Real-time indoor tracking for augmented reality using computer vision technique

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Article Info

ABSTRACT

In recent times, there has been an increase in the stability and integration of augmented reality (AR) technology in everyday applications. AR relies on tracking techniques to capture the characteristics of the surrounding environment. Tracking falls into two categories: outdoor and indoor. While outdoor tracking predominantly relies on the global positioning system (GPS), it is performance indoors is hindered by imprecise GPS signals. Indoor tracking offers a solution for navigating complex indoor environments. This paper introduces an indoor tracking system that combines smartphone sensor data and computer vision using the oriented features from accelerated and segments test and rotated binary robust independent elementary features (ORB) algorithm for feature extraction, along with brute force match (BFM) and k-nearest neighbor (KNN) for matching. This approach outperforms previous systems, offering efficient navigation without relying on pre-existing maps. The system uses the A* algorithm to find the shortest path and cloud computing for data storage. Experimental results demonstrate an impressive 99% average accuracy within a 7-10 cm error range, even in scenarios with varying distances. Moreover, all users successfully reached their destinations during the experiments. This innovative model presents a promising advancement in indoor tracking, enhancing the accuracy and effectiveness of navigation in complex indoor spaces.

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1. INTRODUCTION

Augmented reality (AR) is a technology that augments the real physical world with 2D or 3D computer-generated virtual objects, allowing users to interact with them via their mobile device screens in real-time. AR superimposes virtual content, such as images, sound effects, or text, onto the physical world, resulting in a more efficient display of location-based information [1]. By overlaying digital information onto real-world objects or scenes, AR creates an immersive and interactive experience for users. AR has the potential to revolutionize indoor tracking by providing accurate and real-time tracking of indoor objects and people. AR can track indoor objects and people using sensors, cameras, and algorithms. AR-based indoor tracking technologies have been used in various applications, such as indoor navigation, location-based advertising, and gaming. AR-based indoor tracking technologies offer severals advantages, such as low cost, easy deployment, and high accuracy. In the realm of smartphones, AR tracking techniques can be broadly classified into two main categories: marker-based tracking and markerless tracking [2].

Marker-based AR uses visual markers placed in the real environment to determine the position and orientation of virtual objects. These markers are usually simple black-and-white patterns or symbols with high contrast that can be easily recognized by the AR system. When the device's camera detects these markers, it can track their position in 3D space and superimpose virtual content on top of them [3]. Markerless AR, also known as location-based AR or simultaneous localization and mapping (SLAM), doesn't require predefined markers for tracking. Instead, it uses computer vision algorithms and sensors (such as cameras, gyroscopes, accelerometers) to analyze the real-world environment and create a digital map of the surroundings in real time. By identifying features in the environment, such as corners, edges, or distinct objects, the AR system can track the device's position and orientation relative to the mapped environment. This allows virtual content to be placed and anchored in the real world accurately, without predefined markers [4].

Tracking involves recording the location details through methods such as periodic readings based on time intervals, distance traveled, or changes in direction beyond a certain angle, or a combination of these factors. Tracking applications help users determine their location and assist them in navigating to their desired destinations [5]. There are two categories of tracking: outdoor tracking and indoor tracking. Currently, handheld devices have achieved stability in outdoor tracking. Outdoor tracking uses global positioning system (GPS) technology; it has become an essential component in navigation applications, such as road vehicles, boats, and people on the streets. GPS relies on satellite signals for positioning and performs well under clear sky conditions. However, GPS satellite signals are not accurately detectable for indoor navigation systems. In outdoor tracking applications, GPS is commonly used, and it requires the navigation device to receive signals from a specific number of satellites. To achieve high-accuracy positioning, a minimum of four satellites is necessary. Additionally, the signal strength between the device and the satellites is crucial, which means that the device must be outdoors to ensure optimal signal reception [6]. Tracking indoor locations has long been a challenge due to the limitations of traditional GPS systems. GPS satellite signals are not sufficiently accurate for determining the precise positions of individuals inside buildings [7].

In recent years, there has been a notable rise in the utilization of AR technology for indoor tracking purposes. This technology has been applied in a variety of settings, including museums, airports, and shopping malls. AR-based indoor tracking technologies provide users with an interactive and immersive experience, allowing them to navigate through complex indoor environments with ease. To find solutions to the indoor tracking problem, researchers have developed alternative systems for GPS. The majority of indoor navigation systems employ a combination of technologies, such as Bluetooth beacons and near-field communication (NFC), Wi-Fi fingerprinting, ZigBee, radio-frequency identification (RFID), ultra-wideband (UWB), and infrared [8]. In today's era, smartphones are equipped with high-resolution cameras, powerful processors, and a multitude of advanced sensors. These sensors include GPS for location tracking, wireless communications for connectivity, accelerometers for motion detection, and magnetometers for orientation sensing [9].

In this paper, we present an overview of the state-of-the-art in indoor tracking technologies, focusing on the use of AR for indoor tracking. We also discuss the advantages and limitations of AR-based indoor tracking technologies and the challenges that need to be addressed. Finally, we propose our indoor tracking approach using AR, supporting a real-time system for indoor tracking facilitate navigation in complex and crowded environments. Our approach uses smartphones as a solution to overcome the limitations of GPS satellite signals, calculating the destination through the shortest path. Also, it integrates with an indoor tracking system to help users reach their destinations more clearly and effectively.

We have solved the indoor tracking problem by applying a set of steps. Firstly, we created a three-dimensional map of the College of Computer and Artificial Intelligence in Benha, Egypt, and stored the locations and related feature vectors in a database. Secondly, we used the oriented features from accelerated and segments test and rotated binary robust independent elementary features (ORB) algorithm to extract features from scanned images and create feature vectors. Also, the coordinate (x, y, z) for the related position is detected using acceleration sensors and gyroscope sensors. We then used the brute force match (BFM) and k-nearest neighbor (KNN) matching algorithms to identify the current location, and the A* pathfinding algorithm to produce the most optimal and accurate path within the shortest time. The path is drawn using three-dimensional AR arrows. Finally, we tested the proposed algorithm on a smartphone to obtain tracking accuracy. The main contributions of our proposed work can be summarized as follows:
- We have developed real-time systems for indoor building tracking to facilitate navigation in complex and crowded environments based on smartphones.
- We employed affordable hardware devices compared to the one introduced in the previous study for indoor tracking in multiple-floor scenarios [10].
- We proposed a novel hybrid system integrating the features of smartphone sensor reading and computer vision technologies by ORB, BFM, KNN, and A*, which resulted in high accuracy in reaching destinations in a more effective way than previous systems.
- We conducted experiments without the need for a 2D or 3D predefined map of indoor buildings.

- We evaluated the proposed system using different smartphones with varying specifications and obtained computational time efficiency.
- The results demonstrated that the proposed system showcased impressive performance, characterized by a low error rate. Additionally, the proposed system exhibited swift computational time, making it well-suited for running on smartphones with a high frame rate.
- Regardless of the path length, the system demonstrated an accuracy of approximately 99%.

The article follows the following structure: introduction section in section 1. Section 2 describe an overview of the existing state-of-the-art indoor tracking systems is provided. Section 3 details the proposed system, explaining it is design and functionality. Section 4 the experimental results and evaluation of the proposed system are presented and analyzed. Lastly, conclusion and future work describes in section 5.

2.   RELATED WORK

Indoor tracking remains a significant challenge in AR applications. Marker-based navigation has been the main focus in indoor tracking, image recognition-based navigation is becoming increasingly popular. Huang *et al.* [11] proposed an approach that involves a server, administrator, and user. The server stores the indoor map database created by the administrator, who uses the KNN algorithm to train their module with feature points. The you only look once version three (YOLO v3) object detection method is used to extract real-time features from the tracking process. These extracted features are then compared with the training features to determine the current location. To find the shortest path from the starting point to the destination, we employ the A* algorithm [12].

NFC-based indoor navigation systems are also gaining popularity [13]. In these systems, a smartphone with an integrated NFC component is used to connect to a uniform resource locator (URL) tag, which sends map information to the device [14]. After converting the map data into a link-node model, we employ Dijkstra's shortest path algorithm to calculate the optimal route. This algorithm helps us determine the most efficient path between the nodes in the converted map data. Takahashi and Kondo [15] devised an advanced indoor navigation system centered around the utilization of beacons. These beacons operate by transmitting signals to smartphones via Bluetooth low energy (BLE), as elaborated in reference [16]. The core principle of their system hinges on measuring the signal strength of these transmissions to accurately gauge the distance between a mobile device and a beacon. This distance information is subsequently harnessed to create a comprehensive database that can be used to correlate signal intensity at an unknown location, ultimately enabling precise determination of the device's current position within the indoor environment.

Zegeye *et al.* [17] introduced an indoor localization system based on WiFi-received signal strength (RSS) fingerprinting. This approach does not rely on specific features or beacons but instead represents the indoor environment using a grid-based system [18]. The WiFi infrastructure of the building was used for the experiments. During the offline phase, RSS values are sampled to create a radio map of the designated study area. This radio map is constructed by scanning and collecting information about accessible access points at each sampling location, including their corresponding RSS values. In the online phase, the localization algorithm utilizes this radio map to estimate the position of the mobile device. In a standalone architecture, the response time of this algorithm is approximately 220 ms.

Xu *et al.* [19] developed a pedestrian tracking algorithm to enhance a WiFi-grid-based indoor model. They partitioned the indoor tracking space into grid cells of predetermined size and semantics. The pedestrian algorithm predicts the probability of the device's location within these cells by considering indoor and magnetometer measurements. A grid filter, specifically a Bayesian discrete filter, is employed to probabilistically estimate the target's position based on sensor measurements. The tracking system utilizes a Markov chain model as part of its operation [20], to determine the device's position over time. Chu *et al.* [21] designed an indoor navigation system called waypoint-based indoor navigation (WPIN) that utilizes BLE, beacons deployed at indoor building intersections. Users are provided with 2D images indicating the directions (e.g., turning left, right, and straight) along the path to their destination.

Augmented reality based indoor navigation (ARBIN) [22], is an AR-based navigation system that builds upon the previous work of WPIN. It leverages Google ARCore to display navigation directions directly on the screen, overlaying them onto the real-world environment. This approach addresses the limitations of traditional 2D navigation maps, which can lead to mental strain and confusion for users as they try to relate the map to their surroundings. By integrating AR, ARBIN provides a more intuitive and seamless navigation experience by visually integrating directions with the user's real-world environment. One of the limitations of indoor tracking systems is their dependence on pre-existing infrastructure or fixed beacons, which can limit their applicability in new or temporary environments.

Upadhyay *et al.* [23] introduce a novel approach to indoor visual positioning utilizing a single camera. This method employs intelligent visual feature selection and real-time matching, leveraging a monocular camera to capture and transform video route information into sparse and invariant point-based

speeded-up robust features (SURF) features. The building routes are partitioned into a connected graph, reducing the need for real-time feature search and match data. Additionally, a KNN match is employed with existing databases to enhance the confidence of matched paths in subsequent frames. Empirical results demonstrate a reliable positioning accuracy of approximately 2 meters, even in varying lighting conditions.

Indoor tracking systems can be implemented through various technologies such as markers, communication, and image detection. Marker-based systems exhibit stability when the marker image is appropriately prepared but become ineffective when the mobile camera deviates from the marker. Communication-based systems are widely applicable and computationally efficient, but may not be suitable for applications that require highly accurate tracking. Image-detection technology-based systems can achieve high positioning accuracy and view angle output, but are computationally intensive and rely on preloaded maps, limiting their applicability in low-light conditions. Table 1 compares the common features of indoor position systems. Table 1 compares the previous indoor tracking systems based on the methodology used, the platform utilized, the size of the area covered, and the accuracy achieved through testing within the building.

Table 1. Comparing the common characteristics of indoor positioning systems

Study	Year	Methodology	Platform	Area size	Accuracy %	Limitations
Huey et al. [8]	2011	USB webcams+ ARtoolkit+ Marker+ Laptop+Open GL	laptops	medium	NA	The navigation is very difficult due to a large number of hardware, high cost and complexity, implementation in a very small area, and the inability to accurately track people in low-light environments.
Malek et al.[10]	2017	Marker+ARtoolkit +Open GL+USB webcams+Raspberry pi	glasses	medium	~100	Navigation is difficult due to high cost, complexity, implementation in a small area, and inaccurate tracking of people in low-light environment
Takahashi et al.[15]	2015	iBeacons+local server	smartphone	Small	NA	The iBeacon system is costly and has an average error of 80 cm, which, coupled with its implementation in a small area, can result in signal interference or weak signal strength, leading to inaccuracies in location tracking.
Chu et al. [21]	2019	2D pictures indicating+Lbeacons +positioning module +navigation module	smartphone	large	92.5	The LBeacon system is costly, and its beacons are based on Bluetooth signals that have a range of 3-5 meters. This range, coupled with signal interference or weak signal strength, can result in inaccuracies in location tracking.
Huang et al. [22]	2020	Positioning module +Lbeacons +navigation module+3D arrow	smartphone	large	92.5	The LBeacon system is costly, and its beacons are based on Bluetooth signals that have a range of 3-5 meters. This range, coupled with signal interference or weak signal strength, can result in inaccuracies in location tracking.
Ozdenizci et al. [14]	2015	Link node model+ NFC tags+Dijkstra's algorithm+map server	smartphone	medium	~100	The cost of NFC tags is low, but NFC offers a slow connection, and not all smartphones contain an NFC reader. Additionally, communication over a distance of only 4 cm is possible.
Zegeye et al. [17]	2016	+Radio map+WiFi (access points) +localization algorithm+server	smartphone	medium	80 %	Access points are costly, non-interactive with the user, and may produce inaccurate signals in areas with many walls or with signal interference or weak signal strength, which can lead to inaccuracies in location tracking.
Xu et al. [19]	2018	Kalman filter+ WiFi grid based +Markov chain model +pedestrian tracking algorithm	smartphone	large	92%	Access points are costly and not interactive with users. Additionally, signals can be inaccurate in areas with many walls, and signal interference or weak signal strength can lead to inaccuracies in location tracking.
Wu et al. [24]	2022	2D map+Yolo v3 algorithm+KNN algorithm+A* algorithm	smartphone	medium	NA	Marker-based systems use 2D maps and are not interactive with the live environment view. Moreover, they may not be able to accurately track people in low-light environments.
Upadhyay and Balakrishnan [23]	2022	SURF with KNN	smartphone	medium	2 m error bound	Point-feature matching lacks accuracy, and image matching struggles to produce reliable results in diverse lighting conditions and for localization purposes.
Guo et al. [25]	2022	Annealing evolutionary algorithm (AEA) +Fuzzy C-means clustering (FCM) algorithm+UBW positioning	smartphone	medium	90%	Implementing the UWB real-time locating system (RTLS) can be a costly technical solution, as it necessitates the installation of UWB tracking devices (trackers) and requires smartphones to be equipped with UWB sensors.

3.   MATERIAL AND METHODS

AR-based indoor tracking systems offer a significant advantage by delivering highly precise location information, even within intricate indoor settings. This capability stems from their capacity to amalgamate various data sources, including camera images and sensor measurements, resulting in a more resilient and reliable tracking solution. This amalgamation of data sources empowers these systems to excel in complex indoor environments where traditional tracking methods may struggle. The main objectives of our paper are as follows:

− Create a real-time indoor tracking system based on smartphones to facilitate navigation in complex and crowded environments.
− Provides precise and efficient indoor navigation, directing individuals to their destinations via the shortest path in diverse large indoor spaces, including shopping malls, hospitals, and office buildings, ensuring accessibility under multiple conditions.
− Integrate AR with indoor tracking to develop a real-time tracking system that helps users reach their destinations accurately and effectively.
− Eliminate the need to design 2D or 3D predefined maps for indoor buildings using difficult-to-use programs like AutoCAD, saving time and costs.

The proposed indoor navigation system consists of three modules: creating a map, cloud database, and reading the map. The architecture of the proposed indoor system is provided in Figure 1. The indoor navigation system is built upon a combination of technologies, such as placenote Software Development Kit (SDK), the Unity3D, and cloud computing, to ensure its robust functionality and performance [26]. Xcode integrated development environment (IDE), and various computer vision algorithms such as ORB, BFM, KNN, and A* algorithms [27].

Figure 1 depicts the proposed system architecture, comprising three main components: a create map module, a cloud database module, and a read map module. The create map module involves generating the three-dimensional map and saving the location and relevant feature vectors of the scanned environment in the database. The cloud database module is utilized for storing coordinate locations (Px, Py, Pz) and feature vectors of all images in the map, enabling real-time tracking. Finally, the read map module applies the ORB algorithm to extract features from the scanned images and produce feature vectors. The BFM and KNN matching algorithms are employed to identify the current location. The A* pathfinding algorithm is known for providing the most optimal and accurate path within the shortest possible time. The location changes are detected by acceleration sensors and gyroscope sensors. The path is illustrated using three-dimensional AR arrows.
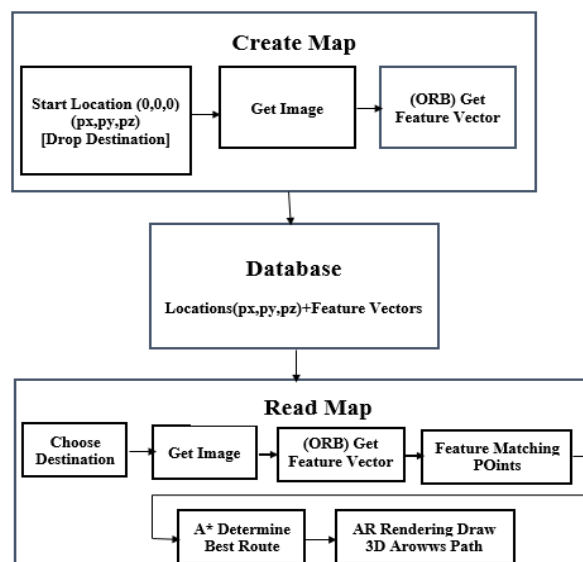
Figure 1. The architecture of the proposed indoor model

3.1. Create map module

Previous indoor tracking systems have faced challenges in terms of cost and effort required to create three-dimensional maps of indoor environments. However, in our system, a user administrator can easily

scan any space and convert it into a 3D map using the placenote SDK. Each key point in the mapped space is assigned specific position coordinates (Px, Py, Pz). In the coordinate system used, the X-coordinate denotes the east-west direction, while the Y-coordinate represents the north-south direction, and the optional Z coordinate represents the altitude or depth. By simply clicking on the screen, users can create a map by placing 3D keypoints along the walkable pathway, as depicted in Figure 2.
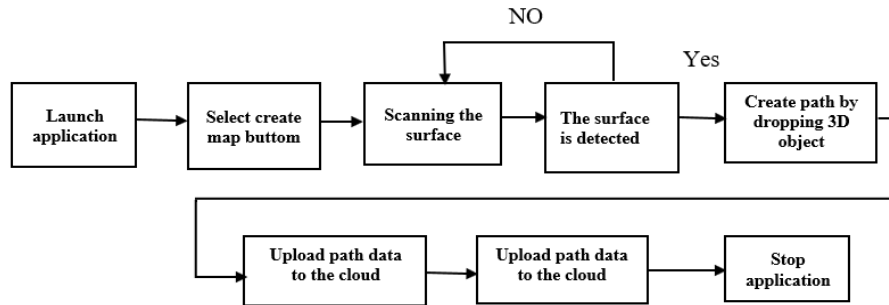

Figure 2. Flowchart of creating and saving the map

To create a map of any building, the original location is set to (0,0,0) at the beginning of the mapping process, which is then updated based on smartphone sensor readings such as acceleration and gyroscope sensors. During the scanning process, the user drops key points and assigns them destinations and names. The ORB algorithm is employed for feature extraction from images. This algorithm offers various advantages, such as being invariant to rotation and scale, resistant to noise, providing high accuracy results, being user-friendly, and consuming low memory. Moreover, it has a low computational cost, making it well-suited for real-time processing on mobile devices [28]. The ORB algorithm can be divided into two stages: features from accelerated and segments test (FAST) algorithm and binary robust independent elementary features (BRIEF) descriptor.

3.1.1. Features from accelerated and segments test algorithm

The key point detection process begins with the utilization of the FAST algorithm, an accelerated segment-testing algorithm. By comparing the intensity of a pixel with its surrounding 9-pixel circle using a threshold, FAST identifies significant differences in intensity that indicate corner points [29]. These corner points are determined based on the calculated difference, as shown in (1). Subsequently, the Harris corner algorithm is employed to compute the Harris score for each corner point, considering the intensity difference in the vicinity of the corner point [30]. The resulting corner points are then sorted to select the most prominent ones. To address the absence of multiscale features in FAST, a multiscale pyramid of images is employed, enabling scale invariance for the detected points. Moreover, intensity-weighted centroids are calculated, and directions are incorporated into the detected points to compensate for the lack of directional components in FAST.

$$S_{p \to x} = \begin{cases} darker, & I_{p \to x} \leq I_p - T \\ similar, & I_p - T < I_{p \to x} < I_p + T \\ brighter, & I_p + T \leq I_{p \to x} \end{cases} \qquad (1)$$

Where $S_{p \to x}$ is represent the result obtained between points p and x, where x is a pixel selected from a circular ring of nine pixels surrounding point p, I_p is the intensity of pixel p, $I_{p \to x}$ is represents the intensity between points p and x, and T is refers to the fast threshold used in the calculation.

3.1.2. Binary robust independent elementary features descriptor

A BRIEF [31], is a binary string vector containing only 0 and 1 s. To prepare the image for BRIEF descriptor computation, it was first smoothed using a Gaussian kernel to make it less susceptible to BRIEF noise. Once the keypoints have been detected using the FAST algorithm, the BRIEF descriptor is applied to generate descriptors for these detected keypoints [32]. To generate the binary descriptor vector, random pixels were extracted from a 31×31 patch around the detected keypoint, and a binary value of 1 or 0 was assigned based on whether the intensity value of point y is greater than that of point x. The ORB algorithm

addresses the rotation invariance limitation of the BRIEF descriptor by utilizing the control BRIEF to calculate the orientation of the detected keypoints and integrate it into the descriptor vector. Figure 3 shows the process of creating a map by creating a set of different paths, whether short, medium, or long.

Figure 3. Creating the map

Once the user finishes scanning the indoor location, they save the map. The map creation process involves saving locations (Px, Py, Pz) and feature vectors in the database. In order to create a high-quality 3D map of a building, it is necessary for the user to capture a detailed environment surrounding the location where the map will be frequently initialized. This involves taking several steps around each object and recording it from various perspectives, including moving the device up and down while keeping the center of the filmed model in focus. The process of map creation, as depicted in Figure 3, involves generating a variety of paths of different lengths, whether they are short, medium, or long. Algorithm 1 has been developed specifically for mapping the environment.

Algorithm 1. Create map
Input: Realtime live video from the user's camera.
Output: 3D map of the building and coordinates (Px,Py,Pz) and feature vectors for all images in the map.
1: Set origin location to (0, 0, 0)
2: Initialize variables for current location (curLocation) as origin
3: Initialize empty database to store locations and feature vectors
4: Repeat the following steps until the map creation is complete:
    5: Capture an image using the camera phone
    6: Extract feature vector using ORB (oriented FAST and rotated BRIEF) algorithm
    7: Add the current location (curLocation) and the corresponding feature vector to the database
    8: Update the current location (curLocation) based on acceleration and gyroscope sensors
    9: If user has set a destination:
    10: Calculate the shortest path from the current location to the destination using a suitable algorithm (e.g., Dijkstra's algorithm, A* algorithm)
    11: Display the navigation instructions to the user
12: Save the locations and feature vectors in the database for future reference

3.2. Cloud database module

After creating the 3D model of any building, the coordinate locations (Px, Py, Pz) and feature vectors are stored in the cloud database. Figure 4 shows an example of a 3D map of a building. Each feature vector is related to specific position coordinates (Px, Py, Pz) and is stored in the cloud database.

Figure 4. Scanned map using placenote

3.3. Read map module

The main objective of this step is to guide users inside large buildings by providing a real-time path from their current location to their desired destination. When the user launches the application and opens the

phone camera, they must choose their desired destination. To determine the current position, the ORB algorithm is used to extract feature vectors from the scanned image. The extracted feature vector is then matched with the stored feature vectors in the cloud database to identify the current position.

We use BFM [33], with KNN is a technique used for feature matching in computer vision and image processing applications, as shown in (2). Feature matching involves finding corresponding points or regions between multiple images, which is crucial for tasks such as object recognition, image alignment, and 3D reconstruction. BFM is a simple yet effective approach that exhaustively compares each feature descriptor in one image with all descriptors in another image. It computes the similarity or distance between the descriptors and selects the best matches based on a predefined threshold. However, BFM can be computationally expensive, especially when dealing with large-scale datasets or high-dimensional feature spaces. To address this issue, the K-NN algorithm is integrated with BFM. KNN is a classification algorithm that finds the KNN to a given data point based on a similarity measure. In the context of feature matching, K-NN helps to filter out potential matches by considering only the top K candidates with the closest feature descriptors. By combining BFM with K-NN [34], the matching process becomes more efficient and robust. It reduces the number of false matches and improves the accuracy of feature correspondence. The K parameter can be adjusted to control the trade-off between computational efficiency and matching accuracy. A smaller K value leads to faster computations but may result in more false matches, while a larger K value provides better matching accuracy at the cost of increased computation time.

$$match = \begin{cases} good\ match, & d_1 / d_2 < R \\ incorrect\ match, & d_1 / d_2 > R \end{cases} \tag{2}$$

Where $\boldsymbol{match}$ is refers to the outcome of the feature comparison between two descriptors, $\boldsymbol{d_1}$ is represents the distance between a descriptor and its closest neighboring descriptor, $\boldsymbol{d_2}$ is represents the distance between the descriptor and its second-nearest neighbor, and $\boldsymbol{R}$ is Lowe's ratio.

After the matching process is completed and the current position is identified, the A* pathfinding algorithm is used to generate the optimal path in real time. The accuracy of path rendering relies on the precision of establishing the positioning. While creating a 3D model of a route is straightforward, ensuring that the virtual environment accurately represents the physical world and incorporates obstacles like doors, walls, furniture, and other significant objects can be a more intricate process. As ARKit progresses, rendering performance will enhance, allowing AR content to be tailored to specific requirements. In Figure 5, the indoor navigation application demonstrates the route through the utilization of AR arrows in a three-dimensional representation, effectively guiding users to their desired destinations. Algorithm 2 is shown the steps and proccess of read map algorithm.

Algorithm 2. Read map
Input: Live streaming video from the user's camera, destination point D, and rendering of 3D arrows.
Output: Navigational route or path.
1: Choose the destination (D)
2: Repeat the following steps until the user reaches the destination:
   3: Capture an image using the camera phone
   4: Extract feature vector using ORB (oriented FAST and rotated BRIEF) algorithm
   5: Identify the current location (S) using the Bellman-Ford-Moore algorithm with k-nearest neighbors (BFM with KNN)
   6: Use the A* algorithm to find the shortest path from the current location (S) to the destination (D)
   7: Identify the path direction from S to D
   8: Display 3D arrows or visual cues indicating the direction of the path to the user
   9: If the user reaches the destination, end the algorithm
10: Exit the algorithm

Figure 5. Navigation and rendering using 3D AR arrows

4.   RESULTS AND DISCUSSION

We developed our tracking system by combining smartphone sensor readings and computer vision technologies. The system extracts features using the ORB algorithm and matches them with BFM and KNN. Additionally, the system utilizes the A* algorithm to find the shortest path and cloud computing for database storage. This system is designed to operate on smartphones.

The experiments were carried out in the specified sequence. Initially, we evaluated the tracking application on a smartphone running iOS 15.2, equipped with 64 GB of storage capacity. Subsequently, we conducted the experiments on the second and third floors of the College of Computer and Artificial Intelligence located in Benha, Egypt. Each floor in the building measured approximately 50×20 m in size and comprised six corridors of varying lengths, ranging from 20 to 100 m. This resulted in a total tracking volume of approximately 2,000 m².

There are certain limitations to the existing method. The accuracy of the indoor tracking system depends on the quality of the sensor data collected, which can be affected by the sensor placement, environmental conditions, and the type of sensor used. The proposed indoor tracking system assumes that the building structure remains static and does not change during the tracking process. The effectiveness of the computer vision algorithms used in the system is influenced by factors such as lighting conditions and occlusions. These factors can lead to inaccuracies in tracking, and in some cases, such as in very dark lighting, the system may fail altogether. The performance of the proposed system is limited by the processing power and memory of the device used.

Regarding the limitations of our work, we acknowledge the following: while creating the map for the indoor environment, there are some limitations. The lighting must be good, and the person who creates the map must move slowly so that the ORB algorithm can capture the features accurately. When reading the map, the user must choose their destination first. To reduce the search for real-time features and data matching, the ORB and BFM with KNN algorithms work initially only to determine the user's current location. Then, the A* algorithm works to determine the shortest path. The readings of the accelerometer and gyroscope sensors are relied upon to calculate the change of locations, which makes the calculations simple on the smartphone and allows the user to move at a normal speed. The gyroscope sensors can only be used to get the change occurring in the x-axis and y-axis. However, we input the z-axis manually to determine the level of the floor in multi-floor buildings. We use placenote technology to build the 3-dimensional map, which works on smartphones.

To assess the performance of the tracking system, several experiments were carried out within a building at different distances. The tracking application was tested under varying lighting conditions, ranging from bright to nearly complete darkness, and the results demonstrated its excellent functionality. As the model relies on image processing to determine the starting location, sensor readings from the smartphone were utilized throughout the path towards the destination. It is worth noting that a study involving ten participants was conducted to evaluate the proposed technique. Each participant was assigned a random path, either short or long, from the stored paths. The outcomes revealed that all participants were able to successfully navigate to their destinations in all trial scenarios.

To ensure the accuracy of the results, we conducted five trials with five participants, testing the technique on a short path spanning approximately 20 meters. The study was performed by 5 participants: 3 males and 2 females. Their age ranged from 18 years to 40 been violated, but when it was violated, the Greenhouse-Geisser corrected tests were reported. For the five trials: there was not statically significant effect between the trials of short distances Fp=1.462, p=.282 as shown in Figure 6. We performed a factorial repeated measures ANOVA analysis for each of the five trials. This analysis has been used to observe the error in distance between the trials. There was not significant difference in all trials. Employing a Bonferroni post hoc analysis on the results of the five trials, there was not significant effect between all of the five post hoc analyses.

The average error of multiple iterations of Path-1, where participants utilized the proposed system with the smartphone application and selected the same destination, is depicted in Figure 6. The path consisted of six known locations, and their values were stored in the cloud database. While navigating to the destination point, the values of the locations were read in real-time and compared with the previously known values stored in the database, which helped create the three-dimensional map. The analysis showed that the proposed indoor tracking technique, which is based on ORB, BRIEF descriptor, BFM, KNN, A* algorithm, and smartphone reading sensors, achieved a meter-level location accuracy of 99.575%, the average error of multiple iterations was found to be 8.5 cm, with a standard deviation of 1.12 cm along the pathway.

To ensure the accuracy of the results, we conducted five trials with five participants, testing the technique on a long path spanning approximately 80 meters. The study was performed by 5 participants 1 males and 4 females. Their age ranged from 18 years to 40 and the Greenhouse–Geisser corrected tests were reported. For the five trials: there was not statically significant effect between the trials of long distances Fp=.864, p=.396 as shown in Figure 7. We performed a factorial repeated measures ANOVA analysis for

each of the five trials. This analysis has been used to observe the error in distance between the trials. There was not significant difference in all trials. Employing a Bonferroni post hoc analysis on the results of the five trials, there was not significant effect between all of the five post hoc analyses.
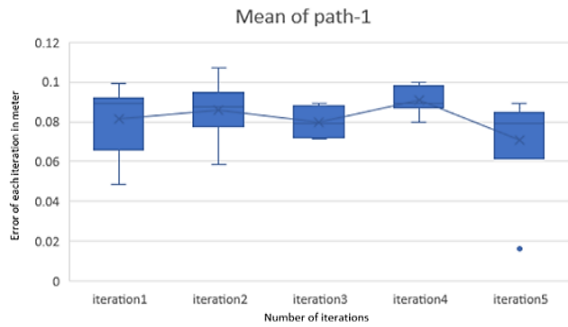

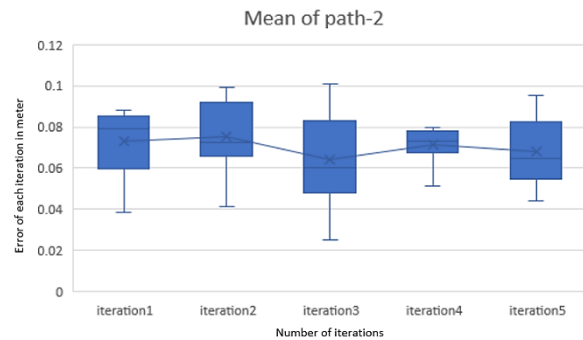Figure 6. Average error of multiple iterations of path-1

Figure 7. Average error of multiple iterations of path-2

We tested the technique combined for short and long paths and repeated this process ten trials with ten participants to ensure the accuracy of the results. The study was performed by 10 participants: 4 males and 6 females. Their age ranged from 18 years to 40 been violated, but when it was violated, the Greenhouse-Geisser corrected tests were reported. For the ten trials: there was not statically significant effect between the trials of short distances Fp=.719, p=.464 We performed a factorial repeated measures ANOVA analysis for each of the ten trials. This analysis has been used to observe the error in distance between the trials. There was not significant difference in all trials. Employing a Bonferroni post hoc analysis on the results of the ten trials, there was not significant effect between all of the five post hoc analysis.

The statistics from the study showed that AR-based indoor tracking provides high accuracy and precision, with an average error rate of only 7-10 cm. Furthermore, the study revealed that AR-based tracking can significantly improve indoor navigation and wayfinding, especially in complex indoor environments. The findings suggest that the average error did not change across multiple trials, indicating that the technology is efficient and stable. The constant error rate throughout the trials further supports the consistency and reliability of the indoor tracking system.

Since there was no fixed database available for comparison, we conducted a comparative analysis of our results with those of other researchers who had addressed the same indoor tracking problem using markerless technology and a similar space size. Table 2 displays the outcomes of this comparison. Upon examining the results presented in Table 2, we observed a consistent average error rate that did not exceed 10 cm. This consistency was evident regardless of the length of the path, be it short or long, and there was no exponential increase in the average error rate. Our proposed indoor tracking technique exhibits an accuracy ratio of approximately 99% across paths of varying lengths, highlighting the robustness of the technology for indoor building applications.

Table 2. Comparative results between the proposed system and previous systems

Study	Year	Build Depend on	Error bound (m)	Area size (m^2)	Floor type
Takahashi and Kondo [15]	2015	iBeacons+local server	0.8	45	single
Zegeye et al. [17]	2016	WiFi (access points)	5	173	single
Xu et al. [19]	2018	WiFi grid base	3.5	1,200	single
Chu et al. [21]	2019	Lbeacons	3-5	2,000	multiple
Huang et al. [22]	2020	Lbeacons	3-5	1,800	multiple
Nguyen et al. [35]	2021	WIFI (access points)+BLE beacons	2	2,400	multiple
Li et al. [36]	2020	UWB modules+neural network approach	1	400	single
Cankiri et al. [37]	2020	WLAN+RFID+SLAM+IMU	-	-	single
Horno et al. [38]	2021	Wi-Fi+magnetic field+the particle filter algorithm and dead-reckoning (PDR)	0.6	183.68	single
Booranawong et al. [39]	2022	RSSI	0.97	22	single
Shi et al. [40]	2022	Gait detection algorithm+complementary filtering algorithm	0.52	450	single
The proposed prototype	2023	ORB+KNN+BFM+A* +phone sensors	0.07-0.1	2,000	multiple

Table 2 compares the proposed system with other previous systems in terms of methodology, error bound values, area size, and number of floors within the building. Among the systems listed in [21], [22], [35], work on multiple floors, while the others work on a single floor. We can note from the table that most systems tend to be applied on a single floor due to the difficulty of locating the position inside the building. This difficulty comes from overlapping signals at the same point vertically on different floors. We can also note from the table that all systems' methodologies depend on signal intensity, such as beacons and WiFi, or depend on computer vision techniques in use.

The iBeacons method is used in some systems by measuring the intensity of signals' strength of predefined positions and comparing them with estimated positions. The method gave decent results with an error bound value of 80 cm. In [21], [22], they used directional Bluetooth beacons method named Lbeacon that also depends on the intensity of signal strength, but it applied to a large area size and multiple floors. The results, when applied to multiple floors, are acceptable with an error bound value of 3-5 m. In [17], [19], they utilized the pre-existing WiFi infrastructure of the building. The RSS values of access points at each sampling location are used to create a radio map of the study area. The error bound value obtained was 3-5 m. According to Nguyen et al. [35], Wi-Fi access points are merged with Bluetooth low energy (BLE) beacons in this system to be applied on multiple floors with enhanced results compared to previous systems. The error bound value obtained was 2 m. According to Li et al. [36], the combined approach of UWB modules and a neural network approach is used in this method. The neural network is used for identifying a user in a specific zone. The method gave better results compared to the previous system applied on a single floor with an error bound value of 1m. Cankiri et al. [37] used different technologies, including wireless local-area network (WLAN), RFID, inertial measurement unit (IMU), and SLAM. The method gave better results with an average error rate of 0.78%. Horno et al. [38] integrated state-of-the-art models of the Wi-Fi interface with the pedestrian dead-reckoning (PDR) approach and the data gathering from all three sensors, the accelerometer, gyroscope, and magnetometer of a smartphone. The best result was with an error bound value of 60 cm. According to Booranawong et al. [39], the real-time mobile target tracking system depended on the RSSI. The method did not improve results compared to the previous method, with an error bound value of 97 cm. According to Shi et al. [40], the gait detection matching algorithm was combined with the improved complementary filtering algorithm. The method, which used computer vision techniques, gave the best results compared to previous systems based on the intensity of signals strength, with an error bound value of 52 cm. The good results are obtained from methods that depend on computer vision techniques or integration between computer vision techniques and intensity signal strength techniques.

The proposed system was tested using a smartphone camera with 12 megapixels by ten participants on different path lengths in the faculty building. In each attempt, the participants tested the efficiency of the system, which uses the ORB algorithm for feature extraction and the BRIEF descriptor to generate detection features. Each descriptor has a specific coordinate (x, y, z) for the related position detected using acceleration and gyroscope sensors and stored in the cloud database. The BFM and KNN algorithms are then used for matching, followed by the A* algorithm to determine the shortest path. Table 2 shows that the proposed system outperforms all previously proposed systems with an error bound value of 7-10 cm.

5. CONCLUSION

In conclusion, our study introduces a cutting-edge real-time indoor navigation system powered by smartphones. Our main objectives include the rapid and cost-effectively creation of highly accurate building maps, outperforming previous systems in accuracy and real-time guidance. Leveraging AR, our system efficiently guides users along the shortest paths. We present a novel indoor tracking model, integrating environmental constraints and utilizing techniques such as the ORB algorithm, BFM, KNN, and A* to achieve superior accuracy. It enables seamless guidance from start to finish within indoor spaces and provides live visual arrows. Compared to previous systems, our system stands out with exceptional efficiency, reaching nearly 99 percent. The methodology was based on error bounds, area coverage, and the number of floors in the building. In our future work, we aim to develop a solution for navigating individuals in low-light environments. Additionally, we plan to explore the integration of machine learning or deep learning techniques into the model to enhance tracking performance by leveraging user behavior data.

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