Corridor-Walker: Mobile Indoor Walking Assistance for Blind People to Avoid Obstacles and Recognize Intersections

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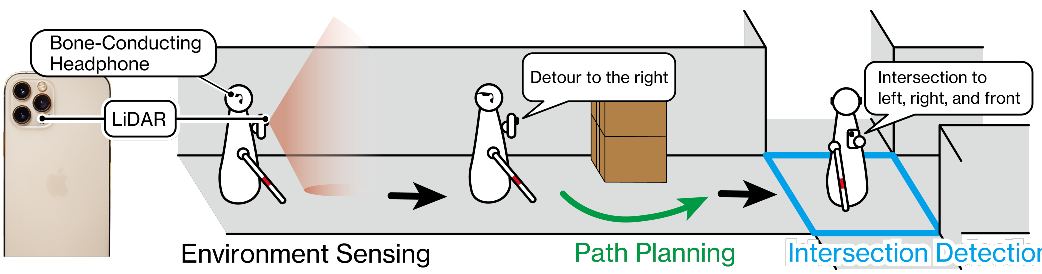

Fig. 1. Corridor-Walker assists blind people in recognizing obstacles and intersections. The blind user can use the system to detect an upcoming intersection and recognize the paths it leads to, while also avoiding obstacles.

Navigating in an indoor corridor can be challenging for blind people as they have to be aware of obstacles while also having to recognize the intersections that lead to the destination. To aid blind people in such tasks, we propose Corridor-Walker, a smartphone-based system that assists blind people to avoid obstacles and recognize intersections. The system uses a LiDAR sensor equipped with a smartphone to construct a 2D occupancy grid map of the surrounding environment. Then, the system generates an obstacle-avoiding path and detects upcoming intersections on the grid map. Finally, the system navigates the user to trace the generated path and notifies the user of each intersection's existence and the shape using vibration and audio feedback. A user study with 14 blind participants revealed that Corridor-Walker allowed participants to avoid obstacles, rely less on the wall to walk straight, and enable them to recognize intersections.

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1 INTRODUCTION

Navigation in indoor corridors can be challenging for blind people. In such environments, they usually rely on the surrounding walls to navigate [2]. As various obstacles may be placed along the wall, such as wall-mounted furniture and objects [33], blind people may collide with these obstacles, resulting in damage to both the blind people and the objects. To avoid obstacles, white canes are commonly used by blind people to detect objects on the ground. In addition to white canes, previous studies have proposed various systems that can alert users to the existence of obstacles at or above ground level [12, 57, 60]. Since only the existence of the objects is captured, the user still needs to determine the path that avoids the obstacle (obstacle-avoiding path). On the other hand, guide dogs can also be used to help navigate along an obstacle-avoiding path. However, not all blind people prefer them as they require certain caretaking [62, 72]. Another drawback is that the number of guide dogs is very small (*e.g.*, 5,000 dogs compared to 360,000 legally blind, approximately about 1.4% in the United Kingdom [62]). To alleviate this issue, assistive technologies for navigating blind people along an obstacle-avoiding path have been proposed using mobile robots [26, 37, 49] and wearable devices [44, 46, 71]. However, these solutions use special hardware, which is not commonly available for blind people and can thereby cause problems in technology adoption [67].

In addition to avoiding obstacles, blind people must be aware of the corridor's geometric structure [17, 66], such as intersections, to navigate to their destinations. Walking past an intersection unnoticed or turning into an incorrect intersection could lead to blind people being lost. To navigate correctly, they need to reliably perceive the position and shape of each intersection that they go through. With the use of only a white cane, they may not be able to locate an intersection, resulting in walking past one unnoticed [27] (Section 6.1, A1). In addition, the white cane does not fully support the shape recognition of intersections (Section 6.3, A7) because it has a limited range of contact. Although guide dogs can help blind people locate an intersection [27], they do not convey the shape to the user. In this regard, indoor turn-by-turn navigation systems can serve as a promising solution [18, 65] for blind users to reach their destinations without being lost by conveying correct information about intersections. However, such systems require static route maps or additional infrastructure. Therefore, it is likely that these systems are not available for every building [16, 68].

In this study, we present *Corridor-Walker*, a mobile indoor walking assistance system for supporting blind people in avoiding obstacles and recognizing (*i.e.*, locate and grasp the paths they lead to) intersections (Figure 1). The system is aimed to be used in indoor corridors where static route maps and infrastructure are not available, but the user has the knowledge of the turns they need to make to reach the destination (*e.g.*, corridors in apartments, offices, or hospitals). They may be familiar with the environment from prior travel or have knowledge from tactile maps [24, 58] or interactive devices [29]. Since many blind people already use smartphones [51, 54] for messaging and accessing the app-store available assistance system to recognize items, read printed letters, and navigate along a recorded route (*e.g.*, Seeing AI [52], Tap Tap See [11], and Clew [75]), we designed our system such that only a single smartphone is needed to allow for better technology adoption. The system assists the user in avoiding obstacles by navigating the user to trace an obstacle-avoiding path using both spatialized audio and text-to-speech (TTS) feedback. For intersection detection, the system will inform the user of the existence and shape of an upcoming intersection through vibration and TTS feedback. To achieve these functionalities, the system first constructs a 2D occupancy grid map [15, 43, 44, 59] of the surrounding environment using a LiDAR sensor equipped with an iPhone 12 Pro [3], which supports accurate grid map construction. Then, the system plans an obstacle-avoiding path on the grid map using the A* path planning algorithm [28]. Simultaneously, the system detects upcoming intersections using the you only look once (YOLO) v3 detector [61]. Since only real-time sensing results are used, these functionalities can be accomplished without the need for a static route map or additional infrastructure.

To understand the usability of our system, we conducted a user study with 14 blind participants. The participants were asked to perform three tasks. In the first task, the participants turned in different types of intersections, and were asked to list all directions to which each intersection led. In the second task, several obstacles were placed in a straight corridor and the participants were asked to walk through it, while avoiding the obstacles. In the last task, the participants were asked to navigate a corridor containing both obstacles and intersections. The study revealed that Corridor-Walker enabled the participants to avoid obstacles while relying less on the wall and to better grasp the intersections shapes.

This study builds on a poster publication by Kuribayashi *et al.* [40]. This paper provides more details on the problem statement, related work, system design, and implementation. It also presents additional contents which are a user study and a discussion of the results.

2 RELATED WORK

2.1 Navigation Assistance Using Static Route Maps

Navigation assistance systems can be classified into those that use static route maps (*i.e.*, maps constructed before being used for navigation) [8, 24–27, 31, 41, 46, 58, 65] or those that do not rely on them [15, 35, 43, 59, 74]. Static route maps have been used to provide users with a turn-by-turn navigation instruction [18, 65]. They can also be used to provide other knowledge about the environment, *e.g.*, the location or shape of intersections via tactile maps [8, 23, 24, 58] or virtual environments [25, 31]. In addition, they can be used to inform the user of an obstacle-avoiding path by combining it with real-time sensing results [26, 46]. However, a static route map may not always be available for every building [16, 68], which limits its usage. Moreover, most indoor walking assistive systems that do not rely on static route maps [15, 35, 43, 59] mainly aim to help users avoid obstacles. Thus, they cannot be used to provide information about intersections. Considering these issues, our system aims to help blind people avoid obstacles and provide information about intersections without using static route maps.

2.2 Obstacle Avoidance System

To help blind people avoid obstacles, many systems have been proposed to inform them of the position of obstacles [12, 15, 34, 57, 60, 63, 69, 71]. A limitation of such systems is that users must determine their path based on feedback from the system. In contrast, there are systems that guide users by generating safe paths to avoid obstacles [26, 37, 43, 44, 46, 59]. Such systems have been implemented using wearable devices [43, 44, 46, 59], suitcase-shaped devices [37], and robots [26, 49]. These systems have the advantage that users only have to follow the generated path for safe navigation. However, they require a user to carry heavy devices, which can incur high operation costs. On the other hand, nowadays a majority of blind people already own a smartphone [51, 54]. Hence, to eliminate these drawbacks, we propose using only a smartphone to generate an obstacle-avoiding path for navigating the user.

2.3 Intersection Detection in Indoor Environments

The problem of detecting indoor intersections without a static route map has been explored in the field of robotics. Lacey and Shane proposed the use of a Bayesian network to detect intersections using a 180° laser range finder attached to a robot [42]. Garcia *et al.* proposed detecting intersections from RGB images taken by a quadcopter using a rule-based approach [21] and a convolutional neural network [22]. These methods can adequately detect various types of intersections in indoor environments in advance. However, applying these methods to navigate blind people may not be suitable as it has been shown that some blind people may not hold smartphones stably [38, 41], and therefore images captured by them may contain motion blur [64]. In addition, images captured by them may miss the entire subject from the camera [32]. To overcome these issues, our approach uses an image of a 2D occupancy grid map of the surrounding environment, which is constructed using a LiDAR sensor equipped on a smartphone and is thus less susceptible to motion blurs. Moreover, we included interactive feedback that can guide the users to scan the environment when more information is needed to identify intersection types.

2.4 Designing Non-visual Feedback for Blind People

To convey navigation information to a blind user, previous studies utilized feedback using either audio feedback (*e.g.*, TTS [18, 19, 36, 41, 46, 65, 70, 74], sonification [1, 12, 19, 60, 75], spatialized audio [6, 12, 47, 48, 52, 53, 63], beep sounds [35, 37, 63, 63]), vibration feedback [34, 38, 41, 57, 71], or thermotactile feedback [39, 56]. Although instructions from TTS are capable of conveying various clear instructions to users, their use should be kept minimal. This is because they may block ambient sounds that blind people often rely on [7], may not be heard in a noisy area [4], and may harm their cognitive load [50]. In addition, although TTS can convey various instructions, it is a challenge for them to use TTS for slight adjustments of their orientation [65] (*e.g.*, rotate 4° to the right). In contrast, according to Lock *et al.* [47], slight adjustment of a user's orientation with spatialized audio using bone-conducting headphones was found to be effective. In addition to audio feedback, vibration feedback is used to convey simple instructions to blind users. Blind people highly prefer them as they can be perceived in noisy environments [37] and do not harm the person's cognitive load compared to audio feedback [50]. Although Nasser *et al.* reported that thermotactile feedback outperforms vibration feedback in providing directional cues [56], it may require additional Peltier modules with smartphones. Based on these previous studies, we design the interface of Corridor-Walker to have multiple feedback modes, where each is used to convey different information in different situations.

3 SYSTEM DESIGN

Our main goal is to support the blind user in navigating indoor corridors to safely arrive at their destination without modifying the infrastructure of the building or requiring its static route map. The typical situation is as follows: *A blind person is walking in an indoor corridor, such as those in offices, hospitals, and hotels. The person knows how many intersections they have to turn to reach the destination. However, there are several obstacles in the corridor, which are blocking the path.* To provide blind people with assistance in such situations, we designed the system to require only a single smartphone with a LiDAR sensor. Since the LiDAR sensor emits infrared lasers to measure the distance between the sensor and objects, the system can work well in an environment without

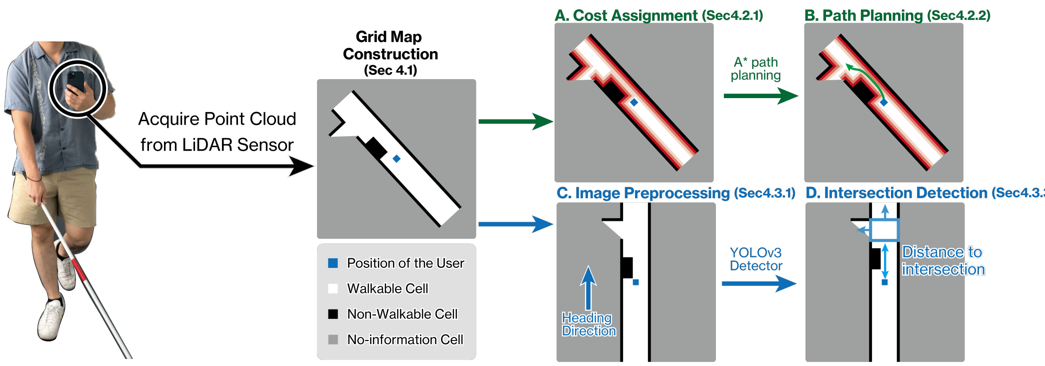

Fig. 2. Overview of Corridor-Walker. First, the system constructs a 2D occupancy grid map from the point cloud acquired from the LiDAR sensor (Section 4.1). A) Then, the system assigns a cost value to each cell (Section 4.2.1), and B) plans an obstacle-avoiding path (Section 4.2.2). Simultaneously, the system C) preprocesses the image of the grid map (Section 4.3.1), and D) detects upcoming intersections through the YOLOv3 detector (Section 4.3.3).

strong sunlight, or even under low-lighting conditions. Finally, the system augments the function of a white cane to help users avoid obstacles and recognize intersections.

3.1 Avoiding Obstacles

Blind people often walk along walls when navigating indoor environments [2]. Simultaneously, many obstacles are usually placed along the wall [33]. This may result in accidents where they collide with obstacles. Therefore, we aim to guide them along a path that avoids such obstacles. We designed the system that can generate a path that keeps a distance from nearby walls and obstacles, and navigates the user to trace the path without veering. In other words, the system assists the user in walking without relying on the wall, preventing collisions with obstacles placed along the wall. If there are obstacles ahead, the system generates a path that circumnavigates the obstacles and guides the user to make a detour around them.

3.2 Detecting Intersections

To navigate to a destination, blind people need to perceive the positions and shapes of intersections they have to go through. However, in situations where they cannot walk along a wall (*e.g.*, there are obstacles along the wall), they may walk past an intersection without noticing [27]. In addition, neither white canes nor guide dogs support recognition of the intersection shape. To augment the ability of traditional navigation aids, we designed our system to inform users of an upcoming intersection and its shape. The system will notify the user of possible existence of an intersection ahead to prevent them from walking past it. Then, information about the shape of the intersection is provided to the user once they reach it.

4 IMPLEMENTATION

Our proposed system, Corridor-Walker, was implemented on an off-the-shelf smartphone, the iPhone 12 Pro. Figure 2 shows an overview of Corridor-Walker. In this section, we present the details of the implementation of the proposed system.

4.1 Grid map construction

The 2D occupancy grid map is constructed through a point cloud acquired from a LiDAR sensor with a maximum sensing range of 5 m [14]. Also, by using the localization algorithm provided by the augmented reality kit (ARKit) [13], the system accumulates grid information in each time frame. Therefore, the grid map will contain the grids that are in front of the user and the grids of the path through which the user walked. To acquire the point cloud, the user will be asked to hold the smartphone in front to scan the environment, as illustrated on the left side of the Figure 2. To determine whether each grid is walkable or not, the normal vector of each point is calculated [30], and the system determines floor plane using the random sample consensus (RANSAC) algorithm [20]. If a point has a normal vector that is parallel to the gravity vector and its height is within 0.1 m from the height of the floor plane, it is classified as a point belonging to the walkable area. Other points are considered as points belonging to the non-walkable area. Then, the cell in the xy-plane grid map on which each point is projected is determined. Each side of a cell is 0.15 m long on a real-world scale. When a cell contains more points that belong to the walkable area than those of the non-walkable area, the cell is labeled as a walkable cell (white pixel in Figure 2). Otherwise, the cell is labeled as a non-walkable cell (black pixel). If a cell contains no points, it is labeled as a no-information cell (gray pixel). Using the above algorithm at the frequency of 10 frames per second, the system was able to recognize static objects such as boxes and chairs as non-walkable areas. Moreover, the system updates the label of each cell each time it is observed. This allows the system to handle dynamic obstacles, *e.g.*, other pedestrians and cleaning robots. This is because the system will initially label the cells occupied by obstacles as non-walkable cells, and once those obstacles move away, the system will update those cells into walkable cells.

4.2 Path Planning and Obstacle Avoidance

The system uses a path planning algorithm to guide the user on a safe path. To generate such paths, we utilized the methods commonly used in the field of robotics [10, 55, 73]. We first assign a cost value to each cell in the grid map and then use a path planning algorithm to generate a safe path. In the following section, we describe these steps in detail, followed by their use to avoid obstacles and prevent veering.

4.2.1 Assigning Cost to Each Cell. First, the system assigns a cost value between 0 and β to each walkable cell (Figure 2–A). This allows the system to obtain a cost map, *i.e.*, a grid map where each cell is assigned a cost value, which can be used to plan a path far from non-walkable cells to guide the user. To compute the cost for each walkable cell, let δ_i denote the distance from a walkable cell i to its closest non-walkable cell. The cost value of the walkable cell i is given by $\text{cost}_i = \beta(1 - \frac{\delta_i - 1}{\alpha})$, if $1 \leq \delta_i \leq \alpha$, or $\text{cost}_i = 0$, if $\delta_i > \alpha$, where α upperbounds the distance for a walkable cell to have a positive cost. Here, walkable cells that are closer to a non-walkable cell will have higher costs than those which are further away. In Figure 2–A, walkable cells with high costs are indicated in dark red, and those with low costs are indicated in light red. Based on our observations, we set $\alpha = 3$ and $\beta = 50$.

4.2.2 Path Planning Algorithm. First, the system searches for the destination to perform a path planning algorithm. To do so, the system samples all walkable cells with the lowest cost at a distance of γ m ahead in a circular sector with a range of 100° forward. Then, the system sets the mid-point of the longest continuous space of the sampled points as the destination. If the calculated destination falls into a non-walkable cell (*e.g.*, pillars or boxes), γ is shortened by 0.5 m and the process is repeated until the destination is found or γ is set to 0 m. Finally, the system calculates the path to the point using the A* path planning algorithm [28, 73] (Figure 2–B). As a result, due to the construction of the cost map, the system generates a path that keeps a distance between every obstacle and wall. The path is updated every time the user walks half of the previously planned path. Based on our observation, we initially set the $\gamma = 3.5$m, which is the distance robustly scanned by the LiDAR sensor on the smartphone.

4.2.3 Obstacle Detection. Although the system can plan an obstacle-avoiding path, it is still necessary to notify the user of obstacles to explicitly alert the user to make a detour. To determine whether a non-walkable cell belongs to a wall or obstacle, the system performs plane detection using the RANSAC algorithm [20] on the 2D occupancy grid map. All the cells in the planes detected by RANSAC are determined as walls, and the remaining cells are determined as obstacles. Then, we consider all cells in the circular sector with a radius of 2 m and a central angle of 30° in front of the user to determine if there is an obstacle ahead. If the number of obstacle cells in the circular sector exceeds 30%, the system determines that there is an obstacle ahead and notifies the user (Section 4.4.3).

4.2.4 Veering Detection. To prevent the user from veering off the generated path, the system determines whether the user is facing the correct direction or not (Figure 4–Veering). First, the system calculates its orientation by using the localization algorithm provided by ARKit on the grid map. Then, the system calculates the angle θ between the system's orientation and the direction on the path that the user is expected to move to. If the angle θ is larger than 10°, it is determined as the user veering off the path, and the system will notify the user (Section 4.4.2). Otherwise, it is determined as the user staying on the path.

4.3 Intersection Detection

The system detects an upcoming intersection using a YOLOv3 object detector [61]. We used the YOLOv3 detector as it runs at around 70 frames per second on iPhone 12 Pro and does not delay the system. For the input, we used an image from the 2D occupancy grid map. The position of the generated bounding box (blue rectangle in Figure 1) represents the position of the intersection in the real world, and its label identifies the shape of the intersection. As the system uses a grid map constructed from the LiDAR sensor, it is not affected by motion blur, which may occur when blind users take photos using RGB cameras [64]. Therefore, the system can detect upcoming intersections robustly.

4.3.1 Image Preprocessing. As the grid map itself does not contain information about the direction the user is heading, we preprocess the image of the grid map such that this information becomes apparent. Thus, the system rotates the image of the grid map so that the heading direction of the user faces up (Figure 2–C). The heading direction of the user is calculated according to their position over the last four seconds. Then, we shift the image so that the user's position is at the center of the image. This preprocessed image (128×128 pixels) is used as the input to the YOLOv3 detector.

4.3.2 Training the YOLOv3 Detector. We trained the YOLOv3 detector to detect upcoming intersections. To train the YOLOv3 detector, we collected 9940 preprocessed images from the corridors of our university. Then we annotated the locations of intersections and their shape labels (*i.e.*, the directions it leads to). For example, an intersection that leads only to the left will be labelled as "*Left, Back*" as it leads to the left and the back of the user. Since the intersections with the labels of "Left, Back" or "Right, Back" have the same topological shape, they are defined as "*L-Shaped*" intersections. Similarly, other intersections are classified as "*T-Shaped*," "*Rotated T-Shaped*," and "*X-Shaped*". We set the confidence threshold of the YOLOv3 detector to 0.2, which is based on our

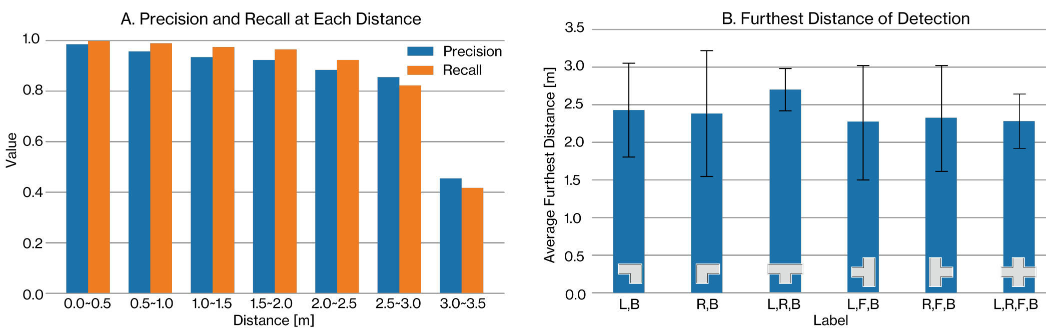

Fig. 3. Evaluation results for intersection detection. A) Bar graph of precision and recall at each distance. B) Bar graph of the furthest distance of detection for each label of intersection.

empirical observation that this value provides early detection of upcoming intersections with good accuracy.

4.3.3 Determining the Distance to Intersection. The distance between the user and the detected intersection is defined by the number of pixels between the bottom side of the bounding box and the center of the image. The blue arrow in Figure 2–D shows an example of the distance between the user and the intersection. As each pixel (*i.e.*, cell) represents 0.15 m in the real world, the number of pixels multiplied by 0.15 m is the distance to the intersection. When the generated bounding box includes the center of the image, it means that the user is at the detected intersection.

4.3.4 Evaluation. To evaluate our detector, we constructed a dataset consisting of 1215 preprocessed images taken in a different location from the training dataset. We measured the following metrics: (1) precision and recall at different distances, and (2) the furthest distance to detect each intersection shape. For the first metric, we measured the precision and recall of the intersection detection at every 0.5 m interval. Figure 3–A shows the results for the first metric. The precision and recall are high when the distance between the intersections and the user is small, but they decrease as the intersection is farther away. Overall, the detector achieved high (> 0.9) precision and recall when the user was approximately 2–2.5 m away from an intersection. The second metric measures the distance between the user and the intersection when the first true positive detection occurs. Figure 3–B shows the results of the second metric. The letters in the x-axis are abbreviations of the intersection shape labels ("L" for Left, "R" for Right, "B" for Back, and "F" for Front). On average, the system was able to detect an intersection 2.47 m before reaching it.

4.3.5 Confirming the Existence of an Intersection. If a corridor has an uneven structure such as an alcove, the YOLOv3 detector may detect it as an intersection, which is a false positive. As a result, the system may convey the wrong detection shape of the intersection to the user. Therefore, confirming whether the detected intersection is a true intersection or not is necessary. We implemented an algorithm to confirm whether the detected intersection is a true intersection when the user enters it. When the user is at a detected intersection, the system measures the furthest walkable cell beyond each side of the intersection by asking the user to scan the sides (left and/or right) that the intersection may lead to (Section 4.4.1). If the distance between the nearest side of the bounding box and the walkable cell is beyond the threshold of ϵ m, the system confirms a path leading to that side. We set the threshold $\epsilon = 1.5$.

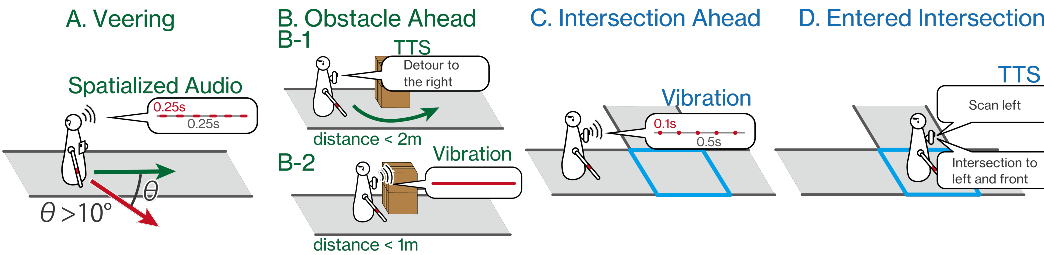

Fig. 4. Interface of Corridor-Walker. When the user is veering off the generated path, the system will correct the user's orientation with spatialized audio feedback. When an obstacle is detected within 2 m, the system will tell the user to make a detour. The system will also vibrate continuously when an obstacle is within 1 m. When an intersection is detected ahead of the user, the system will vibrate, then convey its shape using audio feedback when the user enters it.

4.4 Interface of Corridor-Walker

Figure 4 illustrates the interface of Corridor-Walker. Based on previous studies, we designed our system to use TTS, spatialized audio, and vibration feedback. We kept the use of TTS minimal, as it may provide a high cognitive load to the user [50]. Thus replacing it with other suitable feedback may increase the efficacy of the system. TTS feedback is used to convey the shape of an intersection and tell the user to make a detour. Spatialized audio feedback is used to instruct the user to trace the generated path. Vibration feedback is used to notify the user of the existence of an intersection and to alert them to the imminent risk of collision. The system conveys auditory feedback (TTS and spatialized audio) through bone-conducting headphones and vibration feedback through the vibration of the smartphone.

4.4.1 Conveying Intersection-Related Information. The system vibrates when it detects an intersection ahead of the user. We used vibration to convey this information because the detector can detect an intersection 2.47 m ahead on average (Section 4.3.4), whereas feedback with TTS is too slow (the user would have reached the intersection during the TTS feedback). Previous studies have shown that users perceive more urgency at a lower interval [5, 45]. As we used vibration for both alerting the risk of collision and to notify the existence of intersections, different intervals were used for the two feedbacks. For alerting the existence of an intersection, we designed the vibration to be a single pulse vibration, whose pulse duration was 0.1 s and the interval was 0.5 s (Figure 4–Intersection Ahead). When the user enters the intersection, the system tells the user to scan certain sides (*e.g.*, left and/or right) using TTS feedback (*e.g.*, the system will instruct the user to scan the left side if the label of the detected intersection is "Left, Back" or "Left, Front, Back"). The purpose of this instruction is to allow the user to confirm whether the detected intersection is a true intersection or not. Once the system determines that it is a true intersection (Section 4.3.5), the system will say which way the intersection leads to (Figure 4–Entered Intersection). Otherwise, the system remains silent. An example of the audio instructions when an intersection with the label of "Left, Right, Back" is detected is as follows: **1) The user enters the intersection:** *"Scan Left and Right"*; **2) User scans both sides, but there is a path only to the left:** *"(Intersection to) Left."*

4.4.2 Conveying Veering-Related Information. The system uses spatialized audio feedback to convey the correct orientation to the user (Figure 4–Veering). We used spatialized audio, as it has been shown that slight adjustments of orientation are challenging with TTS [65], but feasible with spatialized audio [47]. When the user veers off the path, the system provides feedback to rectify the user's orientation. If the user is facing the left/right while the user should be facing more to the

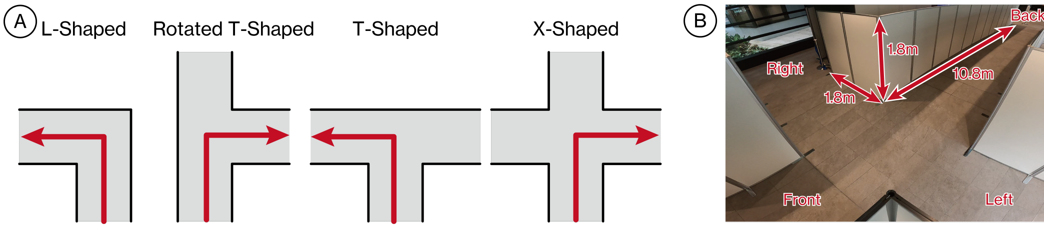

Fig. 5. A) Intersections for task 1. B) The height and length of the corridors are shown.

right/left, the system will produce a sinusoidal tone (duration: 0.25 s, interval: 0.25 s, frequency: 400 Hz, Figure 4–Veering) from the right/left side of the bone-conducting headphone. When users can hear no sinusoidal tone from earphones, it means they are facing the correct orientation.

4.4.3 Conveying Obstacle-Related Information. When an obstacle is detected (Section 4.2.3) within 2 m of the user, the system will notify which way to make a detour through TTS feedback (Figure 4–Obstacle Ahead, Top Panel). For example, when there is an obstacle along the left side of the wall, the system will say *"Make a detour to the right."* If any obstacle, including the wall, is within 1 m in front of the user, the system will continuously vibrate (Figure 4–Obstacle Ahead, Bottom Panel). As the vibration with shorter interval is capable of conveying an urgent situation [5, 45], we set the interval to zero, which means that the system will continuously vibrate until the user faces a safe direction.

5 USER STUDY

We performed a user study at our university building to evaluate the effectiveness of Corridor-Walker. Thus, we recruited blind participants to perform several tasks while using our system with a cane and compared the results to when the participants were using only a white cane but not using the system. We use the term *system-aided* as the condition when the participants used both the system and a white cane to perform the tasks, and the term *cane-only* as the condition when the participants used only a white cane, but not the system. This user study was approved by the university's institutional review board (IRB). The details of the user study are as follows.

5.1 Participants

Through an e-newsletter for blind people, we recruited 14 blind participants who travel independently on a daily basis. Table 1 shows the demographic of the participants. All participants mainly used white canes as their navigation aid and smartphones in their daily lives for more than two years (mean=6.9 and standard deviation = 3.3).

5.2 Tasks and Conditions

Our user study involved the following three tasks.

5.2.1 Task 1: identifying and turning at single intersection. In this task, participants were asked to turn in a specific direction (left or right) at an intersection, and then answer the shape of the intersection after each walk. We simulated intersections of different shapes using room dividers (Figure 5). For each walk, the participants were randomly placed between 6 m and 10 m before the intersection. Then we then asked them to start the task from that location. The participants were notified before the task that they would be asked to answer the shape of the intersection after each walk.

Table 1. Participants' demographic information and corresponding values for system usability scale (SUS) score.

ID	Age	Gender	Total Blindness	Smartphone Usage	Walking Behaviour	SUS
P01	51	Male	40 years	7 years	Far from wall	82.5
P02	26	Male	11 years	6 years	Along wall	92.5
P03	52	Female	49 years	13 years	Far from wall	72.5
P04	61	Female	4 years	2.5 years	Along wall	80.0
P05	71	Male	5 years	6 years	Along wall	85.0
P06	34	Female	19 years	6 years	Along wall	75.0
P07	29	Male	19 years	10 years	Along wall	82.5
P08	35	Female	21 years	8 years	Along wall	87.5
P09	56	Male	5 years	10 years	Along wall	85.0
P10	63	Male	20 years	2.5 years	Along wall	75.0
P11	21	Male	21 years	8 years	Along wall	75.0
P12	53	Female	53 years	5 years	Far from wall	72.5
P13	34	Male	34 years	2.5 years	Along wall	92.5
P14	29	Male	24 years	10 years	Along wall	70.0

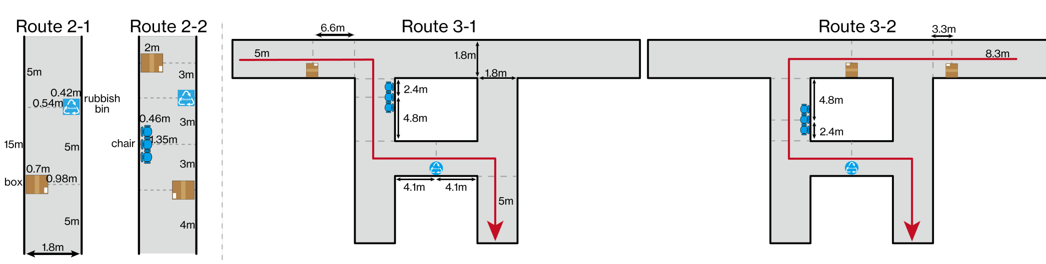

Fig. 6. Routes for tasks 2 and 3. The lengths and the widths of the corridors and the locations of obstacles are shown.

5.2.2 *Task 2: obstacle avoidance.* In this task, participants were asked to walk through a 15 m straight corridor. We designed two routes: **Route 2-1**, which consisted of two obstacles, and **Route 2-2**, which consisted of four obstacles. We placed obstacles on the opposite side in turn (Figure 6). For example, a corridor may first contain an obstacle on the left side followed by an obstacle on the right side. We used a box, a chair, or a rubbish bin as obstacles, as shown in Figure 6. We randomly placed the participants 3 m or 6 m away from the route entrance, where the actual task started.

5.2.3 *Task 3: navigating long corridors with obstacles.* In this task, participants were asked to walk through a corridor with several intersections and obstacles. For this task, we used an existing corridor in our university. We designed two routes (Figure 6). **Route 3-1** had three intersections and three obstacles and was 37.4 m long. **Route 3-2** had four intersections and four obstacles and was 47.4 m long.

5.3 Procedure

We obtained informed consent from all participants, which was approved by the university's IRB. We first conducted a pre-interview, asking the participants about their daily experiences while navigating in indoor environments. Then, a training session with the system was conducted for 30 minutes. After the participants were accustomed to the system, they performed the three tasks in the main user study session. For each task, the participant walked all intersections or routes once in a random order under system-aided and cane-only conditions. The order of the tasks under the two conditions was counterbalanced. The first half (P01–07) of the participants walked the intersections and routes listed in Figures 5–6 with the cane-only condition and the horizontally flipped intersections and routes of Figures 5–6 with the system-aided condition. The latter half of the participants (P08–14) walked the intersections and routes listed in Figures 5–6 with the system-aided condition and the horizontally flipped intersections and routes of Figures 5–6 with the cane-only condition.

After the main session, we conducted a post-interview. First, we asked the participants to rate a set of statements with the 7-point Likert items (ranging from 1: strongly disagree to 7: strongly agree). Each statement was asked for both the system-aided and cane-only conditions. These questions are illustrated in Figure 7, Q1–9. Then, we asked the participants to rate the system using the system usability scale (SUS) [9]. Finally, we asked open-ended questions to gather qualitative feedback on the system. During the experiments, we recorded videos of the participants performing the tasks. These videos were used to calculate the metrics (Section 5.4). We also used the videos to classify each participant's walking behavior, whether they usually walked along the wall or walked far from the wall (*i.e.*, without relying on the wall) on the cane-only condition (Table 1). The whole study took 120-150 minutes in total for each participant. Each participant was compensated with $90 for their participation. To prevent the spread of COVID-19, the experimenter and participants covered their faces with masks and face shields.

5.4 Metrics

We used three metrics to evaluate our system. For each metric, the routes and the intersections that were flipped but had the same topological shape were named the same (*e.g.*, intersections whose shapes were "Left, Back" and "Right, Back" were both grouped as L-Shaped intersections).

5.4.1 Intersection Shapes Answered Correctly. For task 1, we measured the percentage of labels that the participants answered correctly. If the shape given by the participant after turning at an intersection matched the label of the actual shape, then the answer was considered correct. Otherwise, it was incorrect.

5.4.2 Task Completion Time. For each task, we measured the time to complete the task. For task 1, we measured the time it took to walk 5 m, from 4 m before (start) to 1 m after (end) each intersection. We started the timer when the participant reached the start and stopped the timer when the participant reached the end. For tasks 2 and 3, we measured the time it took to walk the route from start to end. We started the timer when the participant started walking and stopped the timer when the participant reached the end of the route.

5.4.3 Number of Contacts Made to Obstacles or Walls with a White Cane. For each task, we measured the number of times the participant made contact with obstacles or walls with their white cane by observing the videos taken during the experiment. For task 1, we only measured the number of contacts with the walls, as no obstacles were used.

6 RESULTS

In this section, we describe the results of the experiments. First, we describe the daily experiences in navigating indoor corridors obtained through the pre-interview (Section 6.1), followed by the overall performance of Corridor-Walker (Section 6.2). Finally, we describe the qualitative feedback obtained from the post-interview (Section 6.3).

6.1 Daily Experiences of Participants in Navigating Indoor Corridors

To avoid obstacles, all participants agreed that they have to tap the obstacles with their white canes. Six participants mentioned that obstacles with hollow lower parts (*e.g.*, chairs and desks) are challenging to avoid (P02, P05, P08, P09, P12, and P13), as the upper body may still collide. Meanwhile, P06, P11, and P12 commented that avoiding low-height obstacles (*e.g.*, boxes and rubbish bins) is also challenging because they cannot rely on their echolocation skills for detection.

As for locating an intersection, 12 participants (P01, P03–11, P13, and P14) mentioned that they walk along the wall and use a white cane to locate intersections, 10 participants (P01–04, P06–08, and P12–14) mentioned that they listen to the ambient sounds, and nine participants (P02–04, P06–08, and P12–14) mentioned that they perceive the flow of air. In a familiar place, in addition to the methods mentioned above, they also used a count of steps (P05) and intuition (P09, P13, and P14). Moreover, seven participants (P01, P03, P07, P08, P10, P13, and P14) reported that they had experienced walking past an intersection without noticing. Two participants reported that they had walked past an intersection when they were distracted (P01 and P03), and five participants (P07, P08, P10, P13, and P14) reported that they had walked past an intersection while avoiding obstacles. P08 described the relationship between intersections and obstacles as follows: **A1**: *"If obstacles or people are standing before an intersection, and because we have to avoid them, I lose track of my position and therefore may walk past the intersection"*[1] (P08).

Nine participants (P01, P04, P05, P07–10, P13, and P14) mentioned that it is difficult to walk straight in an indoor corridor. They mentioned that their main strategy is to listen to the echo of the sound from the nearby wall (P01, P03, P04, P06–09, and P12). P07 described the challenging experience of attempting to walk straight as follows: **A2**: *"It is difficult to walk straight. I think I am frequently veering or walking in a zig-zag shape"* (P07).

6.2 Overall Performance of Corridor-Walker

6.2.1 Intersection Shapes Answered Correctly. For task 1, the percentages of intersection shapes answered correctly for L, T, Rotated T, and X-Shaped intersections in the cane-only condition were 71.4%, 21.4%, 28.6%, and 0%, respectively, and those of the system-aided condition were 92.9%, 92.9%, 100%, and 50.0%, respectively. Statistical analysis using the chi-square test at a significance level of 0.01 revealed that participants significantly answered the correct label on the system-aided condition in T ($p = 0.0004$), Rotated T($p = 0.0006$), and X-Shaped ($p = 0.009$) intersections. In the L-shape, the correct answers were high in both conditions and no significant difference could be observed ($p = 0.3$). The reasons why participants mislabeled the intersection with the system can be summarized: 1) Although the system did convey the correct label of the intersection[2], the user answered another label (Occurred once with L-Shaped intersection, once with Rotated T-Shaped intersection and, three times with X-Shaped intersection), 2) the mapping of the system failed because the participant was holding the phone unsteadily, causing the YOLOv3 detector to output incorrect estimation results (Occurred once in X-Shaped intersection), and 3) the system correctly

[1] All of the communications with participants were done in their native language. In this paper, we translated the communications to English and provide them in a quotation and italic, *e.g.*, *"translated content"*.
[2] This is verified by checking the system log.

Table 2. Quantitative evaluation of the number of contacts the participants made to obstacles or walls with the white cane and task completion time: Mean, SD, and p-value of the Wilcoxon signed-rank test, comparing the system-aided and cane-only conditions. The symbols * and ** indicate the significance found at the levels of 0.05 and 0.01, respectively.

Task	Condition	Task Completion Time (seconds)			Number of Contacts			
		cane-only	system-aided	*p-value*	Contact with	cane-only	system-aided	*p-value*
1	L-Shaped	8.98±1.88	14.06±3.90	**0.0002****	wall	3.86±2.35	0.14±0.36	**0.004****
	T-Shaped	9.20±2.04	14.24±4.48	**0.0001****	wall	3.57±2.31	0.29±0.47	**0.006****
	Rotated T-Shaped	9.22±2.35	16.78±5.02	**0.0002****	wall	3.42±2.28	0.14±0.36	**0.002****
	X-Shaped	9.79±2.71	16.48±8.03	**0.0001****	wall	3.71±2.20	0.14±0.36	**0.002****
2	Route 2-1	18.55±3.61	23.46±7.42	**0.0006****	obstacle	1.28±0.73	0.50±0.52	**0.006****
					wall	3.14±3.61	0.57±0.94	**0.02***
	Route 2-2	20.91±4.85	28.50±7.67	**0.0006****	obstacle	2.21±1.42	1.35±1.00	0.08
					wall	1.86±3.18	0.62±1.01	0.2
3	Route 3-1	50.65±7.91	69.30±15.70	**0.0001****	obstacle	3.07±1.49	1.28±1.32	**0.01***
					wall	12.21±9.67	1.07±1.27	**0.003****
	Route 3-2	63.07±10.95	85.70±25.31	**0.0002****	obstacle	3.71±2.34	0.85±1.29	**0.002****
					wall	15.21±12.75	1.43±2.10	**0.002****

detected the X-Shaped intersection and instructed the participant to scan left and right, but the system did not tell the participant that it was an X-Shaped intersection because the participant only scanned in the direction of the intended turn (Occurred three times in X-Shaped intersection).

6.2.2 Task Completion Time. Table 2 reports the mean and SD of the task completion time. As this metric contains three factors that may affect the results, we first conducted a three-way analysis of variance (ANOVA) at a 1% significance level. Specifically, we compared cane-only and system-aided conditions, the order of conditions they started the tasks with, and whether the route was flipped or not. The analysis revealed that there was no interaction between all factors, and the cane-only and system-aided conditions were the only factors that affected the results. Therefore, to analyze the effect between the cane-only and system-aided conditions, we then separated the data based on the two conditions for each route and conducted the Shapiro-Wilk test at a 1% significance level. The test confirmed that normality could not be assumed for all metrics in each route. Also, as the three-way ANOVA revealed that flipping the route did not affect the result, the flipped routes can be assumed to be the same (*e.g.*, L-Shaped intersections that lead to the right and left can be assumed to be the same intersection). Therefore, we used the Wilcoxon signed-rank test to analyze the data. Our statistical analysis at a 1% significance level revealed that more time was required to complete all tasks using the system. This was because the participants tended to walk slower to follow the instructions and re-orient themselves while walking. Also, they took additional time to stop and scan the surrounding environment to confirm the shape of intersections when they were instructed to.

6.2.3 Number of Contacts Made to Obstacles or Walls with the White Cane. Table 2 shows the result of the metric. Based on the same reason stated in Section 6.2.2, we used the Wilcoxon signed-rank test to analyze the data. Our statistical analysis revealed that the system significantly reduced the number of contacts with walls and obstacles in all tasks except Route 2-2. Although the average value of the metric was lower with the system-aided condition in Route 2-2, the significance was not observed because each obstacle was placed only 3 m from each other (Figure 6), making the task challenging. Overall, the system enabled the participants to avoid obstacles while relying less on the wall to navigate the corridor.

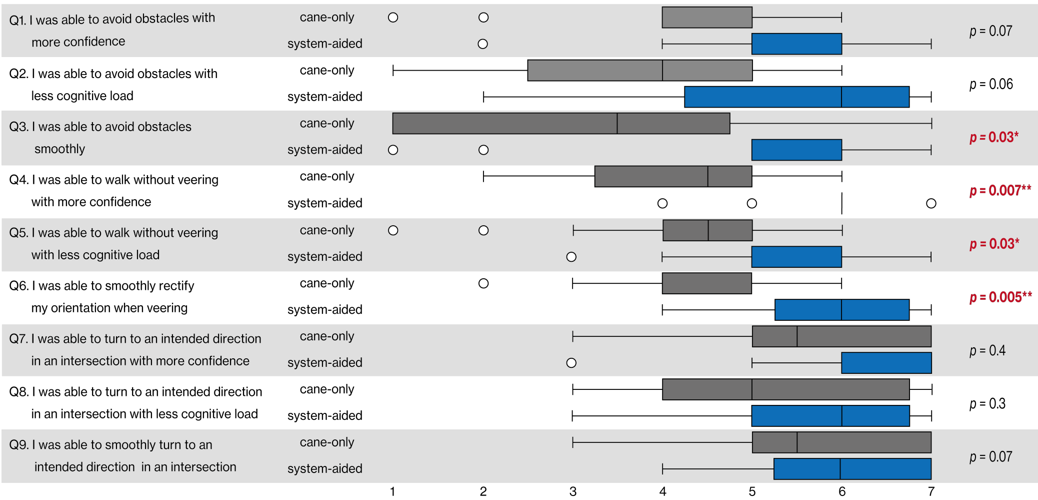

Fig. 7. Likert scores obtained for each question. The *p*-values calculated by the Wilcoxon signed-rank test are indicated on the left side of the figure. The symbols * and ** indicate the significance found at the levels of 0.05 and 0.01, respectively.

6.2.4 Subjective Ratings. Table 1 shows the SUS scores for each participant. The mean SUS score was 80.5 (SD: 7.41). Figure 7 shows the results of the 7-point Likert items. Our statistical analysis using the Wilcoxon signed-rank test revealed that the system received significantly better ratings than the cane-only condition for Q3–6.

6.3 Qualitative Feedback

6.3.1 Positive Feedback. Throughout the interview, we found that each participant found various aspects of the system advantageous. Twelve participants (P01–03, P05–08, and P10–14) felt positive about the obstacle avoidance function: **A3**:*"I was very impressed that I was able to avoid an obstacle without even knowing it was there. It is innovative that the system only signals when an obstacle is in front of me and stops notifying me once I start detouring around it"* (P06), and **A4**:*"Although I had to walk slower to listen to the feedback of the system, I was glad that I did not bump into an obstacle"* (P01). Nine participants (P01, P02, P04–06, and P08–11) especially felt positive about the correction of veering: **A5**:*"The system helped me to walk in a straight line. At first, I did not think it was necessary. However, it was useful because it helped me to walk in the middle when I cannot walk along the wall"* (P09).

Thirteen participants (P01–11, P13, and P14) felt positive about the intersection detection function. Nine participants (P02, P04, P06–09, P11, P13, and P14) mentioned that they want to use this function to build mental maps. **A6**:*"Knowing that I am almost at an intersection means that I do not have to worry about running through it. By checking all the directions to which the intersection extends, I can discover that the road actually extends in another direction"* (P01) and **A7**:*"When I am walking with a white cane, I do not know which way the intersection actually leads to. With the system, I can perceive which way it leads to"* (P14).

6.3.2 Negative Feedback. Three participants (P03, P08, and P09) commented that the obstacle avoidance function of the system was insufficient because they naturally walk fast. **A8**:*"As I naturally walk quite fast, even if the system notifies me of an obstacle, my white cane hits the obstacle. I do not want to walk slower"* (P03). P12, born blind, found neither intersection detection function nor rectifying of orientation useful, as she could do both using only her echolocation skills. Two other participants (P03 and P13) also agreed that the correction of orientation was unnecessary. **A9**: *"I find intersection detection unnecessary because I can determine that I have entered an intersection only with my echolocation skills or by walking along the wall"* (P12) and **A10**: *"Since I think I can naturally walk in the middle, the correction of orientation is unnecessary. It is better if the sound comes from where an obstacle is"* (P12).

6.3.3 Feedback About Using a Smartphone. All participants, except for P03, agreed that one strength of the system was that it requires only a single smartphone. **A11**: *"It is good that the system requires only one smartphone. I always have my smartphone when I go out"* (P08). However, 11 participants (P01, P03–05, P07–12, and P14) felt that holding the phone in their hands was a disadvantage. Especially four participants (P07, P08, P11, and P12) commented that maintaining the angle of the smartphone was challenging. **A12**: *"It was difficult to maintain the smartphone parallel to my orientation, as this system assumes that the orientation of the smartphone and the user is the same"* (P08).

6.3.4 Feedback About Use Cases. We asked participants what types of places they would like to use the system. These include hospitals (P01, P02, P04, P05, P08, and P09), shopping malls (P02, P08, and P09), metro transfers (P04 and P14), and restaurants (P04, P06, P11, and P14). Six participants (P04, P06–08, P13, and P14) mentioned that they want to use the system in an environment in which they do not know how many times to make a turn, such as in other companies' offices. Also, P13 commented that there may be more use cases as follows. **A13**: *"If this application is released in an app store, I think blind people will come up with more situations and use cases of this system"* (P13).

7 DISCUSSION

7.1 Effectiveness of Corridor-Walker

Although it took more time for participants to navigate in an indoor corridor (Section 6.2.2), Corridor-Walker successfully enabled all participants to navigate in an indoor corridor by assisting them to avoid obstacles and recognize intersections. The quantitative results (Table 2) suggest that the system enabled participants to make significantly less contact with obstacles and walls with a white cane. Also, the qualitative feedback (Figure 7) suggests that the system improved their experience while avoiding obstacles (Q3) and re-orienting themselves (Q4–6). Comments from the participants suggest that they were glad to avoid obstacles without knowing that they were present (A3) and with less reliance on walls (A5). On the other hand, we did not observe statistical significance in questions about their experience when turning in an intersection (Q7–9). This is because Q7–9 mainly asked about locating and turning in an intersection that can already be performed with only a cane (A9) as well as the system. However, the comments from the participants suggest that the intersection detection function of the system improved their experience while navigating by assisting them to prevent walking past an intersection unnoticed A6), better grasp the shape of an intersection (A7, Section 6.2.1), and make a mental map (A7, Section 6.3).

7.2 Individual Preferences

Although Corridor-Walker enabled participants to safely navigate an indoor corridor, different preferences for functions and interfaces were observed. Some participants still made contact with obstacles when using the system (Table 2) although the sensing range of system for obstacles was 2 m. P03 found the detection range of obstacles short, as she naturally walks fast (A8), whereas P01 did not find walking slower to be a disadvantage (A4). Thus, the default obstacle detection range does not need to be longer, but should be adjustable for every user with a different walking speed.

P03 and P13, who had a high level of echolocation skills, did not find the intersection detection function (P13) or orientation correction function (P03 and P13) necessary (A8, A9, and A10). As they can naturally walk far from the wall (Table 1) by listening to the reflection of sound from the wall, they can locate an intersection when they enter it. However, P01, who also had high echolocation skills (Table 1), still felt positive about the intersection detection function as it can prevent the user from walking past it and tell the user the shape of an intersection, which is not supported by a white cane (A6). We observed that although blind people with high echolocation skills may walk without relying on walls and can locate intersections with only a white cane, they still have different individual preferences.

7.3 Limitations and Future Work

For the limitations of this study, the experiment was conducted in a limited environment with perpendicular intersections and a corridor with a fixed width. In actual usage, there may be an intersection that consists of five paths or gradual turns. As the current intersection detection function assumes that all intersections consist only of perpendicular paths, the system may not detect such intersections. A more general labeling method for complicated intersections may allow us to create detection engines for a wider variety of intersections.

Also, the use of the system may be limited due to the sensing range of the LiDAR and its cost. As the sensing range of the LiDAR sensor is 5 m [14], the system can detect intersections only up to 3.0–3.5 m ahead (Figure 3). Moreover, the system assumes that both sides of the wall must be visible, thus limiting the use of the system in an open space such as a lobby or large foyer area. In such environments, both functions of the system will fail because the system cannot assign cost values to walkable cells for path planning and cannot extract features of the geometric structure of the environment to the grid map (*e.g.*, wall or corners in an intersection) for intersection detection. In addition, a smartphone with a LiDAR sensor is not yet common and affordable for all blind people. As smartphones are rapidly being improved in recent years, we believe that LiDAR-equipped smartphones with affordable prices and longer sensing ranges may appear and be widely adopted in the future, and these issues may be naturally solved along with the evolution of smartphones.

In terms of the ergonomics, 11 participants stated that there is a problem with how the smartphone should be held (Section 6.3). Since the optimal performance of the system requires users to hold a smartphone in an uncommon manner, they found it uncomfortable to hold it stably in front of them (A12). One failure in task 1 (Section 6.2.1, Reason (2)) occurred because of this reason (1.8%). Such a failure could become more pronounced because of fatigue of holding a smartphone if the person needs to use the system in the real world for longer periods of time. Despite this inconvenience, 13 participants still stated that the strength of this system is that it is implemented on a single smartphone (A11). As smartphone-based systems are highly accepted by blind people for their usefulness [41, 70], more longitudinal studies may provide insights into how to improve the ergonomic issue by further training and the extent of fatigue of holding a smartphone for a long period of time in real world situations. Therefore, collaboration with orientation and mobility (O&M) training communities could provide essential information and suggestions for designing methods to train the usage of such mobile navigation systems in addition to current methods such as white canes and echolocation for navigation.

For future work, we aim to distribute the system and provide assistance to anyone who has a LiDAR-equipped smartphone, as they may discover new use cases and needs of a mobile-based system. While the participants raised many situations in which the systems could be used (*e.g.*, hospitals, shopping malls, metro transfers, and restaurants), six participants came up with the use case of using the system to facilitate the construction of mental maps of environments that they had never visited. As P13 pointed out (A13), we expect that distributing the system will allow us to discover such unintended use cases and apply them to a greater variety of situations.

8 CONCLUSION

In this paper, we present Corridor-Walker, a system that assists blind people in avoiding obstacles and recognizing intersections. First, the system uses a LiDAR sensor of a smartphone to construct a 2D occupancy grid map of the surrounding environment. Then, the system simultaneously plans an obstacle-avoiding path and detects upcoming intersections. Based on these two functions, the system provides spatialized audio feedback to guide the user along the generated path while notifying the user of upcoming obstacles and intersections through vibration and TTS feedback. The user study with 14 blind participants revealed that the system significantly reduced the number of contacts made with a white cane and enabled participants to avoid obstacles while relying less on the wall. The system also enabled participants to better recognize intersections compared to the case using only a white cane. For future work, we plan to consider the different preferences raised by the participants to provide an adjustable interface to match personal use cases. We also aim to design a method to detect general intersections so that the system can be used in a wider variety of environments.

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