Autonomous Wheelchair Navigation in Unmapped Indoor Environments

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***Abstract*—Recent developments in robot automation have fostered the development of many assistive devices to improve the quality of life for individuals with disabilities. Notable among these devices are autonomous wheelchairs, which are capable of navigating to given destinations while avoiding obstacles. However, the method of destination selection and navigation in unmapped indoor environments remains a challenge for these autonomous wheelchairs. In this work, a novel approach to selecting a destination for an autonomous wheelchair in an unmapped indoor environment using a camera, ranging LIDAR, and computer vision is presented. The system scans the environment at startup and compiles a list of possible destinations for a user to easily make an selection. The proposed system was tested in a simulated shopping mall environment where destinations included various stores. The computer vision system was tested with images of store-fronts at various distances and angles. Ten trials were conducted to test the navigation system with destinations at close-range, mid-range, and long-range. The system successfully navigated to the destination in 100% of the trials for close-range destinations and 90% of the trials for mid-range and long-range destinations. Based on these results, we conclude the proposed design is a promising means of destination selection for autonomous wheelchairs in unmapped indoor environments for individuals with severe disabilities.**

***Index Terms*—Unmapped indoor navigation, Computer Vision, Machine Learning, Ranging-LIDAR**

I. Introduction

2.2 million individuals in the United States use wheelchairs for daily tasks and mobility according to the National Institute of Child Health and Human Development (NICHD) [1]. There are an additional 300,000 individuals in the US have spinal cord injury (SPI) and 11,000 more SPIs every year. Over 40% of SPI patients are quadriplegic with no control over their limbs [2] and require wheelchairs for mobility.

Individuals with severe injuries can regain mobility through the use of electric wheelchairs, but most conventional electric wheelchairs use an armrest-mounted joystick for control [3]. Individuals with amyotrophic lateral sclerosis (ALS), a neurological disease that targets motor neurons responsible for controlling muscle movement [4], or SPIs cannot operate conventional electric wheelchairs due to limited mobility in their limbs. As a result, ALS patients are immobile for prolonged periods of time or heavily dependent on others for mobility. Reduced mobility and autonomy is linked to a lower quality of life [5] and causes frustration and anxiety leading to depression [6].

There has been interest in developing smart wheelchairs to alleviate the problem of limited mobility for many years. Several wheelchairs have been developed which use eye blinks, eye movements, and facial/head gestures for control [7]. [6], [8], [9] use various brain signals and Brain-Computer Interface (BCI) to control an electric wheelchair. These wheelchairs are limited by the high cost of specialized hardware and the strain placed on the user during navigation. Recent developments in automation have been incorporated into wheelchairs to automate navigation in an effort to reduce strain on the user [10], [11].

While autonomous navigation in outdoor environments has been extensively explored, indoor environments present a challenge for autonomous navigation due to unavailability of GPS signals for localization. WiFi signals, Bluetooth modules, and Radio Frequency transmitter/receivers are commonly substituted for GPS and used to localize a wheelchair during navigation [12]-[15]. This approach requires a robust infrastructure to localize properly and cannot be scaled to large indoor environments, i.e. shopping malls, airports, etc.

In this paper, an autonomous wheelchair navigation system for indoor environments is proposed. The proposed system uses an onboard LIDAR unit to localize and detect obstacles in real time, thus eliminating the need for a network for transmitters and receivers. Recent developments in machine learning and logo detection [16]-[20] are incorporated to scan for potential destinations for navigation.

The paper is organized as follows: Section II provides a detailed description of the components as well as their implementation; Section III consists of the experimental study as well as its results discussed in detail; and Section IV concludes this paper.

II. Methodology

A. Detection Arm

A robotic arm with 2 degrees of freedom is constructed and fitted with a camera and ranging LIDAR. The primary camera used for the arm is the Logitech c310 HD Webcam [21] (See Fig. 1). It supports HD 720p video capture and 5 megapixel photos with a resolution of 1280 x 720 pixels. The secondary

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camera is the Ausdom AW615 [22]. It supports HD 1080p video capture and 12 megapixel photos with a resolution of 1920 x 1080 pixels. The ranging LIDAR is LIDAR-Lite v3 from GARMIN [23] (See Fig. 1). Lite v3 has a range of 5 cm to 40 m with resolution of 1 cm and accuracy of +/- 2.5 cm.

At system startup, the detection arm rotates capturing images at 1 degree intervals. Images are captured to 640 x 480 pixels in size with RGB 24-bit data and up to 180 images can be captured per scan. The captured images are sent to the computer vision system for feature extraction and detection. If a potential destination is detected, the LIDAR-Lite is used to measure its distance. All potential destinations are sent to the autonomous navigation system and made available to the user for selection. Fig. 2 shows the operation of the detection arm.

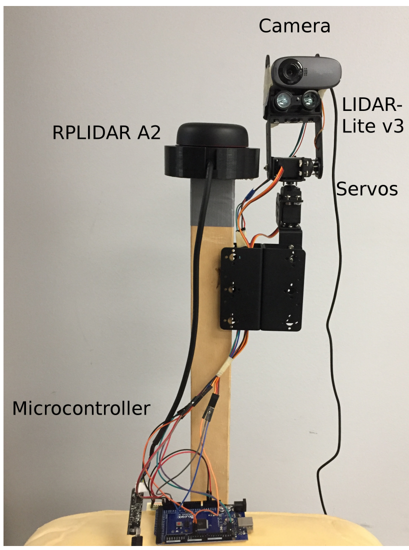


Fig. 1. Selection Arm with RPLIDAR A2, Camera, LIDAR-Lite v3, servo motors, and Microcontroller

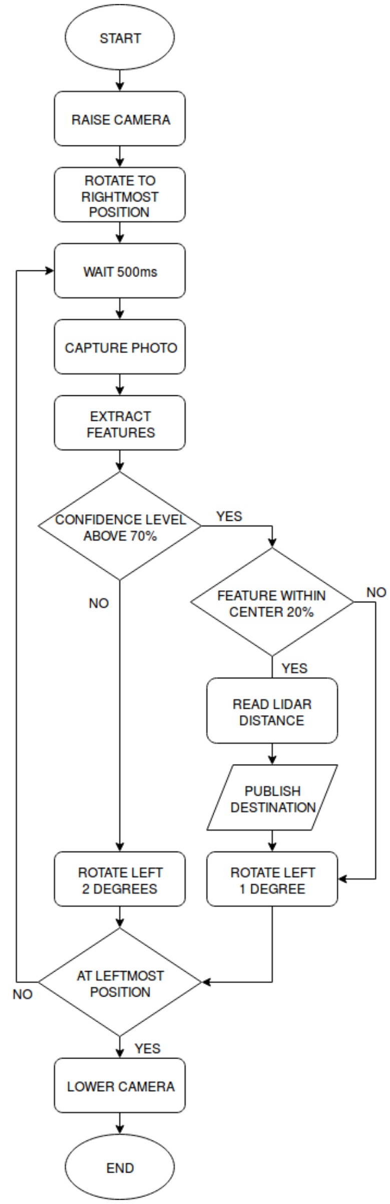


Fig. 2. Operation of Selection Arm

B. Computer Vision System

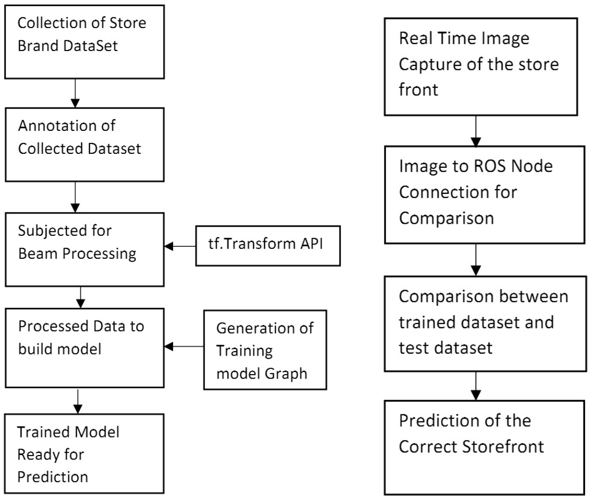
The computer vision system uses TensorFlow™[24], an open source software library for numerical computation using data flow graphs. Nodes of a data flow graph represent mathematical operations and the edges represent multidimensional data arrays (tensors) communicated between nodes. The computer vision system is divided into the training and testing phase. During the training phase, TensorFlow uses pre-trained models along with a data-set of images to build a new model. Pre-trained models are used to reduce training time. In the presented approach, Single-Shot-Detector (SSD) mobilenet pre-trained model was used along with a data-set of 900 images of storefronts to build a new model. SSD mobilenet pre-trained model was selected for the proposed design due to its near real-time processing of images. The images used in the data-set vary in size lighting, angle, and distance. The data-set is converted into the TensorFlow (TF) Record file format and used for training a model. Out of the 900 images in the data-set, 90% of the images are used to train the model while the remaining 10% are used by TensorFlow to verify the trained model. Once TensorFlow has completed training, the trained model can be exported and used for detection.

During the testing phase, the computer vision system receives captured images from the detection arm. The images are passed to TensorFlow to extract features from the images and compare them with the trained model. TensorFlow determines if the image matches features in the trained model and determines a confidence level for each match.

Training process and testing process for computer vision is shown in Fig. 3.

C. Autonomous Navigation System

The autonomous navigation system used in the proposed design is based on the work done by [11]. The navigation system



(a) Training Process (b) Testing Process

Fig. 3. Computer Vision

is improved to enable navigation in unmapped environments, allowing the wheelchair to navigate to any given destination. The autonomous system is capable of detecting both static and dynamic obstacles, obstacle avoidance, path planning, and path correction. It is composed of ROS, a LIDAR unit, and odometry system. (Refer to [11] for detailed description of the autonomous navigation system.)

1) Robot Operating System [11]: ROS is an open source platform that runs on top of a Linux environment and provides a flexible framework for writing robot software [25]. The abundance of packages available by developers provides the necessary tools for navigation and obstacle avoidance.

ROS receives a list of potential destinations from the computer vision system and allows the user to make a destination selection. Once a selection is made, ROS sends velocity commands to the wheelchair control system for navigation to the destination. While the wheelchair is navigating, ROS checks the environment for new obstacles and send new velocity commands to reroute the wheelchair if any obstructions are encountered.

2) LIDAR: The RPLIDAR A2 is used by the autonomous navigation system to navigate and localize properly. It is primarily used to detect obstacles in the surrounding environment and dynamically detect new obstacles that arise while en route to a destination.

The RPLIDAR A2 from Slamtec is a low cost 360-degree laser range scanner produced by the Robopeak development team [27]. It can take up to 4000 samples per second with a scanning frequency of 10 Hz (600 rpm) with a range of 6 meters. It has a resolution of 0.9-degrees at scanning frequency of 10 Hz. The scanning frequency can be adjusted as needed within the range of 5-15 Hz. The RPLIDAR A2 uses a low-cost laser measurement system which yields optimal performance for indoor environment and outdoor environment without direct sunlight exposure.

The RPLIDAR A2 emits modulated infrared laser signal and detects the laser signal once it is reflected by an object. The reflected signal is sampled by the vision acquisition system in RPLIDAR and the DSP embedded in RPLIDAR starts processing the sample data outputs distance value and angle value between the object and RPLIDAR. The RPLIDAR outputs distance in millimeters and the current heading angle in degrees. The laser scan data can be processed by the host computer and used for navigation and localization as well as obstacle detection.

The LIDAR unit is placed 1.4 meters above the ground, mounted on a wooden plank, and attached to the rear of the wheelchair's backrest. The vantage point allows for the LIDAR to raytrace its surroundings from a position slightly above a seated individual's head. The LIDAR sends laser scan data to ROS through a USB connection. ROS then creates a map using the laser scan data implemented through a SLAM algorithm (See [11] for details about SLAM).

D. Laptop

Computer Vision and Autonomous Navigation systems require a laptop to function. The laptop used in the proposed design is the Dell®Inspiron™15R 5537. It has a 4th Gen Intel®Core™i5-4200U running at 1.60 GHz and 8 GB of DDR3 RAM. The laptop is running Ubuntu 16.04 LTS operating system.

III. Experimental Design

A. Environment

A simulated shopping mall is used as a test case to evaluate the efficacy of the computer vision and autonomous navigation systems. Images of storefronts for Macy's, Forever21, and JCPenny are placed in an indoor environment and serve as potential destinations.

The first destination (Macy's) is placed 3 meters away from the starting point. At this range, the destination is clearly visible and within the range of the RPLIDAR A2. The second destination (JCPenny) is placed 6 meters away from the starting point. At this range, the destination is partially visible to the camera and beyond the range of the RPLIDAR A2. The third and final destination (Forever 21) is placed 9 meters way from the starting point. Fig. 4 shows the test environment and destinations.

B. Evaluation Metrics

1) Metrics for Computer Vision: Two main metrics are used to test to the image computer vision system: detection and confidence level. Detection refers to the computer vision system successfully detecting a storefront in a image based on its trained model. Confidence level is a measure of how closely the input image resembles images used in training of the model.

(a) First Destination (b) Second Destination

(c) Third Destination

Fig. 4. Test Case of a Shopping Mall

2) *Metrics for Autonomous Navigation:* The following metrics were used to evaluate the efficacy of the navigation system:

- *Scan Time* – Time taken by detection arm to scan the environment for potential destinations (in seconds)
- *False Detection* – Number of instances where the computer vision system detected storefronts were none were present or misidentified detected storefronts
- *Distance* – Distance traveled by the wheelchair to reach destination (in meters).
- *Navigation Time* – Time taken by wheelchair to navigate to destination (in seconds).
- *Speed* – Distance traveled divided by navigation time (in meters per second)
- *Collisions* – The number of collisions between the wheelchair and an obstacle during navigation

C. Results

1) *Computer Vision:* Images were taken of the storefronts in the environment at various angles and distances to test the computer vision system. Each image was passed to the TensorFlow for processing. TensorFlow detected whether a storefront was present in the image along with a confidence level for the detection. Results for images of storefronts at various angles and distances with Logitech c310 HD camera are shown in Table I. Results for images of storefronts at various angles and distances with Ausdom AW615 camera are shown in Table II.

TABLE I. Confidence level for Macy's detection at various angles and distances with Logitech c310 HD Camera

	Angle (degrees)			
Distance (m)	30	45	60	90
3	89%	90%	99%	99%
5	64%	86%	98%	99%
6	62%	76%	81%	94%
8	35%	36%	53%	81%
9	25%	34%	56%	79%
10	13%	22%	21%	72%

TABLE II. Confidence level for Macy's detection at various angles and distances with Ausdom AW615 Camera

	Angle (degrees)			
Distance (m)	30	45	60	90
3	93%	96%	99%	99%
5	82%	86%	91%	96%
6	78%	79%	82%	89%
8	45%	58%	62%	73%
9	32%	45%	52%	56%
10	21%	35%	37%	43%

2) *Autonomous Navigation System:* Ten trails were conducted to test the autonomous navigation system. During the trial, detection arm first scanned the environment for potential destinations. Destination 1 (Macy's) was detected and the wheelchair navigated to the destination. The detection arm scanned the new environment and detected the second destination (JCPenny). The wheelchair navigated to destination 2 and the detection arm scanned the environment again. Destination 3 (Forever 21) was detected and the wheelchair navigated to the destination concluding the trial. Fig. 5 shows environment at various points of the trail. Results for the ten trials are shown in Table III.

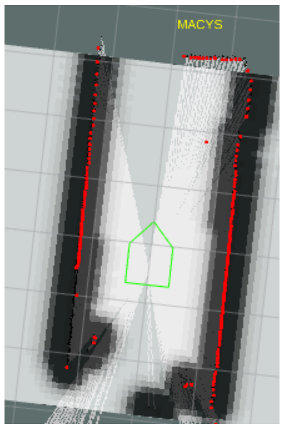
D. Discussion

1) *Computer Vision:* The results for the computer vision system (shown in Table I and II) show that the system correctly detects the storefronts at short distance and straight angles with a high confidence level. The confidence level decreases when storefronts are placed at a larger distance. The storefront occupies a smaller section of image reducing the confidence level at large distances. The confidence level also decreased when storefronts are viewed from steeper angles. In these cases, the shape of the image is distorted when compared

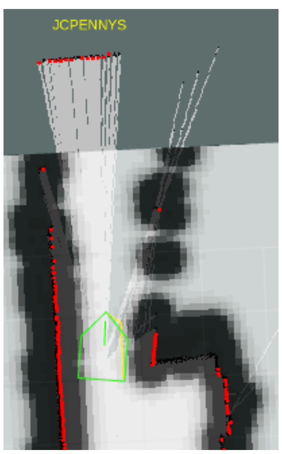
TABLE III. Ten Trials for Autonomous Navigation to Destinations in Unmapped Environment

	Destination 1 - Macy's				Destination 2 - JCPenny				Destination 3 - Forever 21			
	Min	Max	Mean	Std.	Min	Max	Mean	Std.	Min	Max	Mean	Std.
Scan Time (s)	197	229	218	11.79	204	252	219.3	15.02	196	237	214.9	10.26
False Detection	0	14	2.2	4.29	1	17	5.3	5.67	0	16	3.3	4.78
Distance (m)	3.27	4.1	3.706	0.22	4.2	4.55	4.37	0.13	3.2	3.54	3.39	0.11
Navigation Time (s)	9.75	12.59	11.25	0.84	13.07	22.3	14.68	2.87	10.65	12.02	11.15	0.47
Speed (m/s)	0.29	0.42	0.33	0.04	0.19	0.34	0.31	0.05	0.27	0.33	0.30	0.02
Collisions	0	0	0	-	0	0	0	-	0	0	0	-

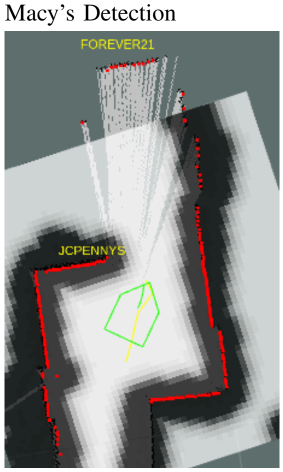
(a) Initial Environment



(b) Environment after Macy's Detection



(c) Environment after Navigating to Macy's with JCPenny Detection



(d) Environment after Navigating to JCPenny with Forever 21 Detection

Fig. 5. Environment at various points of trial

to training data-set images. TensorFlow detects and matches fewer features from these images which results in lower confidence level.

The confidence level from TensorFlow can be improved by using a higher resolution camera for capturing images. These images will contain more data allowing TensorFlow to extract more features and match them with a trained model. A larger training data-set will also improve the confidence level by improving the quality of trained model. Confidence level for detection at steep angles can be improved by including more diverse images in the training data-set. However, these improvements produce larger time penalties. Large data-sets take more time to train and are slower to process images with more complex models.

2) Autonomous Navigation: The autonomous navigation system was able to successfully navigate to Destination 1 in 100% of the trials. The system successfully navigated to Destinations 2 and 3 in 90% of the trails. During trial 4 for Destination 2, the system detected false obstacles in its path and tried reroute the wheelchair. The system determined that not viable path were available and aborted navigation. During trail 6 for Destination 3, the wheelchair moved too close to an obstacle and aborted navigation to avoid a collision.

The scan time was a bottleneck for the navigation system with the destination detection taking approximately 218 seconds. The long scan time was caused by the number of images taken and the time to process each image. The scan time can be improved by reducing the number of images captured. However, this reduces the probability of correctly detecting the destination. There were few false detections during the trials caused by some features in the environment that were incorrectly matched to trained data-set. The number of false detections can be reduced or even eliminated by using a larger data-set for training.

The average navigation time for the trials was approximately 11 seconds and there were no collision during the trails. The results show the robustness of the navigation system in unmapped environments.

IV. Conclusion

An autonomous wheelchair capable of navigating in unmapped indoor environments was presented. The wheelchair used computer vision to detect potential destination. The computer vision capabilities of the proposed designed were tested with image taken of storefronts at various angles and distances. The computer vision system successfully detected the storefronts at close distances and straight angles with high confidence levels.

The autonomous navigation capabilities of the proposed design were tested in an unmapped indoor shopping mall environment. Ten trials were conducted and the system correctly detected and navigated to Destination 1 in 100% of the trials.

The system correctly detected and navigated to Destination 2 and 3 in 90% of the trials. These results validate the presented design and offer areas of further improvement.

The strength and novelty of the presented approach is the ability to navigate in an indoor environment without prior mapping or the need for external hardware for localization. Additionally, the proposed design approximately costs $1,000 and consumes 100 watts of power (including the laptop), making it a low-cost, low-power solution.

Acknowledgment

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