Augmented Reality indoor tracking using Placenote

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Abstract

Recently, augmented reality technology became more stable and integrated into our daytime applications. Augmented reality adds virtual content to enrich physical environments. Augmented reality uses tracking techniques to capture environments features. The tracking is classified into two types: outdoor and indoor tracking. Currently, outdoor tracking becomes popular for outdoor navigation applications using GPS. However, GPS has low performance in indoor tracking due to the imprecision of GPS satellite signals. The deficiencies in the signals make it difficult to navigate through malls, hospitals, museums, and airports. Indoor tracking provides a solution for vast, complex indoor environments navigation. Nowadays, most indoor applications rely on predefined two- and three-dimensional maps of buildings to direct users to their destinations. Our paper presents an indoor tracking model that combines placenote technology with cloud computing technology and A* navigation algorithm. Our model enables users to select a destination without predefined maps, and at the same time, it can calculate the shortest path. Experiments demonstrate that our suggested model achieves an average accuracy about 99 percent within a 7–10 cm error bound in scenarios involving different distance paths. At the same time, the experiments show that all users reach their destinations successfully. The error of the proposed model is significantly lower than the errors reported in the literature for research conducted with markerless technology and tested in similar area sizes.

1. Introduction

Currently, navigation technology becomes stable on handheld devices. Users rely on navigation systems in the daytime. Usually, it is difficult to determine the position of users who are not familiar with a large and complex campus such as universities, hospitals, airports, supermarkets, shopping centres, or any other large indoor area (Khayyat, 2020). Most navigation applications use GPS for outdoor tracking, in which satellites determine the positioning (Koyuncu, 2010). GPS satellites need some requirements to use for positioning. First, the navigating device has to acquire signals from a specific number of satellites. To achieve high accuracy signals to determine the user’s position, you need to use around four satellites. Second, the signal strength between the device and the satellite is still a must, so the device must be outdoors (Mehta, 2011). GPS satellite signals are not accurate and cannot determine people’s position inside (Hameed, 2018) (Zhang, 2019).

Nowadays, smartphone devices have high-resolution cameras, powerful processors, and several advanced sensors such as global positioning systems (GPS), wireless communications, accelerators, and magnetometers (Gang, 2019). Augmented reality tracking techniques on smartphones can be defined as marker-based and markerless tracking (Brito, 2018).

Marker-based augmented reality uses a predefined image to track an object in the physical world. The image is used as a tracking trigger. Users can scan the image using their smartphone, which will track the physical image using feature extraction approaches. Marker-based tracking usually uses a square marker

with edge detection and registration of virtual content only valid when four vertices of a square marker are identified (Cheng, 2017).

Marker-less-based augmented reality scans the real environment and places digital elements on a recognizable feature, like a flat surface. So, instead of being tied to a marker, the digital elements are placed based on geometry. the gyroscope is used to determine the relative angle relationship, and the camera is used to turn the display background into the real environment (Viyanon, 2017). Most indoor navigation apps use various technologies, including Bluetooth Beacons, Wi-Fi Fingerprinting RFID, UBW ZigBee, NFC, and Infrared (Huey, 2011).

In our paper, we present a real-time three-dimensional model for indoor tracking. we used placenote technology to build spatial user interfaces for real-world environments. We used A* in our model to determine the shortest path from the initial to the destination and suggest it to the users (Deepa, 2018). We depend on Unity and AR Foundation Framework that uses ARKit for iOS support to build our model (Çankırı, Maraşlı, Aktürk, & Sonlu, 2020). The key contributions of our paper are as follows:

• Building a 3D model for indoor buildings makes navigation easy in complex and crowded environments.

• The accuracy of testing our model achieved about 99 percent regardless length of the path.

• No need for a 2D or 3D predefined map for the indoor buildings.

• The data of places stored on the cloud can be used and expanded with other people's navigation.

• The cost of establishing the model in any indoor building is low, and it does not need extra sensors or hardware components.

• Our proposed model runs using smartphones.

Through the following sections of our paper are organized as follows. Section 2 includes the related work of indoor tracking systems. Our proposed work is presented in Section 3. In section 4, we describe the methodology of our model. The experimental results and discussion are shown in section 5. Finally, the conclusion and future Work of our model are presented in Section 6.

2. Related Work

This section discusses augmented reality tracking for indoor navigation and mobile computing. This section explains the existing AR techniques and their constraints.

Indoor tracking is still one of the main challenges facing augmented reality applications. Low Chee Huey et al. implemented the initial indoor technique (Huey, 2011), using laptops and USB webcams to gather camera frames. They used ARToolkit to detect a marker and compare it to previously stored markers in the database. When a marker is identified at a precise position, it is converted to the location ID for

processing. The OpenGL API loads the VRML model using the marker's coordinates. The route planner module determines the shortest path between the current and destination locations.

To reduce the difficulties associated with utilizing a laptop for indoor tracking, a Raspberry Pi was used in place of the laptop. Muhammad Fadzly et al. implemented a system composed of a web camera, a Raspberry Pi, display glasses, and an input controller (bin Abdul Malek, 2017). Each component connected to the Raspberry Pi has a unique set of capabilities. The client initiates the execution of the application by specifying the desired location, at which point the camera begins capturing live images to detect area markers. The system is shown in Fig. 1.

This diagram is updated from (Huey, 2011), which describes the architecture of the Augmented reality marker indoor navigation system.

Currently, most applications aim to replace marker-based navigation with image recognition-based navigation. Jia- Hua Wu et al. implemented an approach consisting of three parts: the server, the user, and the administrator (Wu, 2020). They used the server to store databases used to create the indoor map. The administrator will need to create a map of the internal space and the surrounding feature points. They used KNN nearest neighbour algorithm in their approach to training their module. They uploaded trained characteristics of the images for an internal place to the backend and used the Yolo v3 object detection method to extract characteristics from real-time tracking. The Yolo v3 extracted characteristics are compared with the training characteristics to determine their current location (Huang R. a., 2019). The images were then binarized to remove extraneous numbers from the final result. Finally, the users scan their surroundings and enter their destination, and then the indoor system is used directly. The A* algorithm assists them in calculating the shortest path from their starting point to their final destination.

Indoor navigation system based on NFC, has become more popular (Ozdenizci B. a., 2011). The primary source of the idea is a smartphone with an integrated NFC component and an application running on it, which helps to guide the user (Deak, 2012) (Ozdenizci B. a., 2015). The mobile device connects to the URL Tag by touching it, and the map-server responds by sending the map information to the mobile device, which is then loaded onto the mobile device. Following the loading of the map, the indoor navigation system turns the map data into a link-node model, which is a 2D network with topological relationships. The user then selects a destination point, and the application uses Dijkstra's shortest path algorithm to compute the most efficient route rapidly. Data from NFC tags are collected to determine the current location. The user is only required to touch the mobile device to a tag on his way to validate his navigation.

Chiaki Takahashi and Kazuhiro Kondo developed an indoor navigation system using beacons (Takahashi, 2015). Mobile devices can estimate their distance to the beacon based on the signal strength (Campaña, 2017). Through the use of Bluetooth Low Energy, beacons transmit advertising signals to smartphones (BLE). The beacons are placed in the corners of the area that use to construct a database of radio wave strength. Then, they used the database to match the detected intensity at an unknown site to determine the current position.

Wondimu K. Zegeye et al. developed an indoor localization system based on WIFI-RSS Fingerprinting (Zegeye, 2016). This technique is not dependent on any particular features or beacons. The indoor environment is represented by the system using a grid-based (Brevi, 2009), representation. Experiments were conducted using the building's pre-existing WIFI infrastructure. The offline phase of this method requires the use of sampled RSS values to create a radio map of the area under consideration. To build radio maps, the application scans and collects information about reachable access points (APs) at each sampling location, including their RSS values. Succeeding then, the localization algorithm estimates the device's position during the online phase. This algorithm's response time in a freestanding architecture is approximately 220 ms.

Weilin Xu et al. developed the pedestrian tracking algorithm to improve WIFI- grid-based indoor model (Xu, 2018). Indoor space is subdivided into grid cells of a defined size and semantics. The pedestrian algorithm repeatedly predicts that the probability of being located above these cells is dependent on indoor and magnetometer measurements toward a mobile cell. The grid filter is a Bayesian discrete filter that probabilistically calculates the position of a target based on sensor measurements. The tracking system uses the Markov chain model (Hayes, 2013), to determine its position over time.

Edward et al. progressed to build the indoor navigation system (WPIN) using Bluetooth low energy (BLE) beacons called Lbeacons deployed at each indoor building intersection (Chu, 2019). Users were provided with 2D pictures indicating their direction along the path to the destination, such as turn left, turn right, and straight. The WPIN application comprise of three layers: the user interface, navigation, and indoor positioning. The navigation module used to detect the user's location after receiving input, including the destination. Within the positioning module, the BLE advertising messages are received from various Lbeacons. Each advertising message contains the sender's coordinates. WPIN application determines the user's position by selecting the message with the greatest RSSI (Received Signal Strength Indicator) value among the filtered messages. If the user arrives at a new waypoint, the WPIN application displays a direction indicator on the screen, such as turn left, turn right, or continue straight. Until the user reaches the destination, the positioning-navigation procedure is paused. The architecture of WPIN application is shown in Fig. 2.

This diagram is adapted from (Chu, 2019), which describes the architecture of WPIN application.

The ARBIN (Huang B.-C. a.-H.-M., 2020), an augmented reality-based navigation system developed, extends the previous work, WPIN. The architecture of ARBIN and WPIN looks the same based on Bluetooth beacons. However, due to the limitations of a 2D navigation map, users may experience mental strain and become confused as they attempt to connect the real surroundings and the 2D navigation map before proceeding. As a result, they developed ARBIN, an augmented reality-based navigation system that conveniently displays navigation directions on the screen of real-world environments by Google ARCore.

Indoor tracking systems are commonly implemented using marker, communication, or image detection technologies. We discussed briefly how each indoor tracking system is implemented. From my perspective, after reading about how all systems work. When the marker image is prepared appropriately,

the marker-based system is stable. The marker-based approach is ineffective; when the mobile camera is moved away from the marker, the augmented reality experience is lost, and the marker photo must be scanned again. Scanning will not operate in some scenarios where markers reflect light. The communication-based system is widely applicable, computationally efficient, and can integrate with two- and three-dimensional maps. Usually, communication-based technology is unsuitable for applications requiring highly accurate tracking. A system based on image detection technologies can achieve great positioning accuracy. Not only can image detecting technology output the position, but also the view angle. The current limitation of image detection methods for indoor tracking is that they rely on pre-loaded maps, and low light levels reduce their accuracy. On the other hand, tracking image detection technology is computationally intensive and requires high performance hardware. The comparison of common features in indoor position systems is shown in Table I.

Table I. Comparison of common features in indoor position systems

Paper	Build Depend on	Client platform	Area Size	Accuracy
(Huey, 2011)	- Marker, ARtoolkit, Open GL, USB webcams and laptops.	laptops	medium	NA
(bin Abdul Malek, 2017)	- Marker, ARtoolkit, OpenGL, Raspberry pi and USB webcams	glasses	medium	∼100%
(Takahashi, 2015)	- iBeacons and local server	smartphone	Small	NA
(Chu, 2019)	- Lbeacons, navigation module, positioning module and 2D pictures indicating	smartphone	large	92.5% 3–5 m
(Huang B.-C. a.-H.-M., 2020)	- Lbeacons, navigation module, positioning module and 3D arrow model (in real-time)	smartphone	large	92.5% 3–5 m
(Ozdenizci B. a., 2015)	- NFC Tags, Map Server, Link node model and Dijkstra's shortest path algorithm	smartphone	medium	∼100%
(Zegeye, 2016)	- WIFI (Access points), radio map, server and localization algorithm	smartphone	medium	80% – 5m
(Xu, 2018)	- WIFI grid based, pedestrian tracking algorithm, Kalman filter and Markov chain model	smartphone	large	92% – 3.5m
(Wu, 2020)	– 2D map, server, Yolo v3 object detection method, KNN nearest neighbor algorithm and A* algorithm	smartphone	medium	NA

3. Proposed Work

The fundamental objective of our model is to develop an application capable of directing users to their destinations using augmented reality. The indoor tracking model runs on a smartphone. There are several features are included in our presented indoor tracking model, including:

- Mapping Creation Module: The model provides users to create pre-loaded indoor pathways that enable them to navigate easily.
- High Accuracy Navigation: The model capable of directing people in shopping malls, hospitals, office buildings, or any other large indoor space in an accurate and easily accessible manner at all times and under multiple conditions complex area, different light intensity.
- Attractive User Interface: The model's user interface is simple and allows the user to select his destination.

The architecture of our indoor proposed model is shown in Fig. 3.

Our suggested indoor navigation model is composed of five essential modules: mapping, cloud database, positioning, augmented reality navigation application, and finally, rendering augmented reality path showing. Our indoor navigation model is constructed on top of several different technologies, including the unity game engine, the Placenote SDK, cloud Computing (Namasudra, 2021), and the XCode IDE.

We developed our model using a unity game engine as the industry's most advanced framework for interactive, real-time three-dimensional multimedia. Placenote SDK is a real-world spatial user interface that enables rapidly creating and deploying spatial apps on mobile devices. Cloud computing is a term that refers to the delivery of various services via the Internet. These resources include data storage, servers, databases, networking, and software. XCode is an immensely productive platform for developing Mac, iPhone, iPad, Apple Watch, and Apple TV applications. XCode provides the Command Line Tools (CLT), which enable UNIX-style programming using macOS's Terminal app.

4. Methodology

The proposed model consists of five main components: mapping creation module cloud, database module, positioning module, navigation module, and rendering module.

4.1. Mapping creation module

One of the most significant challenges in indoor tracking systems is the effort and cost involved in creating three dimensional maps of the inside environment. In our model the users can dynamically scan any space and convert it to a trackable map for positioning digital content using the Placenote SDK. The scenario's flowchart is presented in Fig. 4. Users drop 3d points through the walkable pathway by clicking on the screen to create the map, as shown in Figure-7. Each POI (Points of Interest) along the pathway has a three-dimensional coordinates axis.

To create a map for any building, the user needs to open the application and scan the area using the camera of the iPhone. The user, through scanning, determines destinations that any user will need to go to them. After the scanning, the user uploads the map to the cloud. After the user's arrival at the destination point and saving the map. The path map's metadata is saved to Placenote's cloud storage. One or more destinations can create when creating the mapping process. Placenote utilizes the surroundings as a single large three-dimensional marker. It must identify feature spots on which it can cling. Feature points are formed at areas of great contrast, at the corners of sharp edges, and in other locations. To construct a high-quality map for a user, record a feature-rich environment near the location where the map will be initialized the most frequently. Take a few steps around each object, recording it slowly and from various vantage points (move your device up and down, still aiming at the center of the filmed model). Figure 7 conveys the process of creating a map by creating a set of different paths, whether short, medium, or long distance. The following algorithm was designed to map the environment.

Input: Streaming live video from the user’s camera.

Output: Mapping the environment.

Algorithm 1

Mapping the environment

1: Scanning the environment

2: Extract feature vector map

3: Set POI (point of interest) 3-dimensional coordinate axis to the cloud database

4: Repeat 2,3 until the user reaches the destination.

4.2. Cloud database module

Cloud computing is a term that refers to the delivery of on-demand computing services ranging from apps to storage and processing power via the internet. Each cloud-based project has a unique API key that is used to store data about the pathways. The pathways are stored as metadata in Placenote's cloud storage, as shown in Fig. 5.

4.3. Positioning module

An indoor positioning system (IPS) (Kim, 2015), is a network of connected devices that may be used to identify items or persons within buildings. GPS and other satellite technologies cannot be employed due to the scattering and attenuation of satellite signals. It is imprecise and inaccurate, as satellites have no line of sight inside structures.

To begin our system, ARKit must be initialized. Carry out this action by slowly moving your device in a sideways direction. When the calibration image vanishes, the ARKit tracking has been configured, the

ground has been detected, and the relative coordinates system created. The relative predicted coordinates are compared with the saved coordinates on the cloud to identify the current position. The flowchart in Fig. 6 illustrates how the user navigates to the destination by loading the map from the cloud.

4.4. Navigation module

Our indoor tracking model aims to guide users inside massive buildings by establishing a path from the user's current location to their desired location in real-time. To navigate within enormous buildings, we must choose the shortest path from among the numerous options. Numerous algorithms exist to determine the shortest path, including Dijkstra's algorithm, the best initial search algorithm, and the Astar(A*) pathfinding algorithm. Among these, A* pathfinding algorithm produces the most optimal and accurate path in the shortest amount of time. As a result, we applied the A * pathfinding algorithm for navigation systems. A* is a general-purpose search algorithm that may be used to solve a wide variety of problems, including pathfinding (Cui, 2011). For pathfinding, the A* algorithm evaluates the most promising unexplored location it has encountered repeatedly. When a place is explored, the algorithm terminates if that location is the objective; otherwise, it records all of that location's neighbours for future exploration. A* is almost certainly the most widely used pathfinding algorithm in variety of fields of computer science such as navigation systems (Sandra, 2021). The following algorithm was designed to navigate the users in indoor environments.

Input: Streaming live video from the user’s camera, Destination D, 3D arrow rendering.

Output: Navigation path

Algorithm 2 The navigating in the environment

1: Scanning the environment

2: Identify POI (current location S)

3: Get requests from cloud database data

4: Run A* algorithm to find the shortest path

5: Identify path direction through 3D arrows from S to D

6: Repeat 3:5 until the user reaches the destination

4.5. Rendering module

The rendering is dependent on the precision with which positioning can be established. It's simple to create a 3D model of a route. However, it is more complex to ensure that the virtual environment corresponds to the physical world, taking into account obstacles and things like doors, walls, and any furniture or other significant items. Rendering performance will continue to improve as ARKit evolves. moreover, we can customize the design of augmented reality content to our needs. Finally, our indoor

navigation application illustrates the path using the three-dimensional augmented reality arrows to navigate the users to their destinations, as shown in Figure 8.

5. Results And Discussion

We developed our tracking application based on placenote technology, which is designed to work on iPhones. Our experiments were conducted in the following order. Our experiments took place on two floors (second and third) of the computer and artificial intelligence college in Benha, Egypt. Each floor in this building is approximately 50m * 20m in size, with paths ranging in length from 20 to 100 meters, equating to a tracking volume of around 2.000 m2. Our tracking application tested on an iPhone 8 plus, iOS 15.2, and 64 GB capacity storage.

Many experiments were done in the building with different distance paths to demonstrate the tracking application's performance. We tested our tracking application in different lighting conditions, from bright to almost dent light; the results showed that it works very well. Since our model relies totally on the image processing approach, the tracking process in very dark lighting will challenge to reach the user to its destination.

It is essential to highlight that we ran a pilot study by five participants; they went through three different paths (long, medium, and long) to their destinations. The results showed that the participants could reach their destinations in all cases, and the results are shown in Table II and Table III on the short and long paths.

5.1. Short pathway

We tested our technique on a short path length of about 20 meters and repeated this process five times to ensure the results were correct. Table II shows the statistical results for path-1 during the actual trial to reach the destination. Figure 9 is shown the average error of multiple iterations of path-1.

Table II. Short path results

pathway point number	iteration-1	iteration-2	iteration-3	iteration-4	iteration-5
pathway point 1	0.0892	0.0892	0.0892	0.0892	0.0892
pathway point 2	0.0717	0.107	0.0881	0.0975	0.0975
pathway point 3	0.0899	0.0905	0.078	0.0894	0.0894
pathway point 4	0.0896	0.0838	0.0714	0.0999	0.0999
pathway point 5	0.0991	0.0865	0.0805	0.0896	0.0896
pathway point 6	0.0486	0.0586	0.0718	0.0795	0.0795
Mean	0.08135	0.08593	0.07983	0.09085	0.09085
Standard deviation	0.0183	0.0156	0.0076	0.0072	0.0072
Min	0.0486	0.0586	0.0714	0.0795	0.0795
Max	0.0991	0.107	0.0892	0.0999	0.0999

The results of the analysis showed that the average error of multiple iterations Mean=8.5 cm and the standard deviation=1.12 cm through the pathway as shown in Fig.9

The proposed indoor tracking technique, which is established on placenote positioning technology, can achieve meter-level location accuracy = 99.575 \% within 8.5 cm of error.

5.2. Long pathway

We also tested our technique on a long path length of about 40 meters and repeated this process five times to ensure the results were correct. Table III shows the statistical results for path-2 during the actual trial to reach the destination. Figure 10 is shown the average error of multiple iterations of path-2.

Table III. Long path results

pathway point number	iteration-1	iteration-2	iteration-3	iteration-4	iteration-5
pathway point 1	0.0386	0.041	0.0418	0.0511	0.0439
pathway point 2	0.0514	0.0761	0.076	0.0738	0.0517
pathway point 3	0.0831	0.0636	0.0599	0.0731	0.0607
pathway point 4	0.0839	0.0724	0.0604	0.077	0.0573
pathway point 5	0.0775	0.0709	0.0537	0.08	0.0649
pathway point 6	0.0676	0.0684	0.0686	0.0642	0.0767
pathway point 7	0.0867	0.0935	0.1011	0.0705	0.0954
pathway point 8	0.0794	0.0901	0.0899	0.071	0.0747
pathway point 9	0.0883	0.0993	0.025	0.0796	0.0882
Mean	0.07294	0.07503	0.06404	0.07114	0.06816
Standard deviation	0.01725	0.01773	0.02335	0.00898	0.01696
Min	0.0386	0.041	0.025	0.0511	0.0439
Max	0.0883	0.0993	0.1011	0.08	0.0954

The results of the analysis showed that the average error of multiple iterations Mean = 7.02 cm and the standard deviation = 1.68 cm through the pathway as shown in Fig. 10.

The proposed indoor tracking technique, which is established on placenote positioning technology, can achieve meter-level location accuracy = 99.7875 \% within 7.02 cm of error.

There is no fixed database for comparison. My comparison is done with researchers who worked on the same indoor tracking problem using markerless technology and almost the same space size, Table IV. shows the results of the comparison.

Table IV. Comparison between indoor position systems that using markerless technology

Paper	Year	Build Depend on	Error bound	Area Size	Floor type
(Takahashi, 2015)	2015	iBeacons and local server	0.8 m	45 m2	single
(Chu, 2019)	2019	Lbeacons	3–5 m	2000 m2	multiple
(Huang B.-C. a.-H.-M., 2020)	2020	Lbeacons	3–5 m	1800 m2	multiple
(Zegeye, 2016)	2016	WIFI (Access points)	5 m	173 m2	single
(Xu, 2018)	2018	WIFI grid base	3.5 m	1200 m2	single
(Nguyen, 2021)	2021	WIFI (Access points)	2 m	2400 m2	multiple
(Sandoval2, 2020)	2020	UWB modules based on Decawave UWB chipset	1 m	400 m2	single
(Auysakul2, 2022)	2022	received signal strength indicator (RSSI).	0.97 m	22 m2	single
(Ling-Feng Shi, 2022)	2022	The particle filter algorithm and Dead-Reckoning (PDR).	0.52 m	450 m2	single
The proposed model	2022	Placenote technology	0.07–0.1 m	2000 m2	multiple

Based on the analysis of the previous results in Table IV, we noticed that there is consistency in the average error rate, as it does not exceed 10 cm. The average error rate during any path is not proportional to exponential, regardless of the length of the path, whether long or short. The accuracy ratio of our proposed indoor tracking technique can achieve correct accuracy about 99 percent, regardless of the length of the path.

6. Conclusion And Future Work

With our paper, our contribution is to make navigation easy in complex and crowded indoor environments. The main goal is to improve the accuracy of the user's arrival at his destination through the shortest route. Our paper proposes an indoor tracking model which combines the environmental constraints in a placenote positioning model with the cloud computing technology and A* navigation algorithm. The proposed model is based on a smartphone with a magnetometer and a three-dimensional rendering module. Our model has many characteristics that distinguish it from other systems that solve the indoor navigation problem. Our model does not need predefined two- and three-dimensional maps of buildings to direct users to their destinations. Our model stores the paths data of indoor environments on the cloud. The stored data on the cloud can be trained and expanded with other people's navigation. The

application works on the smartphone; it does not need extra sensors or hardware components like NFC sensors. It is applied on indoor multiple-door buildings with correct accuracy of about 99 percent, regardless of the length of the path.

Our model allows users to follow another user's exact location by uploading their path to the cloud and guiding a user from a source point to a destination point in indoor spaces. Our model tracked environmental features by utilizing pre-scanned 3D paths. These features included directional data, which enabled instructions to be displayed in the live visual at the proper locations. The user was provided with directional information via a three-dimensional arrow during navigation. Our system demonstrated excellent performance despite some constraints in a real-world environment, such as varying light conditions and user movement speeds.

In future work, we will find a way to navigate people in dark light environments. Later on, our model can integrate with machine learning to improve tracking performance by taking advantage of tracking user behaviours.

Abbreviations

AR: Augmented Reality; GPS: Global Positioning System; NFC: Near-field communication; WIFI: Wireless Fidelity; RFID: Radio-frequency identification; UWB: ultra-wide band; BLE: Bluetooth Low Energy; RSSI: Received Signal Strength Indicator;

Declarations

Availability of data and materials

There is no fixed database for use. Our experiments took place on two floors (second and third) of the computer and artificial intelligence college in Benha, Egypt. Each floor in this building is approximately 50m * 20m in size, with paths ranging in length from 20 to 100 meters, equating to a tracking volume of around 2.000 m2.

Competing interests

The authors have declared that no competing interests exist.

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Authors' contributions

The author designed and conducted the study and wrote, revised, and approved the final manuscript.

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1 https://docs.unity3d.com/Manual/index.html

2 https://docs.placenote.com/

3 https://developer.apple.com/documentation/xcode

Figures

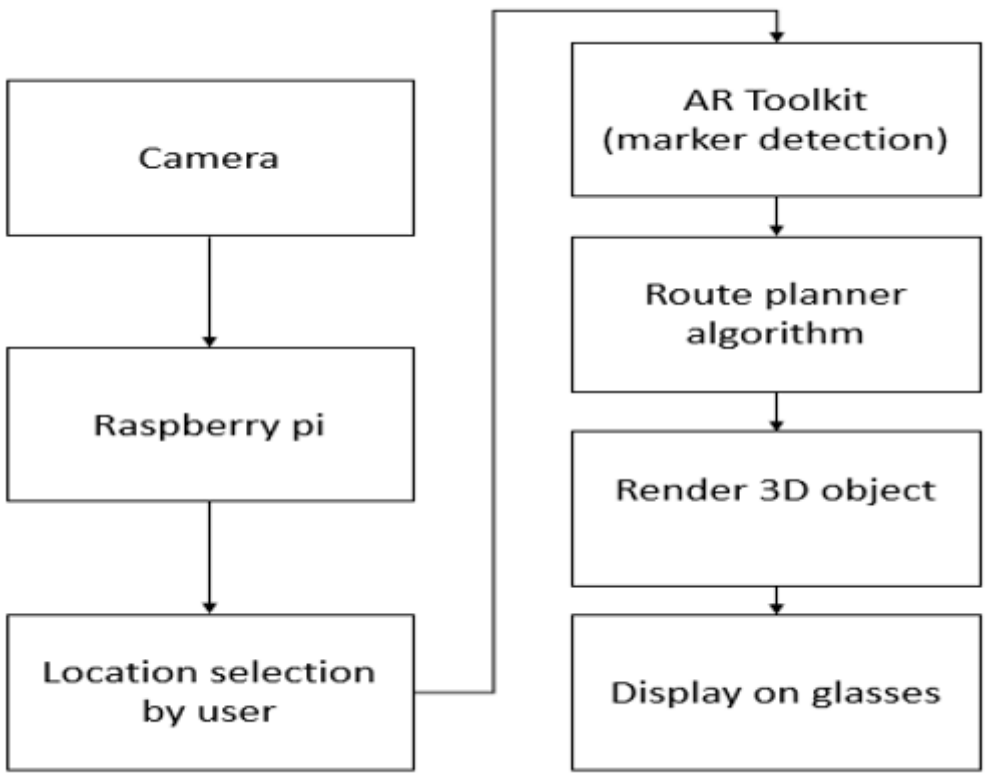

Figure 1

AR marker indoor navigation

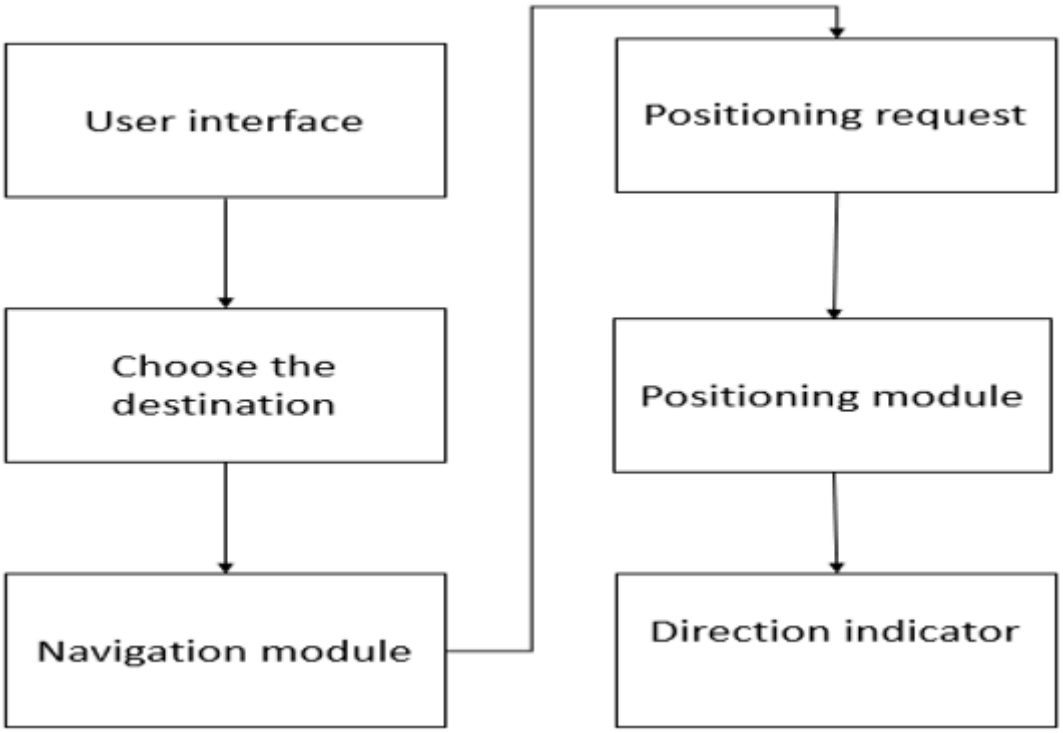

Figure 2

The architecture of WPIN application

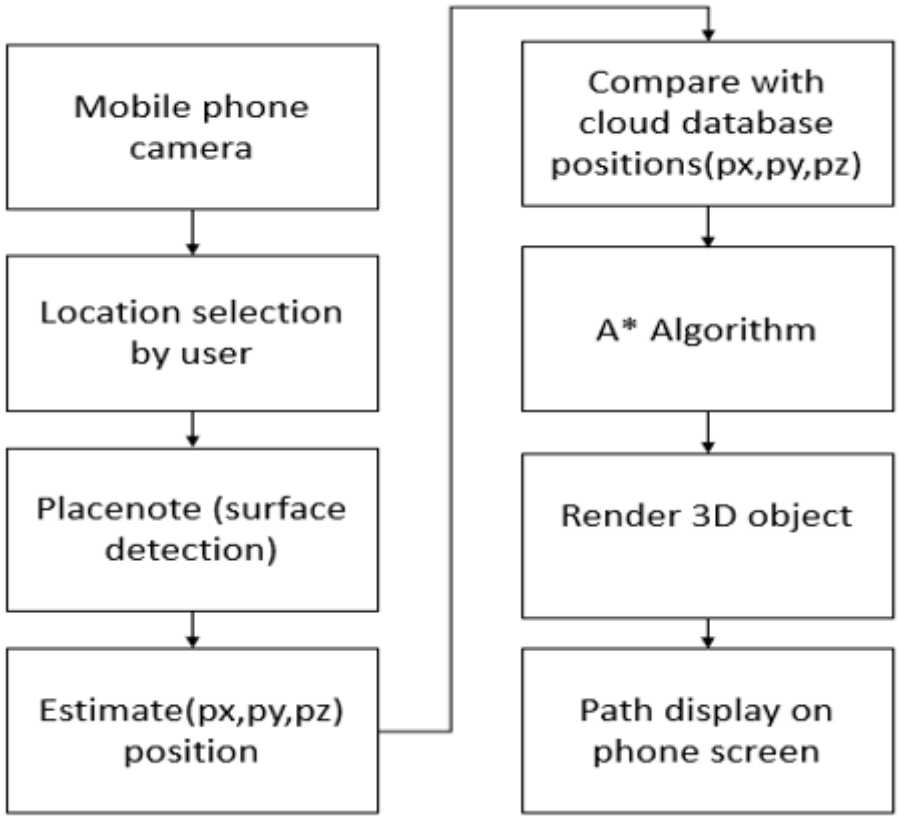

Figure 3

Architecture of indoor proposed model

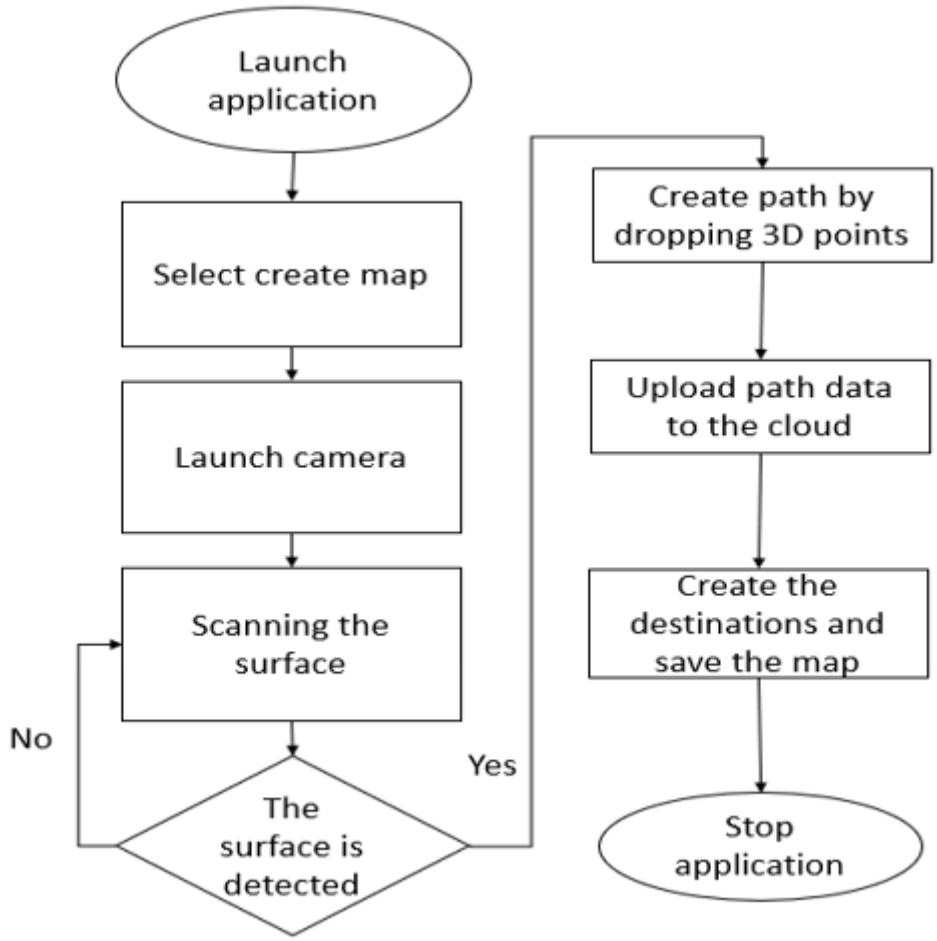

Figure 4

Flowchart of creating and saving the map

Metadata

Id: eb67d25b-7ba9-4edd-8201-4bc15aaef017

Time created: Wed Mar 17 2021 01:26:24 GMT+0200 (Eastern European Standard Time)

Location: altitude: 21.9494038, latitude: 29.9899521, longitude: 31.1411839

Place name: GenericMap

Place size: 2.409 MB

Userdata: { "shapeList": { "shapes": [{ "colorType": 0, "px": 0.2874572, "py": -0.5, "pz": 0.4856425, "qw": 1, "qx": 0, "qy": 0, "qz": 0, "shapeType": 0 }, { "colorType": 0, "px": -0.0295661651, "py": -0.5, "pz": -0.54754436, "qw": 1, "qx": 0, "qy": 0, "qz": 0, "shapeType": 0 }, { "colorType": 0, "px": -0.365903348, "py": -0.5, "pz": -1.55469489, "qw": 1, "qx": 0, "qy": 0, "qz": 0, "shapeType": 0 }, { "colorType": 0, "px": -0.6724823, "py": -0.5, "pz": -2.56430936, "qw": 1, "qx": 0, "qy": 0, "qz": 0, "shapeType": 0 }, { "colorType": 0, "px": -0.4782296, "py": -0.5, "pz": -3.59772253, "qw": 1, "qx": 0, "qy": 0, "qz": 0, "shapeType": 0 }, { "colorType": 0, "px": 0.155889064, "py": -0.5, "pz": -4.48336267, "qw":

Figure 5

Metadata of storing the paths

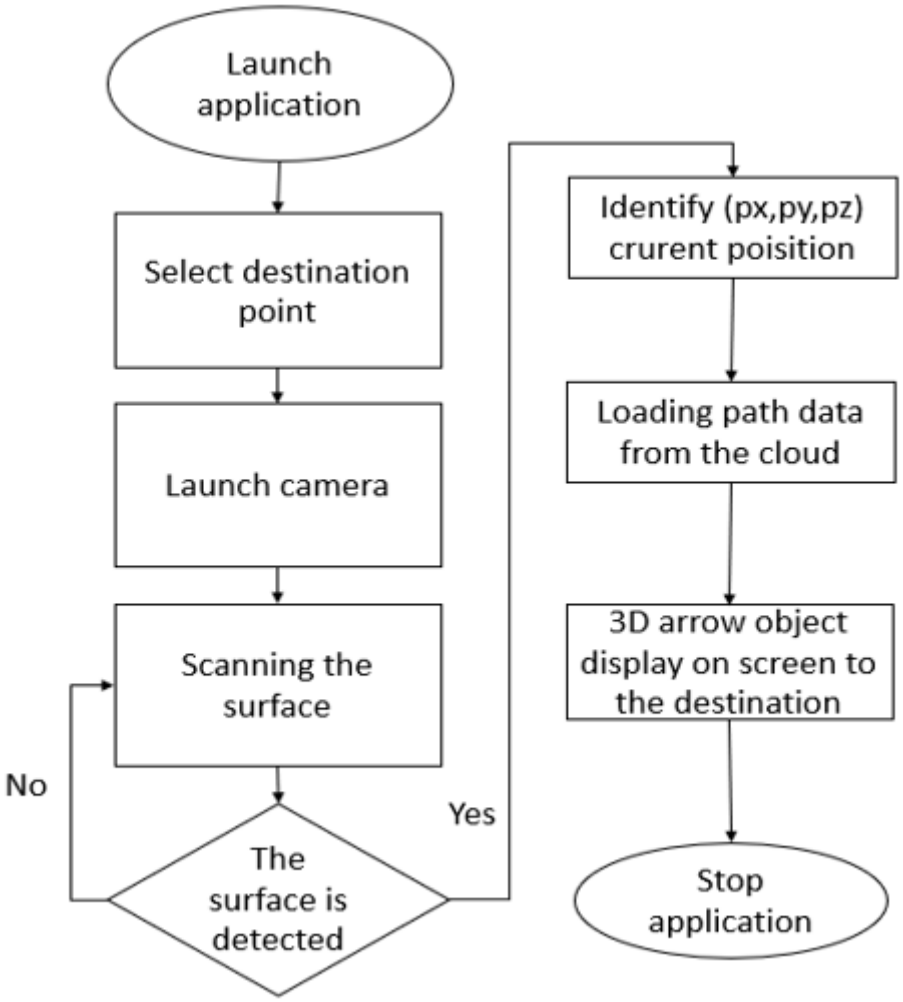

Figure 6

Flowchart of loading the map

Figure 7

Mapping creation module

Figure 8

Navigation module

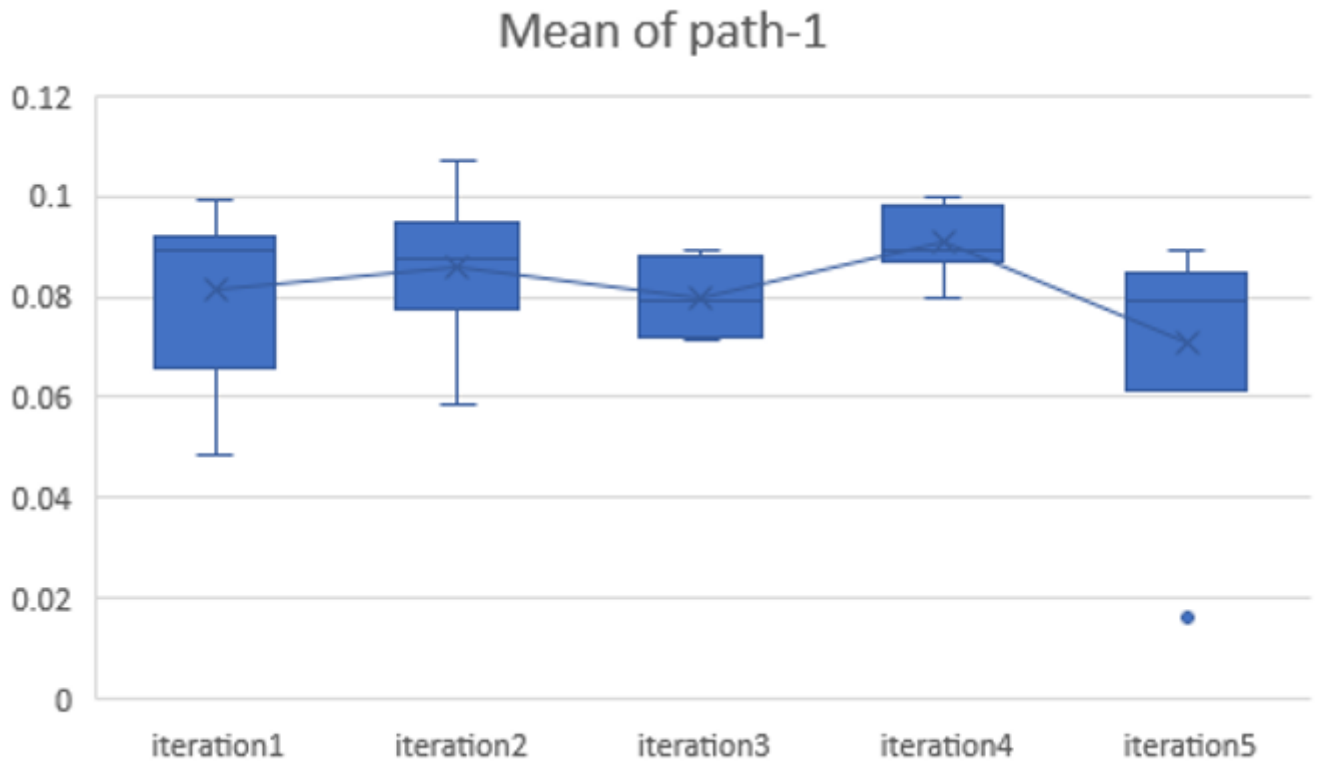

Figure 9

average error of multiple iterations of path-1

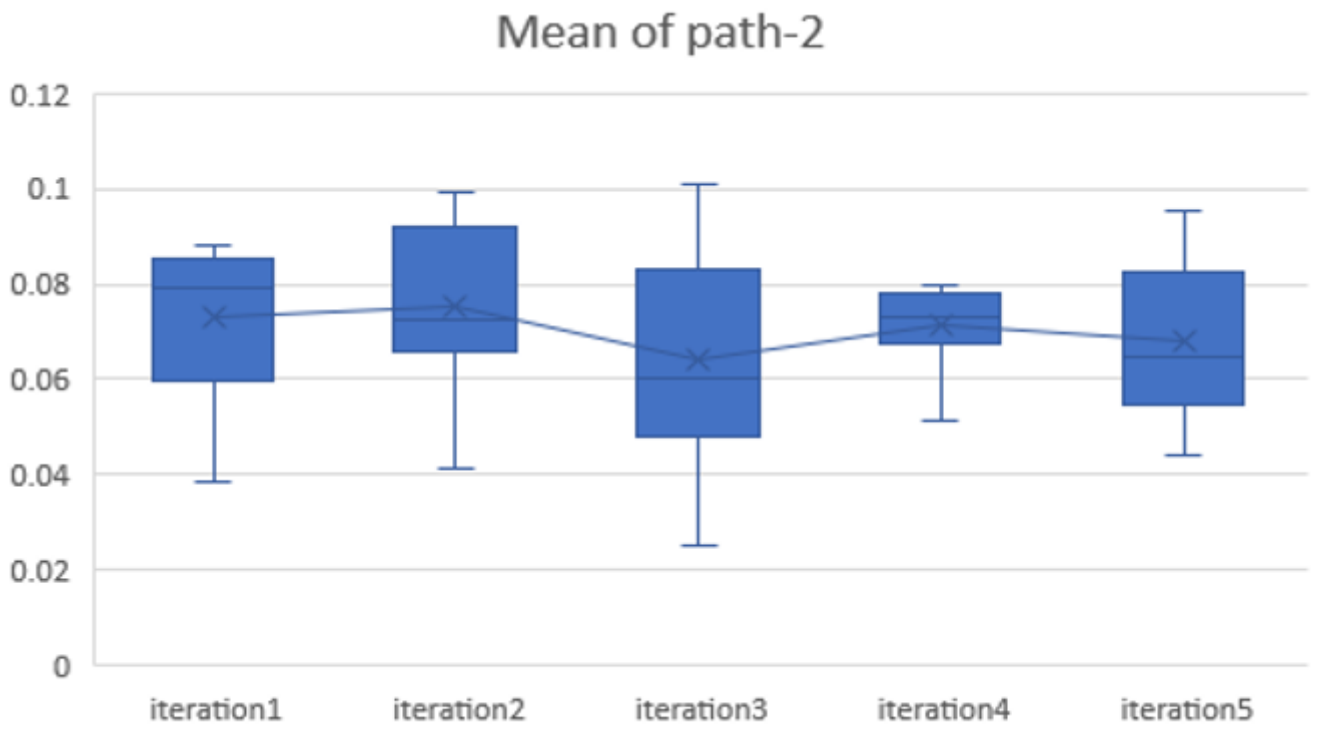

Figure 10

Figure is shown the average error of multiple iterations of path-2.