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Research Article

A Hybrid Indoor Positioning Model for Critical Situations Based on Localization Technologies

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The domains of positioning and tracking have undergone substantial evolution and advancements recently, especially within the concept of the Internet of Things (IoT) and in health care. Unfortunately, neither the current satellite positioning systems nor the standalone cellular systems remain useful for successfully localizing and tracking inside buildings. This paper proposes a new model that could improve the accuracy of localization in indoor environments. In addition, a broad review is conducted to discover the state-of-the-art indoor localization technologies appropriate for disasters and rescue situations. After a comprehensive study, three important technologies that need to be deeply reviewed are identified, which are wireless local area network (WLAN), dead reckoning (DR), and hybrid approaches. Based on these, a novel architecture is introduced that is more convenient to meet the operation of rescuing injured or older people in critical situations, where other technologies might be unavailable or require some extra infrastructures. The proposed model has two modes and selects one of these modes automatically. The first mode assumes the existence of both WLAN signals and smartphone sensors to be used for identifying the position of the object; otherwise, only smartphone sensors will be employed to achieve positioning. Significantly, the designated components and the flow control depicted provide a proper and suitable horizon for the next researchers who desire to develop a new indoor positioning system in this discipline with a low positioning root-mean-squared error on the centimeter scale that can later be incorporated in numerous applications relating to the IoT, health care, and evacuation plans.

1. Introduction

Navigation can be defined as the procedures involved in determining the initial position of an object, its final destination, and the information required to identify the path from initial to destination points, as mentioned in [1]. For many years, people have practically applied the concept of navigation when they tracked ancient guiding stars. Therefore, as it was already prevalent throughout history, people were very familiar with the navigation system. Tremendous progress has been achieved in this field, and technological growth and advancement have occurred [2]. Finally, the outcome of these efforts was the emergence of satellite positioning systems, such as the global positioning system (GPS), the Beidou navigation satellite system (BDS), and the Galileo's discovery.

Satellite positioning systems have revolutionized navigation [3]. People received tremendous benefits from services provided by these systems [4]. Such systems enable a wide set of applications including always available health monitoring, enhanced first responders' safety, and providing richer context for indoor mobile computing applications. Users became able to share their accurate locations with each other. These results were generally reliable and satisfactory [5]. However, the signals of these systems have some drawbacks and limitations in areas where line-of-sight (LOS) transmission is absent. Due to existed obstacles, the signals of satellite positioning systems will be affected, and they are accordingly fading severely, especially in indoor building and non-line-of-sight (NLOS) areas [6]. Additionally, grave changes to the satellite signals, such as scattering, diffraction, refraction, and reflection, have been caused by modern architectures [7]. Therefore, it became very difficult to repeat the success of these systems in some vicinities or in indoor environments. They no longer remained the most favorable solutions in these areas [8]. Wang and Park [9] mentioned that GPS signals that belong to the outdoor positioning system were vulnerable to multipath effects and, as a result, led those systems impossible to apply in indoor positioning. Thus, the aforementioned limitations of satellite positioning systems encouraged researchers and developers to find an alternative positioning solution for indoor environment [2]. A corresponding solution is yet to be found for indoor environment where signals of the satellite positioning system cannot penetrate and provide sufficient accuracy performance, as mentioned in [10]. Persistent endeavors to find equally, or more scalable and accurate, tracking system for indoor environments have been achieved over the last decade, as mentioned in [3].

An indoor localization system can be defined as a system of navigation that is made of networked devices in an indoor environment to localize objects inside the environment [2]. This system provides various services, including automatic resource routing, security, emergency, safety, and the location of materials [2, 11]. With the rapid development of the Internet of Thing (IoT), location-based services for the indoor environment have become more important [6, 12]. This is because of the demand for a technology with a high level of localization accuracy. The process of determining the object's location accurately in the network of the IoT is considered one of the key challenges in the ever-changing environment [5]. It should be noted that various applications have different requirements for scalability, cost, and accuracy. Therefore, indoor localization does not have a standard technique yet [3, 13]. In 2017, Elhamshary and Youssef [14] mentioned that an everywhere indoor localization technology that mimics the success of satellite positioning systems, applies virtually in any building with the lowest overhead, and props of the heterogeneous devices of the IoT is still missing.

Mobile phones, and smartphones in extension, have become the most widely used and popular devices throughout the last several years. They are currently considered irreplaceable devices [15]. The applications of these devices, such as Google+, Facebook, Twitter, and Foursquare, have changed the way in which a person interacts with the surrounding environment [16]. The location of a user was the critical issue to the proper functioning of these applications. Moreover, great advancements in the smartphone industry of have been achieved during the last few years. In addition, various sensors have been presented [5]. Therefore, providing an accurate indoor localization system has become important since people spend most of their time in an indoor environment.

In this study, a broad and comprehensive investigation is conducted to discover and classify the state-of-the-art indoor localization technologies. Based on this, the best three technologies applicable in rescue related environments are determined and deeply investigated. Consequently, a new model is derived from the selected technologies, and a novel architecture is proposed that is more convenient to meet the operation of rescuing injured or older people in critical situations, where other technologies might be unavailable or require some extra infrastructures. As a result, a proper and suitable horizon is achieved for the other researchers who desire to develop a new indoor positioning system in this discipline.

The rest of this paper is organized as follows: Section 2 provides an overview of the previous related studies and how we conduct the next step accordingly. The categorization of the state-of-the-art indoor localization technologies together with their key features and limitations is presented in Section 3. Section 4 provides the criterion used to choose specific indoor localization technologies. The details for WLAN, DR, and hybrid approach that combines them are included in Sections 5, 6, and 7, respectively. The proposed model has been included in Section 8. The results and findings, along with the recommendations for future studies, have been introduced in Section 9. Finally, the conclusion of the paper is presented in Section 10.

2. Related Work

Various studies and efforts have been achieved recently in the fields of indoor positioning and object tracking. There are several techniques employed for this purpose.

Tariq et al. [3] specified five broad categories for these techniques. The specified techniques include fingerprinting, inertial sensors, proximity, triangulation, and vision analysis. There are different indoor localization technologies convenient for each of these techniques. Both of these techniques and technologies have their own localization process, key features, and limitations. Unfortunately, none of the current singular indoor positioning technologies has the ability to meet the general needs for positioning, as mentioned by Zhang et al. [17]. The limitation of any technology is compensated by combining it with one or more technologies. The fusion approach has emerged as more successful than other isolated indoor positioning approaches in particular application environments.

In this section, we mention some of the hybrid approaches achieved previously using diverse technologies to enhance the accuracy of localization in indoor environments.

Jim'enez et al. [18] combined both pedestrian dead reckoning (PDR) and visible light communication (VLC) technologies to propose an indoor localization system. GeoAware, a hybrid and unified localization architecture, was proposed by Lilis et al. [19]. This architecture utilized both radio frequency identification (RFID) technology and Google location services.

A hybrid indoor localization mechanism was adopted by Su et al. [20] based on combining both Bluetooth (BLE) and WLAN technologies. He et al. [21] proposed a linear regression matrix model that combined both ultrawide band (UWB) technology and DR technology. A multipronged indoor positioning approach was adopted by Kim et al. [22] to combine WLAN technology, cellular network technology, and magnetic field technology. Park [23] presented a hybrid indoor navigation approach positioning based on the WLAN positioning system (WPS) and PDR technology.

Finally, Li and Rashidzadeh [24] presented a new hybrid indoor location positioning approach by combining both Bluetooth technology and acoustic positioning technology. It is worth mentioning that each of the aforementioned studies has its own assumption or base to achieve the combination. The major challenge of the hybrid positioning approach is located in the process of multi-information fusion from two or more techniques, as mentioned in Frattasi and Rosa [25]. Therefore, the choice of combination should not be arbitrary build or chosen based on the dominant available approaches. Thus, enough knowledge about state-of-the-art indoor localization technologies should be known. Accordingly, a convenient justification to combine two or more technologies would be available.

3. The Indoor Localization Technologies

Various classification approaches have been adopted over the years to classify the technologies of indoor positioning. Since 2003, Collin et al. [26] adopted an approach for categorization according to the hardware existence in two separate groups: technologies that presuppose the existence of special hardware and technologies that are already equipped. The second approach adopted by Gu et al. [27] was achieved depending on the network existence in two separated groups as well: technologies that are network-based and those that are non-network-based. Additionally, they subgrouped three categories: self-positioning architecture, where the object estimates its position on its own; infrastructural positioning architecture, where the available infrastructure is exploited to estimate and track the object; and the self-oriented infrastructure-assisted architecture, where the estimation is achieved in collaboration form. The localization system initially calculates the position of an object and then sends it to the object as a response to the object's request.

Two years later, a different approach was adopted by Al Nuaimi and Kamel [28] to classify technologies based on the residential nature of the system into two groups: technologies used with a fixed system and technologies with a pedestrian system. A new categorization approach was adopted later by Chóliz et al. [29] to split the technologies into two groups. These two groups involved technologies with parametric information, where the object's position was estimated depending on prior knowledge, and technologies with non-parametric information, where the object's position was estimated by processing the data with the assistance of some statistical parameters. In 2014, Al-Ammar et al. [30] adopted a new categorization approach based on the dependency of the building. They first split the technologies into two main groups: technologies that used the building infrastructure or the map of the building to estimate the object's position and technologies that relied on their own without regard to the building. The first group further split into two subgroups according to the nature of the infrastructure used in buildings: technologies that presupposed a dedicated infrastructure and technologies that utilized the preexisting infrastructure. The criterion for identifying the need for a dedicated infrastructure would have been related to the structure of the most prevalent buildings.

This study adopts the same approach used by Ammar et al. [30] to classify the state-of-the-art indoor localization technologies since it was more specific in identifying the technologies depending on the behavior and the needs of the positioning system, as depicted in Figure 1 below. A comparison table for those technologies, with regard to their key features and limitations, would have been included as well.

It is worth mentioning that an overlap of two technologies in this categorization is obtained: image-based technologies and unmanned aerial vehicles (UAVs). Image-based technology mainly depends on the camera. Therefore, if the positioning system and camera are located in a separate device, then this technology should be located under the building independent group; otherwise, it should be added as a building-dependent technology with a utilized infrastructure subgroup, since the camera system is not prevalent in current buildings. This technology is mentioned as a separate technology in the review section, but it is depicted in two separate groups. However, in relation to UAV technology, most UAVs acquire location information from either the existing satellite navigation system or from WLAN access points, as mentioned in [31]. Thus, it is possible to be located under the building independent group, but in this case, it will no longer be useful for indoor localization. Therefore, it is located under the building-dependent group with the utilized infrastructure subgroups, since WLAN is currently the most commonly used infrastructure.

The hybrid approach is a combination of two or more positioning technologies. To decrease the limitations and increase the overall performance and scalability of the available technologies, researchers have investigated the schemes of the combination. Since this approach could be located under any two or more convergent or remote technologies in the categorization, it does not depict at all. Nevertheless, the hybrid approach is mentioned as a separate section.

4. The Adopted Criterion for Choosing Indoor Localization Technologies

In this section, technologies that are investigated in more detail are emphasized in the rest of this paper. Various schemes of the combinations of technologies have been investigated during the last few years. According to Xiao et al. [32], considerable attention has been given recently to the idea of combining between WLAN and inertial sensors in a smartphone for positioning consideration. In addition, the previous section provided a categorization of the state-of-the-art technologies for indoor localization. Moreover, a comparison between these technologies is shown in Table 1 with regard to the key features and limitations.

Since DR technology that exploits inertial sensors is efficient for short-term positioning, it could be enhanced with an external source to update its errors. Additionally, the wide use of the smartphones that have already been equipped with the necessary sensors enables this technology to be convenient for localization in the indoor environments with no infrastructure and installation. Therefore, a deep investigation is conducted to identify the algorithms and

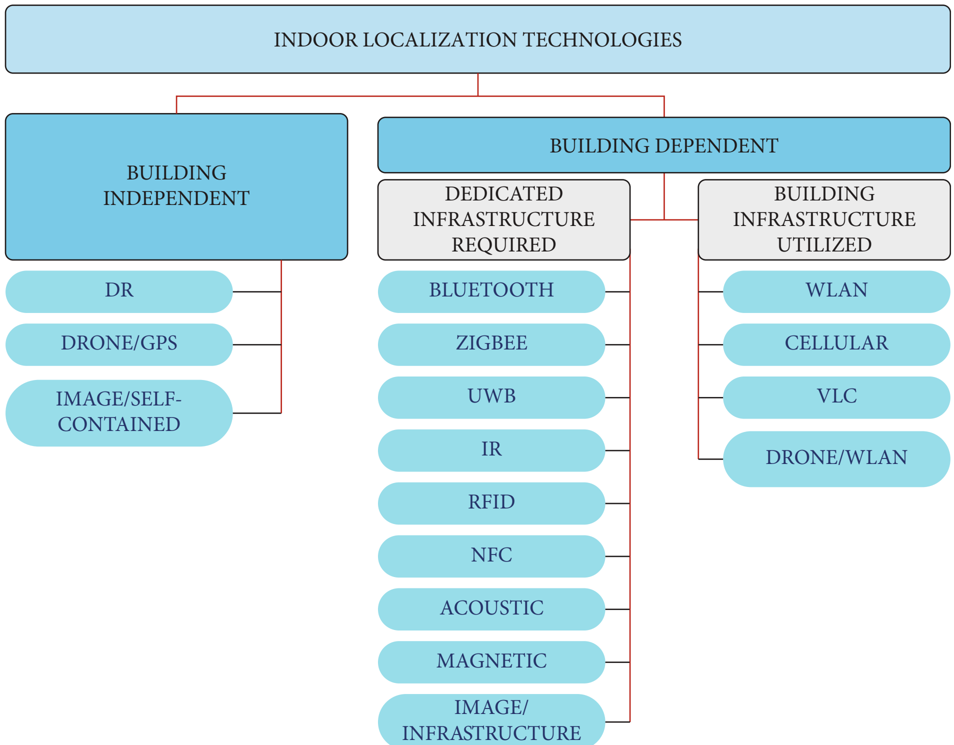

Figure 1: Categorization of the state-of-the-art indoor localization technologies.

systems achieved with this technology. In addition, WLAN technology, which has a preinstalled infrastructure, is widely used, and it does not require LOS. Moreover, a large number of studies in the field of indoor localization are achieved. Hence, WLAN seems to be the better candidate that can serve as an external source for updating DR.

Thus, a deep investigation is conducted for WLAN to identify the high-quality algorithms and systems that can support WLAN to be utilized in addition to PDR. There are three main topics that should be explored widely, which are:

(i) The first one describes the use of WLAN technology for indoor positioning

(ii) The second describes the use of DR technology for indoor positioning

(iii) The third describes the integration of both WLAN and DR technologies, which produces a hybrid approach for indoor positioning

5. Wireless Local Area Network Technology

Since the reification of the IEEE 802.11 WLAN standard in June 1997, this standard became the dominant local wireless networking standard [30]. Diverse terms were assigned by the literature to define this technology, such as Wi-Fi, WLAN, and IEEE 802.11. This technology was adopted mainly for communications. The concept of estimating the location of mobile devices that exist in the coverage area has also been adopted. The use of this technology for estimating mobile objects did not necessarily require LOS. Obstacles could be treated with mathematical models implemented with off-the-shelf devices. This standard included a range from 50 to 100 meters. This range surpasses that of other technologies, such as RFID, ZigBee, BLE, or other dedicated sensors [25].

Wi-Fi was one of the signals of opportunity that was not originally meant for localization purposes, and it was conveniently accessed by a modern smartphone, as mentioned in [18]. It already existed most of the time in almost the almost public building with deployed WLAN hotspots. The use of these hotspots in public places became a must. Hence, one of the reasons that made WLAN the mainstream technology for indoor localization was its widespread use [33]. In addition, the main advantage of positioning with WLAN was the positive effect of the available assets that utilized the unwitting usages of this technology. Moreover, Frattasi and Rosa [25] stated that even with only one access point existing, minimal information about the location could be achieved. Therefore, there was no doubt that this technology was one of the most promising technologies for the localization in the indoor environment.

There were various methods and techniques adopted for localization base systems (LBSs) that relied on WLAN for positioning or passive tracking purposes. The received signal strength (RSS) method was the most popular one. It is easy to extract in the WLAN network and could run seamlessly on off-the-shelf Wi-Fi devices [34]. However, in addition to the positive criteria for this technology, there were some limitations. One of these limitations was related to the sensitivity of the RSS to people's existence and the surrounding

Table 1: Comparison among indoor localization technologies.

No.	Technology	Key features	Limitations
1	Bluetooth	Uses FHSS to avoid a collision, low power consumption, robustness, NLOS, low cost, and most mobile devices already equipped with a Bluetooth chip.	Short-range and localization accuracy will depend on the class type of cell, unlicensed band, estimates the position of one device at a time, and infrastructure required.
2	ZigBee	Low power consumption, low complexity, and low cost.	The short-range, unlicensed band, and special infrastructure required.
3	UWB	Low power consumption, achieve positioning precisely in a harsh environment, low complexity, and high speed.	High cost, tracks a single target at a time, and special infrastructure required.
4	IR	Less parasitical comparing to other indoor positioning technologies that are based on visible light.	Interfere with light, short-range, and special infrastructure required.
5	RFID	Penetrate wall, and low cost.	Influenced by the antenna and requires LOS, does support multitag localization, and special infrastructure required.
6	NFC	Connection setup within one-tenth of second, very good positioning accuracy, low cost	Short-range, the position of the user does not update automatically, and special infrastructure required.
7	Acoustic	Does not overlap with the electromagnetic waves, low-cost, and emits by almost every mobile device.	Short range, loss of signal, interference from high-frequency sound, false signals due to reflection, only stationary or slow-moving object is possible to be tracked, and special infrastructure required.
8	Magnetic	NLOS, robust, magnetic sensor is small, low cost, high positioning accuracy, the stability of the magnetic field, and supports multiposition tracking.	Small coverage range, magnetic signal interference, variance with altitude, implementation difficulty on a smartphone, required a three-dimensional map, and special infrastructure required.
9	WLAN	NLOS, obstacles can be treated with a mathematical model, long range, accessible by smartphones, minimal information about the location is accessible even with only one access point, and their infrastructure already utilized.	Sensitivity to the people existence and surrounding environment, propagation of NLOS and multipath problems, and the offline phase of fingerprinting is labor and time-consuming.
10	Cellular	Excellent reliability in urban areas, licensed band, and their infrastructure already utilized.	Low accuracy and reliability in an indoor environment, and their signal will be correlated with the wall's type of building.
11	VLC	Does not have a fluctuation of signal and multipath effect, secure, low cost, controllability, ruggedness, long lifetime, friendliness of the environment from the safety perspective, very accurate positioning, used underground tunnels and underwater, and their infrastructure already utilized.	Actual usage for this technology still has problems, nonrobustness to NLOS, and multitransmitters overlapping within the coverage area.
12	Drone	Increase the number UAVs virtually, small size, low cost, and their infrastructure already utilized.	The allocated frequency band is dedicated to control only, NLOS worsen the accuracy of localization, and dependent on GPS or WLAN.
13	DR	NLOS, smartphones integrated with different sensors, efficient for short-term positioning, and it is building independent.	Presupposes the existence of previously estimated position or fixed reference points, drift problem, and requires an external source to update the drift.
14	Image	Accurate and efficient, smartphones equipped with a camera, and it is building independent in case the system had been installed on the smartphone.	Correlated with various factors such as (detection technique, image processing algorithm, and type and quality of camera), high cost if the system should be installed in the building, violates the privacy, unreliability with dynamic change environment, and special infrastructure required in case install the system in the building.
15	Hybrid	Decrease the limitations and increase the overall performance and scalability	Complexity.

environment. This limitation led to this approach to struggling with both long- and short-term changes in the environment [25]. Additionally, the complexity of the indoor environment produces propagation of NLOS and multipath problems. This propagation led to the loss of signal and, as a consequence, produced less accuracy for distance evaluation [35]. Moreover, a WLAN fingerprint-based indoor localization scheme, which was a typical indoor localization scheme, had a prerequisite to achieving its task. The prerequisite involved the creation of a database with a site survey, which was labor and time-consuming. An adequate signal source was required to guarantee the fingerprint resolution, as mentioned in [36].

Localization represents one of the most critical services required in the network of the IoT in an indoor environment, and it is still considered as demanding problem [37]. Traditional localization frameworks in indoor environments commonly exploit different infrastructures. The WLAN infrastructure, among others, recently became the center of interest, as mentioned in [38]. The WLAN-based localization approach, among other approaches, is the most promising approach for indoor positioning services [33, 39]. This is due to the prevalent Wi-Fi-equipped mobile devices and the preinstalled infrastructure, as well as the ubiquitous coverage in indoor environments.

To measure the relative coordinates of the object in the indoor environment, there are two behaviors used with the scheme of WLAN-based localization [35]. The first behavior implies the measurement of coordinates from appointed reference points, such as WLAN access points. The other behavior assumes the measurement from premeasurement location information.

Network-based categories and mobile-based category are the two main categories used for indoor positioning [25]. The first category implies that the required signals are gathered from the mobile target by the access point and, thereby, estimate the location in the network. In contrast, the mobile-based category assumes that a mobile target itself gathers the information from the nearest access point and the process of location estimation is later achieved locally.

Fingerprinting and propagation methods are the two ways of implementing WLAN-based localization systems [40]. The fingerprinting method has two separate phases: offline and online phases [41]. The offline phase requires the creation of a database with a site survey, which is labor and time-consuming [35]. In addition, the number of deployed access points and the strength of received signals identify the performance of the positioning system [42]. In this context, WLAN positioning systems based on fingerprinting have attracted a lot of attention as a promising approach for indoor localization, as mentioned in [43]. The key feature that makes fingerprinting the most popular method is its ability to provide accuracy up to approximately two meters only, as mentioned in [44]. However, fingerprinting requires regular recalibration due to signal attenuation and dynamic changes in the indoor environment [45].

With the propagation method, also referred to as the radio signal-based localization method, a radio map is created by a mathematical model and, thereby, estimates the

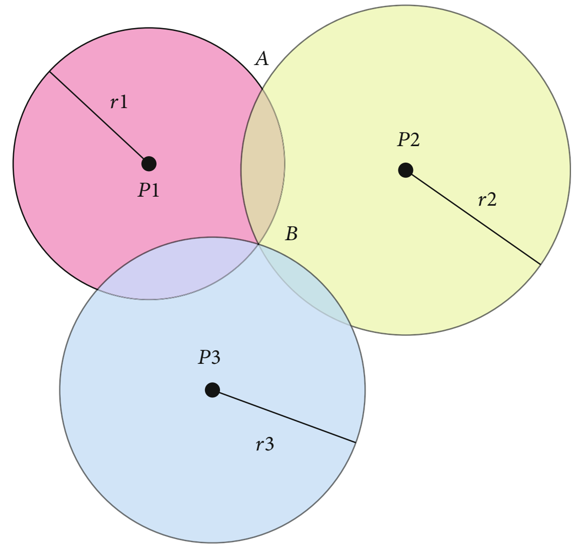

Figure 2: Determining the location of B using signal-based localization technique with three different access points (P1, P2, P3) [2].

values of the received signal into geometrical parameters and measurements [40]. Time of arrival (TOA), trilateration, and angle of arrival (AOA) are examples of propagation methods where at least three different signals are required to obtain the target's location [45], as shown in Figure 2. The key feature of the propagation method is that it is computationally light [46]. However, there are two challenges associated with the propagation method. First, it is difficult to achieve the distribution of RSS accurately through the use of a mathematical formula. Second, it is difficult to estimate the distance due to localization errors [40]. Therefore, the fingerprinting method is an alternative for settling these challenges. Hongpeng and Jia [40] applied a hybrid approach for both fingerprinting and propagation methods for a WLAN localization system. This approach benefited from the high positioning accuracy of the fingerprinting method and the simplicity of the propagation method. Unfortunately, this approach had high cost, low speed, and high complexity, as mentioned in [47].

Within the WLAN infrastructure, there are three requirements that the system of indoor localization should ideally satisfy. These requirements include accuracy, universality, and deploy ability [48]. Regarding accuracy, the system should be ideally accurate without any issues related to the two other requirements. This means that the available localization system that exploits wireless signals acts as the best-known localization system. Considering universality, a commodity chip of Wi-Fi is the only hardware required from the localization system to be able to localize any target device that has been equipped with this chip. Finally, the deployment implies that no additional changes for either hardware or firmware of WLAN infrastructure are required. The system should be easily deployable via the use of access point information that has already been exposed by these devices. Thus, satisfying the aforementioned requirements leads to the production of a ubiquitous indoor localization system that has services similar to those provided by favorable outdoor systems, such as GPS.

Mautz [34] mentioned that the signal of radio frequency is generally subject to various issues, such as interference, attenuation, multipath, absorption, refraction, reflection, and scattering. These issues cause the signal to be exhibited with special propagation effects or behaviors. Therefore, a substantial degradation and loss in the WLAN signals are caused by these issues. Thus, providing an indoor localization system that relies on WLAN infrastructure and satisfies the aforementioned requirements is not a trivial job and should not be underestimated.

According to Kotaru et al. [48], no precious system satisfies all three requirements. The WLAN-based indoor localization system can achieve both universality and deployment, but not enough accuracy. Recent techniques, such as LTEye and ArrayTrack mentioned in [49], are universal and accurate, but they require hardware modifications; thus, they are not deployable. Other techniques, such as Ubicarse mentioned in [50], are deployable and accurate, but they are not universal since they presuppose that the object device has access to other sensing modes, which does not exist in all devices.

The SpootFi system employed by Kotaru et al. [48] was a centimeter-level indoor localization system that was deployable on the commodity infrastructure of WLAN with no hardware or firmware changes. SpootFi was robust enough to address the hindrances that exit in an indoor environment, such as multipath and obstacles. Two key technical contributions have been achieved by SpootFi. Super-resolution algorithms have been incorporated to allow SpootFi to precisely compute the AoA of multipath components even when only three antennas of the access point were available. Moreover, novel techniques for filtering and estimation have been incorporated to identify the AoA of a direct path between the access point and the localized target. Notably, SpootFi did not consider coherent signals, as mentioned in [6].

A novel accurate indoor localization system was proposed in 2018 by Tian et al. [6]. This system was able to achieve median angle errors five degrees more than those achieved by SpootFi. It was deployable on the commodity infrastructure of WLAN as well. A spatial smoothing algorithm has been incorporated to estimate the AoA of multipath components accurately. Additionally, a classification of the multipath components existing in the indoor multipath environment had been achieved via the use of a clustering algorithm. Moreover, this system was able to distinguish the direct path among multiple paths by using a weighting factor. Therefore, the system has the ability to identify both LOS and NLOS propagations. Al-Ammar et al. [30] mentioned that the problem with a system that uses AoA estimation was that it struggled from performance degradation as the target moved farther away from the antennas. Therefore, both SpootFi and the system proposed by Tian et al. [6] struggled with this problem since they used AoA estimation.

A difference in positioning results, varying from small to large, could have been influenced by the obstacles and surrounding signals. A trilateration technique had the ability to estimate the target with an average positioning error of nearly two meters. An improved algorithm for indoor localization based on the RSS-trilateration technique was applied by Rusli et al. [2]. This algorithm was able to estimate the target with an average positioning error of nearly one meter only. The problem of signal blocking caused by hindrances exiting in an indoor environment was settled by the improvement in the received signal strength measurement. Reference points were used to improve the positioning results. Therefore, the performance of this system would correlate with the number and location of the reference points.

The resolution allocated in each fingerprint identified the practicability of fingerprint-based localization. This resolution was correlated itself to the available number of signal sources. The path-loss-based approach adopted in 2017 by Zhang et al. [35] targeted the limitation of signal resources in today's wireless environment. A path-loss exponent had been utilized as a fingerprint factor through the RSS to improve the fingerprint quality. Two related localization schemes were presented in this approach. The first scheme was the path-loss-based fingerprint localization (PFL), where the system tried to improve the positioning accuracy and decrease the installation cost of signal resources. The second scheme was named the dual-scanned fingerprint localization (DFL). This scheme intended to guarantee the reliability of positioning. In addition, it analyzed the differences in the location of multiple similar points in addition to scanning the similarity of fingerprints. The authors claimed that their WLAN fingerprint-based localization approach in an indoor environment had produced high precision in positioning and had high reliability.

In WLAN fingerprint-based localization systems, most of the current algorithms rely directly on the accuracy of fingerprint database to identify the final positioning accurately. In 2021, Cui et al. [51] proposed localization approach to effectively correct the position coordinates after obtaining the raw data. This was done by fusing the Levenberg-Marquardt method with a Kalman filter algorithm. They claimed that coordinates of a position after filtering were closer to the real coordinates, which led to improve the positioning accuracy by 60% compared with the traditional Kalman filtering method.

6. Dead Reckoning Technology

Dead reckoning (DR) is a technique of navigation that presupposes the existence of previously estimated position(s) or fixed reference point(s) to predict the current position of the object, as mentioned in [25]. Thus, knowledge regarding speed, direction, elapsed duration, and external factors will be obtainable. DR has been widely used in the past in marine navigation. Currently, a range of different fields utilize this technology via advanced inertial systems [30]. An example of this technology that simply predicts the position of the walking object is the pedestrian dead reckoning (PDR). Wang et al. [52] defined PDR as a potential autonomous technology of localization that obtains the position estimation by employing smartphone built-in sensors.

The kinematics of human walks could be exploited by a self-contained positioning system to estimate the current position of a user without relying on any infrastructure. This approach is referred to as PDR [53]. Additionally, this approach does not require any prior training phase, such as that applied in fingerprinting systems [3]. Both step detection operations and the calculation for step length are achieved in PDR using an accelerometer. In addition, PDR employs a compass for heading estimation purposes. Therefore, PDR is later being able to provide the new position of the user depending on the previously known position with the assistance of both step length and heading information. Thus, this approach can overcome the issue of positioning in areas where the signals of satellite positioning systems are not available, such as indoor environments, urban canyons, and dense forests, as mentioned in [54]. Modern mobile devices can be used to adopt this approach since they had already been equipped with both accelerometers and compasses. In addition, all these sensors have low power consumption, low cost, and small size [55]. This approach is efficient for short-term positioning [56]. However, PDR over time can obtain unavoidable errors in positioning produced from the mistakes in calculating both step lengths and heading information. Therefore, these errors accumulate over time and, in conclusion, lead to making PDR no more useful for positioning with long-term usage, as mentioned in [57]. The accumulative drift error caused by the low accuracy of IMU sensor is still a challenge of PDR and cannot be eliminated by itself [58]. Khedr and El-Sheimy [59] mentioned that PDR systems that suffer from the inherited errors are reliable for a limited period, and in order to correct and compensate those errors, an aid by other technologies is required. Within multiple floors building, it is very difficult for pedestrian to be tracked using PDR only, since this technology has challenge in detecting floor transitions and identifying the correct floor number [60].

PDR-based indoor positioning has recently shown a growing trend in the literature [61]. The implicit power of positioning that has been located in PDR encouraged researchers to pay more attention to control or reduce the accumulated error (drift) as much as possible. It is worth mentioning that the primary source of errors that had been accumulated in PDR was caused by heading estimation [62]. Mikov et al. [63] proposed a strategy with the independence of device orientation. The estimation of the step length relied on a dynamic threshold, which was dependent only on the readings of the accelerometer. The accumulated error remained within 5% of the total traveled distance. Therefore, some researchers tried to settle this issue through the enhancement of the heading estimation [62], while others tried to employ an external source to update or recalibrate the PDR drift [61]. In this part of the paper, only the work presented by Abadleh et al. [45] is reviewed to show how the drift of PDR could be reduced through the use of an external source. Different external source issues had been adopted previously, such as the use of calibration marks and map matching or the use of combinations of PDR with other positioning technologies. Various algorithms and systems

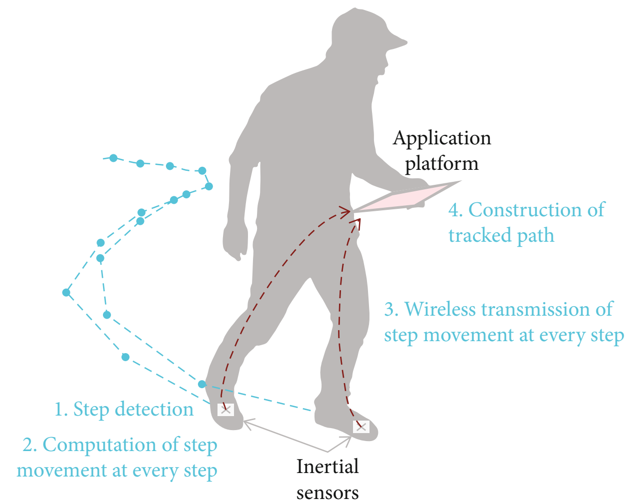

Figure 3: Foot-mounted pedestrian navigation system.

are later reviewed deeply in the section about the hybrid approach.

Over time, various attempts had been conducted to fix the accumulated errors in PDR by placing sensors on special locations of the pedestrian's body [3]. Foxlin [64] adopted zero velocity update (ZUPT) strategy with the extended Kalman filter (EKF) to reduce these errors. In the proposed technique, the author placed inertial sensors on the user's foot; thus, the movement of the foot while walking would be used to update the reading of PDR using ZUPT, as depicted in Figure 3. This was done through the alternation among moving and stationary step phases. The positioning system, thereafter, would recognize the stationary phase and, accordingly, reset the pace to zero for the stationary phase. The final accumulated errors with this technique reduced less than 5% of the total errors in the total traveled distance, as mentioned in [3].

However, in 2013, Jayalath and Abhayasinghe [65] mentioned that the positioning accuracy within PDR would be more degraded in some situations, such as walking on inclined planes, climbing up and down stairs, and walking slowly on flat land. They believed that single-point gyroscopic sensor could address this issue and mitigate these errors. Therefore, they produced a new algorithm that used a gyroscope sensor with zero crossing and threshold detection techniques. Moreover, this algorithm made use of the motion of a human's leg. The authors reported that the overall obtained accuracy with this approach provided more than 94%, with a remarkable increase in accuracy at a slow walking speed.

The pervasiveness of smartphone devices and their advanced sensing and computing capabilities provided new opportunities for acquiring positions and tracking users [45]. The recognition of human activities employed for autonomous calibration of the PDR system was a particular trend [61]. This trend aimed to enhance the accuracy of positioning since the context of the activities provided clues about the current position of the user. The development of a performance model for PDR with the collaboration of human activity updates was the first attempt in this concern reported by Hassan [61]. The author recognized two obtainable motivating issues in closed-form expressions from an uncorrelated and unbiased arbitrary walk of the pedestrian user. The first issue was related to the distance of a user, where he/she was expected to tour before the recalibration of PDR. This distance was mutual with the density of activity switching points that were achieved in an indoor environment. Therefore, providing extra activity switching points would be able to enormously curb the continuous dependence on PDR. The second issue the author encountered was related to the false negatives of algorithms concerning the activity detection. There would be no more major impacts on the system performance for the range of these negatives varying from 0 to 30%, while performance degradation would be increased rapidly with the growth of false negatives beyond 30%.

An enhanced pedestrian dead reckoning (EPDR) approach for tracking using a smartphone was proposed by Tian et al. [66]. The movement orientation had been determined depending on the gyroscope or magnetometer, along with the employed approach to calculate the step length to achieve the overall tracking task. Because of the limitation when performing tracking with different modes for the user carrying the device, identifications for three typical modes were presented to support the robustness of the system. Later, the proposed approach exploited the identified modes to enhance the accuracy of tacking. The use of a lightweight step-based tracking algorithm was developed later depending on the real-time identification of modes. In addition, a novel model for step length estimation was proposed to work with a tracking algorithm as well. Real-time tracking was achieved with typical submeter error only for localization performance.

A PDR-based indoor localization algorithm proposed by Nabil et al. [67] was intended to enhance localization in an indoor environment. A low-pass filter (LPF) was adopted to reduce the noise for both the accelerometer and a digital compass. Additionally, a relative threshold detection scheme was used to accurately estimate the step length. Since heading estimation represents the primary source of drift in PDR, as mentioned above, a quaternion-based extended Kalman filter algorithm was employed to enhance the heading estimation. This was done through the use of the inputs of three inertial management units, the accelerometer, magnetometer, and gyroscope sensors. The experiment in this study was taken over 210 meters, which was not considered short, and the output of experiments showed an average error of 0.14% of the total traveled distance. This approach achieved a positioning accuracy higher than the accuracy achieved by Tian et al. [66]. It is worth to mention that this algorithm was developed later with the collaboration of an IoT device, in addition to the smartphone, to average the readings of the IMUs, as reported in [68]. The performance of the enhanced approach increased 46% compared to the original approach. To the best of our knowledge, the study presented by Nabil et al. [67] was almost the promising one that relied only on inertial management units equipped in a smartphone and did not exploit any external source to update the drift of PDR.

7. Hybrid Indoor Localization Approach

The combination of two or more positioning techniques was generally known as a hybrid approach. The process of combining had various challenges, and in some environments, it might have been very difficult or impossible. Frattasi and Rosa [25] reported that the combination of data acquired from two or more technologies often represented the major challenge of the hybrid positioning approach.

Since each positioning technology had its own advantages, limitations, and circumstances, Tariq et al. [3] mentioned that there explicitly became no clear winner of an isolated indoor positioning technology that could satisfy all needs and metrics. No one admitted with certainty that independent indoor localization technology could overcome all the problems of indoor positioning systems [17]. To decrease the limitations and increase the overall performance and scalability of the available technologies, researchers investigated the schemes of the combination. A hybrid approach emerged as more successful than other isolated indoor positioning approaches in particular application environments. The development of hybrid schemes has been done by compromising features that belonged to various smartphone modalities to consider the indoor localization problems.

The issue of localization in the indoor environment is considered an open problem that does not yet have a convenient universal solution [32]. It is one of the most critical modules in indoor location-based services (ILBSs). Zhang et al. [17] reported that "a single indoor positioning system cannot meet the general needs for positioning." We mentioned previously that no one admitted with certainty that independent indoor localization technology could overcome all the problems of indoor positioning systems. In addition, a hybrid approach emerged as more successful than other isolated indoor positioning approaches; in particular, application environments are mentioned as well. Unfortunately, the process of multi-information fusion from two or more techniques often represents the major challenge of the hybrid positioning approach, as mentioned in [25]. Therefore, the choice of technologies that anyone may plan to combine represents the essential issue of a hybrid approach. Thus, the choice must be made carefully, and should not be underestimated.

However, the proliferation of indoor localization systems is because of both the advancements in wireless communications technologies and the wide existence of various sensors in smartphones [69]. Ding et al. [57] mentioned that the approach of fusion between wireless and inertial sensors as well as the collaboration of map matching was considered the better-employed approach to enhance the positioning performance. Additionally, Davidson and Piché [70] mentioned that the approach of combining between Bluetooth BLE, wireless local area network WLAN, map matching, magnetic field, and the inertial sensor was the most accurate navigation solution.

The key features and limitations for both WLAN and DR that exploit the IMUs are not rementioned in this section since enough review for both in the previous sections is already provided. Regarding Bluetooth, its localization accuracy is determined itself by the class type, as mentioned in [25]. Regarding the magnetic field, Davidson and Piché [70] stated that it was difficult to implement it on a smartphone. If the universality of the positioning system is considered, the issue of landmarks and map awareness should not be regarded. Chen et al. [71] claimed that " both the PDR system and the WLAN positioning system are expected to be complementary to each other." Therefore, the concentration is specified only by the combination of WLAN and inertial sensors that have already been equipped in smartphones, while collaborating with landmarks or map awareness if universality is not the concern. With the combination of these two approaches, it could be ensured issues related to no preinstallation infrastructure, reasonable level of accuracy that can be enhanced later, low-level of complexity, and reliability.

One of the continuous endeavors that aimed to improve the accuracy of the existing indoor localization technologies was the transparent middleware Social-Loc proposed by Jun et al. [16] in 2013. Both the WLAN fingerprinting scheme and particle-filter-based dead-reckoning scheme were combined by Social-Loc to estimate the initial position of the user. To refine the errors of the technologies used, social events were exploited later by Social-Loc to be used as virtual sensors. The Social-Loc reported was robust, scalable, and accurate for a long period. The experiments applied Social-Loc showed that the accuracy of localization in terms of both DR and WLAN fingerprint schemes was enhanced by at least 37% and 22%, respectively.

One of the drawbacks that encountered the deployment of systems of WLAN indoor positioning with a smartphone was the issue of energy consumption. These systems require periodic updates. In addition, the resources of battery life in a smartphone are limited. Therefore, this issue should be conserved. An energy-efficient indoor positioning architecture, named GreenLoc, that had been presented by Abdellatif et al. [72] was applied for this purpose. This was done by filtering out unnecessary wireless measurements. GreenLoc exploited the WLAN RSS measurements, mobile sensors, and the patterns of group mobility. GreenLoc intended to decrease the consumed energy with a reasonable trade-off in positioning accuracy. Moreover, GreenLoc provided the ability to be easily adapted with different strategies of energy-reduction. A novel clustered-based algorithm (CLoc) was integrated with GreenLoc to work as a representative strategy. The movement of individuals would then be detected and clustered by CLoc. GreenLoc allowed only a limited set of users to be localized, while the others would be able to infer their locations accordingly. The authors claimed that the GreenLoc experiments obtained a reasonable accuracy penalty that did not affect the performance with a 60% decrease in the average energy consumed.

The DR technique presupposed the existence of a previously estimated position or fixed reference points [25]. Since the existence of a previously estimated position was not necessarily obtainable when the positioning service was requested by a user, Chen et al. [71] proposed an intelligent indoor positioning system that combined both WLAN and PDR approaches to address such situations. The proposed system did not necessarily require information on both the initial position and the moving direction in advance. A maximum likelihood (ML-)-based fusion algorithm was proposed instead of the particle filter to reduce the time consumption and enhance the positioning accuracy. The authors claimed that the experimental results of this system showed better positioning accuracy than the WLAN positioning system or PDR system alone.

In 2014, Abadleh et al. [45] proposed ILPS as a new hybrid approach for indoor localization that provides the real-time position of a user. All WLAN signals, inertial sensors of a smartphone, and physical maps were combined in ILPS. The MAC addresses of the public access points were initially collected in a blueprint database during the offline phase. This database divided the building into sections and connected them using a direction table. The current database together with the available access points would be exploited to work as reference points. Each time a reference point was recognized, the position of a user was adjusted accordingly. Later, both the received signal strength RSS of WLAN and the MAC address of the public access point, which should exist in the database, were used by the tracking algorithm to determine the initial location of a user. Finally, the peak detection algorithm (PDA), which exploited both the accelerometer and compass, would be applied by the tracking algorithm to estimate the final position of a user. It is notable to mention that the multifloor localization was supported by ILPS. Additionally, the use of a static blueprint database was less costly than the other approaches that required regular database updates. The authors reported that ILPS was able to produce a 3-meter mean error for the initial positioning accuracy and a 2-meter mean error for distance estimation.

In 2015, Luna et al. [73] proposed an integrated indoor localization system to track pedestrians in an indoor environment. This system combined both a WLAN fingerprinting-based approach and a PDR approach using foot-mounted sensors. Two extended Kalman filters were employed in this system. In addition, a zero velocity update (ZUPT) strategy was adopted. The retrieved information from both WLAN and ZUPT was exploited by the system to mitigate the accumulated errors of PDR. The authors mentioned that the field experiment in a range of 300 meters showed an enhancement in the PDR localization accuracy from 6.3 to 1.2 meter.

Since electronic devices could easily affect the magnetometer of a smartphone, the combination of magnetometer sensor together with gyroscope sensor could compensate for this effect. The approach proposed by Chen et al. [74] employed a new Kalman filter that combines the reading of both magnetometer and gyroscope to enhance the direction estimation of a pedestrian. Moreover, the authors employed a specific pattern of a landmark for a known location to minimize the effect of PDR drift. This approach combined PDR, WLAN fingerprint, and landmarks. A weighted

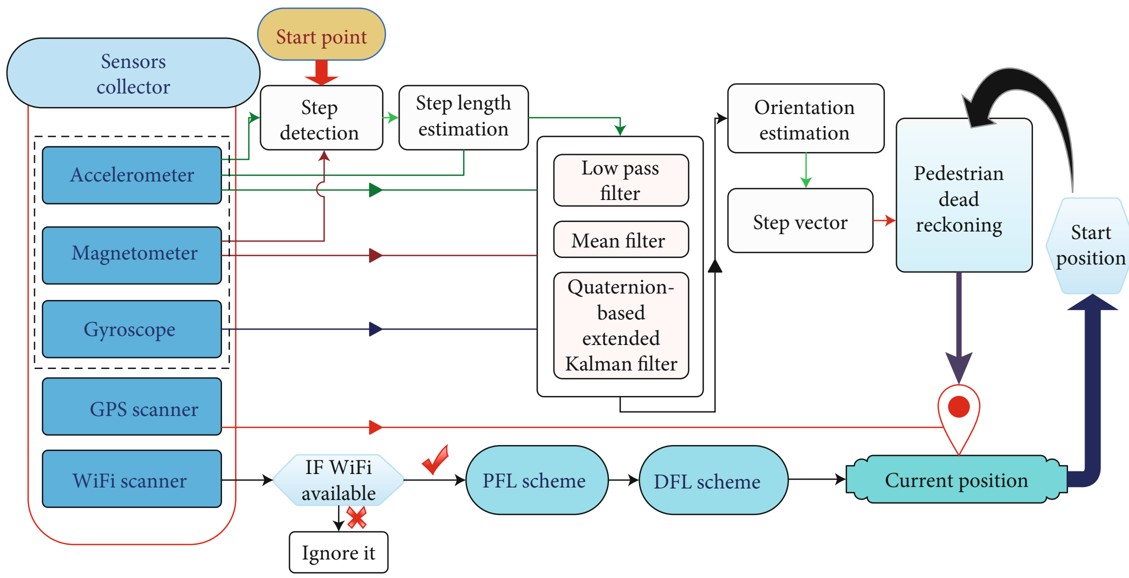

Figure 4: The architecture of the proposed hybrid model.

path-loss WPL algorithm, which was accurate and flexible, was also applied in this approach. Zou et al. [75] mentioned that WPL was commonly used to overcome the problem of the WLAN fingerprint approach. Because of the resource limitation in a smartphone, and the need to obtain the real-time information on the current position, the events were formulated linearly in the fusion part to address these issues. The reason behind the use of the Kalman filter algorithm instead of a particle filter was to deal with these events since the Kalman filter algorithm was computationally light. Unfortunately, the authors mentioned that an impressive and unsatisfactory enhancement in the positioning accuracy was achieved in the experimental results.

However, the reliability and availability of a system should be provided with an acceptable level of service in the presence of failure [76]. Therefore, the steady-state availability for any system should be considered when everyone wants to deal with this system. In situations of disasters, such as earthquakes or fires in indoor buildings, including residential complexes or shopping malls, people deaths or serious injuries might be possible. The positioning inside these places in such situations might prevent or decrease the catastrophic consequences. The process of estimating the position of an evacuee in emergency rescue is critical [69].

The key features and limitations of state-of-the-art indoor localization technologies are already mentioned. Most of these technologies would not be reliable if the infrastructure breakdown during disasters is considered, and they are not expected to work precisely as they function in unaffected situations. In 2017, Son et al. [69] proposed an indoor localization system that can deal with such situations. Priority was given to the PDR approach considering the malfunction of the infrastructure since this approach could estimate the position of people without any infrastructure. To provide an external source to update or recalibrate the PDR drift, they mentioned that the measurements of WLAN access points could be exploited as a reference point to PDR, even if only some part of the infrastructure was intact. Accordingly, their system was proposed to operate in two modes. The first mode includes the use of PDR only. This mode operated with the worst case when all infrastructures had malfunctioned. The other mode included the use of both PDR and WLAN access points in the case that partial infrastructure is still available. Their system was designed to automatically operate according to the number of access points that were still working. The localization accuracy was correlated with the number of available access points. The authors claimed that the proposed system could acquire better performance and reliability than the PDR only approach.

8. An Accurate, Low-Cost, and Reliable Hybrid Indoor Positioning Model

This section represents the proposed model depending on what has been founded in this research. Depending on the previous inferences, we can imagine the power of the indoor positioning system that can cover all the issues considered in the previous three studies. Therefore, a theoretical model has been proposed that follows the approach adopted by Son et al. [69] to combine the algorithm proposed by Nabil et al. [67] that employed PDR technology, as well as the path-loss WLAN fingerprint-based approach adopted by Zhang et al. [35] to be used as an external reference of correction to the PDR drift. The system framework shown in Figure 4 is able to provide two modes and select one of these modes automatically. The first mode assumes the existence of both WLAN signals and smartphone sensors to be used later with the proposed framework to identify the position of the object; otherwise, only smartphone sensors are exploited to achieve positioning.

In Figure 4, the sensors collector box represents the smartphone device, where all of the sensors are equipped within it, and they are running through the application. The progress is then starting within two main approaches:

the PDR approach, which invests the first three sensors (accelerometer, magnetometer, and gyroscope), and the auxiliary WLAN fingerprint-based approach, which invests the Wi-Fi sensor. Once a human step is detected, the proposed system should first identify whether it is valid or not. This represented the starting point of the system. If the detected step is valid, then its length should be estimated. Otherwise, the system remains pending. Both the accelerometer and the digital compass in smartphones give noisy measurements. Therefore, a low-pass filter (LPF) is used for noise reduction. In addition, a digital mean filter is applied to the signals to erase high frequency-noise components and remove the random error of the estimated directions. A quaternion-based extended Kalman filter (EKF) algorithm has been used to improve heading estimation. The step is oriented to produce the step vector that includes both the step length and its orientation. Depending on the previous location, the final location of the smartphone is calculated. It is worth mentioning that the last known position of the GPS when the GPS signal was not faded represents the final location of the device, and its value will be invested by PDR to calculate the next location. In case the Wi-Fi scanner discovers an acceptable level of wireless signal strength, a WLAN fingerprint approach is applied to these Wi-Fi signals to identify the location with the cooperation of both PFL scheme, which improves the accuracy of positioning. The path-loss exponent (PLe) is a sensitive factor related to the signal propagation distance and signal fading factors. The PFL utilizes PLe to create a fingerprint database in the offline phase. It then matches the patterns of calculated signal propagation distances in positioning unknown targets in the online phase. The PFL improves the positioning precision by analyzing environmental path-loss factors instead of RSSs, which reduces the cost of guaranteeing a certain level of precision. The DFL scheme applies clustering algorithms to estimate a set of potential locations of an unknown target in an online phase. This is achieved by scanning the values of RSS and analyzing the physical distances among reference points (RPs). The DFL guarantees the reliability of positioning in resource-limited wireless environments. The locations calculated by both approaches should be averaged. In case no acceptable level of wireless signal strength is detected, the location obtained by the PDR approach is only followed.

9. Discussion

(A) The outcome of the revision and the most promising indoor localization technologies according to different considerations are introduced in this part. Depending on what was noticed in previous studies, there was an extreme agreement with the statements mentioned by Zhang et al. [17] and Tariq et al. [3] in that the general needs for localization could not be fulfilled with a single indoor localization technology. Therefore, a hybrid approach seemed to be a more successful approach than other isolated indoor positioning technologies, and, in particular, application environments. The front-runner technologies and techniques are presented as follows. Both landmarks and map awareness issues could be useful to collaborate with the indoor localization system if scalability, universality, and complexity are not considered

(B) The expectancy of light emitting diode (LED) devices to work as universal lighting systems has led VLC technology being a promising indoor localization technology. In addition, it is very applicable to serve as an alternative to the WLAN since VLC can run in underground tunnels and underwater areas, where the radio frequency signal cannot be used. However, VLC localization technology is a recent trend, and the actual usage of this technology still has problems

(C) There is an implicit power of positioning has been located in PDR together with its key features. This power and the wide use of devices that has already been equipped with the required sensors make this technology promising for estimating the location of an object in an indoor environment. To the best of our knowledge, the study proposed by Nabil et al. [67] has adopted the most efficient algorithm to estimate the position without an external source of updating to the drifts of PDR

(D) The widely preinstalled infrastructure and their ubiquitous coverage in indoor environments together with the prevalent Wi-Fi-equipped devices make the WLAN-based localization approach the most convenient candidate that can serve as a reference for PDR. To the best of our knowledge, the path-loss WLAN fingerprint-based localization approach adopted by Zhang et al. [35] is the most reliable and precise approach that can estimate an object in an indoor environment considering the limitation of signal resources in today's wireless environments

(E) Tremendous endeavors and efforts have been made to invest the benefits of combining two or more indoor localization technologies. Our knowledge recognizes the hybrid approach adopted by Son et al. [69] as the most applicable and reliable choice to combine PDR with any other suitable technology(ies) in the future since it has two separate modes

10. Conclusion

With the development of the IoT and the rapid evolution of smartphone devices, providing an accurate, scalable, reliable, and universal indoor localization system that could be equivalent to that growth has become important. The initial stage of this paper comprised discovering state-of-the-art indoor localization technologies. Moreover, a systematic categorization approach has been achieved to assort these technologies. According to the key features and limitations of those technologies, a criterion is adopted to select only three approaches to be studied deeply. This selection involved

WLAN technology, DR technology, and the hybrid approach that combines both of them.

After a deep investigation of the selected approaches, it became clear that single indoor localization technology could not meet the general needs of the indoor localization system and repeat the success of the satellite positioning systems in indoor environments. Therefore, it became clear that the hybrid approach which combines two or more indoor technologies is a better approach than other isolated indoor positioning technologies in particular application environments. The hybrid approach has the opportunity to increase the overall performance and scalability of the available technologies and decrease their limitations. The potential positioning power embedded in PDR should not be underestimated. Therefore, combining PDR with WLAN or VLC technologies could produce an indoor localization system considering most of the performance criteria. Both landmarks and map awareness issues could be auxiliary to collaborate with indoor localization, but their existence of them leads to a more complicated system.

Finally, a new hybrid indoor localization framework for critical situations is proposed. This framework could meet the needs of the current evolution in the IoT and smartphone industry. In addition, it will play an important role in locating the evacuee in disaster situations. Because it does not require any special infrastructure, the proposed solution is easy to implement, and it would be easy to use it in most indoor environments, such as the apps of IoT, and the evacuee and rescuing of the injured people in disaster situations. The proposed model together with the recommendations could be useful for researchers to be invested as a guide for future studies in the field of indoor localization.

Data Availability

No datasets were generated or analyzed during the current study.

Ethical Approval

This study does not involve any human participants or animals performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflict of interest.

Authors' Contributions

The author Alaa A. Mahdi conceived and designed the analysis, collected the data, and wrote the manuscript. The corresponding author Dr. Abdolah Chalechale contributed data, supervised the process of writing the manuscript, and revised it. The author Dr. Ashraf AbdelRaouf contributed data, supervised the process of writing the manuscript, and revised it.

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