Indoor Location Identification Technologies for Real-Time IoT-based Applications: An Inclusive Survey

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Abstract

The advent of the Internet of Things has witnessed tremendous success in the application of wireless sensor networks and ubiquitous computing for diverse smart-based applications. The developed systems operate under different technologies using different methods to achieve their targeted goals. In this treatise, we carried out an inclusive survey on key indoor technologies and techniques, with to view to explore their various benefits, limitations, and areas for improvement. The mathematical formulation for simple localisation problems is also presented. In addition, an empirical evaluation of the performance of these indoor technologies is carried out using a common generic metric of scalability, accuracy, complexity, robustness, energy-efficiency, cost and reliability. The empirical evaluation of the performance of different RF-based technologies establishes the viability of Wi-Fi, RFID, UWB, Wi-Fi, Bluetooth, ZigBee, and Light over other indoor technologies for reliable, IoT-based applications. The survey advocates for increased hybridization of technologies as an effective approach to achieving reliable IoT-based indoor systems. Furthermore, the findings of the survey could be useful in the selection of appropriate indoor technologies for the development of reliable real-time IoT-based indoor applications. The study could also be used as a reliable source for literature referencing indoor location identification.

Index Terms: Indoor Localization, Internet of Things, Indoor technologies, Hybridisation

1. Introduction

The numerous breakthroughs in the Internet of Things (IoT), have invariably enabled the requirement for accurate real-time location information by most applications for tracking of people and objects [1, 2]. Location identification involves the determination of the spatial position of targets using different possible methods with key parameters including precision, accuracy, cost, reliability, scalability, energy efficiency and robustness [3]. The range of pervasive applications using real-time location-based information is diverse, with many applications regardless of the environment are required to operate independently and intelligently [4]. Thus, these key parameters become some prime design requirements.

The progress achieved in the research of outdoor applications is remarkable in recent times. With the Global Positioning System (GPS), a reliable and accurate location identification is possible for diverse outdoor applications whenever there is a direct line of sight (LOS) between the satellites and its receiver [5, 6]. The GPS remains a prime example of the relatively high localisation accuracy obtainable through very long distance wireless communication link with effective global coverage of over 10 m [7, 8]. However, the level of accuracy of GPS become unreliable in indoor environments, often affected by several factors including multipath from reflections of signals by walls and ceiling, NLOS (non-line-of-sight), attenuation and signal scattering, noise, and physical obstruction of signals [9-12]. The unreliability of GPS indoors necessitates the search for alternative exciting, innovative methods for efficient location-based applications.

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Indoor location identification or simply *indoor localization* is an interesting research field that is receiving intense attention due to the high demand for smart location-based application and services within diverse indoor environments [13-21]. In addition, since most people assign a sizeable amount of their time (over 80%) indoors to perform various activities, accurate information of the position or location of people for diverse purposes becomes a necessary compulsion. From Fig 1, indoor localisation can be categorized as active or passive, based on the participation of the target in the location identification process. Active location identification is reliant on target action, basically, dedicated devices or tags are attached to targets for communication with dedicated servers to identify their position. Conversely, passive location identification locates people and target objects without their action. Target object and people are often unaware of passive location identification system's existence, barring any legal restrictions a prior location identification. Based on this category, indoor location identification can be subdivided into *device-based* or *device-free*. Most active location identification systems are device-based, whilst passive location identification is usually device-based and device-free. In *device-based* location identification, the target wears a device (RFID tags, mobile devices) that is located by other devices. As an example, a patient with an RFID tag band can be tracked from the RSS between the RFID tag band and the reader nearby. The concept of device-free location identification was first introduced in [22] for the location identification of a non-equipped entity. In device-free location identification, location identification or tracking is achieved explicitly through the interaction of the human body with radio signals in the form of reflection, absorption, scattering and/or diffraction. Though most classic indoor location identification involves the active, and or device-based location identification. However, with the introduction of the Internet of Things (IoT), migration into device-free location identification research has intensified bringing diverse innovative applications such as smart homes, smart building, and smart city.
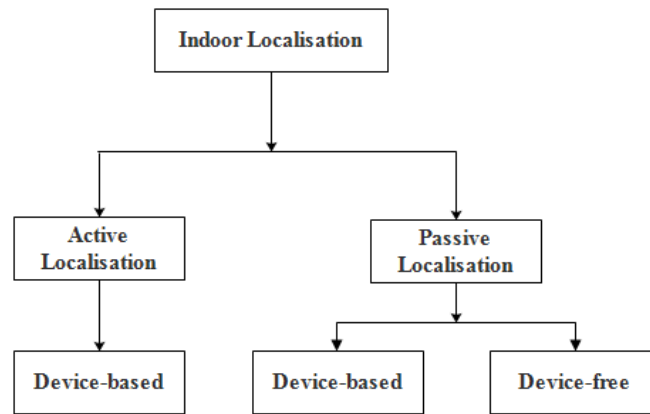

Fig.1. Schemes of indoor location identification

Furthermore, among the various methodological technologies used for indoor localisation include ultrasound [23], infrared [24], Wi-Fi (*IEEE 802.11*) [25, 26], Bluetooth (*IEEE 802.15*) [27, 28], ZigBee [29, 30], Ultrawide Band (UWB) [31, 32], inertial navigation [33], magnetic-based methods [34, 35] and Radio Frequency Identification (RFID) [36-38]. These technologies differ in scope, method, location type; symbolic or geometric, and cost bringing a suitable level of diversity to indoor location identification. Moreover, indoor location identification is applied for a diverse range of applications including fitness monitoring [39], healthcare [40, 41], building automation [42, 43], security [44], automated activity and assisted living [45-47], retail [48], pedestrian navigation [49] and smart parking [50]. Indoor location identification becomes a more challenging research due to the requirement of indoor location-based applications and systems to achieve high accuracy and precision in presence of the complexities of the indoor environment. In effect, achieving accurate indoor systems with preferably sub-meter level location error often presents a daunting task. Nonetheless, many location identification systems have been proposed and developed to address these challenging issues with most of these emerging indoor systems making huge ROI on deployment [51]. In addition, these innovative location identification systems are constantly raising the bar of demand for real-world indoor deployment that is both cost-effective and accurate [52]. Nevertheless, most existing indoor location identification systems suffer from one form of limitation or another, which affect their overall performance.

1.1   Motivation of the Survey

In today's world, the Internet of Things (IoT) has become the de facto concept in engineering and computing due to the vision of global infrastructure interconnectivity. IoT involves the combination of different emerging technologies such as an embedded sensor, localization, near-field communication, and the internet. IoT supports the integration of objects, devices, and systems equipped with sensors and microcontrollers to interacts with one another and their users [53]. Moreover, since most people usually expend a considerable amount of time daily within various indoor environments for different purposes, location identification becomes an interesting research area for safety and emergency measures. Therefore, the motivation for conducting this survey is to carry out an intense appreciation of the methods, technologies, and techniques used to achieve efficient location identification. This will help new and existing researchers in the research field to elucidate and characterize viable technologies to design innovative IoT-based location identification applications and system. However, we shall take "location identification" to mean "indoor location identification", to avoid repetition.

The remaining article is structured as follows. A review of the different location identification technologies with different experimental simulations of some of the technologies are covered in Section 2. Section 3 highlights the various techniques used for measuring the propagating signal using the different indoor technologies. In section 4, we formulate a simple location identification problem using two key techniques. Section 5 presents the key evaluation metrics used to measure the generic results obtained. A discussion on the generic evaluation and sampled comparison of RF-based technologies is presented in Section 6. Section 7 concludes the survey.

2.   Location identification Technologies

In this section, we cover the various positioning and location identification technologies. The operating principles of each indoor technology which include sound, photonics, mechanics, radio frequency, and environmental factors are also highlighted. Moreover, a real-world experimental example of each technology is a showcase for a deeper appreciation of each technology for various position and location-based applications. Nonetheless, a comprehensive overview of this section is presented in Fig. 2.
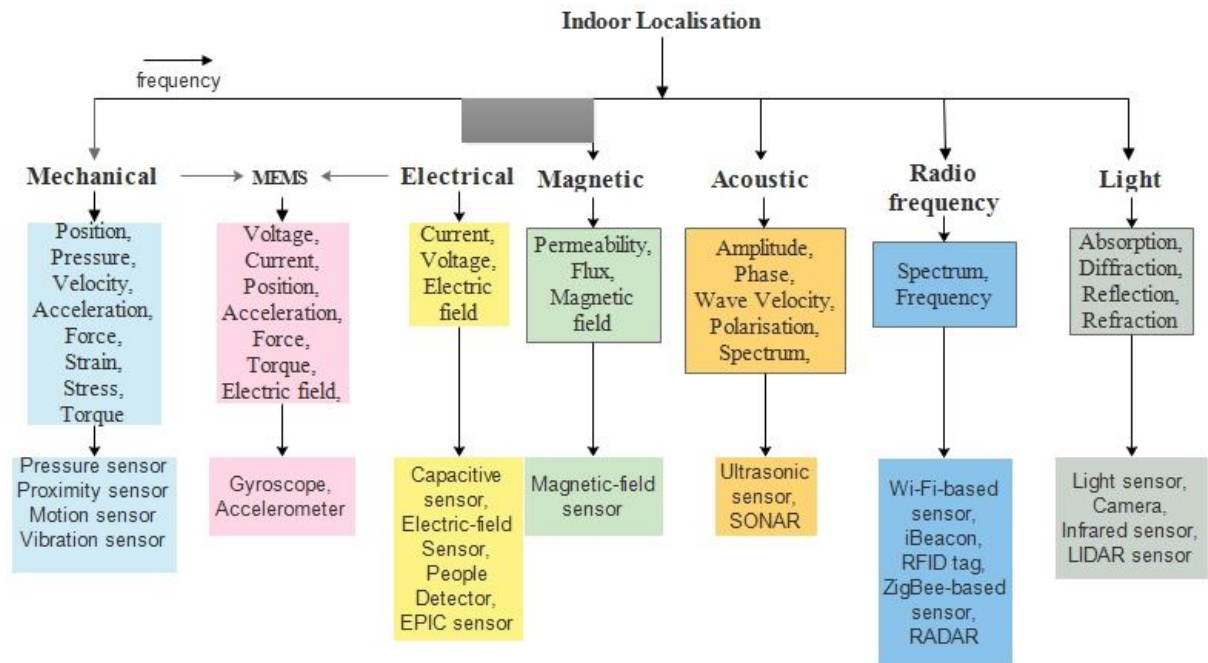

Fig 2. Taxonomy of location identification technologies and various devices deployed under each field[†]

[†] The block between the electric and magnetic technology indicates that both technologies operates around the same frequency.

2.1 Mechanical-based

Inertial navigation system (INS) is a composite indoor/outdoor location identification technology that utilizes inertial measuring units (IMU) such as accelerometer and gyroscope, for determining the position and angular motion of target objects relative to an initial starting point, angle and velocity. Inertial navigation also referred to as reduced reckoning, is useful in determining the position of the target object using the measurement of previously-estimated position along with the speed and direction of the target object. INS was initially designed for outdoor applications (such as aircraft), but have proved over time as an effective indoor technology due to its high accuracy, high mean time between failure (MTBF) and efficient energy management [54]. However, most INS-based applications are invasive and obtrusive since the inertial sensor must be attached to the surface area of the target. The strap-down system of INS, which are the micro-machined electromechanical systems (MEMs), possesses several desirous features for location identification such as miniaturized size and weight, low power consumption, cheap in cost and short start-up time [55]. Fig. 3 highlights a real-time INS-based experiment using a wireless IMU for estimating the motion and orientation of targets.
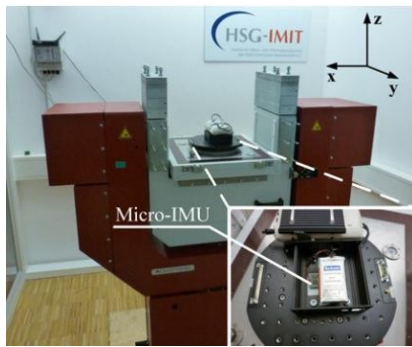
(a). An experimental setup using micro-IMU

(b) A micro-IMU V2 with chip antenna mounted on a shoe for motion and orientation determination

Fig. 3. A wireless INS-based experiment and its target application (**Source**: Holfinger et al. [56])

Moreover, because INS involves the estimation of target position from a known initial position using direction and speed measurement, it is subjected to drift and cumulative error, which necessitates the implementation of the location identification approach using filtering methods such as Kalman filtering.

2.2 Acoustic

Ultrasound-based location identification utilizes the TDoA measurement of the acoustic pulse transmitted by the audio beacon generator (ABG) to a number fixed or mobile client device (e.g. smartphones, laptop…) deployed at particular mapped locations for indoor positioning [57]. The ABG broadcasts its acoustic signal that is encoded with the uniform resource locator (URL) of the web-based service, in form of a service code mapped to a particular location or service, such that surrounding client devices attached to the mobile target can thus identify themselves within the particular mapped location [58], as the location of the mobile target is processed by a specialized communication algorithm run on a web-based server. Fig. 4 highlights an example of a target location identification in a crowded office space using an acoustic sensor.

(a). A general crowded office environment deployed with acoustic sensors

(b) An acoustic microcontroller board

Fig. 4. An acoustic-based indoor localization experiment using acoustic sensors (**Source**: Wang et al.) [59]

Ultrasound has several attractive features such as negligible penetrating power in walls, cheap transducers, and hardware compatibility with almost all handheld devices. Generally, the ultrasound-based approach offers higher accuracy and is suitable for short-range applications, thus scaling up the coverage area will incur higher deployment cost [60]. In addition, the time of flight method often used in the signal propagation to estimate the distance between the receivers and the transmitting object do require synchronization between the sensor nodes, which is practical in an electrical pulse system of wired connection, but unreliable in a wireless network [61]. However, due to the relatively slow speed of sound (i.e. around 344 meter/seconds), ultrasound location identification is affected by scattering owing to the reflection of the acoustic pulse resulting in reverberation. In addition, ultrasound location identification is affected by inconsistent frequency due to Doppler shift effect.

2.3   Magnetic-based technology

Magnetic-based location identification system utilizes the effect of the magnetic field since it is vectorial in nature, for localizing the position of target objects. Location identification is achieved using reference stations which generate a periodic magnetic field that can be measured by a mobile magnetic sensor. The position of the mobile target is localized from the measurement of the magnetic field strength of the magnetic field sensor equipped with the mobile target of at least three reference station using trilateration approach [62]. Magnetic-based location identification offers high accuracy on the order of few centimeters and degrees at 10 Hz.
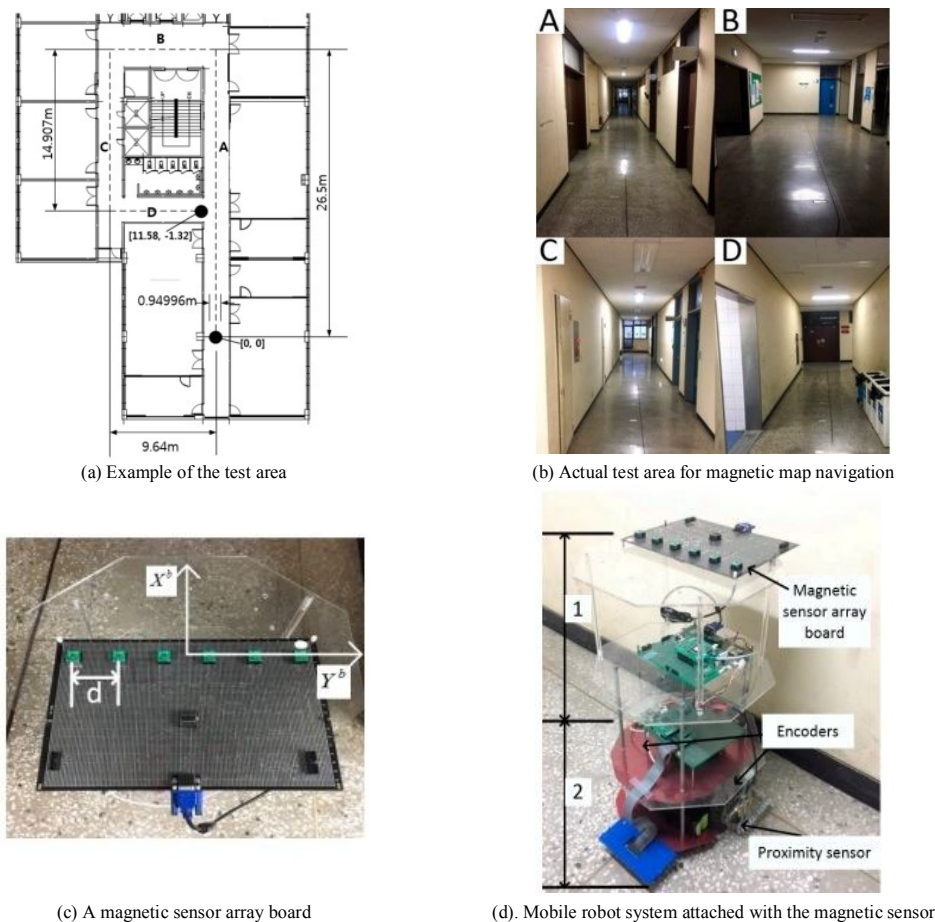

(a) Example of the test area

(b) Actual test area for magnetic map navigation

(c) A magnetic sensor array board

(d). Mobile robot system attached with the magnetic sensor

Fig. 5. A real-world example of magnetic field mapping for indoor navigation using a mobile robot system (**Source:** Kim et al) [63]

Here, Fig. 5 shows a real-world example of magnetic field mapping using a mobile robot system for sampling the indoor environment. Moreover, unlike most location identification technologies, magnetic-based location identification has the potential for no federal communication commission (FCC) since they operate at low

frequencies, lower to those censored by the FCC. However, the reliability of magnetic-based location identification is challenged owing to their sensitivity to conductive and ferromagnetic materials.

2.4 Optical-based location identification

Infrared operates on the principle that infrared wavelengths are longer than visible light, although shorter than ultraviolet. Infrared is less intrusive, owing to the invisible nature of infrared signal to the human eyes under virtually all conditions. Infrared-based location identification employs three methods based on (i) active beacons [64] (ii) thermal radiation [65] and (iii) artificial light sources [66].

- The active beacon method uses infrared receivers placed in different known locations and mobile beacons on target objects whose positions are unknown, such that with an IR location identification system, the unknown positions can be estimated.
- The thermal infrared radiation method exploits the natural thermal radiation of humans. Detection using this method usually occurs by the combined estimation of the sensor measurement within the coverage area using passive, low-resolution sensors, easy to integrate into any existing environment. The full anonymity of the localized target object is achieved when low-resolution sensors are used, making identification of the heat sources practically impossible, [67, 68].
- The artificial light source method utilizes a set of infrared light emitting diodes (LEDs) and usually a phototransistor. Light modulated at a frequency of 38 kHz is passed through a phototransistor with a filter, such that interference between the modulated light and other illuminating sources such as sunlight can be reduced. Each LED emits a unique ID depending on the pulse train of the modulated light. Location identification occurs when each LED installed at specified locations in a coverage area emits a unique ID, whereas the LED tracker determines the location of the two-dimensional location of the LED in the sight of its infrared image sensor by recognizing the unique ID of each LED [69].

Infrared technology using a light source and other methods offer some advantage over RF-based technology in that, light signal suffers negligible reflection, thus it is not significantly affected by multipath effect compare to RF signals which are affected by multipath effects [70]. Infrared technology is also cheap and reliable for open space applications. However, the technology always requires a line of sight for its signal propagation, making it suitable only for short-range applications. Accuracy is dependent on factors such as physical obstruction, long computational time and low data rate [71].

2.5 Radio frequency-based location identification

2.5.1 WLAN/Wi-Fi (IEEE 802.11g)

WLAN or Wi-Fi is a technological communication standard for wireless data transmission, which operates between 2.4 GHz and 5 GHz and recently in the 60 GHz frequency band of the electromagnetic spectrum, i.e. Wi-Fi utilizes electromagnetic waves for the transmission of data. The effective range of Wi-Fi is comparably large with a coverage range of between 50 to 100 m [72, 73]. Wi-Fi signals are often used opportunistically for location identification as highlighted in an experiment shown in Fig 6, which offers an accuracy of around a few meters in an adequately examined environment with dense Wi-Fi coverage [74],

Fig. 6. An experimental measurement of subcarriers in Wi-Fi to achieve highly accurate indoor localization (Source: Chen et al) [75]

Wi-Fi-based location identification focusses on RSS and fingerprinting methods for target object positioning [73], and these methods are easy to compute since most standard compliant devices utilize the RSS, which is suitable for position estimation [76] and signal-to-noise ratio of the transmitted signal from the wireless devices to position mobile target [77]. Moreover, with the intense research in location identification using CSI of wireless devices, the accuracy of location identification systems improves significantly using Wi-Fi signals and CSI of communication links resulting increased overall performance [78-80]. Thus, location identification using Wi-Fi signal is an attractive approach for estimating the location of mobile targets due to its availability in many environments, with relatively cheap transceivers. However, for an object to be localized, the object must also support the Wi-Fi system.

2.5.2 Bluetooth

Bluetooth operates in an analogous way as Wi-Fi, as it transmits radio signals at the same frequency and utilizes the same location identification principles for several applications. Bluetooth is a highly ubiquitous technology, as it operates in the 2.4 GHz unlicensed frequency band, which makes the technology pervasively available, deployable for a wide variety of applications [81, 82] including collaborating with other network services [83, 84]. The availability of Bluetooth also contributes to it being relatively cheap. Bluetooth operates by specifying a set of mandatory protocols for each Bluetooth module that must be implemented. Fig. 7 highlights the deployment of a Bluetooth iBeacon for localization of a target.

(a) Bluetooth beacon attached to various part of the indoor testing space

(b). Bluetooth module (HM-10) used for indoor location beacon experiment
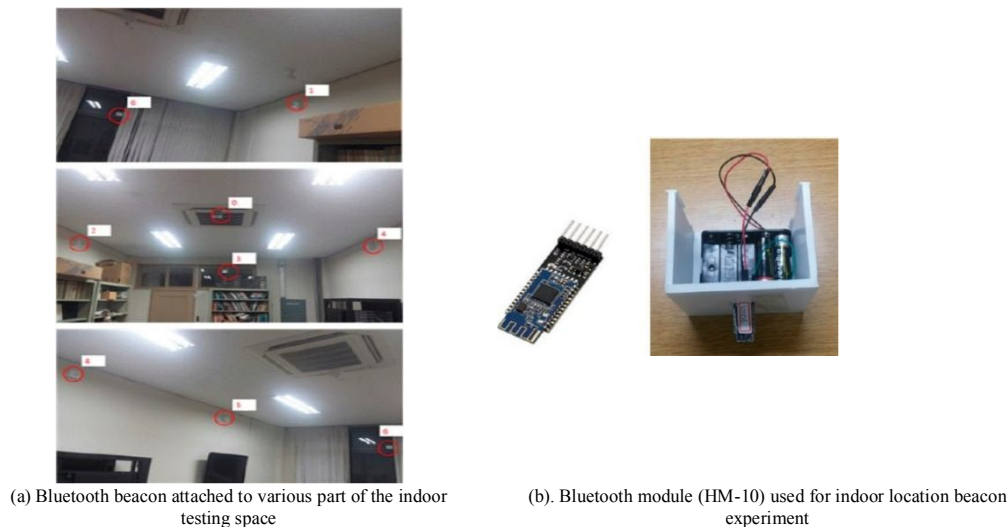
Fig. 7. A deployment of Bluetooth technology using an iBeacon for location detection (Source: Huh et al.) [85]

Like other RF-based technology, Bluetooth is short-ranged and supports low power wireless connections [86]. Bluetooth often has an effective bit rate of 1Mbps and a precision range of 1 to 5m which makes it less effective for longer-range applications [87].

2.5.3 ZigBee (IEEE 802.15.4)

ZigBee is a wireless standard defined by a set of communication protocols designed for wireless personal area networks, thereby making it a short-range technology. Wireless devices using ZigBee operate in the 868 MHz, 915 MHz, and 2.4 GHz ISM band. The effective signal range of ZigBee is up to 100m in free space [88-91], and typically 20 to 30m in indoor environments [7]. ZigBee is suitable for most low power consumption applications of about 60 mW with a data rate of about 250 kbps, and its devices can function either as a coordinator or as a slave. The coordinating ZigBee device forms the root of the network by initiating a connection between other networks and nodes of up to 255 nodes, whereas the node receives data from the coordinator [92].

Fig. 8. (a). An experimental environment using ZigBee technology (b). XBee - A ZigBee series 2 module **(Source**: Aykac et al.) [93]

From Fig. 8, we show an established experimental deployment of ZigBee technology for indoor positioning using an XBee module. Furthermore, ZigBee uses the RSS method for distance estimation between two or more ZigBee nodes [94]. ZigBee offers several desirable advantages as described in the literature by several researchers [90, 95-100]. However, ZigBee suffers from some drawbacks as well, as the operating frequency of ZigBee, which lies in the unlicensed ISM band, makes the technology prone to interference from signals operating at the same frequency. In addition, since the technology is only suitable for short-range applications with low-data-rate [101], the range of applications is limited [89].

2.5.4 Ultra-Wide Band Technology

Ultra-Wideband (UWB) technology exploits the diverse interactions between electromagnetic fields and matter [102], operating on the principle that images gained from scattering of electromagnetic waves provide a detailed geometrical dimension of the surrounding environment since wavelengths are smaller compared to the real size of objects [103]. Although, electromagnetic scattering does not reveal detailed information of certain objects, for example, opaque and hidden objects. UWB is designed to operate in the microwave frequency occupying a very large bandwidth of more than 1.5 GHz [104], thereby giving the technology an exceptionally high resolution but low penetrating power especially to most non-metallic materials for easy detection of hidden objects. In addition, the higher bandwidth of microwave frequency enables UWB-based location identification to achieve higher object resolution in the decimetre, centimetre, and millimetre range, and better object recognition capabilities than narrowband technologies [102, 105, 106]. Fig. 9 illustrates the application of UWB technology for localization in a large indoor environment.
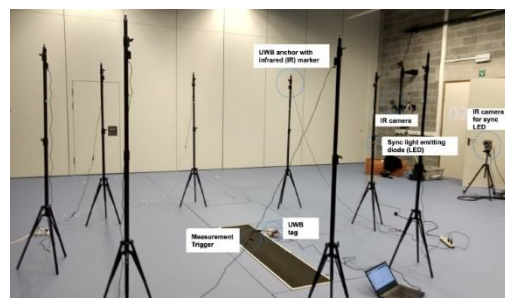

Fig. 9. An indoor localization experiment at the Sports Science Laboratory-Jacques Rogge, Ghent University using eight UWB anchors installed to position a mobile tag. **(Source**: Ridolfi et al.) [107]

Moreover, since UWB operates by sending ultra-short pulses with low duty cycle across many frequencies [108], this enables the technology to provide accurate ToA positioning information even in the presence of multipath. Other desirable features of UWB include high data rate that is short-range at very low power density [109, 110], low EM radiation and low processing energy consumption [111]. However, the large bandwidth of UWB causes inevitable interference in the presence of other devices, thereby necessitating a strict low power consumption limit, which makes the technology a conservative approach and impractical for many location identification applications [112-114].

2.5.5   RFID

RFID is a pervasive technology, effective for tracking and positioning. RFID systems usually consist of tags, readers, and a server equipped with RFID middleware, thus RFID technology is often categorized as either tag-oriented or reader-oriented. RFID tags are made up of transceivers and a chip and can be active, passive and semi-active depending on the availability of power for their functioning. Each tag is uniquely identifiable and able to transmit stored data, which may be read-only or writable. Active tags are equipped with an inbuilt battery embedded in their circuitry, while passive tags do not have inbuilt batteries but backscatter the signal received from the base station. Semi-active tags, although they do backscatter the carrier signal received from a base station, also have an inbuilt battery embedded in their circuitry, which powers the circuitry, thereby giving it the flexibility to function in dense environments [115]. Fig. 10 illustrates the experimental application of RFID technology using passive tags to determine the various categories of activity performed within the mock room. RFID is popular and is useful for a wide variety of applications owing to its cognitive intelligence [116-118], and wireless sensing functionality as highlighted in Fig. 10 where RFID technology is applied for activity recognition. RFID offers other desirable advantages which include high data rate, adaptability to various environment, availability in non-line-of-sight (NLOS), wireless capability, wireless zero-power sensors and low maintainability [18, 119-121].

Fig. 10: An indoor localization experiment using passive RFID tags for touchless activity recognition [122]

RFID technology, however, suffers from several limitations arising from the issue of operating frequency standardization, invasive nature, and requirement of additional infrastructure in location identification techniques like proximity [123]. Furthermore, improved accuracy and higher resolution often require the deployment of several tags around the coverage area of interest, which sometimes results in high computational cost.

2.6   LIDAR

LIDAR (Light Detection and Ranging) also known as laser radar is an efficient remoting sensing, outdoor/indoor technology, which originated in the early 1960s. LIDAR technology operates on the principle of light propagation and the time it takes the transmitted signal to returns from its source. LIDAR systems operate by emitting near-infrared laser pulse at a high rate of typically $10^4 - 10^5$ per second. The precise position and attitude of the laser scanner unit at the time each pulse is emitted is determined from the flight data collected by the reference units. The distance between the scanner and a target that reflects the pulse is computed using the return time of the pulse to complete the return trip distance from the scanner to target. The distance information, position and orientation of the scanner are used to calculate the precise coordinate for each reflection points represents each target location [124]. Therefore, as illustrated from Fig 11, mobile LIDAR sensor are reliable to provide *2-D/3-D* points cloud with intensity information for precise acquisition of dense surface information that supports the enhancement of MMS in high depth indoor environments [125].
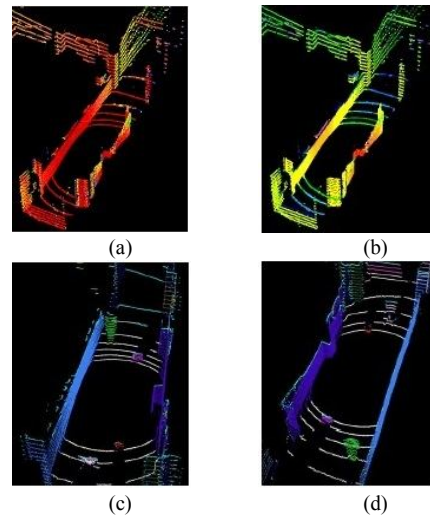
Fig. 11. Object segmentation for 3-*D* environmental measurement and reconstruction based on Point Cloud Map using LIDAR for (a) horizontal (b) Vertical (c) Front view, and (d) Rear view distance extraction (Source: Fan et al.) [126]

LIDAR technology was originally applied for outdoor monitoring including meteorological monitoring to measure cloud, airborne and terrain mapping system. Nevertheless, due to the detailed and accurate elevation measurement that the technology provides, it is applied in recent times for 2D/3D indoor applications [127-129].

3. Techniques for Signal Measurement

Accurate real-time location identification involves the extraction of location-based information from wireless reference nodes (often term *anchor*, *base station*, *landmark*) deployed at fixed locations, with a mobile node (often term as *mobile users, target object* or *agent*) using any of the technologies discussed in the previous Section. Moreover, location identification could imply an opportunistic use of definite methods in estimating the communication between reference nodes and the mobile node [130]. For example, if node *X* wants to know where node *Y* is, there are three possibilities: *i.* node *Y* determines where it is and communicates the location to node *X* or *ii.* as non-cooperative technique where nodes which are randomly deployed, responds to a beacon signal transmitted by node *X* from several known locations in the field, and *iii.* a cooperative technique where node *Y* carries a beacon or RFID tag permitting node *X* to accurately locate it, thereby allowing each other to determine their location. Fig. 12 highlights a simplified smart home testbed with four reference nodes (RFID readers) and a mobile object (smartphone) attached with an RFID tag for target location.
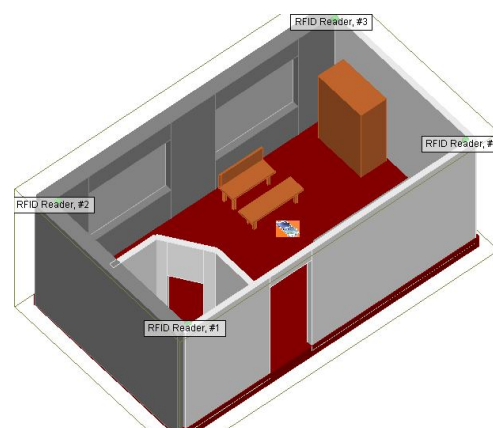

Fig. 12. Simplified testbed for smart home having four reference nodes for target location identification

Location identification techniques based on their applications is either *range-based* or *range-free*. *Range-based* techniques are geometric, and depend on the absolute distance or angle estimated between two or more points whose values are usually a function of the relative position between the reference node and the mobile node. Range-based techniques offer higher accuracy but are often hardware-intensive. Range-based techniques include (a) time-based techniques, such as *Time of Arrival* (ToA) [131, 132] and *Time Difference of Arrival* (TDoA)

[133-135], (b) angle-based techniques, such as *Angle of Arrival* (AoA) and *Direction of Arrival* (DoA) [136-138], and (c) *received signal strength methods* [139, 140]. Comparatively, r*ange-free* techniques, on the other hand, are dependent on the hops between two or more nodes within a network, so they only use the content of information transmitted [141]. Techniques utilizing this principle include *proximity detection* [142, 143],*V-hop* [144] and *fingerprinting* [145-147]. A summary of the taxonomy of these techniques used for target positioning and other applications is shown in Fig. 13 based on the parameter used in determining target location.
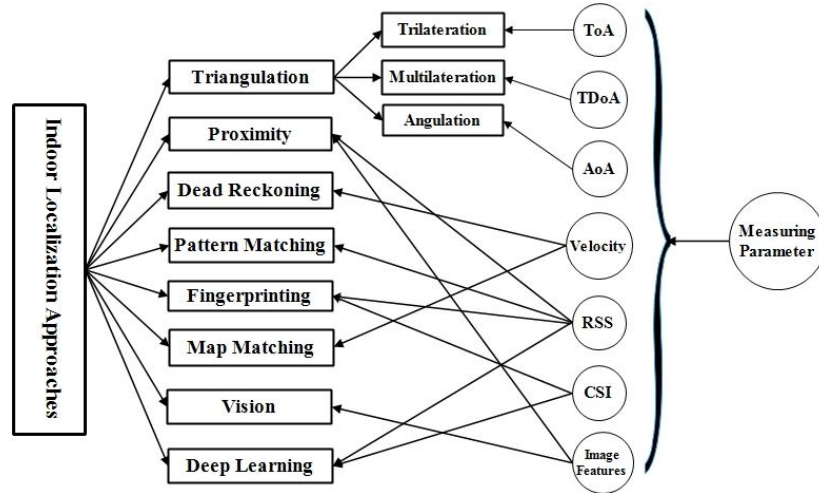

Fig. 13. Taxonomy of location identification techniques

3.1 Triangulation

Triangulation utilizes the geometric property of a triangle in localizing target objects and people. Triangulation can be categorized into three techniques since to know where a target is required multiple distance measurements, multiple angle measurements or a combination of angle and distance. These three methods are often referred to as trilateration, multilateration, and angulation, and they involve the measurement of three lengths from a known baseline or measuring two angles from a known baseline and finding their intersection or finding only the angle but then physically follow the signal until the target object is located [148]. Both trilateration and multilateration use the time of propagation of the signal or the received signal strength as a basis of measurement [149, 150], whereas angulation method uses the direction (angle) of the arrival of the mobile signal coming from a predefined location to multiple base station [151]. Triangulation is an effective technique for estimating the location of a wireless device by measuring the distance of the mobile station (MS) to several fixed terminals in determining the position of the mobile target [152].

3.1.1 Trilateration

Trilateration is an indoor/outdoor location identification technique, where the MS computes its distance to several BS of known locations using either RSS or ToA of the signal. If the distance is known, a circle with a radius of that distance can be imagined has been around the position of measurement and along the circumference of the circle, which indicates all possible locations of the object. Moreover, for effective 2-D position estimation of an MS or target object, the distance measurement to three BS locations using their ToA is required. Trilateration is also an effective outdoor location identification technique used for GNSS positioning. However, effective trilateration is achieved when the distance of the MS to the BS is synchronized, this condition affects its accuracy since MS - BS distance cannot be computed accurately and easily with models [153].

▪ Time of Arrival (ToA)

ToA is the travel time between the transmitter and receiver, often measured by the subtraction of the time at which the signal is transmitted from the time the signal reaches the receiver [154]. From Fig 14, it can be seen that ToA can be correlated with the Euclidean distance, derived by the multiplication of the signal travel time by the speed of light. However, the estimation of the Euclidean distance is dependent on the wave speed, which in

effect is dependent on the properties of the propagation mode and medium, thereby necessitating an accurate understanding of building materials properties [13] and e.g. waveguide modes in corridors. Effective computation using ToA requires the nodes to be synchronized and the time stamp information must be included in the signal [155].
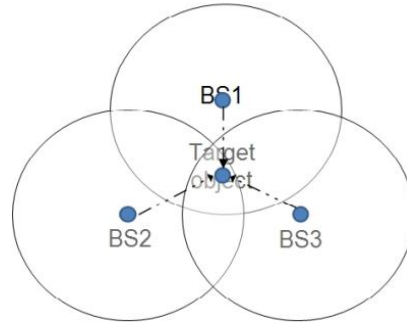

Fig. 14. Time of arrival method

However, accuracy is challenged in environments where multipath effects or interference exist. The need for constant synchronization necessitates the deployment of other time-based techniques such as TDoA and Relative Time of Arrival (RToA) which do not require a common time reference between the nodes [20].

- ▪ Time Difference of Arrival-based location identification

Time Difference of Arrival (TDoA) method is based on the time difference at which each RF signal arrives at the receiver from different transmitters [156]. TDoA can be estimated using two approaches; one approach uses the time of arrival of transmitted signal record common to each base station and then subtracting these times over terminal pairs, using the autocorrelation property of the received signal. Another approach is by cross-correlating the two received signals while their relative timing is adjusted until a peak occurrence is noted [8, 157]. A simplified arrangement of hardware infrastructure used in TDoA method is shown in Fig. 15, where three base stations, BS_1, BS_2 and BS_3 are used to provide two TDoA measurements $d_3 - d_1$, $d_2 - d_1$ such that the intersection of these points produces a *2-D* location of the mobile target.
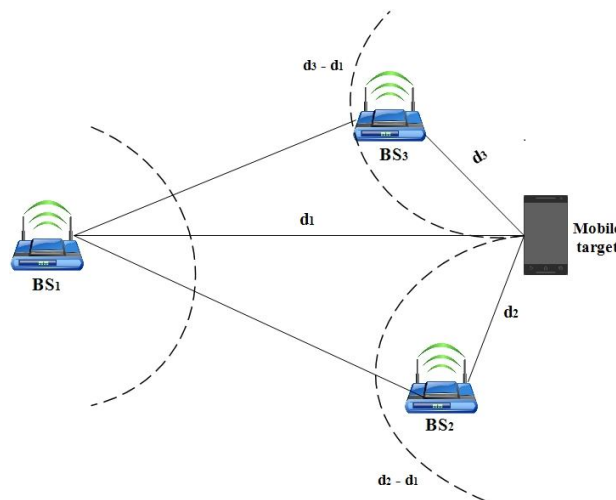
Fig. 15. Time Difference of Arrival Method[158]

These approaches require any two receivers at predefined locations to locate a transmitter on a hyperbola at which the signals have the same time difference. The intersection of the hyperbolas formed by the different pair of base stations locates the position of the target object [159]. The conventional TDoA technique which requires 3 or more sensors has been intensely investigated and extended to newer techniques such as *Frequency Difference of Arrival (FDoA)* [160-162]. One major advantage of TDoA over ToA is that receivers can listen

passively to the transmitted signal, which invariably locates the position of the transmitter [163], and TDoA does not suffer from the drawback of accurate time synchronization, thereby making it a more effective method [72, 164].

- ▪ Round Trip Time of Arrival-based location identification

Round Trip Time of Arrival (RToA) overcomes the drawback of accurate time synchronization as required in the ToA method. As shown in Fig. 16, the return trip time of arrival can be measured as the time it takes the transmitted signal to travel from the transmitter to the receiver and return back to the transmitter [165]. However, RToA suffers from latency whenever it is used to measure multiple targets concurrently.
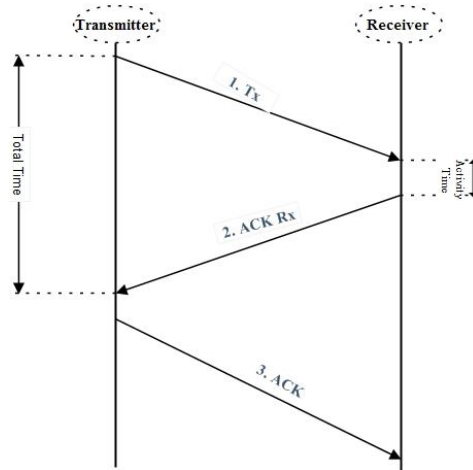
Fig. 16: Round Trip Time of Arrival Method

3.1.2 Angulation – Angle or Direction of Arrival-based location identification

Angulation methods use the angle of arrival of the received signal coming from a predefined location to multiple base stations in determining the location of a target object [166]. The typical arrangement of hardware infrastructures for the angulation method is represented in Fig. 17. The direction of angle inclined by the transmitted signal is estimated using the TDoA method at predefined sections of an array of highly directional antennas with the capability of measuring the angle inclined by the transmitted signal [167-169].

Fig. 17. Angulation method using four anchors and a mobile target

For effective estimation of angles, only two beacons are required for AoA in a 2-dimensional plane, whereas three or more beacons are needed in a 3-dimensional plane. The AoA/DoA method offers higher accuracy when there is LOS, and usually does not require synchronization. However, accuracy using the method is affected by

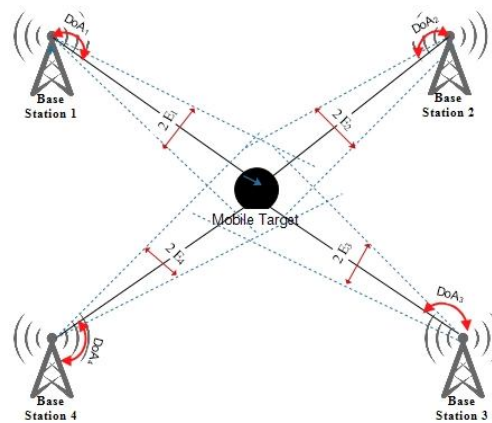several propagation effects such as fading, scattering, reflection, diffraction, shadowing and by the directivity of the antenna [170-174].

3.2 Proximity-based location identification

Proximity detection is a location estimation method often based on the relative proximity of the mobile device to predefined known locations as shown in Fig. 18, or it can rely on indirectly inferring the absolute position of the target object [175]. Proximity detection can also be initiated by the sensing environment using computer vision techniques [143], for example using ordinary cameras or Kinect-like depth cameras [176, 177]. More generally, proximity detection is dependent on the dense deployment of antennas in which the sensor nodes are grouped into clusters, and the target location is determined by the *Cell of Origin (CoO)* method, where a predefined location and limited range is utilized [178, 179]. Moreover, the CoO will only forward the position of the highest received signal strength to the base station, which is regarded as the most probable target location. Accuracy using proximity detection is related to the density of the beacon points and the signal range. Thus, it is mostly implemented with RF propagation-based technologies such as RFID, Bluetooth, Infrared and custom radio devices [180-183].
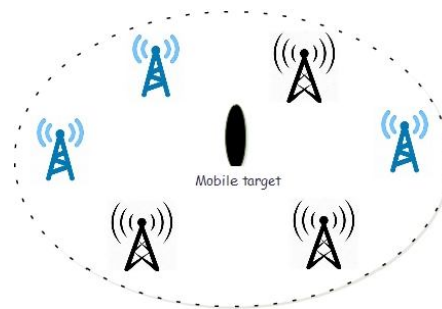

Fig. 18. Proximity Detection Method

Nevertheless, CoO method is easy and cheap to implement does not involve any complicated algorithms and is suitable for most applications. However, the method is impractical for target identification as it offers low accuracy.

3.3 RSS and CSI-based location identification

The RSS method, unlike time-based methods, uses the received signal strength indicator which is on virtually all receivers and to interpret these readings using a dedicated location estimation software [184]. RSS is the average of signals received from different paths at any given location [185], and as such the propagation power loss or attenuation of the transmitted signal is used in estimating the target location. The target location is often estimated using at least three reference points and the corresponding signal attenuation of the signal. The RSS-based method is effective and can be implemented on any existing wireless communication system with almost no hardware changes. However, the method is sensitive to environmental factors such as multipath effects and shadowing [186]. Also, since signal strength attenuates with distance, the accuracy of RSS methods decreases with large distance [156, 187], thus it is suitable for short distance application. A significant problem in using RSS as a method for measuring distance is that when an EM signal propagates over a plane earth (rather than in free space) the relationship between signal strength and distance is not single-valued, resulting in ambiguity. However, the RSS-based method suffers from high variability over time for fixed location-aware service due to high multipath effects in the indoor environment, resulting in large location error. In addition, RSS values are often coarse information, therefore the method is often not exploited in the many subcarriers of an *orthogonal frequency-division multiplexing* (OFDM) systems for improved multipath information. A fallout of the limitations of the RSS-based method is the utilization of *channel state information* (CSI). CSI estimates the channel through the channel property of communication links such as network interface card (NIC) as the signal propagates between the transmitter and receiver [188]. CSI, therefore, combines the effect of various propagation properties such as fading, scattering and power decay with distance which invariably improves the overall performance of location identification [189, 190]. Nevertheless, CSI in comparison with RSS largely applies different location identification techniques including ToA, AoA, and Fingerprinting [52, 191-193].

3.4 Dead Reckoning

Dead reckoning estimates an updated position by using the last known location information of the target object. This is achieved by either incrementing the known location based on the velocity of the target object or the known traveled distance [179, 194]. Dead reckoning utilizes the reading of *Inertial measurement unit* (IMU) sensors such as gyroscopes, magnetometers, and accelerometers [195-198], thereby making the method independent of external signals [199]. Dead reckoning is relatively simple and efficient in estimating target positions in real time, in comparison with absolute positioning methods [60]. Moreover, hybridization of dead reckoning with absolute positioning updates becomes more efficient using a Kalman filter. However, dead reckoning often suffers from accumulating errors which often necessitates the use of diverse correction methods [200, 201].

3.5 Pattern Matching

Pattern matching often referred to as scene analysis, utilizes the features of a scene in estimating the location of people or target objects. Pattern matching approach compares the measured data with the closest a priori location data, i.e. positioning of mobile targets is based on the comparison of the actual measurement of ToA or RSS with a radio map, which is a pattern database formed by a set of measurements earlier performed with tags placed at known coordinates. Pattern matching differs slightly from pattern recognition as the latter requires the compared match to be exact, although both methods adopt the fingerprinting approach in localizing target objects. Pattern matching, when used in combination with a neural network, improves location identification in 3D environments [202, 203].

3.6 Fingerprinting

Fingerprinting is a database correlation in which the distance between a beacon and transmitting objects is found by comparing the received signal strength pattern with a pre-recorded measurement pattern in the database. Fingerprinting is an efficient location identification approach often applied opportunistically for tracking people and target objects. As shown in Fig. 19, fingerprinting is usually conducted in two distinct phases: an offline (*training* or *survey*) phase followed by an online (*query, test or positioning*) phase [204, 205].
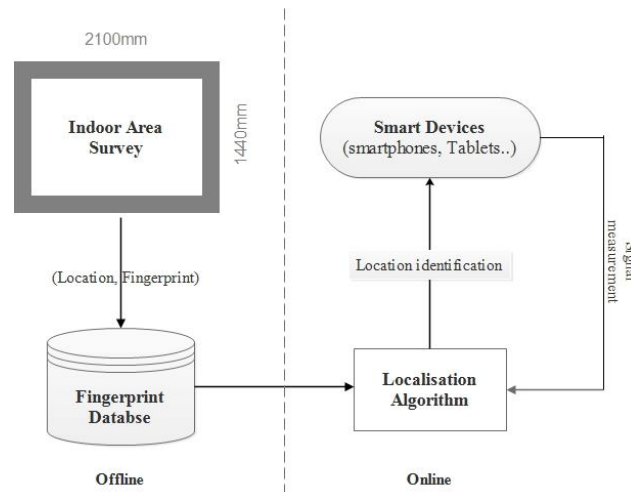
Fig. 19. Distinct phases involved in fingerprinting-based location identification

In the offline phase, signals from each reference node at each training location or site survey are collected by determining the *received signal strength indicator (RSSI)* and recorded in vectors or radio maps. Each RSSI vector represents the fingerprint of each known training location and is stored in a database for the online query [206]. In the online phase, if a *target* (*user,* or *mobile device*) as shown in Fig 10b samples an RSSI vector at his location and reports it to the server. The location identification algorithm in the server, using some similarity

metrics, estimates the target location by comparing the vector of the *RSSI* of the mobile target with the database of the network. The database returns the location with the best correlation with the sent vector [207]. Fingerprinting offer high accuracy with a coverage range of (1–5)m, and effective in the presence of non-line of sight (NLOS) [208], Common algorithms often used for fingerprinting includes (plural) *nearest neighbour, probabilistic, neural network, small M-vertex polygon* and *support vector machine* [15]. However, comparison of data often presents a serious location identification challenge in most environments since the signal strength at any fixed location is not always constant. This challenge is overcome by modeling the signal strength using random variables. In addition, fingerprinting becomes inefficient in the offline phase, as it suffers significantly owing to overhead from composing vectors. Thus, efforts are made in developing a more robust algorithm for easy implementation of the technique as found in [209-218].

3.7   Map Matching-based location identification

Map matching is an outdoor/indoor location identification approach which involves the process of estimating a continuous target's position on a road network [219]. In general, the concept behind map matching is that the tracking data and mobility models are related to maps. This implies that map matching estimates location from the sampled map information often taken from cameras in accordance to known location parameters to improve the estimation accuracy using various map matching algorithms. In addition, the overall objective of map matching is to increase the accuracy of positioning using the knowledge that the tracked target is restricted in movement or location according to the map [220]. Fig. 20 highlights matching approach using selected key frames acquired from a smartphone camera.
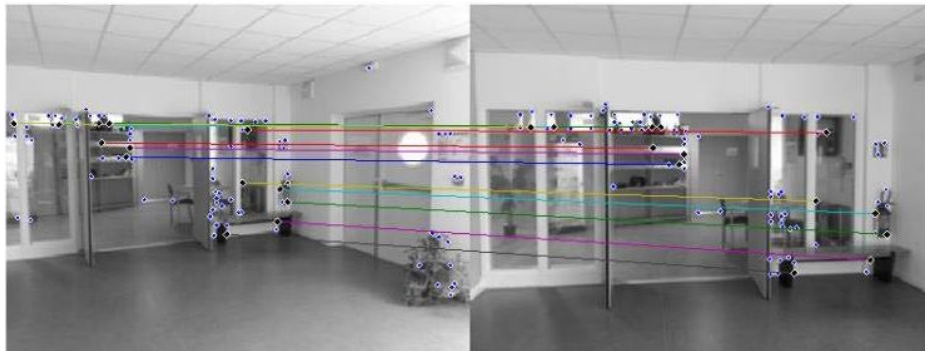

Fig. 20. Map matching approach based on vision using key frames with the highest number of inliers [221]

Map matching approach overcomes the reliability issue associated with proprioceptive sensors used for inertial navigation which often results in their rapidly drifting accuracy with time [222]. Map matching approach utilizes different algorithm approaches which could be: geometric, based on the proximity of the target estimated position to the road network [223, 224]. Probabilistic; where an error region from the error variances associated with the location identification data and road network is derived and overlaid on the road network for identifying the true road segments [225, 226]. Topological; which compares the geometrical and topological features of the road network with the vehicle trajectory [227, 228], and a more advanced hybridized approach using special decision-making model [229-233]. Nevertheless, the advanced hybridized approach is more reliable and accurate than geometric-based since the approach overcomes all the limitations of geometric-based map matching [234, 235].

3.8   Vision-based location identification

Vision-based location identification approach is achieved through the utilization of camera sensors. The camera sensor is used to capture visual features and images or to estimate human motion in reference to some features or landmarks that are used as references for determining the image position of the person or object. Furthermore, the vision-based approach also utilizes stored image database annotated with the position information of the cameras. When an image query is received, feature extraction and image matching between the query image and the database images is performed using an efficient algorithm such as the vocabulary tree [236]. Vision-based location identification offers low complexity, as the approach often does not require pre-installation of any

dedicated infrastructure which serves as a key advantage [221]. However, vision-based location identification suffers from several drawbacks: First, the approach is intrusive in nature resulting in the use of CCD and other low-resolution cameras. Second, the approach becomes unreliable in occlusion situations where objects are blocked by camera detection resulting in low-resolution recognition and poor accuracy [237].

3.9   Location identification by Deep Learning

Deep Learning often refers to as hierarchical learning is a dynamic algorithm-based technique used for learning several levels of representation as a means of modeling complex relationships among data [238]. Deep learning offers an effective object recognition and location identification in comparison to the classical machine learning pipeline of feature extraction and classification using a different approach like support vector machine (SVM). Deep learning requires the consistent utilization of object position information which is obtained from the relative posture of the person or the object image regardless of the object distance from the camera for effective object detection and location identification [239]. In addition, the application of Deep Learning using the CSI of NICs for location identification provides an efficient approach to determining the target location. This efficient location identification approach has resulted in the development of several innovative systems like DeepFi, BiLoc, and PhaseFi among others [240-242]. A comparison of these positioning techniques is highlighted in Table 1 with a view to highlighting some of their strengths and weaknesses. High, moderate, low and none are used in classifying the effect of the considered factors on each of the location identification techniques.

Table 1: Comparative summary of indoor techniques for location identification

Indoor Technique	Measuring Parameter	Accuracy	Cost	Energy Efficiency	Complexity	LOS/ NLOS	Multipath Effect?
Triangulation							
• Lateration	ToA	High	High	Low	High	LOS	Yes
	TDoA	High	Moderate	High	Moderate	LOS	Yes
Trilateration	ToA, RSS	High	High	Moderate	High	LOS	Yes
• Angulation	AoA	Moderate	High	Moderate	High	LOS	Yes
Proximity	RSS	Moderate	Low	High	Moderate	None	No
Dead reckoning	Velocity	Moderate	Moderate	High	Low	LOS	Yes
Pattern matching	RSS	Moderate	Moderate	Low	Low	None	Yes
Fingerprinting	RSS, CSI	High	High	Low	High	NLOS	Yes
Map matching	Velocity, Acceleration	High	High	Moderate	High	LOS	Yes
Vision recognition	Video	High	High	Moderate	High	LOS	No
Deep Learning	CSI, RSS	High	High	Moderate	High	LOS/NLOS	Yes

4. Formulation of Localisation Problem

In this section, we formulate a simple location identification problem using ToA and AoA as the location identification techniques for predicting the location and orientation of the target within an indoor environment. Fig. 21 shows a 3-D representation of a target position in an indoor environment having i anchors. The target motion is defined as a function of time, whilst the target position vector in any of the *3-D* Cartesian coordinates at any time instance is a piecewise continuous function of time. The base stations send signals to locate the target such that within an interval, the path described a function of time.
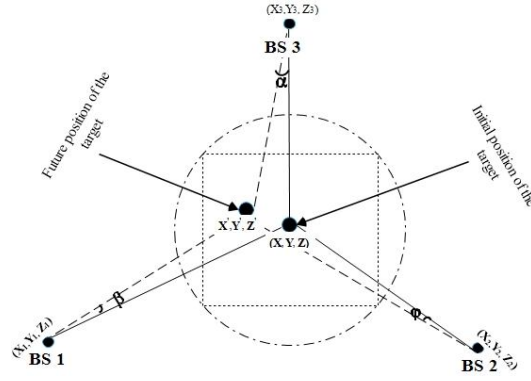

Fig. 21. ToA with three base station.

A curve C in space can be represented by a vector function represented in Eq. 1

$$\vec{r}(t) = \left[x(t), y(t), z(t)\right] = x(t)i + y(t)j + z(t)k \tag{1}$$

Going by the above, the location of the anchor in an indoor environment can be represented as (x_i, y_i, z_i) from Fig. 21. However, the position vector of the ith base station can be expressed as:

$$\vec{r} = (x_i, y_i, z_i) = x_i i' + y j' + z k' \tag{2}$$

Thus, the location vector of the target with respect to the anchors can be estimated from:

$$\vec{r_a} = \left(x_i - x(t)\right)_i + \left(y_i - y(t)\right)_j + \left(z_i - z(t)\right)_k \tag{3}$$

Assume the new (future) location of the target is at $\left[x'(t), y'(t), z'(t)\right]$, then the vector function of the new location can be expressed as:

$$\vec{r}(t) = \left[x'(t), y'(t), z''(t)\right] = x'(t)_i + y'(t)_j + z''(t)_k \tag{4}$$

Therefore, the position vector of the new location will be given as:

$$\vec{r_{fp}}(t) = \left[x_i - x'(t)\right]i + \left[y_i - y'(t)\right]j + \left[z_i - z'(t)\right] \tag{5}$$

Algebraically, rewriting Eq. (5) as d_i, which represents the distance between base station and target. Therefore,

$$d_i = \sqrt{\left(x_i - x(t)\right)^2 + \left(y_i - y(t)\right)^2 + \left(z_i - z(t)\right)^2} \tag{6}$$

$$d_i' = \sqrt{\left(x_i - x'(t)\right)^2 + \left(y_i - y'(t)\right)^2 + \left(z_i - z'(t)\right)^2} \tag{7}$$

Using the cosine rule, the distance between the anchors and the target position can be estimated from:

$$d_i = d_i' \cos\phi_i \pm \sqrt{d_i' \cos^2\phi_i + 4\left(k_i^2 - d_2'^2\right)} \tag{8}$$

where $\phi_i = \alpha, \beta, \gamma$ as shown in Fig. 21 and k represents the distance between the initial and present location of the target in a coordinate of interest.

4.1 Modelling the look angle of the reference node

In sensor location identification, an opportunistic use of the look angle is critical in obtaining an accurate location and orientation position of the target. Fig. 22 shows the formation of the Look angle, as the angle formed by the two angles of the inclination (θ, φ) of the *BS*. θ represents the angle a sensor makes with $x(t)$

axis measured in the horizontal (x, y) plane, whilst φ is the angle of inclination of the sensor to the horizontal (x, y) plane as measured from the vertical $(z, \in)$ plane. Here, (θ, φ) is estimated by drawing a straight line from the position of the sensor to the predicted coordinate location of the intercept which indicates the location of the target. In addition, (θ, φ) also describe the orientation of the sensors in that signals are aimed at the direction of the target location at a future time t_n.
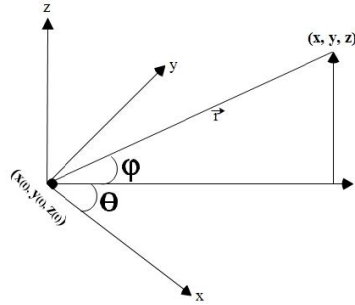
Fig. 22. Azimuth and elevation components of the look angle

If x, y, z axes at t are defined as shown in Fig. 22, then the angle of inclination, φ, in the z, t plane can be expressed as:

$$\varphi = \tan^{-1} \frac{z - z(t)}{\sqrt{(x - x(t))^2 + (y - y(t))^2}} \tag{9}$$

Here, the denominator in Eq. (9) gives the magnitude of $\vec{r}_{tF}$ in the direction t, whilst the angle θ in the x-y direction can be expressed as:

$$\theta = \tan^{-1} \left(\frac{y - y(t)}{x - x(t)} \right) \tag{10}$$

Referring to Fig. 21, the target new position k_i can be estimated. Therefore, by applying the cosine formula, the position of the target orientation can be obtained, i.e.

$$k_i = d_i^2 + d_i^2 - 2 d_i d_i' \cos \phi_i \tag{11}$$

where

$$\phi_i = \beta, \alpha, \gamma \tag{12}$$

Thus, the new position of the target orientation with respect to d_i can be estimated from Fig. 23.

Fig. 23. Determination of target orientation using AoA

Also, applying sine rule,

$$\frac{d_i'}{\sin \psi_i} = \frac{k_i}{\sin \phi_i} \tag{13}$$

and rearranging Eq. (13) gives

$$\sin \psi_i = \frac{d'_i \sin \phi_i}{k_i} \tag{14}$$

$$\therefore \qquad \psi_i = \sin^{-1}\left(\frac{d'_i \sin \phi_i}{k_i}\right) \tag{15}$$

$$\psi_i(t) = \sin^{-1}\left(\frac{d_i(t)\sin\phi_i(t)}{k(t)}\right) \tag{16}$$

5. Selection Metrics for RF-Based Location Identification

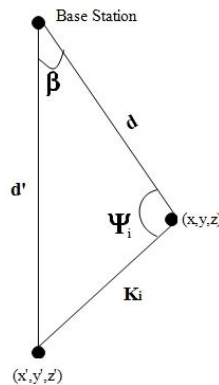In this section, we shall focus on the performance of RF-based location identification technologies using a common generic metric of scalability, accuracy, complexity, robustness, reliability, energy efficiency, cost, and throughput. The metrics are used for the empirical evaluation of each indoor technology with a view to establish the viability of each RF-based technologies.

5.1 Scalability

Scalability describes the adaptive ability of a location identification system to allow many instances of the technology to operate independently without interfering with each other, while at the same time the system stability is still maintained [243]. Scalability is a critical factor that guarantees the overall performance of location identification systems since the number of cooperating small-scale, low-powered nodes with limited sensing and computational capability may often need to be replaced or increased. However, location identification efficiency degrades with an increase in distance between the nodes and the receiver, which usually require most techniques used to be modified. To modify the system to make it more scalable, recent location identification techniques scale the target on two axes i.e. the density and the geography.

5.2 Accuracy

Accuracy gives the degree of deviation of the estimated position from the actual position, i.e. it is the closest calculated position to the true position without *a prior* knowledge of the target known location often termed location identification error. Location identification error refers to the measurement that gives the average Euclidean distance between the estimated location and the true location. Thus, since obtaining accurate information of a target location is the primary objective of any location identification system, accuracy can be improved through joint detection and estimation of the sensor nodes.

5.3 Precision

Precision is an indication of the repeatability of a measurement. Precision is a sensitivity-based performance metric that determines the reliability of a location identification system in presence of changing environmental conditions. Precision is often used interchangeably as resolution in much location identification literature. However, precision and accuracy are closely related, as precision relates to the deviation of the distance error, whilst accuracy relates to the mean of the distance error. Therefore, an accurate location identification system might not necessarily be precise, but a precise location identification system will have high accuracy. Nevertheless, the precision of most location identification systems is often around 5 - 20 cm.

5.4 Complexity

The complexity of location identification systems can be described as the degree of hardware, software and operating factors applied to the overall system. Complexity is often more difficult to support when there is no power. It is, however, less of a problem when the algorithm used for location identification runs on a server with a power supply. However, it can be challenging when the platform running the algorithm is mobile where strong processing power and durable power supply can affect the reliability of the system. Thus, location rate estimates the delay between the mobile target reaching the new location and the time of estimation of the new location.

5.5 Robustness

Location identification systems often face the challenge of one or more failing components within the network. In addition, factors such as the complexity of the indoor environments and other physical effects often do present the location identification system with incomplete data to localize a target, which affects the system performance. Thus, robustness describes the ability of location identification systems to continue to provide reliable and accurate measurements even when conditions are adverse, e.g. in the presence of interfering sources or many targets co-located.

5.6 Reliability

Reliability is a crucial performance metric as it measures the percentage of measurements for which the accuracy meets some threshold. This is because a system might sometimes give an accurate measurement and at other times give no measurement or an inaccurate one. Thus, reliability indicates the level of dependability of the overall system.

5.7 Energy Efficiency

Location identification applications often do require reasonable longevity, and since most sensor nodes are likely to be battery-powered. Charging or recharging of these batteries for the nodes is not usually feasible in many applications [244], thus an aggressive energy management policy is crucial for these battery-powered nodes [245]. Moreover, energy efficiency in sensor-based applications is affected by environmental factors resulting from collision, overhearing and idle listening and control packet overhead. Therefore, energy efficiency in most indoor applications is considered one of the current design challenges and a critical performance metric.

5.8 Cost

Cost divides between the various hardware infrastructures (beacons, servers, tags) used in a location identification system, which can be evaluated in several diverse ways such as roll-out, operating/maintenance, and space cost. Roll-out costs involve the cost required in either installing the new hardware infrastructures or extending the existing infrastructure. Operating or maintenance costs are cost involved in maintaining the optimal functionality of a location identification system, thereby reducing the overall complexity of the system [3]. Space cost relates to the number and size of the hardware infrastructure. Thus, overall cost trade-offs will depend on how many hardware infrastructures are deployed. In addition, system complexity will increase cost and invariably increase its complexity. Hence cost in a relatively small number of servers etc. so that cost of tags can be reduced may lead to overall cost reduction where there are many tags and few servers.

5.9 Throughput

Throughput describes the number of successful messages delivered per unit time. Indoor applications using different technologies exhibit throughput specific to the technology. For example, a fingerprinting system using Wi-Fi can keep track of 100 targets spread over a spatial area of 1000 m^2 within an RMS position error of 2 m. The RFID system, on the other hand, can identify up to 400 separate targets within a 1 m range and takes 1 second to reliably register changes in the population of targets in its captured range. Therefore, in this survey, we assume all indoor technology possess reliable throughput.

Table 2: Empirical Assessment Scale

Assessment	Score
Excellent	5
High	4
Moderate	3
Low	2
Extremely Low	1

Table 3. Empirical evaluation of RF-based indoor technologies

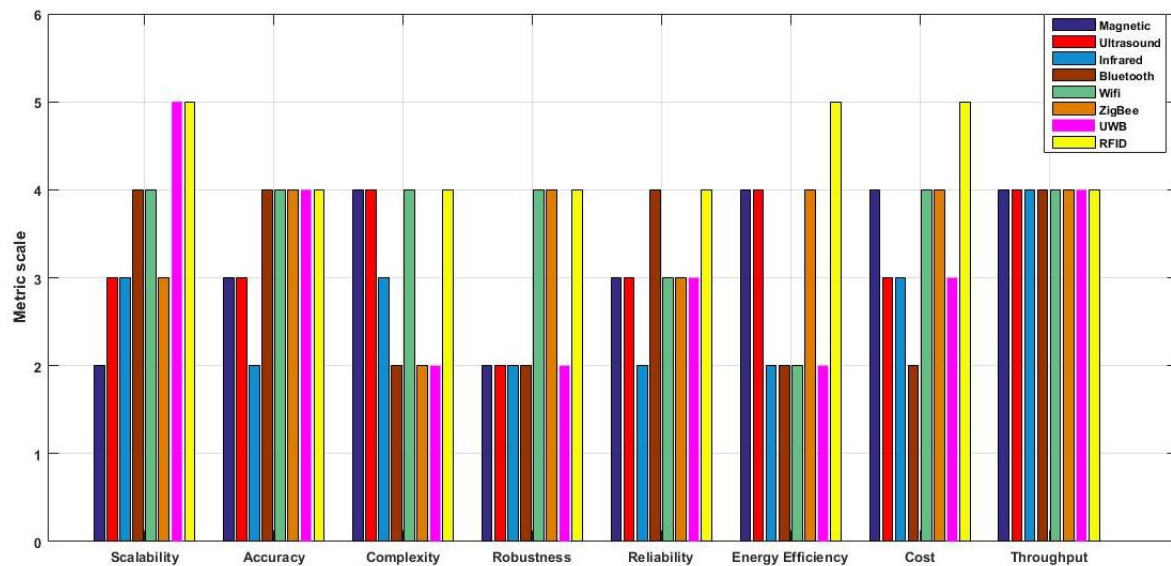| Performance Metric	Scalability	Accuracy	Complexity	Robustness	Reliability	Energy Efficiency	Cost	Throughput
Magnetic-based [246-252]	2	3	4	2	3	4	4	4
Ultrasound [253-255]	3	3	4	2	3	4	3	4
Infrared [254, 256-258]	3	2	3	2	2	2	3	4
Bluetooth [82, 259, 260]	4	4	2	2	4	2	2	4
Wi-Fi [73, 260-262]	4	4	4	4	3	2	4	4
ZigBee [263-266]	3	4	2	4	3	4	4	4
UWB [106, 112, 113, 267, 268]	5	4	2	2	3	2	3	4
RFID [2, 42, 269-273]	5	4	4	4	4	5	5	4

Fig. 24. Comparative evaluation of some location identification technologies

Table 4: Overview of various RF-based location identification systems using a common metric of performance[3]

Common indoor technologies and established existing systems	Location identification Technique	Positioning Algorithm	Scalability	Accuracy	Complexity	Robustness	Reliability	Energy Efficiency	Cost	Throughput
Ultrasound Smart LOCUS [274] TELIAMADE [275] CRICKET [276] Active Badge [277]	AoA, ToA, ToF	Genetic Algorithm, Distributed Listener Inference, Outliner Rejection	Poor, 3D	0.01 to 1 m	High	Low	Moderate	High	Moderate	High
Infrared Active Badge [277] Firefly [278] OPTOTRAK [279] EIRIS [280] IRIS_LPS [281]	ToA, Proximity	Genetic Algorithm, Ray-tracing, Angle adaptation	Poor, 3D	1 to 2 m	Moderate	Low	Low	Low	Moderate	High
Bluetooth TOPAZ [282] ZONITH [283] Apple iBeacon [284]	RSSI	Extended Kalman Filter	Good, 3D	2 to 5 m	Low	Low	High	Low	Low	High
Wi-Fi RADAR [35, 285] Ekahau [286] Horus [287, 288] SmartCampusAAU [289] Nibble [290] WhereMops [291]	ToA, TDoA, Fingerprint	KNN, Bayesian Approach, Probabilistic method	Good, 2D, 3D	1 to 5 m	High	High	Fair	Low	High	High
ZigBee CC2431 [292] ZigBEACON [293]	RSSI, TDoA, ToA, AoA, Fingerprint	Signal Propagation Exponent	Moderate	3 to 5 m	Low	High	Fair	High	High	High
UWB Sapphire Dart [294] Zebra Dart UWB [295] Ubisense [296] Decawave Scensor [297]	RSSI – Fingerprint TDOA, ToA	Least Square	Excellent 2D, 3D	≥ 10 cm	Low	Low	Fair	Low	Low	High

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[3] Table 4 is based on the author's opinion as established in the literature.

RFID											
LANDMARC [298]	Proximity, ToA,	KNN,									
SpotON [299]	RSSI	Ad-Hoc Lateration	Excellent	1 to 5 m	Low	High	High	High	Low	High
WhereNET [300]			2D, 3D							
RADAR [285, 301]										

Table 5: Existing and proposed indoor hybrid systems for reliable IoT-based location identification

Existing and proposed Hybridized location identification systems	Scalability	Accuracy	Precision	Complexity	Robustness	Reliability	Energy Efficiency	Cost	Throughput	Feasible points for hybridization	Possible challenges and drawbacks	Possible areas of applications
INS + Wi-Fi + Fingerprinting [302-304]	√			√	√	√	√			Since RSS measurement can be used for both technologies, where a database of vector map of the field strengths can be constructed and accessed even outdoors. Thus, longer detection range and high accuracy can be achieved.	Mapping of RSSI must be done with an in-depth accuracy. The approach could face accumulated error over time. External references or human input is required	Multimodal transportation network, Pedestrian navigation, Activity recognition
INS + RFID [305]	√	√			√		√	√	√	High range, Cheap,	The requirement for system parts that supports high precision tolerance. Complex assembly technique. Obtrusive. Constant recalibration is required. Computational processing,	Vehicular positioning, Healthcare, Aircraft, Missile Defence System, Animal and Human motion
INS + Bluetooth + ToA/TDoA/AoA [306]	√	√		√	√			√	√	No user input is required, as the user will provide input passively.	Constant recalibration is required. Inaccurate results are highly possible due to errors in measurement	Robot and Vehicular navigation
INS + UWB		√			√	√		√	√	Improved accuracy over 150 m		Vehicular navigation, tracking
RFID + UWB + ToA [307]	√	√		√		√	√	√	√	High detection range and signal transfer due to large bandwidth, which can satisfy most of the multimedia applications.	Interference and Clock Drift	Precision asset location, digital homes, Multimedia applications
UWB + Ultrasound + Fingerprinting	√	√			√	√	√	√		Both require wideband for higher efficiency,	Severe noise sensitivity, Complexity hardware, and computational power is required	Medical Imaging
RFID + Ultrasound + ToA or TDoA [308]		√		√	√			√	√	Low cost, robust in the presence of multipath. Higher capacity reduced exposure of the user to ultrasound due to the non-wearable ultrasound transmitter	Effective read range requirement for high accuracy. Low robustness due to external noise	Robot navigation, indoor positioning of stationary target objects
Bluetooth + ZigBee	√	√		√	√				√	Higher flexibility and reliability in various dimension and mesh network architectures. Longer energy management.	Poor energy management, interference from collisions,	Industrial wireless communication;
RFID + ZigBee	√	√			√	√	√		√	Robust system with support for more advanced mesh network application and high capability. Computational effectiveness. Improved performance and reliability.	The requirement of multiple receivers,	Healthcare, Home Automation, Inventory tracking
ZigBee + Bluetooth +										Similar operating frequency, high	Increased interference from multipath which	Home Automation for smart home

Wi-Fi	√	√		√	√	√	√		√	throughput, supported by most mobile devices, wider coverage area and range	can be delimited by ZigBee	
ZigBee +Wi-Fi + Fingerprinting		√		√		√	√	√	√	High throughput, high energy efficiency, improved accuracy	RF congestion resulting in energy consumption	Home Automation

6. Discussion

To compare the RF-based technologies, we develop an assessment scoring scale as presented in Table 2. Table 2 is used in generating Table 3, which presents our empirical evaluation of each sampled RF-based technologies based on established assessments in the literature. It is noteworthy to state that under complexity and cost metric, the scoring system is reversed since the lower the metric, the higher its effect on the overall performance of each indoor systems. However, from Table 4, we present an overview of each RF-based technologies and their equivalent commercially available systems. A graphical representation of the performance of each RF-based technology based on our evaluation is illustrated in Fig 24, where it can be observed that none of these technologies can satisfy the performance requirements of any location identification application since each technology exhibits certain limitations. However, in our opinion, Wi-Fi, RFID, UWB, Wi-Fi, Bluetooth, ZigBee shows higher viability over most other technologies due to their exceptional advantage of cognitive intelligence, compatibility with most devices, higher precision, low EM radiation, large bandwidth, high penetrating power, lower and effective coverage area exhibited in applications.

A combination of two or more of these technologies (hybridization) will, therefore, enhance the accuracy standard requisite by international authorities for most indoor applications especially in the extreme context of enhanced emergency services. Table 5, therefore, highlights some existing and proposed hybridized indoor system with their expected characteristics.

Hence, we advocate increased hybridization of technologies as an effective approach to achieving reliable IoT-based indoor systems. Although the advantages of hybridization are being exploited by different authors, who have "navigated" their research interest towards this direction [309-322], however, an increased exploitation of hybridization would raise the bar toward attaining a more robust, reliable IoT-based indoor applications and systems.

7. Conclusion

In this work, an inclusive survey on indoor location identification methods, underlying principles, deployment approach technologies and techniques. The survey highlight the complexity of the indoor environment due to the propagation of different signals often propagated within it resulting in the unreliability of the outdoor systems. In addition, since most people usually expend a considerable amount of time daily within various indoor environments for different purposes, location identification becomes an interesting research area for safety and emergency measures. The empirical evaluation of *RF-based* technologies in this study highlights the viability of Wi-Fi, RFID, UWB, Wi-Fi, Bluetooth, ZigBee, and optical technologies. However, since each of these technologies exhibits one form of limitation or another due to their operating parameters. Therefore, we advocate for the combination of different technologies to leverage their limitation and improve the overall performance of developed hybridized systems.

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