Space Perception and Navigation Assistance for the Visually Impaired Using Depth Sensors and Haptic Feedback

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Abstract

Lightweight and low-cost 3-dimensional depth sensors have gained much attention in the computer vision and gaming industry. While their performance has been proven to be successful in the gaming industry, these sensors have not been utilized successfully for assistive devices. Leveraging on this gap, this study focused on the design, implementation, and evaluation of a depth-sensor-based navigation assistive device for the visually impaired. The proposed portable embedded system interprets the field-of-view, converts it into a depth matrix, and processes the information in order to recognize objects, humans, and to provide relevant haptic feedback for navigation of the visually impaired. Through design and evaluation, the proposed system was shown to successfully identify, detect, and track the closest objects, including humans, and perform real-time distance measurements.

Introduction

The World Health Organization (WHO) estimates that 285 million people are visually impaired worldwide [1], and the U.S. Census Bureau reported that 54 million people live with disabilities [2]. While many of these individuals live and interact independently, it is reported that the majority lack the ability to live and function independently. One of the major issues these individuals face is their inability to interpret surroundings and identify obstacles in their path of commute. This challenge led to the introduction of many assistive devices for navigation assistance, with the two most common being white canes and guide dogs [3]. The white cane is only partially effective as it does not detect objects above about knee height, and does not provide cues in sufficient time to avoid a collision in a populated area. As for the guide dog, unfortunately, not all visually impaired individuals have access to dogs, due to an ongoing shortage of properly trained dogs.

Research has demonstrated that assistive technologies can be used to help more people with disabilities to become a part of regular learning environments [4]. This, when combined with the number of calls from blind individuals for impending action in the design of assistive devices [5]. This current study focused on a depth-sensor-based haptic feedback system, as shown in Figure 1, which belongs to the category of vision substitution. This haptic feedback system helps blind people overcome challenges of dependence, and lets them participate in more social and civic activities to improve their quality of life.

Figure 1. Prototype of the Haptic Feedback System on a User

Literature Review

Over the past three decades, research has been conducted to design new navigation devices [6-29]. Benjamin et al. [7] built a laser cane that used optical triangulation with three laser diodes. The first laser pointed at the ground, detecting a drop in elevation; the second pointed straight in front of the user and parallel to the ground; the third pointed straight ahead at an angle of 45 degrees from the ground in order to protect the user from overhanging obstacles. Bissit and Heyes [8] developed a hand-held sonar device to give the user auditory feedback with eight discrete levels. Bousbia-Salah et al. [9] proposed a method of detecting obstacles on the ground through an ultrasonic sensor integrated on the white cane and the user's shoulders. Shoval et al. [10] proposed a navigation belt made up of an array of ultrasonic sensor to detect obstacles, but it was not an ideal method for operation in dense and noisy environments. Na [11] proposed an interactive guide system for indoor positioning. Wong et al. [12] proposed using virtual reality technology to capture images of the house via cameras, and use this information for indoor navigation. Kulyukin et al. [13] proposed a robot-assisted navigation method for indoor environments.

Vision-based situational awareness and haptic feedback systems were proposed and implemented by many researchers. Castells et al. [14] used a vision sensor to detect possible obstacles in order to supplement the feedback provided by a traditional white cane. They used the images to detect sidewalk borders and obstacles in a predefined window, but the system had poor accuracy in dense environments. Sainarayanan et al. [15] presented a fuzzy-clustering-based algorithm to identify obstacles in the path and provide feedback to the user through stereo earphones, but their system required high computational power, and it was difficult for the user to comprehend signals in a noisy environment. Filipe et al. [16] presented a depth-sensor-based system but did not present any mechanism to provide feedback to the user for navigational assistance. Khoshelham and Elberink [17] presented the depth-sensor-based approach for indoor mapping of objects but did not include a feedback system for effective navigation. Han et al. [18] presented an overview of applications from a similar depth sensor but did not provide a solution for navigation and feedback. Zeng et al. [19] and Ishiwata et al. [20] presented an exploration and avoidance system with haptic feedback that used an expensive time-of-flight camera for obstacle detection, limiting its adoptability, due to economic constraints.

Also, many of these existing systems increase the user's navigation-related physical load, as they require the user to wear heavy body gear, contributing to physical fatigue. Based on the principles of universal design, the navigation-based assistive devices for the blind should encompass design characteristics such as equitable use and flexibility, be simple and intuitive, offer perceptible information, be portable, and allow for periodic updates.

Design and Implementation

Figures 2 and 3 show the architecture and data flow for the proposed haptic feedback system (HFS). The first module in the architecture was an ASUS Xtion Pro depth sensor for scanning the environment for the user. It could also filter the visual scene to generate a depth profile. This was accomplished through PrimeSense's 3-D sensors, which used light coding to code the scene with the aid of active infrared illumination [23]. The coded light was processed through the built-in chip to obtain depth information of the environment [5]. With a horizontal field of view of 57 degrees and a vertical field of view of 43 degrees, a distance map across the user was generated in an image with a resolution of 640 x 480 pixels at 60 fps.

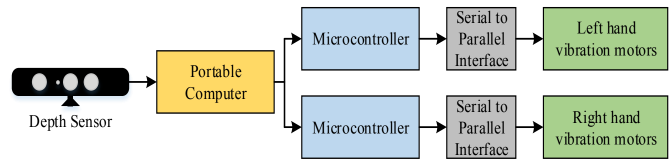

Figure 2. Architecture of the Haptic Feedback System

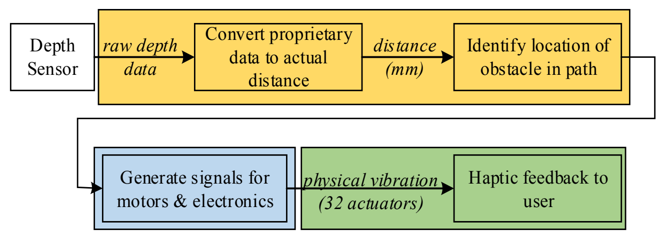

Figure 3. Data Flow and Manipulation

The second module in the proposed system was a portable computer that could decode the proprietary data from the sensor into a meaningful format through a custom java-based program running on the Processing Integrated Development Environment (PIDE) [30] and the open-source SimpleOpen NI library [31]. This portable computer obtained the depth images generated by the depth sensor and decoded them into a matrix of 640 x 480 elements, with each element representing the distance to the object with respect to the user. Upon generating this matrix, it divided this into eight smaller zones, four on the left (L1, L2, L3, and L4) and four on the right (R1, R2, R3, and R4), each corresponding to a respective column in the vibration module. Then, it used the nearest neighbor algorithm to find the location of the nearest obstacle with respect to the user and generated appropriate signals for the haptic feedback unit.

Furthermore, the system could also identify whether the obstacles were static or dynamic and provide real-time information to the user through an audio feedback system. Once the location and distance information of the nearest obstacle were found through the custom java program in PIDE, an Arduino microcontroller generated signals to actuate the appropriate vibration motors. As the number of vibration motors far exceeded the number of available output ports on the microcontroller, a 16-bit input/output (I/O) expander was used to decode the information from the I2C bus of the microcontroller. This I/O expander transmitted this information to the left-hand and right-hand vibration modules to activate the respective number of actuators.

The left-hand and right-hand vibration modules were arrays of shaftless, 8 mm motors woven into gloves, and served as a vibrotactile feedback delivery mechanism. Figure 4 shows the architecture of the haptic feedback system with 16 motors woven into the left-hand glove (one column of four motors into each finger sleeve). Figure 5 shows the prototype board with all of the electronics. Figure 6 shows the wiring connections of the motors in the glove. These motors vibrated based on the signal generated from the I/O expander, which inherently was generated based on the presence of the obstacle that was within the depth sensor's field of view. For instance, if a static obstacle were found in zones L1 and L2 of the sensor's field of view, motors in the first two columns of Figure 4 would vibrate, with the number of vibrating motors inversely proportional to the proximity of the obstacle. Also, while operating in a densely populated environment, this feedback system could be used to inform the blind user of the location of an open space or a direction to pursue in order to avoid a collision during a commute.

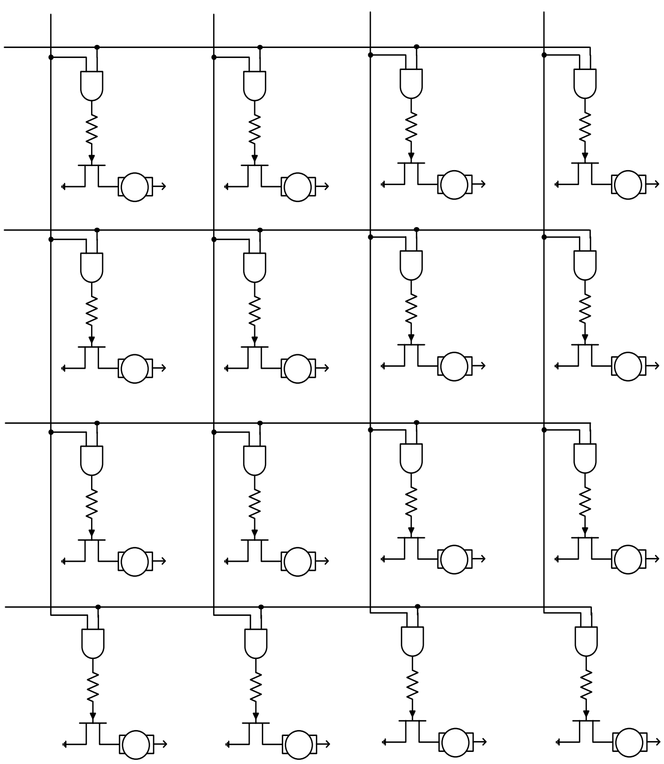

Figure 4. Architecture of the Haptic Feedback Array

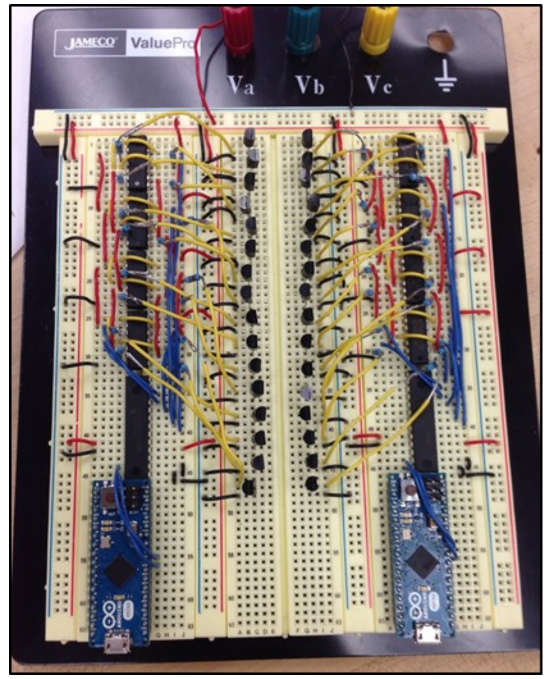

Figure 5. Prototype Board with the Electronics of the Proposed System

Figure 6. Vibration Motors in the Left-hand Glove

Testing and Evaluation

To validate the fundamental operation and feasibility of the proposed system, it was subjected to multiple tests with different programs, each designed to perform a specific task. Any of these programs could be combined to perform a combination of tasks as well. Due to the infeasibility of visually demonstrating the operation of the vibration motors here, a simplified test system of motors replaced by LEDs is presented here.

Test 1: Identify the closest object
In this test, the system was programmed to obtain the depth matrix, filter the data to identify the closest single point in its field of view, and turn on the appropriate number of LEDs with respect to distance of closest object from the system. Figure 7 shows the depth image, as obtained from the sensor, and the zone partitions (L1, L2, L3, L4, R1, R2, R3, and R4). Upon filtering and data processing from this image, the closest single point (marked with a red dot) was detected in zone L3. This information was transmitted to the left-hand microcontroller, which activated two LEDs in zone L3 through the I/O expander, as presented in Figure 8. It should be noted that this test was designed to represent the system's ability to detect only the closest point in the field of view, not the whole object or a human, which will be performed in a future test. With the primary goal of this test being identification of closest object, when multiple objects at similar distances are identified in different zones, appropriate motors/LEDs in respective will be activated to inform the user accordingly.

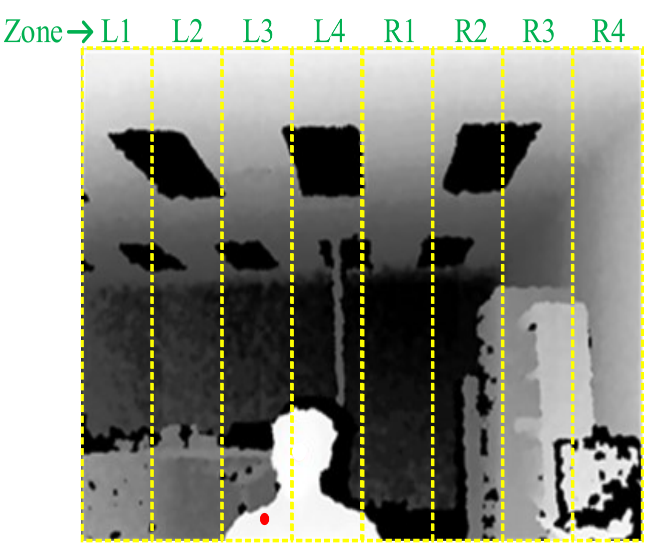

Figure 7. Depth Image for the Closest-object Detection Test

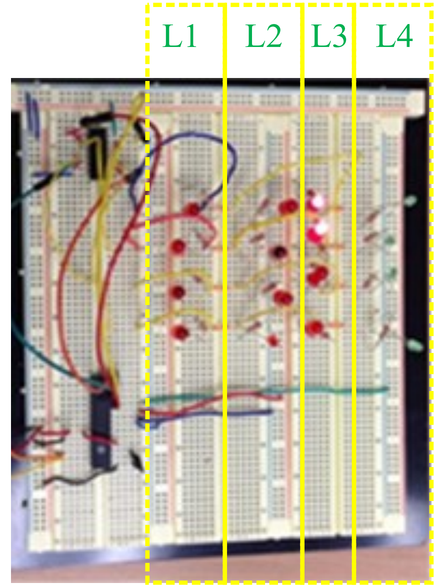

Figure 8. Verification of the Closest-object Detection Test

Test 2: Identify humans
While Test 1 was designed to merely identify an object, it cannot distinguish between a physical object and a human. With human detection being a fundamental requirement in navigation assistance devices, Test 2 was drafted to scan the field-of-view, distinguish between physical objects and humans, and inform the user about the proximity and location of a human. Figure 9 shows the depth image, as obtained from the sensor, zone partitions, human detected (marked with in blue), and their respective center of mass (marked with a red dot) in zone L3. This information was transmitted to the left-side microcontroller in order to activate three LEDs in zone L3 through the I/O expander, as presented in Figure 10. Furthermore, extended tests were performed to evaluate efficiency of the system in detecting both static and dynamic (walking) humans, as presented in Table 1. The total time from start of program to providing feedback through the motors/LEDs in this test was found to be approximately 2.5 seconds, an acceptable time in real-time navigation when compared to results from other studies [19, 32].

Test 3: Measure the distance between points
As it is not uncommon for humans to stretch their hands while walking, this test was designed to identify if any humans in the path of navigation had stretched their hands, and mark this region as a no-pass region. If so, the system identified the location of the human, measured the distance between the two hands, and informed the blind user so that he/she could navigate around the obstacle in his/her path. The depth image, obtained from this test, is shown in Figure 11, where the presence of a human is marked in blue, and

the red dots represents the location of the head, center of mass, left hand, and right hand, and the distance between the two hands, presented in mm on the left side (mag: 1373.8055), validating that the proposed system could identify movement of humans in real-time.

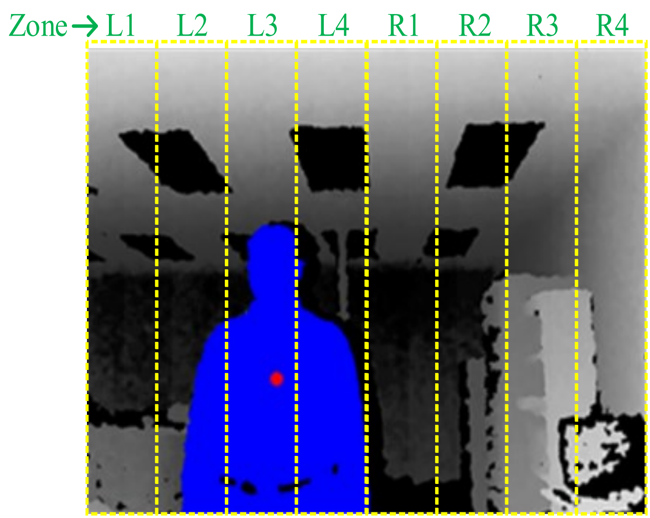

Figure 9. Depth Image for the Human Detection Test

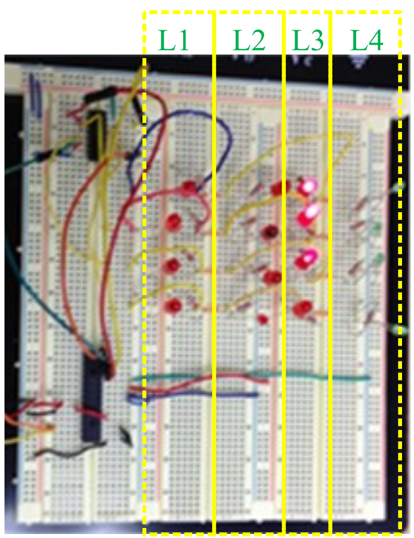

Figure 10. Verification of the Human Identification Test

Table 1. Human Detection Time Results

Distance to Human (m)	Average Detection Time (sec)	
	Static Human	Dynamic/Walking Human
1.0	1.144	0.859
2.0	2.114	0.529
3.0	2.572	1.660
4.0	1.517	1.568
5.0	2.535	1.254

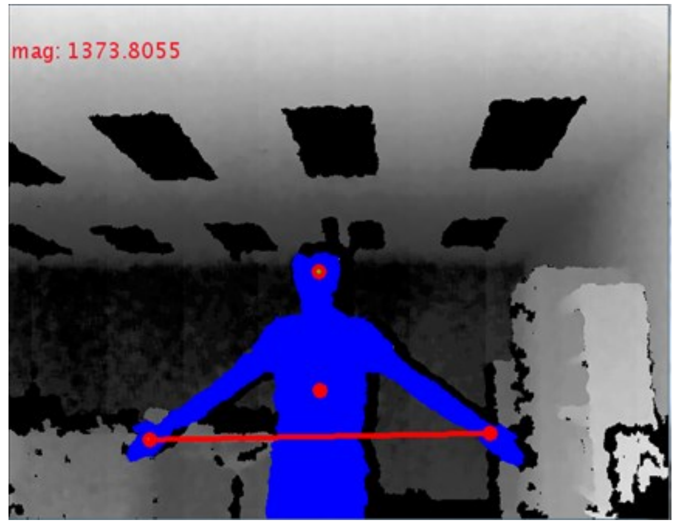

Figure 11. Depth Image for the Test of Distance Measurement between Two Points

<u>Test 4: Dynamically find the closest objects</u>

This test was designed to extend the results found in Test 1. A new algorithm was developed to dynamically detect multiple obstacles. Each motor in a column was designed to turn on when an object was found within a certain threshold, similar to Test 1. The depth image was scanned in order to detect the closest object in each zone, L1-L4 and R1-R4, and inform the user accordingly. Unlike the results in Test 1 (see Figure 7), this test could detect that the closest object was present in zones L3, L4, and R1, and would activate the LEDs accordingly. The number of LEDs that turn on for each zone varied, based on distance of the closest object in each zone (four LEDs for distances of less than 50.0 cm, three LEDs for 50.1- 61.0 cm, two LEDs for 61.1-91.5cm, and one LED for 91.6-122.0 cm).

<u>Test 5: Detection probability for diverse objects</u>

As detection of static objects is equally important as detecting humans, a different test was performed to evaluate the detection probability of diverse objects at various distances. Two key metrics in real-time navigation are the probability of detection accuracy and distance measured. Accordingly, diverse objects were placed at different distances (1 m, 2 m, 3 m, 4 m, and 5 m) and the test program was executed to obtain 1000 measurements for each object-distance combination. Results of the probability of detection and average error in distance measured from this test, presented in Table 2, clearly demonstrate the efficiency of the proposed system. While the system was able to detect objects of household materials such as Styrofoam, plastic, cotton, aluminum, and rubber with a probability of nearly 1.0, the nature of the infrared signals emitted by the depth sensor were absorbed by steel, thus drastically limiting its performance. Lastly, the processing latency of each of these tests was evaluated and found to be in the range of 1.8 sec – 2.9 sec, with an overall average of 2.1 sec, an acceptable value when compared with previous studies [19, 30].

Table 2. Probabilities of Object Detection

Material	Probability of Detection					Average Distance Error (%)
	1m	2m	3m	4m	5m	
Styrofoam	1.00	1.00	1.00	1.00	1.00	3.67
Solid Plastic	1.00	1.00	1.00	1.00	0.98	1.02
Cotton	1.00	1.00	1.00	1.00	1.00	0.97
Aluminum	1.00	1.00	1.00	1.00	1.00	0.75
Rubber	1.00	1.00	1.00	0.87	0.02	0.73
Steel	1.00	0.40	0.80	0.91	0.00	1.45
Water Bottle	0.02	0.00	0.00	0.00	0.00	4.01
Trash Bag	1.00	1.00	0.32	0.03	0.00	5.70
Static Human	1.00	1.00	1.00	1.00	1.00	2.23

Conclusions

In this paper, the authors presented the design, implementation, and evaluation of a simple, light, and low-cost depth-sensor-based haptic feedback system. The proposed system proved that it could overcome challenges of computational power, comprehension of signals in noisy environments, and heavy body gear, as presented in the previous study. Through testing, the prototype was demonstrated to: i) detect the presence and location of obstacles in the path of navigation; ii) identify an obstacle-free path in the field of view for the user to follow for safe navigation in a crowded environment; and, iii) detect obstacles in the navigation path in real-time.

Further testing can be done to gather more qualitative and quantitative data on user reaction time to process the signals, as well as overall ability to navigate. This will be done upon obtaining approval from the Institutional Review Board (IRB), as it involves human subjects. Optimization of the proposed algorithms will be performed for implementation on a portable microcontroller, such as Raspberry Pi, to further improve portability. Overall, while designed and implemented as a navigation system for the blind, the proposed architecture has a broad range of applications including, but not limited to, body tracking for clinical assessment and monitoring, body tracking during rehabilitation, and touchless interaction in image-guided interventional medical treatment.

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