in the air, benefit from the fact that sound travels at a much slower speed than electromagnetic signals, thus allowing the measuring of time between the emission and the arrival of a signal much more easily. The emission time is often measured by simultaneously transmitting a radio signal and a sound signal, because the radio signal arrives at the sensor almost instantaneously and the sound signal arrives at the sensor later, so the difference between these two times can be used to calculate distance; this method has long been exploited by farmers, who estimate the distance to lightning by counting the time between seeing the flash and hearing the thunder. Of course, there is also the option of using the ToA or TDoA, also with the advantages of a slow signal.

4.2.1. Ultrasound. Ultrasonic location-based systems use sound frequencies higher than the audible range (beyond 20 KHz) to determine the user position using the time taken for an ultrasonic signal to travel from a transmitter to a receiver. One evident advantage of ultrasound signals against audible signals is that the former are not detectable by humans, while the latter would be annoying. Ultrasound systems, like many other IPS, can be "active" or "passive."

A pioneering ultrasound work is the *Bat system* [54], dating from the mid-nineties, in which an array of fixed microphones is used, and a tag is carried by the user (see Figure 6(a)), giving thus an active configuration. User location is calculated using the principle of trilateration; at least 3 microphones receiving a sound pulse are needed for finding the user position. Using the information about the relative strength of the signal received in the microphone array, it is also possible to find out which direction the user is facing, assuming that the sound transmitter is carried in



(a) (b)

Figure 6: Examples of ultrasonic devices: (a) Active Bat prototype and (b) Cricket beacon (http://www.cl.cam.ac.uk/research/dtg/attarchive/bat/).

front of the user. Other advantages of the Bat system are that it is able to locate simultaneously more than 70 separate transmitters and that its precision is in the order of a few centimeters, the authors claiming almost 3 cm.

One disadvantage is that, as in most active systems, the location information is disclosed to the infrastructure administrators, creating a privacy risk.

Another seminal work is the *Cricket system* [55], which uses a passive configuration. It places transmitters called "beacons" (see Figure 6(b)), which are part of the infrastructure attached to fixed points like ceilings or walls, and receivers called "listeners," which are carried by users. The Cricket is actually a hybrid system, as it combines ultrasound waves as well as radio frequency signals. The algorithm of the Cricket system tries to find the closest beacon, taking into account the possible bouncing of ultrasound signals against the walls and other surfaces. In order to avoid systematic or persistent collision between the signals of two beacons, randomization is used for separating two subsequent signal emissions. Other more recent works like *LOSNUS* [24] also prefer the arrangement of fixed emitters and mobile sound detecting devices.

Regarding the scalability of ultrasonic systems, in the active configurations, the number of simultaneous tags in an environment affects system performance and eventually renders the system unusable because with too many tags the sound emissions will collide with each other. In contrast, the number of receiving devices does not affect the performance of a passive system, and collisions from beacons can be avoided as synchronization mechanisms are not difficult to put in place.

From the point of view of accuracy, we see better results in the passive configurations. Schweinzer and Syafrudin [24] reported a precision of nearly 1 centimeter.

4.2.2. Audible Sound. It is also possible to use audible sound signals to encode information for location systems. Of course, the naive idea of just delivering an artificial audible sound has too many drawbacks, mainly that it would annoy humans nearby. But there are more sophisticated schemes, like watermarking an already available sound such as music in malls and other public places in a manner nondetectable to the human ear.

For instance, Nakashima et al. [50] presented a method for estimating user location using digital watermarking of audio signals, in which a pseudorandom sequence is used to modulate in amplitude several frequency bands of the host signal (which is just music). This is done using different pseudorandom sequences for each speaker deployed in the public space. The user, who carries a microphone, receives the sound mixed in real time from several speakers, which appear to play the same music but actually have different watermarking. The rest of the process analyzes the sound in order to separate the watermarks coming from each speaker. By means of correlation and time shifting, the system recognizes the amount of delay of each speaker, and using trilateration the system calculates the position of the user. The signal strength is used as a redundant indicator of each speaker's distance to the microphone, improving precision and allowing a moving user to be located. The authors claim an accuracy of 1.3 meters.

4.3. Radio Frequency Technologies. While most radio-based technologies used in indoor positioning systems employ radio signals restricted to a small range of frequencies (narrow-band signals), there are also applications that use large parts of the spectrum (spread spectrum signals). In this section, we present first the narrow-band technologies and then the spread spectrum ones.

4.3.1. Wi-Fi. Wireless Local Area Network (WLAN), also referred to as "Wi-Fi," transmits and receives data using electromagnetic waves, providing wireless connectivity within a coverage area [48]. These waves substitute for twisted pair, coaxial, or optical fiber used to transmit data in conventional LAN.

While for outdoor location it is sufficient to get the identification of a detectable base station (i.e., the symbolic name or SSID of an access point), in indoor location it is necessary to go beyond the mere access point identification in order to achieve better precision. Three approaches are commonly used to locate a user using WLAN technology:

(i) The propagation model of a known antenna can be used, calculating the distance to a known base [40, 41, 48].

Figure 7: Ekahau Tags (https://www.ekahau.com/wifidesign/about).

(ii) The relative strength of several known Wi-Fi bases is used to solve the position by a multilateration method.

(iii) *Fingerprinting*: a pattern of known Wi-Fi bases with their relative strengths is matched to a database of known patterns associated with locations [44]. Of course, this requires an extensive previous mapping activity and storing Wi-Fi patterns for each mapped point in order to build the database.

An early system that uses WLAN technology is RADAR, developed by Microsoft Research [56] (website: http://research.microsoft.com/en-us/projects/radar/). It uses both fingerprinting and propagation models to calculate location. Their propagation model considers an attenuation factor for the walls (WAF) and the floor (FAF). WAF takes into account the number of walls (obstructions). The authors argue that the second approach addresses the limitations of the first approach. The RADAR system claims an accuracy of 2 to 3 meters in a space the size of a typical office.

A state-of-the-art system is Freeloc [11], in which the users themselves collect Wi-Fi location information by running on a portable device (smartphone) a process that makes the map construction of fingerprinting automatic, which is normally its most expensive aspect. Mapping is done without explicit user intervention; of course, as the users carrying a smartphone with the Freeloc app continue doing their normal activities, they do not remain static nor stay still a predetermined period of time, which makes the measurements difficult. Another problem is that each user could have a different mobile device, so signal strengths are not measured the same. So, in the Freeloc system, it is not the value of the signal intensities that is considered, but their relative strengths. Freeloc is not intended to achieve the maximum accuracy in ideal conditions (system developers report accuracies in the range of 2 to 3 m), but to make Wi-Fi fingerprinting practical in realistic settings.

An example of a commercial system that uses WLAN fingerprint is Ekahau [57]. It uses an Ekahau tag, a small device that includes a button, lights, motion sensors, and an audio alarm (see Figure 7). The Ekahau tag must be worn by a person or attached to an object to be located and transmits Wi-Fi packets periodically, as the button is pressed or as the person or object moves. Ekahau claims accuracy from submeter range to 3 meters.

4.3.2. Bluetooth. *Bluetooth* is a wireless communication technology that uses digitally embedded information on radio frequency signals. Originally intended for data exchange in short distances, it was defined by the standard IEEE 802.15.1. The main objectives of the technology are to facilitate communication between mobile and fixed devices or two mobile ones, in order to eliminate cables and connectors between devices (e.g., in the use of wireless headphones), and to facilitate data synchronization between personal devices [58].

Bluetooth technology has been considered for indoor position systems as a competitor to Wi-Fi, in particular since the widespread adoption of Bluetooth Low Energy (BLE), due to its availability (it is supported by most modern smartphones), low cost, and very low power consumption, which allows fixed emitters to run on batteries for several months or even years [59].

We notice that, in some of its profiles, Bluetooth is symmetric, so in those cases we could not differentiate active or passive configurations. But most modern proposals consider fixed beacons and smartphones, very much in the idea of passive configurations.

One of the seminal projects using Bluetooth technology for localization is the work of Feldmann et al. [60], which uses RSS triangulation with least square estimation. The authors claim an accuracy of 2.08 meters in a small room. However, the system is sensitive to signal attenuation and reflection due to obstacles between the person who carries the Bluetooth device and the access points.

As Bluetooth beacons compete with Wi-Fi, Faragher and Harle [59] provided a quantitative comparison with Wi-Fi fingerprinting. Some systems combining both Wi-Fi and Bluetooth have been reported as well [61].

A commercial proposal is Apple's iBeacons, which is basically an application of Bluetooth Low Energy (BLE) [62] for location purposes. It takes advantage of the short range of BLE in order to determine when the user is in the proximity of a beacon. The suggested commercial application is that the infrastructure responds with an appropriate action, such as delivering shopping advice or special offers to the user. A beacon can determine an approximate degree of proximity to the user in three broad regions: immediate, less than 50 cm; near, between 50 cm and 2 to 5 meters; and far, between 2 to 5 meters and some 30 meters. Accuracy across these regions depends on other factors such as interference from physical barriers. From the software point of view, iBeacons has been buried into the operating system of Apple devices (from iOS7), so that applications can be launched even without user intervention. iBeacons has already been deployed in hundreds of Apple stores as well as some public events. From the privacy point of view, there is the problem that at all times the user location is known to the iBeacons system, which could be undesirable for the user. An additional problem is that it is not an application the user could easily delete, as it is part of the operating system. On the other hand, integration with the operating system could be attractive to commercial firms.

4.3.3. ZigBee. *ZigBee* is a wireless communication standard developed by the ZigBee Alliance. It was proposed to specifically address the need for low-cost implementation of low-data-rate wireless networks with ultralow power consumption. The ZigBee standard has adopted the IEEE 802.15.4 as its physical layer and medium access control [63].

Due to its energy saving and improved security, ZigBee technology was originally intended for applications like home automation (remote lights and thermostat monitoring and control), urban traffic light control, health care, and agriculture, among many others [64]. In addition, ZigBee has been used to develop indoor positioning systems because it is a low-cost, low-power consumption technology and because it is easy to obtain RSSI levels as these are incorporated in each of the packets sent, with no additional hardware needed.

An indoor positioning system based on ZigBee is composed of a network of sensors and wireless sensor network algorithms. Most of the algorithms used in these systems use the RSSI values to estimate the location, relying thus on the same techniques as Wi-Fi and Bluetooth, that is, fingerprinting and propagation models.

In particular, Fang et al. [65] used a network of several ZigBee nodes and a combination of different approaches, both propagation and fingerprinting types. After all those methods have been applied, a combination of them is calculated to find a location prediction that, as they show, is better than any individual method. Needless to say, the application of several location algorithms taxes the computational costs of the system.

A commercial project using ZigBee is Netvox (website: http://www.netvox.com.tw), in which location is part of a complete home automation platform.

4.3.4. RFID. *Radio Frequency Identification* (RFID) [66] is a technology that uses radio waves to make a specialized circuit produce a response containing a unique identifier; as the circuit could be attached to people, animals, or objects, it provides a method for identifying them. An RFID system consists of RFID readers and RFID tags. The RFID reader can pick the data emitted from RFID tags.

Tags or RFID “transponders” are fitted with a microchip and a printed circuit board acting as an antenna, capable of emitting radio signals carrying information, mainly its unique ID [66]. Tags can be classified depending on how they get energy to respond to an RFID reader: they can be “passive” if they answer back to a reader using just the tiny energy emitted by the reader, collected by means of a little antenna, or “active” if they have their own power supply and transmit periodically their ID signal. Some RFID tags are intermediate “semipassive,” using a small battery and transmitting only when a reader signal is detected (do not confuse these “active” and “passive” terms with the terms we have used for classifying IPS).

RFID technology has many applications and areas of use, like personal/vehicle access control, department store security, equipment tracking, baggage, fast food establishments, logistics, medical equipment, and so forth [67]. In addition, RFID systems have been used for localization, especially when the user location does not need to be known at all times, but only when passing through important control places, like entrance gates. In these cases, user location is often given in the form of a logical location, as, for instance, “before the gate,” “inside the waiting room,” and so forth, and not in a coordinate system.

Two variants of user positioning are possible: in one of them, the user carries the tag, and the tag is read by readers in the infrastructure. The other option is that the user carries a reader, and many tags are embedded in key places of a given area. The first option has been the most popular for good reason: the tags are inexpensive and very light, while the readers are bulky and very expensive.

LANDMARC (Location Identification based on Dynamic Active RFID Calibration) is a pioneering RFID system [4]. It belongs to the category of systems in which the tag is attached to the object or person to be located. LANDMARC requires information about the signal intensity of each label reader to calculate the position of RFID tags using the k-nearest neighbor (k-NN) algorithm. Authors claim an accuracy of 1 meter. However, the system presents the limitation that the reader does not provide directly the signal strength; it only reports “detectable” or “not detectable.” LANDMARC needs to scan periodically the power levels to estimate the signal strengths of the tag; this produces a latency when locating a tag. An additional problem is that there is a great variation in the behavior of RFID tags, due to the loss of battery power.

The opposite configuration (user carrying the reader, with tags attached to the infrastructure) is seldom used, but there is an interesting example of indoor/outdoor use: in the SeSaMoNet deployed in Italy [68], the user to be located (who happens to be a blind person) carries the RFID reader, which is at the tip of a cane, and passive tags are buried inside sidewalks all over the city. Each tag is associated with a place in town, so as the blind person passes the cane over the floor, the embedded RFID tag answers with its ID, which is associated with information about that place (which is read audibly to the user) by means of a database. The authors indicate that the system is most accurate at guiding the blind person when the cane is 20–25 centimeters away from the passive tag.

A commercial system using RFID for location is offered by Zebra (https://www.zebra.com).

A variant of RFID is NFC (near-field communication [69]), which has become important in recent times because it has been incorporated in many popular Android smartphones and also because it has been proposed as a way of making secure mobile payments. NFC provides a two-way communication between two devices touching each other or in close proximity, and because of this requirement it can be used for registering the user's location, which is obviously close to a fixed terminal. Nevertheless, its future as a device for location purposes is uncertain at this point, as its requirement of an active user intervention (i.e., taking out a smartphone and putting it in contact with a terminal) is a severe inconvenience compared with traditional RFID, in which it suffices to carry a tag.

4.3.5. Ultrawideband. *Ultrawideband* (UWB) is based on the transmission of electromagnetic wave forms formed by a sequence of very short pulses using a very big bandwidth.

UWB has many applications and areas of use: cable TV, asset management, radar and imaging, security applications, medical applications, vehicular radar systems, high-penetrating radar systems, and location and tracking, among others [70]. UWB technology has been considered to deploy indoor positioning systems because UWB techniques offer distinct advantages in precision of time-of-flight measurement, multipath immunity, and low-power requirements for extended operation [71].

Two different measures can be used in a UWB positioning system to determine the distance between the target and a reference point: Time of Arrival (ToA) and the Time Difference of Arrival (TDoA); these measures are explained in books on the subject [35].

Bai and Lu [72] presented an IPS based on UWB, which consists of four fixed transmitters and some mobile users. The transmitters, which are synchronized using a time division scheme, send a UWB signal to the mobile users. The estimation of location was calculated using a triangulation method based on the measure TDoA between transmitters and receivers. The system claims an accuracy of 1 meter when the bandwidth of UWB signal is 528 MHz.

An example of a commercial system based on UWB is Ubisense Real-Time Location System [28]. This system has two types of components: a network of Ubisensors fixed to the infrastructure in known positions, distributed throughout the area to be covered, and connected to the Internet using Ethernet cables and a set of "Ubitags," which are the mobile devices attached to people and objects to be located; they include a radio transceiver and a UWB transmitter. Tags are small, active radio frequency devices that transmit both a UWB signal for location and a standard 2.4 GHz signal for communication. Tags come in a number of different shapes and sizes; for instance, the "slim" tag is typically used as an individual tag because of its directional antenna and interactivity options (buzzer buttons and LED; see Figure 8). To communicate with the active tags, a building space is equipped with sensor devices at key points of visibility within the tracking space. The system uses both AoA and TDoA of the UWB signal to calculate a location. The sensors are configured in groups called cells, each one with a Ubisensor playing the role of a master and up to 10 slave sensors. The master uses a Time Division Multiple Access (TDMA) scheme, assigning a slot to each tag for communication. UWB signals are received at the sensors and are used to calculate the Angle of Arrival (AoA). Just two sensors receiving a tag signal are enough to deliver a 3D location. If sensors are synchronized, the TDoA between each pair of sensors is calculated; this makes the location robust. The system's authors claim an accuracy of 15 centimeters. The disadvantages of the system are that it requires dedicated infrastructure and devices, that it limits the number of mobile devices in one cell, and finally that the user's location is disclosed to the system, raising some privacy concerns.

Figure 8: Ubisense Tags (http://ubisense.net/en).

4.4. Passive/without Embedded Information Technologies. In this section, we will discuss several technologies that all rely on naturally occurring signals. Thus, the signal does not contain any embedded information. For the most part, sensors in this type of scheme are passive because they just pick up available signals from the environment.

4.4.1. Magnetic Field. Though there are some approaches for indoor localization using artificially generated magnetic fields [73], most modern systems make use of Earth's natural magnetic field strength and/or orientation to perform a localization process, so in the following we are only going to consider systems based on Earth's natural magnetic field.

An IPS based on magnetic fields uses a magnetometer to measure magnetic field variations, which will be used to determine the position of a person or object. The position estimation is commonly performed through methods such as fingerprinting.

Haverinen and Kemppainen [6] proposed an approach for dynamic localization in corridors in a building. The moving target, starting from an unknown position and following the centerline of the corridor thereafter, sensed the magnetic variations and used pattern analysis to identify the position.

Gozick et al. [74] reported another indoor positioning system based on mobile phones that measures location using disturbances of Earth's magnetic field caused by structural steel elements in a building. They developed magnetic maps taking measurements along corridors and landmarks and then identified places based on a magnetic signature. Their magnetic intensity maps are extremely detailed, which is of course a problem from the practical point of view, as we would have to construct those maps for every location where the system is deployed. We compare this with the facility for using a system like Galvan's, discussed in the following.

In the research project of Galván-Tejada et al. [20], another magnetic field indoor location method is presented. It uses the magnetic sensor of a mobile phone to estimate user location at the room level; that is, no precise coordinates are calculated. As previously, this method requires to first create a fingerprint database of magnetic field variations, but in this case there is no need to map each point of a grid. Instead, a pseudorandom path is followed to collect a "typical" magnetic variation in a certain room, and then a Fourier transform is done to the collected measures, which are sent to the frequency domain; so a frequency magnetic pattern for each room is stored in the database. For detecting a location, the user walks randomly inside a room and scans the magnetic signal data (a Fourier transform is applied to this information), and then the result is compared against the database, locating the user in the room. The advantage of this method is that no detailed map is necessary for building the database in the first place, which opens the possibility of constructing maps automatically by random users who carry a mobile application on their phones. Another advantage is that it uses the standard inexpensive magnetometers that come with many modern cell phones. The limitation of this method is that it gives only the "logical" location of the user (i.e., in which room he/she is), not the exact position in a coordinate system.

An example of a commercial system that uses a magnetometer is IndoorAtlas (website: http://www.indooratlas.com). This system utilizes the magnetic field irregularities inside buildings to estimate the location of an individual. It requires a floor plan image to be added to IndoorAtlas Maps using the tool *IndoorAtlas Floor Plans web application* and also to collect the magnetic field data of a given path in an indoor environment and then create the magnetic field map with the tool *IndoorAtlas Map Creator*. After that, the system can estimate the user's location by comparing the magnetic field data from the current position against the magnetic field data previously collected.

The system's authors claim an accuracy of less than 2 meters. Their documentation shows typical applications in environments such as retail surfaces for easily locating merchandise.

4.4.2. Inertial Technology. The estimation of a future position given an initial one and a speed and direction is indeed one of the oldest methods for navigation, often called "dead reckoning"; it was used by ancient sailors like Christopher Columbus. One obvious problem with dead reckoning is the progressive accumulation of errors, as a small error in direction could mean a huge error as a long distance is traveled.

In modern systems, inertial methods use digital *accelerometers* and *gyroscopes* and generally combine their information with other sensors in order to achieve a good performance, as we will see in the following.

Accelerometers can be used to determine the modifications in user position when acceleration in a certain direction is detected. Of course, this is a very rough estimation, which can be improved by using a gyroscope for direction changes. The evidence of initial acceleration could be confirmed by the fact that a user is walking, by recognizing (also with an accelerometer) the typical shake associated with the walking movement [75].

Dabove et al. [10] and Leppäkoski et al. [76] reported inertial IPS. The latter devised a way of countering the error accumulation typical of inertial systems by refining inertial navigation with particle filtering.

The system reported by Leppäkoski et al. handles a prestored map on which the user's position is tracked in a continuous way. The particle filtering algorithm (see Section 3) is used to refine the overall position by discarding impossible paths that collide with the boundaries of the map, thus killing the associated particles in the particle filtering algorithm and further refining the user location. This avoids the accumulation of errors as time passes.

4.4.3. Passive Sound-Based Technologies. In this section, we discuss sound-based location systems that use sound without embedded information, in contrast to the technologies we presented in Sections 4.2.1 and 4.2.2.

Location by sound without embedded information generally takes already available sounds in the environment as characteristic of a given place and uses a database of known places. A user detecting ambient sounds with a portable microphone could be located by matching the registered sound against the available places in a database.

A typical work is the one by Vildjiounaite et al. [30]. It calculates a "fingerprint" of the ambient noise by taking 10-second samples and then doing a calculation that involves dividing a sample in time frames, calculating a frequency spectrum for each frame, filtering some frequencies, sorting the remaining frames by energy, and taking the logarithm of a certain percentile. Authors claim a precision of 69 percent for recognizing rooms from a set of 33 different rooms. They implemented an iPhone application, *Batphone*, available for download, which recognizes in real time which room the user is in, using nothing but ambient sound (see Figure 9) (website: http://www.mccormick.northwestern.edunewsarticlesarchive-20092012article_935.html).

A more modern system using background noise is reported by Galván-Tejada et al. [77], but this one is actually a hybrid system that uses also visible light and magnetic field.

4.4.4. Passive Visible Light. In this section, we discuss systems that use the position of known light sources like lamps to find a location, but without making use of any information embedding, in contrast to those seen in Section 4.1.2. The techniques we discuss in the current section are of a "passive" nature, as the sensors just pick up the available light using

Figure 9: Batphone mobile application (https://itunes.apple.com/us/app/batphone/id405396715?mt=8).

sensors, instead of producing light with the explicit purpose of localization. We start by discussing the use of available light sources.

The idea of exploiting the measurement of known light sources is at the root of works like Randall's *LuxTrace* [78]. In this work, standard solar cells are used to register luminosity (intensity of light), besides their intended use to collect energy. They leverage the advantages of passive technologies, as no infrastructure at all needs to be installed. Further, as every building in the world has particular luminosity conditions, this technology has universal coverage. *LuxTrace* learns variation signatures in straight trajectories (measurements were taken using a trolley), and then, when following those same trajectories, the system identifies the user's position. System developers achieved an average position estimation error of only 21 cm. Of course, the limitation to straight trajectories is a serious one.

Other passive visible light works combine light with other sources for getting the location. For instance, Azizyan and Choudhury [79] combined passive visible light with ambient sound (see Section 4.4.3). Similarly, Galván-Tejada et al. [77] combined passive visible light with ambient sound and magnetic field, all three passive signals with no infrastructure requirements.

4.4.5. Computer Vision. IPS that use computer vision make use of the information collected by cameras and image processing techniques for identifying and tracking objects. We identify two configurations for IPS using computer vision: in the *passive* approach, the camera is worn by the user or object to be monitored, and it captures images or video from the user's perspective. The captured images could be compared with files previously stored in a database with location information. In the *active* approach, one or several cameras are fixed in the environment in which the subjects will be monitored (the terms "active" and "passive" are not common in the terminology of computer vision, but we use them for uniformity with the terms used here for all the other technologies).

Some works belonging to the passive mobile camera approach use *visual odometry* (VO) to update the user position. VO is "the process of estimating the egomotion of an agent (e.g., vehicle, human, and robot) using only the input of a single or multiple cameras attached to it" [80]. VO is not a recent approach and has been around for some 30 years but has been gradually improved both in efficiency and in precision [81]. An example of VO work is presented by Kitt et al. [82], who used a sequence of stereo images and, with filtering techniques, were able to achieve good precision with less computational cost than competing methods. VO has many variants: it could involve 6 degrees of freedom or more restricted movements (such as in the case of a wheeled vehicle on a flat floor) and could be done with the help of a model such as a map, either previously available or constructed as the camera is moving (also known as *SLAM* for Simultaneous Location and Mapping). Also, it could use a single camera or a stereo set of two cameras.

A recent positioning system that uses computer vision methods and a smartphone camera to estimate the user location is MoVIPS [83] using a passive approach. It consists of two phases: calibration and localization. The calibration phase is intended to create a database with images taken by mobile phone users together with their location. In the localization phase, the user uses a mobile application to take an image of the environment; it is uploaded to a server component. The server executes a "Speeded Up Robust Features" (SURF) algorithm, which compares this image with a database of the calibration phase. Once the server has the results of image comparison, the user position is estimated. This information is sent to the mobile phone to be displayed to the user in the mobile phone application. The authors claim a position error of 1.3 meters. The system presents the problem that if the image or video has a low resolution or motion blur, the accuracy of the system drops [83].

One computer system difficult to classify is SignPost [9], an indoor positioning system which uses an off-the-shelf camera phone and 2D barcode markers; each barcode identifies a unique position. In SignPost, smartphone cameras are used in continuous mode to capture barcode signs as they fall inside the field of vision, and the software uses the perspective distortion to further refine the position of the user relative to the sign. The authors claim that SignPost can estimate target position with a centimeter level accuracy. It could be argued that this system falls in the category of IPS "with embedded information," because the barcode markers are a form of encoded information, but there is no explicit "transmission" of a produced signal. The SignPost system was deployed in a real-world commercial event.

A project based on the active (fixed camera) approach is EasyLiving of Microsoft Research [84], intended for building intelligent environments. It uses computer vision for person tracking and visual user interaction, as EasyLiving spaces must respond to user's actions and voice commands. Its accuracy is reportedly about 10 cm in the horizontal plane. This visual tracking system was a precursor of the recent Microsoft Kinect product line [85].

4.5. Hybrid Technologies. The systems that rely on technology fusion are called "hybrid." While in surveys like that of De Gante and Siller [86] the term "hybrid" refers to the combination of different techniques like AoA, TDoA, and so forth; in the context of the current survey "hybrid" refers to the combination of different technologies, such as magnetic and Wi-Fi technologies. In a hybrid system, one of the technologies is commonly considered more relevant for estimating the location of the user, while the rest of the technologies are considered as complementary, and they are used to improve the features of the system such as accuracy and coverage area.

Evennou and Marx [87] presented a system that combines inertial and Wi-Fi location technologies. The inertial part is done using standard accelerometers and gyroscopes, introduced in Section 4.4.2, and the Wi-Fi location is estimated using fingerprinting from signal strength measures (see Section 3). Authors argue that pure inertial systems are weak because errors in the estimation tend to accumulate progressively and also that pure Wi-Fi location systems lack precision and responsiveness to user movements. Therefore, they propose to counter these respective weaknesses by means of a combination. In this work, the Wi-Fi location is estimated by means of RSS fingerprinting [88], which implies the construction of a database of existing Wi-Fi bases with their RSS at each measurement point. At run time, the k points of the database with profile closest to the measurement are found, and then the barycenter of them is considered as the calculated position. Then, the inertial part of the system is incorporated to the location by means of a Monte Carlo simulation method, in particular particle filtering [89]. Based on experiments, the authors report a precision of 1.53 m after the subject has made a round walk near the edges of a 40 m by 40 m room. For comparison, using only Wi-Fi fingerprinting, the precision is 5.73 m.

A recent example of another hybrid system is presented by Kriz et al. [7]. This system is based on Bluetooth and Wi-Fi technologies; they propose to use these technologies because they do not require high computing resources and are both cheap and available off-the-shelf. To merge these technologies, they propose an algorithm that combines fingerprinting for both Bluetooth and Wi-Fi. In their experiments, an error of 0.77 m is reported, with an improvement of 23 percent over Wi-Fi alone.

Another hybrid system is MaWi [90]. Its authors argue that Wi-Fi signals are not stable and do not allow for fine grained localization and that the magnetic signals are not good for discriminating distant places but are very stable and discriminate well between close locations, so their respective strengths are combined when used together. In some cases, the fusion of technology seeks to address the limitations of a positioning system. For instance, the work of Liu et al. [23] uses VLC technology, which has limitations (it cannot detect the direction of the person and it is affected by sunlight and the reflection of light off of walls), so they proposed merging VLC with RFID and Bluetooth [91]. Furthermore, hybrid technologies sometimes aim to increase the accuracy of IPS; for instance, Kriz et al. [7] used Bluetooth and Wi-Fi, while Kim and Choi [92] used ultrasonic sensors and digital compasses.

Another hybrid research system, combining RFID, Bluetooth, and VLC, is presented by Liu et al. [91]. In their experiments, precision of about half a meter is reported.

A commercial hybrid system with Wi-Fi and inertial technologies is the LightHouse Signal System (website: http://www.lighthousesignal.com).

5. Technologies Comparison

For more than two decades, several scientific and industrial research groups have proposed indoor positioning systems using different technological approaches, encompassing many types of sensors. In this section, we present a comparison of the different technologies that have been used to develop indoor positioning systems. There are several parameters that have been used to compare an IPS with others, like accuracy, localization type (2D or 3D), method (e.g., triangulation, fingerprint), algorithm, signal measure (AoA, ToA, TDoA, and RSS), coverage, and cost [12, 13]. From those parameters, we consider accuracy, coverage, and cost, because we identify that these parameters are commonly used to make the benefit of using a specific technology known to develop an indoor positioning system. For each technology presented in Section 4, we selected an indoor positioning system with the best values regarding accuracy, coverage, and cost. The information of each system is presented in Table 2.

Accuracy roughly refers to the difference between the estimated position and the actual one; as this difference could change depending on the conditions, it is rather a statistical distribution, which should be expressed in terms of parameters like a distance and a percentage, such as "less than one-meter error in 95 percent of cases," though authors rarely express accuracy in these terms.

Coverage is the territorial extension in which the system can locate a user or object. Although some technologies may offer extensive coverage in an ideal environment, when these are used indoors, their coverage may be limited by environmental factors. An IPS may locate a person or object in a range of meters or even locate them at different levels inside a building.

Cost is the amount of resources invested for the installation and operation of a positioning system. In this survey, cost is determined based on two parameters. The first is installation and maintenance cost (IC in Table 2). The second is cost for each end user (UC in the table). We identify that IPS that make use of existing infrastructures (e.g., lighting, ambient sound, and Earth's magnetic field), as well as systems that reuse technology that exists in the indoor environments (e.g., Wi-Fi access points) or those that are carried by the user (e.g., mobile devices), require low (L) investments for installation and maintenance and low cost of the service for the user.

Furthermore, in the case of indoor positioning systems based on technologies that use special purpose devices and specialized infrastructure (e.g., sensor networks, readers, and encoders), the installation and maintenance cost is high (H).

Table 2: Comparison of main indoor positioning technologies. UC: end user cost; IC: installation and maintenance cost; H: high; L: low; ML: multiple levels.

IPS	Technology	Approx. accu.	Coverage	Cost IC	Cost UC	Strengths	Weaknesses
Technologies with signal encoding							
[22]	Infrared	57 cm–2.3 m	Room	H	L	Cheap for user	Sunlight interference
[23]	VLC	10 cm	Building (ML)	H	L	Cheap for user, unintrusive	Expens. infrast.
[24]	Ultrasonic	1 cm–2 m	Room	H	H	Good precision	Cost, interfer.
[25]	Audible sound	Meters	Room	L	L	Low cost	Low precision
[26]	Wi-Fi	1.5 m	Building	L	L	Low cost, good precision	Vulnerable to access point changes
http://research.nokia.com/news/11809	Bluetooth	30 cm–meters	Building	L	L	Low cost, good precision	Intrusive; needs signal mapping
[27]	ZigBee	25 cm	Building	L	H	Could reuse infrastructure	Low precision; user needs special equip.
[4]	RFID	1–5 m	Room	H	L	Very low cost passive side	Very low precision
[28]	UWB	15 cm	Building	H	H	High precision	High cost
Passive technologies without signal encoding							
http://www.indooratlas.com/	Geomagnetic	2 m	—	L	L	No need for infrastructure, good precision	Requires mapping
[29]	Inertial	2 m	—	L	L	Low cost, private	Accumulates error
[30]	Ambient sound	Meters	—	L	L	Cheap, not intrusive	Not accurate, sensitive to changes
[23]	Ambient light	10 cm–meters	—	L	L	Cheap	Sensitive to sunlight and changes such as a bulb and a window
[9]	Computer vision	1 cm–1 m	—	L	L	Low cost, privacy if cellphone camera is used	Sensitive to light conditions

Sometimes the devices are expensive as well (e.g., RFID readers or ultrasonic sensors); therefore, the cost to the end user could also be high (H). For instance, the system Ubisense [28] has expensive devices and needs a dedicated infrastructure and the end user needs to use a specific device, so the system ranks high (H) on both cost parameters (see Table 2).

5.1. Comparison Discussion. It is important to take the information provided by the authors themselves with some reservations, because very often their results are not in agreement with independent evaluations. For instance, the 2014 Microsoft Indoor Localization Competition [34] offered a uniform setting for testing different indoor localization methods. From the competition results, we can see that the best competitor using ultrasonic technology got an average location error of 2 m, even though Schweinzer reported an error as small as one centimeter. We think this huge difference is explained because in their lab authors set ideal conditions and report the highest precision achieved, which is not realistic. This wide range is reported in Table 2 in the rows for ultrasound and also for ambient light.

Similarly, for infrared technologies, the best self-reported result was around half a meter, but in the independent assessment IR got 2.3 m for average precision error.

Wi-Fi technologies, combined with fingerprinting, have surprisingly good results in the independent assessment, getting the overall second best [93]; they incorporated the use of a Bayesian filter. Of course, Wi-Fi systems are cheap because they reuse existing equipment, but they need a mapping activity, which could be expensive, and each time an access point is changed, mapping should be redone, unless a crowdsourcing automatic method is in place (see below), but there are no reliable precision measures for such methods yet.

One difficulty in using the Microsoft competition [34] for assessing individual technologies is that competitors often combined several technologies in their systems, and it is difficult to know how much of each system's achieved precision is attributable to any one of its component technologies. This is, for instance, the case of Li et al. [94], who combined VLC encoding with Wi-Fi and achieved the 4th place with a 2 m average error.

Another aspect to incorporate in the discussion is that the number of transmitters affects the performance of most systems (excluding passive technologies). For instance, in the mentioned competition, they installed an unusually high number of Wi-Fi access points (10 for a small area), which gave some advantage to Wi-Fi methods. Of course, increasing the transmitters quantity is going to raise the costs and affect the system scalability.

Finally, in some technologies, we did not find a reliable specific figure to report, so we included an approximate annotation like "meters" to give just the order of the accuracy.

6. Conclusions

From the analysis of the IPS presented in this report, we identify the following aspects relative to the technologies used:

(i) *In practice, the evolution of the underlying technologies has had a very positive impact on the evolution of indoor positioning systems*. We realized that changes in the subsequent versions of standards in a given technology can reduce some tasks in the positioning system or even solve some limitations. For instance, positioning systems that use Bluetooth version 1.0 should first establish communication between devices in order to measure the Received Signal Strength, but in later versions of the standard (version 1.2) this process is no longer necessary because the protocol has a device discovery mechanism. This avoids user intervention to establish connection and reduces the time of response of the system (latency) [95]. Later on, Bluetooth version 4 drastically reduced power consumption, making portable devices with Bluetooth much more practical. Furthermore, the emergence of new technologies provides the opportunity to develop indoor positioning systems based on these technologies.

(ii) *The method, the technology, and also the implementation details affect the accuracy of the system*. A method commonly used is triangulation; two different systems presented in Section 3 use this method, but with different technologies. For instance, Feldmann et al. [60] use Bluetooth and claim an accuracy of 2.08 meters, while Liu et al. [23] use VLC and claim a far superior accuracy of 10 centimeters. This can also be appreciated by using the same technology with different methods. For instance, the system BluePos uses Bluetooth and the fingerprint method; the system claims an accuracy of 2.5 meters [95]. The system presented by Feldmann et al. [60] uses Bluetooth with triangulation, and the system claims better accuracy, 2.08 meters. Also, the impact of implementation details could be appreciated by examining the results of the aforementioned competition [34], as very similar technologies and techniques, like two teams using Wi-Fi and fingerprinting, obtain such different location errors as 1.56 m and 5.23 m.

(iii) *There is not yet an overall satisfying solution for the IPS problem*. Either very precise solutions are very expensive, or not real time, or cheap proposals are too inaccurate. If we take a standard problem for IPS like locating merchandise in shelves while walking, not a single technology or combination of technologies is both feasible and satisfying.

6.1. Trends in the Development of IPS. Additionally, the analysis of IPS enables us to identify the past, present, and future trends in the development of indoor positioning systems.

6.1.1. Past. In the past, the purpose of the prototypes of indoor positioning systems was to investigate whether the technology was suitable for locating objects or persons in indoor environments with accuracy and cost-effectiveness. The systems were composed of expensive devices (i.e., badges, bats, and crickets) or required a dedicated infrastructure; some examples in this category are Active Badge [5], Cricket [55], Active Bat [54], and RADAR [56]. Those were not practical systems because they were almost a "proof of concept." But today we would require from a system that it be a practical solution to IPS.

6.1.2. Present. As we write this survey (2017), we can identify the following rapidly developing trends, which we guess will be mainstream in the next few years:

(i) *Reuse Existing Infrastructure in Indoor Environments (e.g., Access Points, Lamps, and Sound Systems) for Location Purposes.* In Section 4 of this article, we presented several examples of positioning systems that reuse infrastructure; we have to notice, though, that communication systems were not designed in the first place for IPS purposes, and then, in general, improvements that make communication aspects better will not necessarily improve the IPS reuse of the technology being considered. But it is useful to make the following consideration: most IPS benefit from a high density of transmitters, as this would improve accuracy, but at the same time a high density of transmitters would add cost to the IPS solution. So, if transmitters are reused from communication infrastructure, then the ever increasing transmitter density will benefit IPS solutions.

(ii) *Technology Fusion (Hybrid Positioning Systems).* Hybrid approaches leverage the complementarity of several technologies in positioning systems, as we presented in Section 4.5. Several especially attractive combinations are becoming popular, like Wi-Fi with Bluetooth, Wi-Fi with magnetism, and Wi-Fi with inertial navigation.

(iii) *Use of Mobile Devices as an Essential Component of a Positioning System.* This approach considers the mobile device as appropriate technology for developing positioning systems, as these can easily collect user information due to the large number of sensors embedded, such as accelerometers, gyroscopes, and magnetometers, as well as some devices not often thought of as sensors, such as the camera, the microphone, Bluetooth chip, GPS (global positioning system) receiver, and wireless network card. For instance, in Li et al.'s study [29], the inertial sensors of a smartphone are used (accelerometer and gyroscope) as well as the compass. Other works [83] use the phone camera. The use of these devices allows the reuse of technology so that it might not be necessary to add new devices to the environment; these devices can be merged with existing infrastructure (e.g., a wireless network or Bluetooth). Therefore, the implementation and maintenance costs are minimal.

(iv) *Crowdsourcing.* One of the current main trends is the use of open distributed collaboration of many users to build or refine location systems. In recent years, as part of Web 2.0 participatory systems like map building, data coming from many users have been consolidated in location-related systems. Crowdsourcing of maps has been done as grass roots efforts in nonprofit organizations like OpenStreetMap (OSM) (http://www.openstreetmap.com) or Wikimapia (http://www.wikimapia.org). Individuals have also helped Google with tools like Google Map Maker (website: https://www.google.com/mapmaker). Participation of individuals in these mapping efforts requires laborious handling of specialized map-editing software. Projects of this kind have been also proposed for mapping indoor locations, like in the Indoor OSM initiative (http://indoorosm.uni-hd.de/). But unlike outdoor efforts, the efforts to include volunteer individuals in the mapping phase of some indoor location technologies are much more limited. In particular, methods like Wi-Fi fingerprinting require a thorough mapping activity which could be very expensive. So, if it is possible to automatically construct signal maps by the spontaneous activity of users, that would be a major improvement; crowdsourcing of indoor maps makes sense as users could contribute even without noticing, if they carry an automated application on their cell phones. For instance, Alzantot and Youssef [96] proposed the *CrowdInside* system that uses smartphone accelerometers for detecting users' movements while users naturally move in the indoor environment. The collected data is fused with semantic information which describes the environment. Something similar is done by Zhang et al. [97], with the *CIMLoc* system. Also, Kim et al. [11] proposed the *Freeloc* system we reviewed in Section 4 which uses open distributed collaboration for building the radio map of Wi-Fi signals. Indeed, building radio maps with crowdsourcing makes much more sense than applying analytic propagation models, because in real environments the walls and furniture create irregularities that are very difficult to take into account, and crowdsourcing approaches do not rely on models, but rather on the way that signals are measured in the real world. In the project *GROPING*, open distributed collaboration also incorporates magnetic field samples, which are collected as users wander in the indoor environment [98].

6.1.3. Future. Finally, for the years to come in the near future, we are forecasting the following trends:

(i) *Indoor/Outdoor IPS.* Outdoor positioning systems will merge with IPS in a seamless way to locate a person with a smartphone anywhere. This means that while current IPS systems involve specialized equipment and applications, future IPS systems will be part of the smartphone operating system and leverage its sensors so any location-sensitive smartphone application will use indoor or outdoor location services as they are available.

(ii) *Consideration of Privacy and Security Issues in the Development of IPS.* From the analysis of IPS, we noticed that the privacy and security issues regarding the user's location are only addressed in very few projects [24, 99, 100]. Nevertheless, some authors provide evidence that these factors may influence the adoption and use of the IPS [5, 78] or argue that the system must give the users the possibility of deciding whether they want to share their locations with others [78]. Though privacy has been a concern since the very beginning of the development of IPS systems, in the future, this will become one of the main considerations for the adoption or choice of specific IPS systems.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

References

[1] A. K. Dey, "Understanding and using context," *Personal and Ubiquitous Computing*, vol. 5, no. 1, pp. 4–7, 2001.

[2] G. Xu, *GPS*, Springer, 2003.

[3] S. Haykin, "Cognitive radio: brain-empowered wireless communications," *IEEE Journal on Selected Areas in Communications*, vol. 23, no. 2, pp. 201–220, 2005.

[4] M. N. Lionel, Y. Liu, Y. C. Lau, and A. P. Patil, "LANDMARC: indoor location sensing using active RFID," *Wireless Networks*, vol. 10, no. 6, pp. 701–710, 2004.

[5] R. Want, A. Hopper, V. Falcão, and J. Gibbons, "The active badge location system," *ACM Transactions on Information Systems*, vol. 10, no. 1, pp. 91–102, 1992.

[6] J. Haverinen and A. Kemppainen, "Global indoor self-localization based on the ambient magnetic field," *Robotics and Autonomous Systems*, vol. 57, no. 10, pp. 1028–1035, 2009.

[7] P. Kriz, F. Maly, and T. Kozel, "Improving indoor localization using bluetooth low energy beacons," *Mobile Information Systems*, vol. 2016, Article ID 2083094, 2016.

[8] W. Zhang, M. I. S. Chowdhury, and M. Kavehrad, "Asynchronous indoor positioning system based on visible light communications," *Optical Engineering*, vol. 53, no. 4, Article ID 045105, 2014.

[9] A. Mulloni, D. Wagner, I. Barakonyi, and D. Schmalstieg, "Indoor positioning and navigation with camera phones," *IEEE Pervasive Computing*, vol. 8, no. 2, pp. 22–31, 2009.

[10] P. Dabove, G. Ghinamo, and A. M. Lingua, "Inertial sensors for smartphones navigation," *SpringerPlus*, vol. 4, no. 1, article 834, 2015.

[11] W. Kim, S. Yang, M. Gerla, and E.-K. Lee, "Crowdsource based indoor localization by uncalibrated heterogeneous Wi-Fi devices," *Mobile Information Systems*, vol. 2016, Article ID 4916563, 18 pages, 2016.

[12] H. Liu, H. Darabi, P. Banerjee, and J. Liu, "Survey of wireless indoor positioning techniques and systems," *IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews*, vol. 37, no. 6, pp. 1067–1080, 2007.

[13] S. Gezici, "A survey on wireless position estimation," *Wireless Personal Communications*, vol. 44, no. 3, pp. 263–282, 2008.

[14] Y. Gu, A. Lo, and I. Niemegeers, "A survey of indoor positioning systems for wireless personal networks," *IEEE Communications Surveys and Tutorials*, vol. 11, no. 1, pp. 13–32, 2009.

[15] R. Mautz, *Indoor positioning technologies [Ph.D. thesis]*, Habil. ETH Zürich, 2012.

[16] G. Deak, K. Curran, and J. Condell, "A survey of active and passive indoor localisation systems," *Computer Communications*, vol. 35, no. 16, pp. 1939–1954, 2012.

[17] A. Ganick and D. Ryan, "Method and system for modulating a light source in a light based positioning system using a DC bias," US Patent 8,334,901, December 2012.

[18] T. Komine and M. Nakagawa, "Fundamental analysis for visible-light communication system using LED lights," *IEEE Transactions on Consumer Electronics*, vol. 50, no. 1, pp. 100–107, 2004.

[19] N. Kumar, N. Lourenco, M. Spiez et al., "Visible light communication systems conception and vidas," *IETE Technical Review*, vol. 25, no. 6, article 359, 2008.

[20] C. E. Galván-Tejada, J. P. García-Vázquez, and R. F. Brena, "Magnetic field feature extraction and selection for indoor location estimation," *Sensors*, vol. 14, no. 6, pp. 11001–11015, 2014.

[21] W. Shao, F. Zhao, C. Wang et al., "Location fingerprint extraction for magnetic field magnitude based indoor positioning," *Journal of Sensors*, vol. 2016, Article ID 1945695, 16 pages, 2016.

[22] S. Sayeef, U. K. Madawala, P. G. Handley, and D. Santoso, "Indoor personnel tracking using infrared beam scanning," in *Proceedings of the Position Location and Navigation Symposium (PLANS '04)*, pp. 698–705, April 2004.

[23] X. Liu, H. Makino, and Y. Maeda, "Basic study on indoor location estimation using visible light communication platform," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 2377–2380, Vancouver, Canada, August 2008.

[24] H. Schweinzer and M. Syafrudin, "LOSNUS: an ultrasonic system enabling high accuracy and secure TDoA locating of numerous devices," in *Proceedings of the International Conference on Indoor Positioning and Indoor Navigation (IPIN '10)*, pp. 1–8, September 2010.

[25] I. Rishabh, D. Kimber, and J. Adcock, "Indoor localization using controlled ambient sounds," in *Proceedings of the International Conference on Indoor Positioning and Indoor Navigation (IPIN '12)*, pp. 1–10, November 2012.

[26] A. Rai, K. K. Chintalapudi, V. N. Padmanabhan, and R. Sen, "Zee: zero-effort crowdsourcing for indoor localization," in *Proceedings of the 18th Annual International Conference on Mobile Computing and Networking (MobiCom '12)*, pp. 293–304, ACM, Istanbul, Turkey, August 2012.

[27] G. Gonçalo and S. Helena, "Indoor location system using ZigBee technology," in *Proceedings of the 3rd International Conference on Sensor Technologies and Applications (SENSORCOMM '09)*, pp. 152–157, Athens, Greece, June 2009.

[28] P. Steggles and S. Gschwind, "The ubisense smart space platform," in *Proceedings of the 3rd International Conference on Pervasive Computing*, vol. 191, pp. 73–76, Munich, Germany, 2005.

[29] F. Li, C. Zhao, G. Ding, J. Gong, C. Liu, and F. Zhao, "A reliable and accurate indoor localization method using phone inertial sensors," in *Proceedings of the 14th International Conference on Ubiquitous Computing (UbiComp '12)*, pp. 421–430, ACM, Pittsburgh, Pa, USA, September 2012.

[30] E. Vildjiounaite, E.-J. Malm, J. Kaartinen, and P. Alahuhta, "Location estimation indoors by means of small computing

power devices, accelerometers, magnetic sensors, and map knowledge," in *Proceedings of the 1st International Conference on Pervasive Computing*, pp. 211–224, Springer, 2002.

[31] G. Sun, J. Chen, W. Guo, and K. J. R. Liu, "Signal processing techniques in network-aided positioning: a survey of state-of-the-art positioning designs," *IEEE Signal Processing Magazine*, vol. 22, no. 4, pp. 12–23, 2005.

[32] J. Hightower and G. Borriello, "Location systems for ubiquitous computing," *Computer*, vol. 34, no. 8, pp. 57–66, 2001.

[33] H. Koyuncu and S. H. Yang, "A survey of indoor positioning and object locating systems," *IJCSNS International Journal of Computer Science and Network Security*, vol. 10, no. 5, pp. 121–128, 2010.

[34] D. Lymberopoulos, J. Liu, X. Yang et al., "A realistic evaluation and comparison of indoor location technologies: experiences and lessons learned," in *Proceedings of the 14th International Symposium on Information Processing in Sensor Networks (IPSN '15)*, pp. 178–189, ACM, Seattle, Wash, USA, April 2015.

[35] D. Munoz, F. B. Lara, C. Vargas, and R. Enriquez-Caldera, *Position Location Techniques and Applications*, Academic Press, 2009.

[36] A. H. Sayed, A. Tarighat, and N. Khajehnouri, "Network-based wireless location: challenges faced in developing techniques for accurate wireless location information," *IEEE Signal Processing Magazine*, vol. 22, no. 4, pp. 24–40, 2005.

[37] C. Vargas-Rosales, J. Mass-Sanchez, E. Ruiz-Ibarra, D. Torres-Roman, and A. Espinoza-Ruiz, "Performance evaluation of localization algorithms for WSNs," *International Journal of Distributed Sensor Networks*, vol. 11, no. 3, pp. 1–14, 2015.

[38] Y. J. Guo, *Advances in Mobile Radio Access Networks*, Artech House Mobile Communications Library, Norwood, Mass, USA, 2004.

[39] S. Kawakami and T. Ohtsuki, "Localization using iterative angle of arrival method sharing snapshots of coherent subarrays," *EURASIP Journal on Advances in Signal Processing*, vol. 2011, article 46, 7 pages, 2011.

[40] H. L. Bertoni, *Radio Propagation for Modern Wireless Systems*, Prentice Hall, 2000.

[41] T. S. Rappaport, *Wireless Communications: Principles and Practice*, Prentice Hall, 2002.

[42] R. Chatterjee, *Antenna Theory and Practice*, New Age International, 1996.

[43] J. Hightower and G. Borriello, "Location sensing techniques," *IEEE Computer*, vol. 34, no. 8, pp. 57–66, 2001.

[44] P. Jiang, Y. Zhang, W. Fu, H. Liu, and X. Su, "Indoor mobile localization based on Wi-Fi fingerprint's important access point," *International Journal of Distributed Sensor Networks*, vol. 2015, Article ID 429104, 8 pages, 2015.

[45] S. Haykin, *Adaptive Filter Theory*, Pearson, 2013.

[46] R. E. Kalman, "A new approach to linear filtering and prediction problems," *Journal of Basic Engineering*, vol. 82, no. 1, pp. 35–45, 1960.

[47] F. Gustafsson, "Particle filter theory and practice with positioning applications," *IEEE Aerospace and Electronic Systems Magazine*, vol. 25, no. 7, pp. 53–81, 2010.

[48] R. K. Crane, *Propagation Handbook for Wireless Communication System Design*, Electrical Engineering & Applied Signal Processing Series, Taylor & Francis, 2003.

[49] E. L. Christensen and G. Mogensen, "Experimental investigation of line-of-sight propagation at 13.5–15.0 ghz.," *Radio and Electronic Engineer*, vol. 49, no. 3, pp. 127–140, 1979.

[50] Y. Nakashima, R. Kaneto, and N. Babaguchi, "Indoor positioning system using digital audio watermarking," *Transactions on Information and Systems*, vol. 94, no. 11, pp. 2201–2211, 2011.

[51] E. M. Gorostiza, J. L. L. Galilea, F. J. M. Meca, D. S. Monzú, F. E. Zapata, and L. P. Puerto, "Infrared sensor system for mobile-robot positioning in intelligent spaces," *Sensors*, vol. 11, no. 5, pp. 5416–5438, 2011.

[52] A. Rogalski, "Infrared detectors: an overview," *Infrared Physics and Technology*, vol. 43, no. 3–5, pp. 187–210, 2002.

[53] K. Y. Yi, D. Y. Kim, and K. M. Yi, "Development of a localization system based on VLC technique for anindoor environment," *Journal of Electrical Engineering and Technology*, vol. 10, no. 1, pp. 436–442, 2015.

[54] A. Ward, A. Jones, and A. Hopper, "A new location technique for the active office," *IEEE Personal Communications*, vol. 4, no. 5, pp. 42–47, 1997.

[55] N. B. Priyantha, A. Chakraborty, and H. Balakrishnan, "Cricket location-support system," in *Proceedings of the 6th Annual International Conference on Mobile Computing and Networking (MOBICOM '00)*, pp. 32–43, ACM, August 2000.

[56] P. Bahl and V. N. Padmanabhan, "RADAR: an in-building RF-based user location and tracking system," in *Proceedings of the 19th Annual Joint Conference of the IEEE Computer and Communications Societies (INFOCOM2000 '00)*, vol. 2, pp. 775–784, March 2000.

[57] Z. Li, Z. Deng, W. Liu, and L. Xu, "A novel three-dimensional indoor localization algorithm based on multi-sensors," in *China Satellite Navigation Conference (CSNC) 2013 Proceedings*, vol. 245 of *Lecture Notes in Electrical Engineering*, pp. 623–631, Springer, Berlin, Germany, 2013.

[58] C. Bisdikian, "An overview of the Bluetooth wireless technology," *IEEE Communications Magazine*, vol. 39, no. 12, pp. 86–94, 2001.

[59] R. Faragher and R. Harle, "Location fingerprinting with bluetooth low energy beacons," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 11, pp. 2418–2428, 2015.

[60] S. Feldmann, K. Kyamakya, A. Zapater, and Z. Lue, "An indoor Bluetooth-based positioning system: concept, implementation and experimental evaluation," in *Proceedings of the International Conference on Wireless Networks (ICWN '03)*, pp. 109–113, Las Vegas, Nev, USA, June 2003.

[61] C. E. Galvan, I. Galvan-Tejada, E. I. Sandoval, and R. Brena, "Wifi bluetooth based combined positioning algorithm," *Procedia Engineering*, vol. 35, pp. 101–108, 2012, International Meeting of Electrical Engineering Research 2012.

[62] C. Gomez, J. Oller, and J. Paradells, "Overview and evaluation of bluetooth low energy: an emerging low-power wireless technology," *Sensors*, vol. 12, no. 9, pp. 11734–11753, 2012.

[63] T. A. Alhmiedat and S.-H. Yang, "A ZigBee-based mobile tracking system through wireless sensor networks," *International Journal of Advanced Mechatronic Systems*, vol. 1, no. 1, pp. 63–70, 2008.

[64] A. Wheeler, "Commercial applications of wireless sensor networks using ZigBee," *IEEE Communications Magazine*, vol. 45, no. 4, pp. 70–77, 2007.

[65] S.-H. Fang, C.-H. Wang, T.-Y. Huang, C.-H. Yang, and Y.-S. Chen, "An enhanced ZigBee indoor positioning system with an ensemble approach," *IEEE Communications Letters*, vol. 16, no. 4, pp. 564–567, 2012.

[66] R. Weinstein, "RFID: a technical overview and its application to the enterprise," *IT Professional*, vol. 7, no. 3, pp. 27–33, 2005.

[67] K. Ahsan, H. Shah, and P. Kingston, "RFID applications: an introductory and exploratory study," *International Journal of Computer Science Issues*, vol. 7, no. 1, 2010.

[68] U. Biader Ceipidor, C. M. Medaglia, A. Serbanati et al., "SeSaMoNet: an RFID-based economically viable navigation system for the visually impaired," *International Journal of RF Technologies: Research and Applications*, vol. 1, no. 3, pp. 214–224, 2009.

[69] K. Finkenzeller, *RFID Handbook: Fundamentals and Applications in Contactless Smart Cards, Radio Frequency Identification and Near-Field Communication*, Wiley Online Library, New York, NY, USA, 2003.

[70] M.-G. Di Benedetto and B. R. Vojcic, "Ultra wide band wireless communications: a tutorial," *Journal of Communications and Networks*, vol. 5, no. 4, pp. 290–302, 2003.

[71] S. Ullah, M. Ali, A. Hussain, and K. Sup Kwak, "Applications of UWB technology," https://arxiv.org/abs/0911.1681.

[72] Y. Bai and X. Lu, "Research on UWB indoor positioning based on TDOA technique," in *Proceedings of the 9th International Conference on Electronic Measurement and Instruments (ICEMI '09)*, pp. 1167–1170, August 2009.

[73] Z. Kasmi, A. Norrdine, and J. Blankenbach, "Towards a decentralized magnetic indoor positioning system," *Sensors*, vol. 15, no. 12, pp. 30319–30339, 2015.

[74] B. Gozick, K. P. Subbu, R. Dantu, and T. Maeshiro, "Magnetic maps for indoor navigation," *IEEE Transactions on Instrumentation and Measurement*, vol. 60, no. 12, pp. 3883–3891, 2011.

[75] E. Garcia-Ceja and R. Brena, "Long-term activity recognition from accelerometer data," *Procedia Technology*, vol. 7, pp. 248–256, 2013.

[76] H. Leppäkoski, J. Collin, and J. Takala, "Pedestrian navigation based on inertial sensors, indoor map, and WLAN signals," *Journal of Signal Processing Systems*, vol. 71, no. 3, pp. 287–296, 2013.

[77] C. E. Galván-Tejada, J. P. García-Vázquez, J. I. Galván-Tejada, J. Rubén Delgado-Contreras, and R. F. Brena, "Infrastructure-less indoor localization using the microphone, magnetometer and light sensor of a smartphone," *Sensors*, vol. 15, no. 8, pp. 20355–20372, 2015.

[78] J. Randall, O. Amft, J. Bohn, and M. Burri, "Lux Trace: indoor positioning using building illumination," *Personal and Ubiquitous Computing*, vol. 11, no. 6, pp. 417–428, 2007.

[79] M. Azizyan and R. R. Choudhury, "Surroundsense: mobile phone localization using ambient sound and light," *ACM SIGMOBILE Mobile Computing and Communications Review*, vol. 13, no. 1, pp. 69–72, 2009.

[80] D. Scaramuzza and F. Fraundorfer, "Visual odometry [tutorial]," *IEEE Robotics & Automation Magazine*, vol. 18, no. 4, pp. 80–92, 2011.

[81] F. Fraundorfer and D. Scaramuzza, "Visual odometry: part II: matching, robustness, optimization, and applications," *IEEE Robotics & Automation Magazine*, vol. 19, no. 2, pp. 78–90, 2012.

[82] B. Kitt, A. Geiger, and H. Lategahn, "Visual odometry based on stereo image sequences with RANSAC-based outlier rejection scheme," in *Proceedings of the IEEE Intelligent Vehicles Symposium (IV '10)*, pp. 486–492, IEEE, San Diego, Calif, USA, June 2010.

[83] M. Werner, M. Kessel, and C. Marouane, "Indoor positioning using smartphone camera," in *Proceedings of the International Conference on Indoor Positioning and Indoor Navigation (IPIN '11)*, pp. 1–6, IEEE, Guimarães, Portugal, September 2011.

[84] B. Brumitt, B. Meyers, J. Krumm, A. Kern, and S. Shafer, "Easyliving: technologies for intelligent environments," in *Handheld and Ubiquitous Computing*, pp. 12–29, Springer, 2000.

[85] T. Leyvand, C. Meekhof, Y.-C. Wei, J. Sun, and B. Guo, "Kinect identity: technology and experience," *Computer*, vol. 44, no. 4, pp. 94–96, 2011.

[86] A. De Gante and M. Siller, "A survey of hybrid schemes for location estimation in wireless sensor networks," *Procedia Technology*, vol. 7, pp. 377–383, 2013.

[87] F. Evennou and F. Marx, "Advanced integration of WiFi and inertial navigation systems for indoor mobile positioning," *Eurasip Journal on Applied Signal Processing*, vol. 2006, Article ID 86706, 2006.

[88] A. Kealy, B. Li, T. Gallagher, and A. Dempster, "Evaluation of wifi technologies for indoor positioning applications," in *Proceedings of the Surveying and Spatial Sciences Institute Biennial International Conference*, pp. 411–421, Surveying and Spatial Sciences Institute, Adelaide, Australia, 2009.

[89] P. M. Djurić, J. H. Kotecha, J. Zhang et al., "Particle filtering," *IEEE Signal Processing Magazine*, vol. 20, no. 5, pp. 19–38, 2003.

[90] C. Zhang, J. Luo, and J. Wu, "A dual-sensor enabled indoor localization system with crowdsensing spot survey," in *Proceedings of the 9th IEEE International Conference on Distributed Computing in Sensor Systems (DCOSS '14)*, pp. 75–82, Marina Del Rey, Calif, USA, May 2014.

[91] X. Liu, H. Makino, S. Kobayashi, and Y. Maeda, "Design of an indoor self-positioning system for the visually impaired—simulation with RFID and bluetooth in a visible light communication system," in *Proceedings of the 29th Annual International Conference of IEEE-EMBS, Engineering in Medicine and Biology Society (EMBC '07)*, pp. 1655–1658, August 2007.

[92] H.-S. Kim and J.-S. Choi, "Advanced indoor localization using ultrasonic sensor and digital compass," in *Proceedings of the International Conference on Control, Automation and Systems (ICCAS '08)*, pp. 223–226, IEEE, Seoul, Republic of Korea, October 2008.

[93] C. Beder and M. Klepal, "Fingerprinting based localisation revisited: a rigorous approach for comparing RSSI measurements coping with missed access points and differing antenna attenuations," in *Proceedings of the International Conference on Indoor Positioning and Indoor Navigation (IPIN '12)*, pp. 1–7, IEEE, Sydney, Australia, November 2012.

[94] L. Li, P. Hu, C. Peng, G. Shen, and F. Zhao, "Epsilon: a visible light based positioning system," in *Proceedings of the 11th USENIX Conference on Networked Systems Design and Implementation*, pp. 331–343, Seattle, Wash, USA, April 2014.

[95] T. King, H. Lemelson, A. Färber, and W. Effelsberg, "BluePos: positioning with bluetooth," in *Proceedings of the 6th IEEE International Symposium on Intelligent Signal Processing (WISP '09)*, pp. 55–60, August 2009.

[96] M. Alzantot and M. Youssef, "CrowdInside: automatic construction of indoor floorplans," in *Proceedings of the 20th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems (ACM SIGSPATIAL GIS '12)*, pp. 99–108, ACM, November 2012.

[97] X. Zhang, Y. Jin, H.-X. Tan, and W.-S. Soh, "CIMLoc: a crowdsourcing indoor digital map construction system for localization," in *Proceedings of the 9th IEEE International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP '14)*, pp. 1–6, IEEE, Singapore, April 2014.

[98] C. Zhang, K. P. Subbu, J. Luo, and J. Wu, "GROPING: geomagnetism and crowdsensing powered indoor navigation," *IEEE*

Transactions on Mobile Computing, vol. 14, no. 2, pp. 387–400, 2015.

[99] M. Paciga and H. Lutfiyya, "Herecast: an open infrastructure for location-based services using WiFi," in *Proceedings of the IEEE International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob '05)*, vol. 4, pp. 21–28, August 2005.

[100] A. Quigley, B. Ward, C. Ottrey, D. Cutting, and R. Kummerfeld, "BlueStar, a privacy centric location aware system," in *Proceedings of the Position Location and Navigation Symposium (PLANS '04)*, pp. 684–689, IEEE, Monterey, Calif, USA, April 2004.