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Survey of indoor tracking systems using augmented reality

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ABSTRACT

Augmented reality overlays virtual content on the physical world, displaying location-based information more efficiently. Tracking is a trace detail of the location recorded, either by taking a reading based on a set time interval, set distance, and change in direction by more than a certain angle, or a combination of these. Tracking is divided into two types, outdoor tracking, and indoor tracking. Augmented reality added value and information to tracking applications, whether indoor or outdoor. Recently, outdoor tracking by the global positioning system (GPS) became an essential component in navigation applications. However, indoor tracking is still challenging in the augmented reality field. Most augmented reality indoor tracking use optical and sensor-based tracking, such as markers, beacons, Raspberry Pi, and route planner modules for the building. With the technology enhancement, indoor tracking started to rely on Wi-Fi, Bluetooth, geographic information system, radiofrequency identification, and sensor chip technologies. Our paper describes the recent augmented reality tracking techniques from 2011 to 2021. The paper compares image detection algorithms with various communication technologies, disscusing the advantages and the limitations of each technology.

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1. INTRODUCTION

Tracking applications assist users in detecting their location and aid in navigating to destinations [1]. According to a recent study performed on mobile phone users who use navigation, approximately 95% of users who own a smartphone device used a mapping application at least once, which means that maps are in daily use for most smartphone users [2]. Guiding users to particular locations in indoor environments is a tough, challenging task. Recently, the systems for indoor areas are greatly developed. To take advantage of indoor tracking technology in various places and fields, it must be quick to determine the current location and destination. Indoor tracking must be and reliable in reaching the specified goal, allow it to expand according to the development of the place, and be independent according to the area used in it [3].

It is still simple to get lost indoors, where the global positioning system (GPS) satellite signals are not precisely detectable for navigation applications. GPS will present the identical position; however the person is on various floors [4]. The systems in this field have been enhanced and became more accurate and can now determine users in real-time [5]. People spend most of their time indoors [6]. These improvements have allowed leveraging location systems in several fields. Guidance systems studies can found applied in monitoring such in faculties, museums, and art galleries [7], [8], medicine [9]–[11], robots [12], [13], education [14], and navigation [15].

These days, the world uses hybrid technologies to use indoor and outdoor tracking in a single system. Some recent researchers are trying to eliminate reliance on predefined maps for indoor tracking and find alternative solutions. In addition to solving the problem of low lighting intensity and application in places with multiple floors [16].

In this paper, we discuss indoor tracking limitations and challenges. Limitations include light intensity, environment complexity, and multiple floors. Algorithms used in outdoor tracking are different from indoor tracking. Most indoor tracking depends on predefined maps leads to more costs in map-making. The paper also introduces comparative studies between various communication technologies and image detection algorithms used in tracking systems.

2. METHOD

In this survey, we restrict the searches to include studies that use various ways for building indoor tracking systems. We are interested in including the studies that used various positioning technologies. Also, we included studies that used different feature detection algorithms. We selected these studies of diverse settings to solve the problem of getting lost indoors, where GPS satellite signals are not precisely detectable for indoor navigation systems. A broad literature search of IEEE Xplore, Scopus, Science Direct, Egyptian Knowledge Bank (EKB) and Google Scholar. We include all the retrieved studies that combined augmented reality, positioning techniques, and image processing algorithms. In addition, the reference lists of all retrieved papers were reviewed to determine other relevant articles. The studies in this survey are organized into the following three groups: active tracking [17]–[19], passive tracking [20]–[22], and hybrid tracking [5], [23], [24].

The taxonomy of indoor tracking systems denotes the localization of persons and objects within buildings. This indoor localization is thus a technical challenge because GPS does not work reliably within interior spaces [25]. Most indoor tracking systems use communication technologies or images based on detection algorithms. Figure 1 shows the techniques used and algorithms in each method.

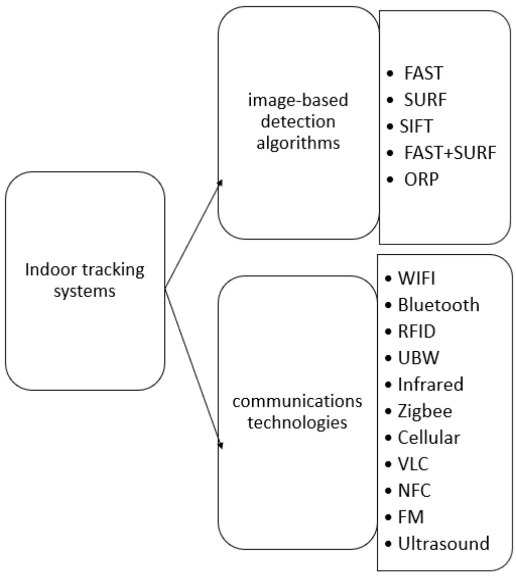

Figure 1. Indoor tracking systems taxonomy

The communications positioning technologies used in our smartphone, known as a GPS or global navigation satellite system (GNSS) [26], do not work effectively inside the home or in the areas covered by trees or surrounded by concrete buildings. Presently, to achieve indoor positioning are using wireless technologies such as wireless local area network (WLAN) [27], Bluetooth [28], near field communication (NFC) [29], Ultrasound [30], Infrared [31], and radio frequency identification (RFID) [32]. A comparison among the communication technologies is shown in Table 1.

Each indoor position technology has its own parameters such as in Table 1. So, the technology's selection will finally be based on accuracy, cost, precision, ease of handling, scalability, and Power consumption. For indoor positioning, the best solution is the fusion of geographic information systems (GIS) features and Wi-Fi technologies to get the best of both worlds [18].

Table 1. Comparison between various communication technologies

Technology	Coverage	Power consumption	Accuracy	Cost
GPS	Outdoor	Very High	6–10 m	High
Wi-Fi	(outdoor/indoor)	High	1–5 m	Low
Bluetooth	Indoor	Low	2-5 m	High
RFID	Indoor	Low	1-2 m	Low
Ultra-wide band (UBW)	(outdoor/indoor)	Low	5-30 cm	High
Infrared	Indoor	Low	1-2 m	Medium
ZigBee	Indoor	Low	3–5 m	Low
Cellular	(outdoor/indoor)	Low	50m-150m	High
Visible light communication (VLC)	Indoor	Low	4-10 cm	Low
NFC	Indoor	Low	4 cm	Low
Frequency modulation (FM)	Indoor	Low	2–4 m	Low
Ultrasound	Indoor	Low	3cm–1m	Medium

Also, we can use image-based detection algorithms to apply indoor tracking systems. The initial processing operation in computer vision is feature detection that extracts the interest points needed for the next processing steps [33]. An interesting point in an image should be pure and well-built under disturbances in the image region [34]. The scale-invariant feature transform (SIFT) is the most used image feature extractor. The SIFT technique is scale-invariant and rotation-invariant. Then it tests each pixel in the image with its eight neighbors and nine pixels in the scale around it [35]. The SIFT algorithm was slow, and advanced applications required a faster version. The speeded-up robust features (SURF) algorithm is dependent on the principles as the SIFT, but with some approximations to execute the method much faster [36]. Similar to the SIFT, this technique is scale-invariant and rotation-invariant. The features from the accelerated segment test (FAST) algorithm have a great advantage in that it is faster than many other popular image detection extractor methods. In the FAST method, if a pixel is significantly distinct from neighboring pixels, then this pixel is a corner point [37]. To verify the performance of the feature extraction module, Feature points of indoor environment images for FAST, SURF, SIFT, and FAST-SURF are tested, respectively. As the results are shown in Table 2 [23]. The oriented FAST and rotated BRIEF (ORB) detector [11] combines FAST keypoint detectors with specified binary robust independent elementary features (BRIEF) descriptions. It is a no-cost alternative to SIFT and SURF that outperforms them in computation time and performance.

Table 2. Comparison between feature detection algorithms

Algorithm	Number of feature extraction	Time of feature extraction (ms)	Real time
FAST	221	20	No
SURF	21	22	No
SIFT	7	20	Yes
FAST-SURF	26	20	Yes
ORB-SLAM	77	20	Yes

The ORB-simultaneous localization and mapping (ORB-SLAM) SLAM algorithm can better suit the needs of mobile augmented reality (AR) systems, such as character detection speed, rotation invariance, and radiation invariance; they can apply it in real-time. As shown in Table 2, each of the FAST, SURF and FAST-SURF algorithms sometimes has the best feature detection numbers but can't be applied in real-time. The ORB-SLAM algorithm is very strong robust and can be applied in real-time.

During the past ten years, multiple researchers sought to apply AR technology to the tour guidance system to increase users' motivation and knowledge. The GPS couldn't be applied to indoor buildings; an alternative method to apply indoor guidance should be researched. Researchers have tended to use different techniques to create an indoor tracking system. In this paper, most methods are divided into three categories: passive tracking, active tracking, and hybrid tracking [38].

2.1. Passive tracking

At the beginning of solving indoor tracking problems using passive tracking techniques [20], built a system based on laptops and universal serial bus (USB) webcams that capture the live view frames. This paper uses ARtoolkit to detect a marker and compare it with trained markers saved within the database as binary data. When the marker at one accurate location is detected, it will be transformed into the location ID for processing. The route planner module calculates the link between the current location and the target. Open graphics library (OpenGL) application programming interface (API) is applied to load the virtual reality modeling language (VRML) model based on the camera's coordinates through the marker. Then an evolution in the research field to improve indoor tracking system occurrence. The enhanced system comprises a web camera, Raspberry Pi display glasses, and an input gadget. All devices associated with the Raspberry Pi have different capacities. The client would begin executing the program by entering the goal point, after which the camcorder would begin execution for catching live pictures for identifying area markers [21]. After area markers are distinguished and perceived, the present area marker data is taken care of into the route planner algorithm to decide the virtual item shown on the marker, which depends on the bearing to be taken to the following marker area or last goal. According to Yadav *et al*. [22], introduce technological development, increasing ease of use and reducing cost. In this paper, a laptop or a Raspberry Pi has been replaced by a smartphone with a rear camera. Figure 2 shows the proposed system in [39].

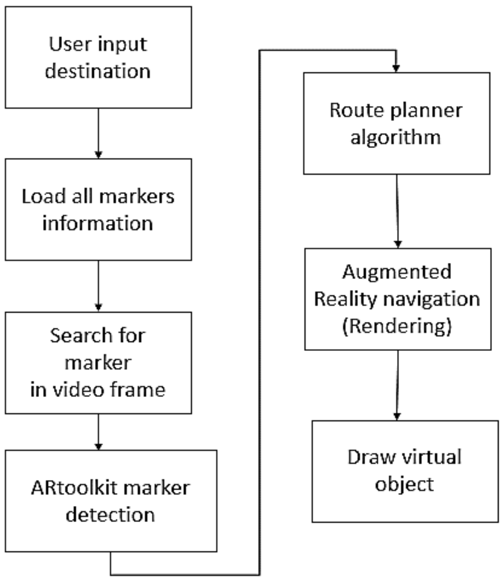

Figure 2. Indoor tracking system workflow

Due to the difficulty of use and the high cost of hardware devices, most researchers have turned to mobile phone image detection. Most of the research in this category relies on pre-defined maps for indoor tracking. The system is based on marker-based tracking and mapping techniques. SLAM algorithm provides computer graphics (signs and directions) to map and renew two dimensions plan simultaneously to the camera scene [40]. In Al Delail *et al*. [41], they merge augmented reality with the SLAM algorithm. The AR layer notifies the user of a nearby point of interest by image marker recognition. Overloading self-explanatory three dimensions virtual objects associated with the location on the real-time video capture provided by the Vuforia software development kit (SDK) it is portable and entirely configurable. It allows object data to be downloadable from the cloud.

In the same year, another researcher [42], concluded that fully detailed two-dimensional (2D) or 3D maps were unnecessary enough use of an accurate indoor positioning method that uses fiducial markers system. This system uses continuous localization to tell users of their current position at all times. The discrete localization is required to discover and detect some markers initially. The user chooses a proper target from the menu and is instantly carried to the viewfinder screen. Every time a target is detected correctly with the Vuforia SDK in the camera frame, the Dijkstra algorithm [43], recalculates the path and gives directions to the user. The parallel tracking and mapping (PTAM) algorithm can create and expand a map while following the camera pose in an unknown environment, for augmented reality requires no markers pre-made maps [44].

ORB-SLAM [45], appeared to expand the versatility of PTAM to environments that are intractable for that system. The true objective of a SLAM system is to create a map that can be used to give accurate localization in the future. Visual SLAM's objective is to make use of the sensors. ORB-SLAM was designed from scratch with a new monocular SLAM system with some new ideas and algorithms but also incorporating excellent works developed in the past few years, such as the loop detection, the optimization framework g2o [46], and ORB features [47]. ORB-SLAM processes in real-time in various locations, both large and small, indoor and outdoor. The system is resistant to severe motion clutter supports broad baseline loop closure and relocalization. Utilizes the same properties as other SLAM algorithms: tracking, mapping, relocalization, and loop closure. ORB-SLAM outperforms other state-of-the-art monocular SLAM techniques. ORB-SLAM3 [48], is the first real-time SLAM framework that supports visual, visual-inertial, and multi-map SLAM with monocular, stereo, and red green blue-depth (RGB-D) cameras and lens models such as lens models pin-hole and fisheye. ORB-SLAM3 uses Atlas for accurate, smooth map merging, location recognition, camera relocalization, and loop closure. The system creates a unique DBoW2 [49], keyframe database for relocalization, loop closure, and map merging. ORB SLAM3 is as robust as the best systems available in the literature and significantly more accurate. ORB-SLAM3 point of failure is low-texture environments.

Some AR-based indoor navigation systems enhance users' spatial learning besides leading them to their destinations safely and quickly. To improve positioning accuracy, bayesian estimation and the k-nearest neighbors (KNN) algorithm are used [50]. Recently, high-frequency radio frequency identification (HF RFID) integrated with kalman filtering and tukey smoothing to improve indoor tracking accuracy [51]. Liu and Meng [52], the interface for indoor navigation is designed on HoloLens. The arrows are used to aid orientation. Semantic meanings in icons with text can assist as virtual marks and help with spatial learning. There are many feature extractors like SURF, gradient location and orientation histogram (GLOH), and SIFT [53], that are most fitting for applications such as image recognition, which are used with marker-based applications. After that appeared research based on building a system on a modified version of the SURF algorithm [54], that is used to extract the real-word features and track objects. Tracking of items handling with the projection (pose) matrix was computed from the extracted features by homography techniques. The advanced algorithm calculates the center pose and visualizes a 3D model over the various image from the standard data set. It was confirmed to be useful and practical in marker-less mobile augmented reality. The advanced algorithm is not applied in a real application, only used on the data set [55]. The indoor tracking is used in the archaeological areas to improve the tourist experience. MAGIC-EYES guidance system [56], uses augmented reality technology. They are using sensors on the mobile phone as a camera and gyroscope. The markers such as plaques, stone tablets, and buildings patterns also have the function to identify the images of recognizable objects, the viewing direction of tourists, and the geographical location information. The pilot study applied to the traditional guidance system and the developed augmented reality guidance system on twelve clients. The test results showed that the MAGIC-EYES system is much better than traditional methods.

Complementing the development process in the indoor tracking HyMoTrack system [57] is developed, where the mapping phase was created upon small SLAM maps, including a wide-angle camera. The SLAM maps and 2D feature markers have been integrated into a global reference map. The markers also have the function of discovering the client's start position if no previous experience is available. While the discovered image marker delivers a position, the SLAM thread operates in parallel to find the match on the sub-map. The planning algorithm A* is used to calculate a path between two points. The blender is used to putting 3D content for augmented reality visualization. During detecting the path, the random sample consensus (RANSAC) algorithm is used to remove outlier features that are not essential areas of the environment. so, it did not solve a problem when using a SLAM algorithm. The HyMoTrack system which depends on a visual hybrid tracking strategy, was enhanced in this research. The enhanced system had a 3D model generation algorithm executed, which automatically generates a 3D mesh out of a vectorized 2D floor plan. field of view path (FOVPath) technique intends to respond not exclusively to the client's location and the target, the performance of visual positioning systems can be adjusted [58]. On the other hand, FOVPath is reliant on the view direction and the field of view (FOV) capacities of the preowned gadget.

Furthermore, the detection algorithm was created to work without any previous knowledge like a layer name or even metadata of different objects. Recognized figures are stored to generate a library for additional research. Likewise, finishing the task varies significantly among the A* based straight path and FOVPath. A median of A* is 33:88 seconds is estimated for achieving the mission through a straight path in adverse 23:32 seconds for the FOVPath [59].

With enhanced augmented reality technologies like object recognition and computer vision, location-based augmented reality becomes more interactive. This application comprises three major part's database, search engine, and output engine. Application imports screen captures and client's area data into a search engine to match with the database as. Afterwards, the output engine generates the match results, including the augmented reality components, 3D model, and fascination data, on the screen of versatile devices. The characteristics of the campus attractions are extracted with SIFT and stored in a onedimensional vector. SIFT utilizes the edge and corner places of a picture to recognize images in various circumstances, including rotated or twisted images.

The output engine lays a 3D model in a particular spot base on a convolutional neural network (CNN) model. CNN is used to decide the specific position of the 3D models in each point of attraction. The application accomplishes an attraction recognition accuracy rate of 90%. The convolution process takes a lot of time, unless we eliminated the training process [60]. As shown in Figure 3.

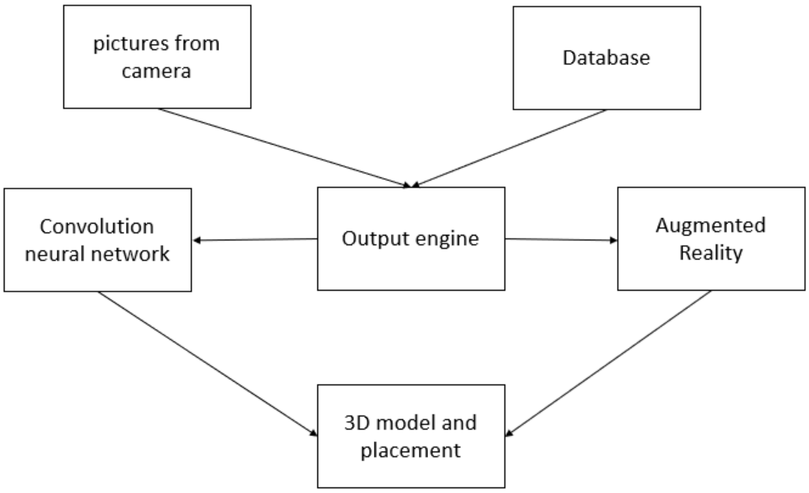

Figure 3. Architecture of output engine

Recently, the building information modelling (BIM) tracker system [61], based on localization performed by matching image flows captured using a camera with a 3D model of the building is used as a visual tracking framework. The study's principal hypothesis is that centimeter-level precision in localization can be performed without any drift using image information with a 3D building model. The camera's pose is determined by the algorithm of Gauss-Newton with least-squares minimization, which frequently minimizes the re-projection errors in an M-estimator sample consensus (MSAC) framework. By using the ray-tracing algorithm of blender, the virtual view is provided, and noticeable edges, just as their corresponding 3D coordinates in the BIM coordinate system, are defined. The canny edge detector is used to identify the edges in the image. After that, the 3D points are sampled and back-projected on the image plane. Similarities are formed by searching for edges on the image in the straight direction of the back-projected model edges of the sampled points. The MSAC estimator is used to eliminating the incorrect 3D to 2D similarities, which can affect shadows or reduplicate texture. Although the direct solution is faster, the iterative method provides more exact estimates. So, we applied the iterative Gauss-Newton approach. Recently systems used advanced feature tracking and augmented reality methods through navigation. Features gain of 3D point cloud localization demands a pre-deployment stage, where the indoor environment must be 3D scanned and stored as anchors. In a database, these anchors correlated with their corresponding locations and navigation-related data superimposed on visual feed through the navigation assistant process.

Based on the anchors recognized of the camera and sensors feed, the client's current position and orientation are determined. After the routes were completely examined, the images were transported to ARCore SDK for AR data overlay. The A* algorithm is used to compute the shortest path in the system [3]. To continually improve with performance and simplify indoor navigation. The next proposed model aims to decrease the use of hardware components and other technologies like artificial intelligence and deep learning, in the track of navigation and alternately use cloud with augmented reality. When the application starts, the system will progress using the sound message of the user and which should be launched by the destination, then the virtual path is loaded using the anchors and the virtual arrow signs will guide the user to his destination. The user has to should point his camera of the phone throw the anchors and a sound will erupt when the user walks throw the anchors. Furthermore, after passing each anchor the next anchor begins erupting sound until the user arrives at his destination [62]. To apply passive tracking, the following architecture must be followed as shown in Figure 4.

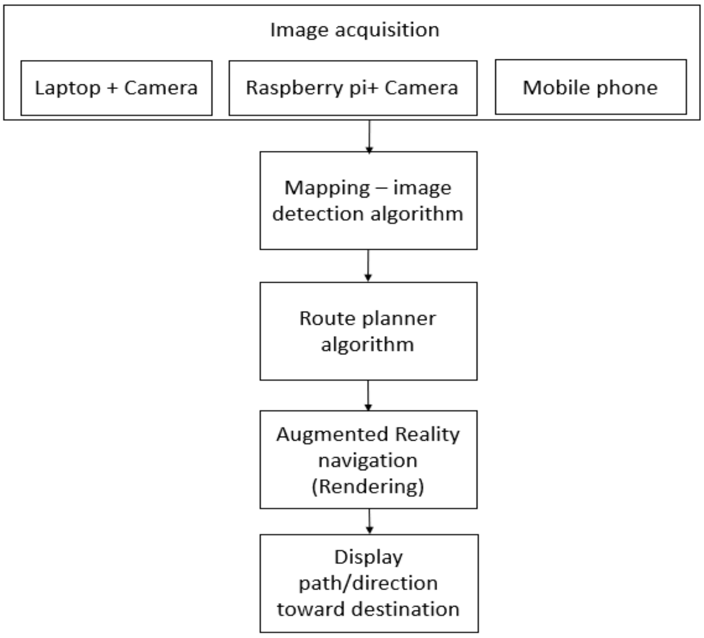

Figure 4. Modular architecture of passive tracking

2.2. Active tracking

At the beginning of the researches on this point, RFID positioning [44], augmented reality and portable route are integrated for building up a 3D expanded reality versatile route framework. Wang *et al*. [17], hardware devices of the RFID indoor positioning system combine a practical RFID reader and tag. The tag used in the RFID positioning method enables the system to obtain information on individual locations. The navigation information server method sends the navigation information at the exhibition area of visitors to their mobile devices. This system's message-markerless augmented reality technology could be combined with the positioning to enhance image recognition performance.

Zegeye *et al*. [63], the new trend in indoor tracking is both Wi-Fi and GIS. It looked through merging between mobile AR technology and Wi-Fi positioning technology. The researchers strive to develop this technology by establishing applying Wi-Fi received signal strength (RSS) in the considered indoor condition to construct radio maps utilizing the Wi-Fi fingerprinting approach. Fingerprinting data gives a coarse RSS estimation to the entirety of the reachable APs. The radio maps are stored as a file of 7×138 comma-separated values (CSV) RSS. When a client demands position estimation, an RSS estimation gathered on-the-fly will be sent from the android-based gadget's customer android application using an attachment to the server as an extensible markup language (XML) record. The received XML file will be parsed at the server, and position estimation performed at the server (remote laptop computer) by running the localization algorithm. The determined location value will be transfer as an XML file contains the expected locations to the client's android application. The predicted location would be displayed for the user by the identical application. The accuracy was achieved, and the system can determine the client position. At 67% of the time over 42 recognition positions.

Then complementing the development process and scientific research to solve some problems and improve the internal tracking process, geographic information systems, and sensor devices measurements appeared. augmented reality engine application (AREA) framework [19], comprises a portable augmented reality kernel that empowers location-based mobile augmented reality applications. AREA kernel shall consist of three created algorithms, the tracking algorithm, the points of interest (POIs) algorithm, and the clustering algorithm. Four specialized issues were vital when building up the kernel. POIs must effectively show regardless of the gadget is held at a slant. Show POIs accurately and efficiently should be given to the user. The idea of POI is coordinated with basic, versatile working operating system (OS) (iPhone operating system (iOS), Android, and Windows Phone)). The kernel provides for dealing with points of interest clusters. The idea of AREA to relate a client to the objects recognized in the camera show depends on five aspects. A virtual 3D world utilizes to connect the client's location to one of the objects. The client is positioned at the origin of this world. Rather than the physical camera, a virtual 3D camera that works with the built virtual 3D world.

The different sensor features of the upheld mobile operating systems include allowing the virtual 3D world. The physical camera of the cell phone changes into the virtual 3D camera depending on the estimation of sensor data. Previous research developed and a system built an indoor tracking system to enhance low positioning correctness and accuracy. The pedestrian tracking algorithm [18], uses indoor environment restrictions within the grid-based indoor model to improve a Wi-Fi-based system's localization. Indoor space is partitioned into grid cells that have a specific size and corresponding semantics. The precision of the grid model relies upon the grid size. The pedestrian algorithm repeatedly estimates that the location probability with these cells depends on the indoor and magnetometer measures toward a mobile cell. Tracking errors as ill-advised areas, wrong heading, and jumps among consequent locations are determined using the Wi-Fi positioning system, which causes a low dynamic tracking efficiency. To decrease predicting error, the tracking outcomes estimate against measurements in each three tracking intervals. The grid filter is a discrete Bayesian filter that probabilistically determines a target's position depending on measurements from sensors. Tracking system estimate positions over time using the Markov chain model. The advanced tracking algorithm, which depends on Wi-Fi positioning technology, can provide location precision at meter level 92% positions within 3.5 m of error. To apply active tracking, the following architecture must be as shown in Figure 5.

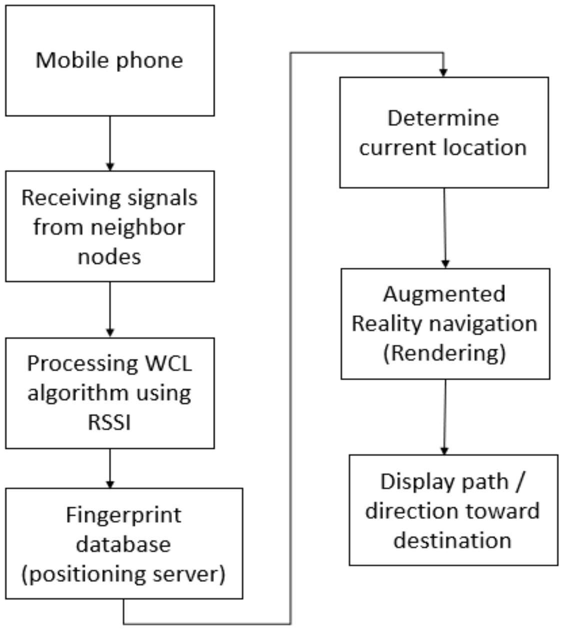

Figure 5. Modular architecture of active tracking

2.3. Hybrid tracking

The hybrid indoor augmented reality tracking system integrates the virtual object into the same position in real views. The feature extractor algorithms [23], are enhanced by merging FAST with SURF to create FAST-SURF that can fit the demand for robustness and real-time performance. To define the mobile phone position information achieved by using the fingerprinting technique algorithm. Set a fingerprint position recognition database of a particular indoor environment to compare and match each detected access point RSS values of detection points with stored records by applying the KNN algorithm and determining the position value.

Build a system [5], that aims to achieve automatic people tracking system that provides mapping Wi-Fi networks to determine people's position. The system consists of multi-agent, which enables the control of both the trolley and client detection agent's hardware, which is responsible for detecting and calibrating the client. The main job of the trolley is to follow the clients during their shopping process. The development of scientific research reduces the percentage of error in accessing positions and the emergence of mapping Wi-Fi networks. The data on vehicle transfer was adopted to capture signal maps to reduce the need to perform manual calibration and, therefore, enhance data updating. A Bayesian network classifier was applied for determined The final position using combining data provided by wireless networks. An obstacle detection agent eliminates collision during the trolley is moving. HC-SR04 distance sensors were used to detect the obstacles. Tablet is further responsible for scanning the Wi-Fi networks and the beacons utilizing a USB adapter of the Edimax brand, EW-7611UL model, including Wi-Fi and Bluetooth. Database organization that has a data agent which is in charge of controlling the data in it.

Wu *et al*. [24], augmented reality, deep learning and the cloud are used to solve the difficulty of GPS that does not work well for indoor navigation. The user is asked to switch on the camera phone to scan the surrounding environment to the database. The Python recognition system will take the first data in the database and match it with the image recognition module [64]. The images are uploaded to the back-end, then it can match with the features of You only look once, version 3 (Yolov3) [65]. The images are processed by binarization, contour detection, and cut redundant edges by scaling [66], [67]. The KNN nearest neighbor algorithm was used to remove unnecessary features in an earlier trained module for digit recognition [68]–[70], and determine the user's initial location positioning [71], [72]. A* search algorithm [73], [74], determines the shortest route from the initial point to the destination and suggests it to the users [75], [76]. Through indoor navigation, users can use AR electronic bulletin boards at a particular location to present relevant information about the location [77]. The common characteristics of most indoor tracking systems are shown in Table 3.

Table 3. Characteristics of most indoor tracking systems

Indoor	Outdoor	With low light intensity	Work in multi -level	Use predefined map	Use hardware requirements	Marker	Markerless	Cloud
√	√	NA	√	NA	√	√	NA	NA
√	NA	√	NA	NA	√	NA	√	NA
√	NA	NA	√	√	NA	√	NA	√
√	NA	NA	NA	NA	NA	√	NA	NA
√	NA	√	√	NA	√	NA	√	NA
√	NA	NA	√	√	NA	√	NA	NA
√	NA	√	NA	NA	NA	NA	√	NA
√	√	NA	√	NA	√	√	NA	NA
√	√	NA	√	NA	NA	√	NA	NA
√	NA	NA	√	√	NA	NA	NA	NA
√	NA	NA	√	√	NA	NA	NA	NA
√	NA	√	NA	NA	√	NA	√	NA
√	NA	NA	√	NA	√	NA	√	√
√	NA	NA	√	√	NA	NA	NA	√
√	NA	NA	√	√	NA	NA	NA	√
√	NA	NA	√	NA	NA	NA	√	√

3. RESULTS AND DISCUSSION

The main objective of using indoor tracking systems is to navigate people through complex and unfamiliar environments. Tracking systems enable users to reach their desired destination, with minimum congestion and time consumption. The adapted techniques in outdoor tracking can not work indoor tracking for the extra challenges such as color intensity and GPS absence. The tracking can be divided into active, passive, and hybrid tracking.

Active tracking systems depend on using one or more communication technologies, such as Wi-Fi or Bluetooth. To reduce the computational complexity, researchers try to improve the connectivity and the localization accuracy. Researchers usually use the weighted centroid algorithm (WCL) to enhance the indoor tracking. Active indoor tracking is commonly used for low cost systems. Moreover, it solves the tracking problem in low light intensity. The current challenge in active indoor tracking is its low accuracy in complex environments with multiple walls and floors, as it affects the signal's strength.

Passive tracking systems depend on using one or more image detection algorithms. Systems use pre-loaded maps to enhance users' navigation. These techniques usually use the route planner algorithm. This algorithm calculates the distance between the current location and the target, to reduce the calculation of the real-time tracking. Passive indoor tracking systems are usually used to solve the problem of complex environments. However, low light intensity can affect passive indoor tracking systems' accuracy.

Hybrid tracking systems integrate communication technologies with image detection algorithms in one system. The communication technology module calculates the position and orientation of the mobile. While, the image detection module extracts and matches feature points, between the current frame and offline environment images. The virtual content about route tracking overlay the real-time camera's view. The advantages of hybrid indoor tracking systems are to enhance the image based tracking with sensors' data. However, its signal strength is affected in complex environment, as in active tracking. We noticed, the active tracking is better to use when the indoor environment is covered by Wi-Fi and use the fingerprinting technique algorithm. Passive tracking is more convenient using when environment maps exist to improve tracking accuracy with image detection and computer vision algorithms.

Usually, hybrid tracking is used when the environment is covered with Wi-Fi and merged with the algorithms of image detection and computer vision. Building a hybrid tracking model is more effective and accurate. Hybrid tracking works in low-light intensity environments because it depends on Wi-Fi RSS fingerprinting to determine the user's location. In addition to making it more effective for the user through image detection algorithms to view actual user tracking in a real environment. The Table 4 shows when to use the three types of tracking techniques.

Table 4. Indoor tracking systems features

Tracking technique	Tracking space	Physical world parameters	User perspective
Active	Small space Single floor	Not affected by the light intensity Affected by the occlusion Not need predefined map System needs extra hardware	Easy to scalability
Passive	Complex space Multiple floor	Affected by the light intensity Not affected by the occlusion Need predifiend map System not need extra hardware	Hard to scalability
Hybrid	Complex space Multiple floor	Not affected by the light intensity Not affected by the occlusion Need predefined map System needs extra hardware	Hard to scalability

As shown in Table 4, when the user environment is small, a single floor prefers to use active tracking. When the user environment is complex, multiple floors prefer to use passive tracking. When lighting intensity in the environment is slightly or almost non-existent, it is preferable to use active or hybrid tracking. The occlusion in complex environments with multiple walls and floors affects the system's accuracy in active tracking. The cost of active and hybrid tracking is high due to the need for hardware components. The scalability in active tracking is easier than passive and hybrid tracking because it does not require predefined maps.

4. CONCLUSION

Indoor tracking systems are usually implemented based on communication technologies or image detection algorithms. This paper demonstrates various indoor tracking systems for augmented reality applications. We compared indoor tracking systems developed based on various communication technologies. Similarly, we compared indoor tracking systems developed based on image detection algorithms. This paper also provides a comprehensive review of the recent relevant applications from 2011 to 2021. Developing active tracking is very stable, with widespread use, computationally inexpensive, and it provides systems that can integrate with 3D models. Active tracking is usually faulty for applications that need accurate tracking and registration. On the other hand, passive tracking can apply more reliable and gives more accurate pose estimation and be tracking. Passive tracking is computationally expensive and needs powerful hardware. For the hybrid tracking, both sensor-based tracking and vision-based tracking are integrated to overcome the limitations of each technique. Recently, hybrid-based methods produce accurate tracking that can be run on handheld devices.

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