

Virtual-Blind-Road Following-Based Wearable Navigation Device for Blind People

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Abstract—To help the blind people walk to the destination efficiently and safely in indoor environment, a novel wearable navigation device is presented in this paper. The locating, way-finding, route following, and obstacle avoiding modules are the essential components in a navigation system, while it remains a challenging task to consider obstacle avoiding during route following, as the indoor environment is complex, changeable, and possibly with dynamic objects. To address this issue, we propose a novel scheme which utilizes a dynamic subgoal selecting strategy to guide the users to the destination and help them bypass obstacles at the same time. This scheme serves as the key component of a complete navigation system deployed on a pair of wearable optical see-through glasses for the ease of use of blind people's daily walks. The proposed navigation device has been tested on a collection of individuals and proved to be effective on indoor navigation tasks. The sensors embedded are of low cost, small volume, and easy integration, making it possible for the glasses to be widely used as a wearable consumer device.

Index Terms—Obstacle avoiding, route following, virtual blind road, wearable navigation device.

I. INTRODUCTION

THE VISUALLY impaired people usually have difficulties in walking in an unfamiliar and complex place independently. To provide them an automatic navigation device with effective guidance on their move, three problems should be considered.

- 1) Where is the person? The device has to know where the person is located in order to make a correct decision for guiding the person. This refers to be the localization problem.
- 2) Where does the person want to go? In order to help the visually impaired person reach his destination, the device has to identify the destination. This is known as goal recognition.
- 3) How does the person get there? This includes way-finding, route following, and obstacle detecting.

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Way-finding is to plan a shortest path from the starting position to the destination, route following is to make sure the blind person follow the planned path, and obstacle detecting is to help him avoid obstacles.

So far, there are many navigation systems trying to solve the above problems, such as the low-cost white cane [1], guide dog [2], and electronic travel aids (ETAs) [3]. However, white cane is unable to find a globally shortest path [2] and provide the location information. Guide dog is incapable of detecting overhanging object, and needs costly training, which may be unaffordable to the visually impaired individuals [1], [2]. Most existing ETAs are only intended for obstacle detecting or/and feedback [4]–[9], and cannot provide way-finding and route following functions. Although some ETAs were designed with way-finding and route following functions, such as the cactus tree-based algorithm proposed in [10], obstacle (especially the dynamic obstacles) detecting and avoiding are ignored. A wearable indoor navigation system based on visual marker recognition and ultrasonic obstacle perception was introduced in [11], but the localization precision is not high enough for guiding the blind due to the error increase of the inertial measurement sensor, and the goal recognition scheme is less efficient on planning a global path. A successful navigation system for the blind is the visual simultaneous localization and mapping (SLAM) and point of interest (PoI)-graph-based indoor navigation system presented in [1] and [12]. However, the obstacle detection heavily relies on the white cane swaying, which is not efficient and portable.

This paper aims to develop an effective wearable navigation system which can locate the user, follow the virtual-blind-road and avoid obstacles at the same time, in order to provide automatic navigation for the visually impaired people. The main contribution of this paper is the proposal of a novel dynamic subgoal selecting-based virtual-blind-road following scheme which combines the obstacle avoiding algorithm [13] for guiding the blind people to follow the globally shortest virtual-blind-road without collision. This scheme can help the visually impaired people to avoid obstacles while following a path precisely to the destination, which realizes the automatic navigation for them. As the GPS-based blind navigation technology [14] cannot be used due to the severely degradation of GPS signal in indoor environment, the visual SLAM (e.g., oriented brief-SLAM (ORB-SLAM) [15], [16]) was adopted in this paper for the building of the virtual-blind-road and the localization. The whole system is deployed on a pair of wearable optical see-through (OST) glasses, which is able to give the visually impaired people visual hints and sound feedback.

The rest of this paper is organized as follows. Section II reviews the related works on the navigation for the visually impaired in indoor environment. The hardware configuration of the proposed navigation device is presented in Section III. Section IV describes the navigation scheme in detail. Section V shows some experimental results, and demonstrates the effectiveness of the proposed blind navigation system. Finally, some conclusions are drawn in Section VI.

II. RELATED WORK

Navigation for the blind in indoor environment should consider the problems of localization, way-finding, route following, and obstacle detecting. Many ETAs were reviewed in details [13], which utilize ultrasonic, laser scan, camera or multisensor fusion technology for obstacle detecting and/or avoiding. These ETAs can help the visually impaired avoid the obstacles, but they are unable to provide the location information, and do not have way-finding and route following functions. Thus, the related works on localization, way-finding, and route following for blind navigation in indoor environment are reviewed in this section.

A. Indoor Localization

Indoor localization can be broadly classified into two categories: 1) wireless localization and 2) vision-based localization.

There are many wireless localization systems that utilize ultrawide band (UWB) radar [17], radio frequency identification (RFID) [18], ZigBee [19], Bluetooth [20], and Wi-Fi [21], [22]. UWB radar has been a particularly attractive technology for indoor localization because it is not susceptible to interference from other signals (due to its drastically different signal type and radio spectrum), and the UWB signal (especially the low frequencies included in the broad range of the UWB spectrum) can penetrate a variety of materials, including walls. UWB radar achieves very high localization accuracy, which can be up to 10 cm. However, the slow progress in the UWB standard development has limited the use of UWB in consumer products and portable user devices. RFID-based systems can be used for localization and object tracking as they have a reasonable range, low cost, and can be easily embedded in the tracking objects. However, the limited range makes them unsuitable for high precision indoor localization. ZigBee is concerned with the physical and media access control layers for low cost, low data rate, and energy efficient personal area networks. It is favorable for localization of sensors in wireless sensor network, but it is not suitable for indoor localization as it cannot provide the distance between the user and the labeled sensor. Most of the existing Bluetooth-based localization systems rely on received signal strength indicator, however, they are prone to multipath fading and environmental noise, lower localization accuracy due to its signal band (2.4 G) which is the same with other signals. Thus, only Bluetooth-based localization system has very large uncertainty in localization. Most of portable consumer devices (e.g., smart phones, laptops) are Wi-Fi enabled, which makes Wi-Fi an ideal candidate for indoor localization.

However, existing Wi-Fi networks are normally deployed for communication (i.e., to maximize data throughput and network coverage) rather than localization purposes. Therefore, their localization accuracy still needs improvement. Moreover, all these systems require special hardware.

The vision-based localization takes advantage of image processing and objects recognition. An effective way for indoor navigation using inertial measurement unit in conjunction with quick response (QR) code was proposed in [23]. QR code-based system requires proximity recognition [24], nevertheless, the blind people have difficulty in approaching the QR code. Therefore, it is inappropriate to blind localization. Recently visual SLAM technology including state filter-based SLAM [25] and pose-graph SLAM [1], [12], [15], [16], [25]–[29] become more and more popular in indoor navigation as its localization error can be effectively reduced at a loop-closing point and the positioning accuracy can be up to the centimeter scale. Besides, the visual SLAM-based localization systems require no other special hardware except for a camera, stereo camera, or RGB-D camera. Therefore, the visual SLAM was utilized to locate the visually impaired individuals accurately in this paper.

B. Way-Finding and Route Following

The sparse map built by visual SLAM module becomes a kind of PoI-graph [1], [12] after some PoIs were tagged on it. This PoI-graph was utilized in this paper as the global map. There are many PoI-graph-based way-finding algorithms, such as Dijkstra [30], A* [1], [12], D* [31], etc. However, this is not the focus of this paper. It is just for providing the global path (i.e., the path to be followed). Hence, any of these algorithms can be used for planning the globally shortest path. In this paper, A* algorithm was adopted as the way-finding algorithm.

After the globally shortest path from the starting position to the destination was found, the route following algorithm will provide accurate guidance information to ensure that the user can follow the globally shortest path and avoid obstacles. The route following algorithm in [10] takes the globally shortest path and *a priori* knowledge of indoor environment as inputs, and outputs a control strategy that makes the user's trajectory remain close to the globally shortest path. It selects some special nodes (e.g., entrance node, room node, intersection node, etc.) as subgoals to guide the user. The method [32] proposed a path deviation detecting method which is based on measuring the similarity between the current frame and the training frame of the predefined path. However, the dynamic obstacles and changes of the environment were not considered. Hence, it is not able to help the blind avoid dynamic obstacles. To overcoming the above problems, a dynamic subgoal-based route following algorithm was proposed in this paper. The subgoal is selected dynamically, which includes but is not limited to the special node as mentioned in [10]. The above route following algorithm combining the obstacle detecting method [13] which takes the dynamic obstacles and changes of environment into account, and the globally shortest path, output the optimal walkable direction to ensure the user follow the globally shortest path closely, meanwhile, avoid obstacles.

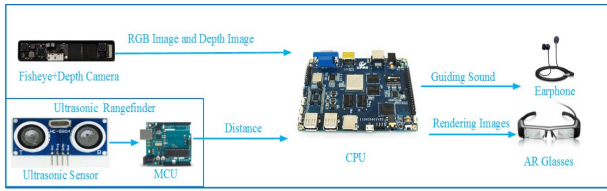


Fig. 1. Hardware configuration of the proposed navigation device.

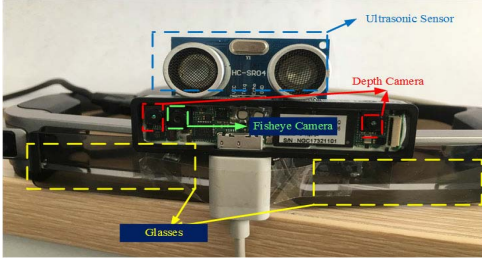


Fig. 2. Prototype of the proposed navigation device.

III. HARDWARE CONFIGURATION

The proposed navigation device consists of a fisheye and a depth camera, an ultrasonic rangefinder, an embedded CPU board, a pair of OST glasses, and an earphone. These sensors are of low cost, small volume, and easy integration, and thus can be widely used in consumer market.

The depth camera and the fisheye camera are used for building the virtual-blind-road and locating the user precisely with visual SLAM algorithm. Besides, the depth camera is also used for obstacle detection [13]. To compensate for the limitations of the depth camera, such as passing through the transparent objects, being absorbed by some special materials, etc., the ultrasonic rangefinder is utilized. It consists of an ultrasonic sensor and a microprogrammed control unit to measure the distance of an obstacle in front of the user. Fusing the depth camera and the ultrasonic rangefinder for obstacle detection can ensure adequate safety of the visually impaired individual. The CPU operates at 1.44 GHz with a 2 GB RAM. All the algorithms such as visual SLAM, obstacle detecting, way-finding, route following, speech synthesis, etc. are performed on the CPU. The OST-glasses have two display screens for displaying the guiding information and surrounding information to the partially sighted individual. In addition, the glasses have two loudspeakers for playing the guiding sound. The earphone is used for playing the guiding sound to the totally blind individuals when they are in a noisy indoor environment (e.g., supermarket). The hardware configuration of the proposed navigation device is illustrated in Fig. 1, and its prototype is shown in Fig. 2.

IV. NAVIGATION SCHEME

The architecture of the proposed navigation system is illustrated in Fig. 3, which includes visual SLAM, PoI-graph, way-finding, obstacle detection, and route following module. The rendering module converts the guiding information produced by the navigation system into audio or/and visual cues. The obstacle detection and rendering modules have been

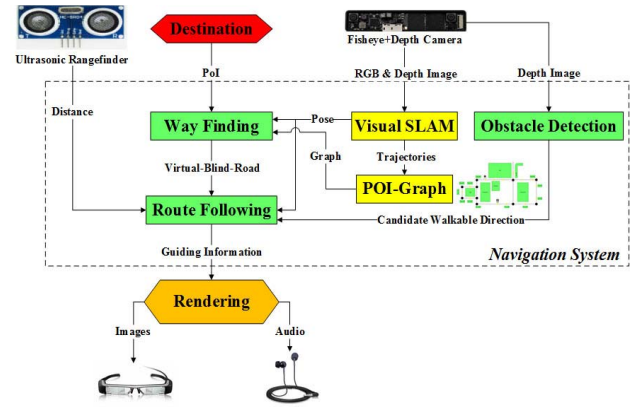


Fig. 3. Architecture of the proposed navigation system.

presented in our previous work [13], and thus will not be repeated here.

The visual SLAM module utilizes the RGB image and depth image to build the virtual-blind-road (offline) and locate the user (online). After the virtual-blind-road is tagged with some key positions (offline), it becomes a sparse map (i.e., PoI-graph). The way-finding module plans a globally shortest path from the starting position to the destination according to the PoI-graph. The obstacle detection module provides many candidate walkable directions according to the current depth image. The route following module takes the current pose of the blind user, the globally shortest path, the candidate walkable directions, and the obstacle distance measured by the ultrasonic rangefinder as inputs, and uses a dynamic sub-goal selecting method to produce the guiding information. This allows the user to follow the globally shortest path as closely as possible and avoid obstacles at the same time.

A. Visual SALM and PoI-Graph

The ORB-SLAM2 [16] was utilized in this paper. It has three main parallel threads: 1) tracking; 2) local mapping; and 3) loop closing. The tracking thread can locate the camera through feature matching with the local map. The local mapping thread can insert new point into the local map and optimize the local map by performing local bundle adjustment (BA). The loop closing thread can detect large loops, and optimize the pose graph. Besides, the loop closing thread will launch a fourth thread to perform full BA after the pose graph optimization, to compute the optimal global structure and motion solution.

In this paper, the ORB-SLAM2 was used to solve two main problems.

- 1) *Building the Virtual-Blind-Road*: Before providing navigation information for the visually impaired, it is necessary to build the virtual-blind-road. The virtual-blind-road is built by a sighted person wearing the proposed navigation device and performing all threads of the ORB-SLAM2. The virtual-blind-road [as is shown in Fig. 4(a)] is actually the motion trajectory of the sighted person. The process of building the virtual-blind-road is completed offline.

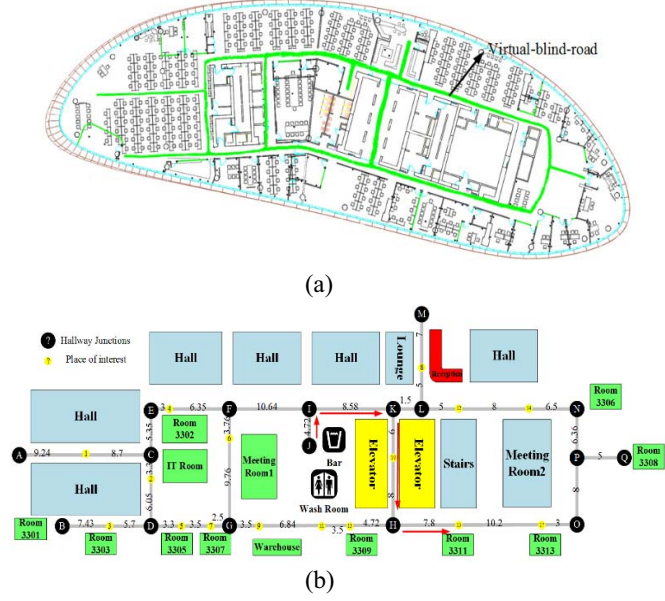


Fig. 4. Example of (a) virtual-blind-road and corresponding and (b) PoI-graph.

2) *Locating the User*: When navigating the visually impaired to walk from the starting position to the destination, only the tracking thread of the ORB-SLAM2 is operated for localization. The 3-D pose of the camera can be computed through feature matching between the current frame and the previous frame or key-frame in the prebuilt map [16]. The matches between current frame and previous frame can cope with the unmapped regions in the prebuilt map, however, this will cause the accumulation of drift. Nevertheless, once the current frame matched with the key-frame in the prebuilt map, the drift will be corrected. Thus, the localization can be robust and accurate. Besides, the fisheye camera can also improve the locating accuracy by providing more feature matching points due to its wide angle of view.

After the virtual-blind-road is built, the PoI-graph will be generated through tagging some PoI such as rooms, toilet, bar, hallway junctions as the nodes on the virtual-blind-road. The edge connecting two nodes in PoI-graph has a weight equal to the real distance between the nodes. Taking an office area as an example, the PoI-graph is shown in Fig. 4(b). Each edge corresponds to a piece of virtual-blind-road and each node represents a place of interest. The PoI-graph is used for finding a globally shortest path from the starting position to the destination (see Section IV-B).

B. Way-Finding

The way-finding module plans a globally shortest path by applying A* algorithm to the PoI-graph. A* algorithm searches among all possible paths to the destination for the one that incurs the smallest cost (shortest distance). For instance, the globally shortest path from the bar to Room 3311 is depicted by the red arrows in Fig. 4(b) ($J \rightarrow I \rightarrow K \rightarrow H \rightarrow \text{Room 3311}$).

C. Route Following

The route following module can be described as follows.

Inputs:

- 1) A globally shortest path (i.e., the virtual-blind-road) produced by way-finding module.
- 2) The current pose output by the visual SLAM module.
- 3) Candidate walkable directions generated from the obstacle detection module.
- 4) Obstacle distance measured by the ultrasonic rangefinder.

Output: Guiding information that ensures the user follow the globally shortest path as closely as possible, and avoid obstacles at the same time.

Terms:

- 1) *Global Path*: $W = \{w_1(x_1, y_1), w_2(x_2, y_2), \dots, w_n(x_n, y_n)\}$, a sequence of position, which is capable of guiding the visually impaired individual from the current position to the destination, where $w_i(x_i, y_i)$ is a point defined in the global coordinate system.
- 2) *Current Pose*: $P_c(x_c, y_c, \theta_c)$, current position and orientation, where (x_c, y_c) is current coordinate in global coordinate system and θ_c is current heading (i.e., the direction of camera optical axis).
- 3) *Subgoal*: The navigation point $P_G(x_G, y_G)$. This is the desired position next step.
- 4) *Candidate Walkable Directions*: The walkable directions $D = \{\theta_1, \theta_2, \dots, \theta_n\}$ produced from the obstacle detection, θ_i is the angle relative to the current heading (i.e., the direction of camera optical axis).
- 5) *Obstacle Distance*: The distance d measured by the ultrasonic rangefinder. If an obstacle is in front of the user and in the view field of the ultrasonic rangefinder, the distance will be used for guiding the user safely.
- 6) *Guiding Direction*: The optimal walkable direction θ_{opt} . It is relative to the current heading (i.e., the direction of camera optical axis), then will be converted to audio and/or visual cue for guiding the visually impaired individual.

Based on the above descriptions, the steps of the proposed route following algorithm are as follows.

Step 1: Get the current pose P_c and the globally shortest path W .

Step 2: Select the subgoal P_G according to the current pose and the globally shortest path. The subgoal is selected as follows.

First, find the closest point to the current position in the globally shortest path, which can be formulized as

$$P_{cls}(x, y) = \arg \min_{(x_i, y_i) \in W} \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2} \quad (1)$$

where $P_{cls}(x, y)$ is closest point to the current position in the globally shortest path, W is the globally shortest path, and (x_c, y_c) is the current position.

Second, select the subgoal, which can be a point having a certain distance from the closest point, a turning point or

destination point, this can be calculated as

$$P_G(x_G, y_G) = \{(x_s, y_s) \mid \sum_{i=1}^s \sqrt{(x_i - x_{cls})^2 + (y_i - y_{cls})^2} \geq d \mid P_{cls} = (x_{cls}, y_{cls})\} \quad (2)$$

$$\arccos \frac{(x_s - x_{cls})(x_{s+1} - x_s) + (y_s - y_{cls})(y_{s+1} - y_s)}{\sqrt{(x_s - x_{cls})^2 + (y_s - y_{cls})^2} \sqrt{(x_{s+1} - x_s)^2 + (y_{s+1} - y_s)^2}} \geq \theta \parallel$$

$$(x_{last}, y_{last}), (x_i, y_i) \in W, i > cls\}$$

where $P_G(x_G, y_G)$ is the selected subgoal (the blue dot in Fig. 5), d is the distance threshold, W is the globally shortest path, (x_{cls}, y_{cls}) is the closest point (the yellow dot in Fig. 5) to the current position (the red dot in Fig. 5), θ is the angle threshold which can be considered as a turning point, and (x_{last}, y_{last}) is the last point of the globally shortest path W , i.e., the destination point. The cases which a point can be selected as the subgoal are shown in Fig. 5.

Case 1: A point P_G is collinear or approximately collinear with the closest point P_{cls} , select the point P_G that its distance to the closest point exceeds the threshold d (e.g., 3 m) as the subgoal. Comparing with key node-based navigation method, this ensures the users follow the path closely, and the users can be informed when they deviate from the global path.

Case 2: A point P_G that its distance to the closest point P_{cls} does not exceed the threshold d , but the angle between $P_{cls}P_G$ and P_GP_{G+1} exceeds the threshold θ (e.g., $\pi/6$). This point is considered as a turning point, which can be taken as the subgoal. This kind of subgoal does not update until the user reaches this point. This ensures the user safely get around a corner.

Case 3: This point is the final point of the globally shortest path in Section IV-B, which does not satisfy the above two cases. It will be selected as the subgoal before it was reached. If the distance between the current position and this point is less than a small threshold, such as 1.0 m, it is considered as reaching the destination.

Step 3: Compute the candidate walkable directions $D = \{\theta_1, \theta_2, \dots, \theta_n\}$ according to current depth image [13].

Step 4: Compute the final walkable direction. First, according to the current pose and the subgoal, the expected direction or angle can be calculated as

$$\theta_{exp} = \begin{cases} \frac{\pi}{2} & \text{if } (x_G - x_c) = 0, (y_G - y_c) > 0 \\ \frac{3\pi}{2} & \text{if } (x_G - x_c) = 0, (y_G - y_c) < 0 \\ \arctan \frac{(y_G - y_c)}{(x_G - x_c)} & \text{if } (x_G - x_c) > 0, (y_G - y_c) > 0 \\ \arctan \frac{(y_G - y_c)}{(x_G - x_c)} + 2\pi & \text{if } (x_G - x_c) > 0, (y_G - y_c) < 0 \\ < 0 & \\ \arctan \frac{(y_G - y_c)}{(x_G - x_c)} + \pi & \text{else} \end{cases} \quad (3)$$

where θ_{exp} is the expected angle, (x_c, y_c) is the coordinate of current position, and (x_G, y_G) is coordinate of subgoal. The angle value is in $[0, 2\pi)$, which is depicted in Fig. 6.

Then, based on the candidate walkable directions $D = \{\theta_1, \theta_2, \dots, \theta_n\}$, expected direction θ_{exp} and current pose $P_c(x_c, y_c, \theta_c)$, the optimal walkable direction can be obtained

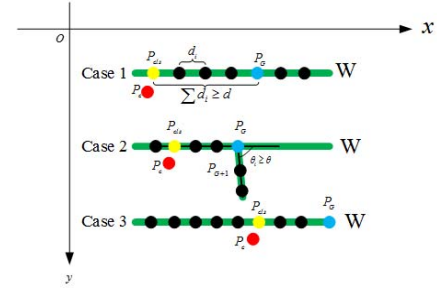


Fig. 5. Cases of subgoal selecting.

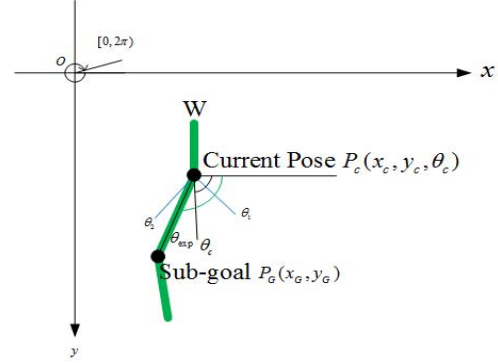


Fig. 6. Expected angle representation.

by minimizing the cost function, which is defined as

$$\theta_{opt} = \begin{cases} \text{Null} & \text{if } (D = \emptyset) \\ \arg \min_{\theta_i \in D} \|\theta_{exp} - \theta_c - \theta_i\| & \text{if } (D \neq \emptyset) \& \left(\min_{(x_i, y_i) \in W} \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2} > 1.0 \parallel \|\theta_{exp} - \theta_c\| \geq \frac{\pi}{6} \right) \\ \arg \min_{\theta_i \in D} \|\theta_i\| & \text{else} \end{cases} \quad (4)$$

where θ_{opt} is the optimal walkable direction and W is the globally shortest path. The intuition of (4) is that when the visually impaired deviated from the globally shortest path, i.e., the minimum distance between the current position and the globally shortest path exceeds a threshold (e.g., 1.0 m in this paper), or the angle between the current heading and the expected direction exceeds a threshold (e.g., $\pi/6$ in this paper), the way following module will correct the user toward the globally shortest path; otherwise, the optimal direction will be selected only from the candidate walkable directions.

Next, ultrasonic rangefinder is fused to determine the final walking direction in order to compensate for the limitations of the depth camera [13]. Since the ultrasonic sensor can detect the obstacles in the range of 0.03 m to 4.25 m, and within scanning field of 15° , the final walking direction is defined as

$$\theta_{walk} = \begin{cases} \theta_{opt} & \text{if } (\theta_{opt} \notin [-7.5, 7.5]) \parallel \\ & \times (\theta_{opt} \in [-7.5, 7.5] \& d_{ultra} > \delta) \\ \text{Null} & \text{else} \end{cases} \quad (5)$$

where θ_{walk} is the final walking direction, d_{ultra} is the distance measured by the ultrasonic rangefinder, and δ is the distance

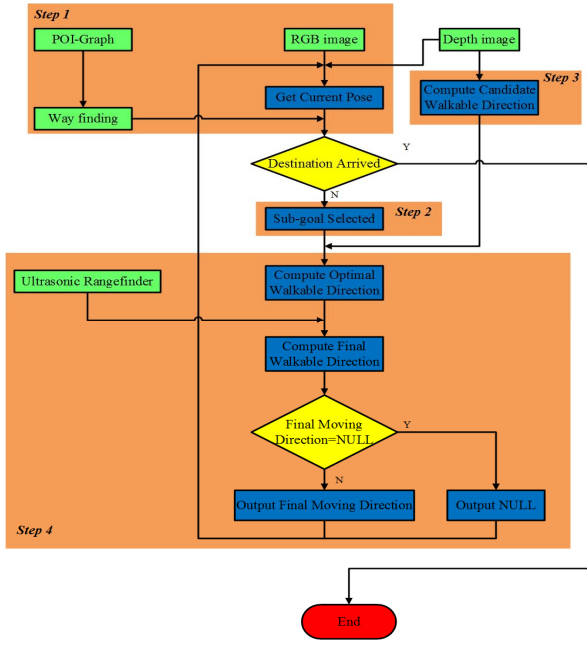


Fig. 7. Workflow of the proposed navigation system.

threshold of obstacle (e.g., 2.0 m in this paper). It judges if the optimal walkable direction θ_{opt} is within the view field of ultrasonic sensor, i.e., $[-7.5^\circ, 7.5^\circ]$. If not, it will directly output the optimal walkable direction, otherwise, the ultrasonic rangefinder then will be used to judge if the measured distance exceeds the threshold δ . If yes, it will also output the optimal walkable direction; conversely, it will output Null, which means no walkable direction in the field of view. This guiding direction will then be converted to audio and/or visual cue for guiding the visually impaired individual [13].

These four steps are continually executed until the destination is reached. The workflow of the proposed navigation system is shown in Fig. 7.

V. EXPERIMENTAL RESULTS AND DISCUSSION

To test the effectiveness of the proposed navigation system, two groups of experiments were conducted, including Experiment 1 without obstacles and Experiment 2 with obstacles. In both experiments, three paths [from A (hall) to B (wash room), D (lounge) to C (bar), and E (Room 3308) to B], as shown in Figs. 8 and 9 are provided. Individuals of totally blind and partially sighted were navigated by the proposed system to follow these paths, and their actual walking trajectories were recorded to analyze both qualitatively and quantitatively.

Experiment 1: There are no obstacles on the three paths. The users can follow the path to destination, as shown in Fig. 8. For quantitative analysis of the route following algorithm, the corresponding maximum, the average distance deviating from the three paths, and the variance were calculated, and the results are shown in Table I. The maximum deviation distance is less than 1.0 m and the average deviation distance is less than 0.3 m, which demonstrates that the proposed algorithm can navigate the visually impaired effectively by following the



Fig. 8. Experiment 1 (without obstacles).



Fig. 9. Experiment 2 (with obstacles).

TABLE I
DISTANCE DEVIATING FROM THE PLANNED PATH (EXPERIMENT 1)

Path		Max. distance (m)	Average distance (m)	Variance(m ²)
A->B	Partially sighted	0.2622	0.0967	0.0054
	Totally blind	0.3045	0.1523	0.0086
D->C	Partially sighted	0.3496	0.1124	0.0083
	Totally blind	0.4369	0.1938	0.0085
E->B	Partially sighted	0.6991	0.1152	0.0127
	Totally blind	0.6991	0.2249	0.0162

virtual-blind-road. Besides, the variance is very small, which additionally verified the effectiveness of the route following algorithm. Once the user deviated from the globally shortest virtual-blind-road, the route following module will inform the user to get back.

Experiment 2: This is to test the ability to solve both the route following and obstacle avoiding problems at the same time. The results shown in Fig. 9 verified that the effectiveness of the proposed navigation system. The user can avoid the obstacles and follow the globally shortest path to reach the destination. Similarly, in order to analyze the proposed algorithm quantitatively, the maximum and average deviation distances, as well as the variance were calculated, and shown in Table II. The maximum deviation distance of partially sighted is greater than that of the totally blind in AB and EB path, this is because the partially sighted individual has his own decision according to his observation, while the totally blind can only rely on the device and they usually do not deviate far from the path even

TABLE II
DISTANCE DEVIATING FROM THE PLANNED PATH (EXPERIMENT 2)

	Path	Max. distance (m)	Average distance (m)	Variance(m ²)
A->B	Partially sighted	1.1394	0.1553	0.0274
	Totally blind	0.9033	0.2920	0.0486
D->C	Partially sighted	0.7609	0.0984	0.0185
	Totally blind	1.3431	0.2960	0.0434
E->B	Partially sighted	1.0821	0.1692	0.0321
	Totally blind	1.0765	0.2897	0.0465

when accounting obstacles. Differently, the partially sighted can keep going in straight line unless there are obstacles on his way, and the average deviation distance is less than the distance of the totally blind. The variance in Table II proved the above descriptions. This experiment verifies that the proposed navigation system can solve the route following and obstacle avoiding problems simultaneously.

It is easy to see that the variance in the results of Experiment 2 is greater than that of Experiment 1. This is because the obstacles force the visually impaired individuals deviate from the path to prevent collisions. When they have avoided one obstacle, the proposed route following module will help them to get back to the prefound the globally shortest virtual-blind-road. Both experiments verified the effectiveness of the proposed route following algorithm. Moreover, Experiment 2 proved that the proposed system could help the visually impaired individual reach the destination by following the globally shortest virtual-blind-road and meanwhile avoiding obstacles. The proposed navigation device proved to be able to serve as a consumer production for the ease of use in the visually impaired people's daily walks.

VI. CONCLUSION

This paper presents a novel navigation device for the visually impaired groups to help them reach the destination safely and efficiently in indoor environment. The visual SLAM algorithm was used to solve the problems of indoor localization and virtual-blind-road building. The PoI-graph was generated to find a globally shortest virtual-blind-road by the A*-based way-finding algorithm. The dynamic subgoal selecting-based route following algorithm was proposed to help the blind follow the globally shortest virtual-blind-road as closely as possible and meanwhile avoid obstacles (including dynamic obstacles). Experimental results verified that the proposed navigation device was effective enough on helping the visually impaired people walk from one place to another. The sensors embedded on the device have the characteristics of low cost, small size, and easy integration. Thus, it has great potential in consumer market, especially electronic travel aids market.

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