NYU Sixth Sense
Experimental Design: Final Report

Spring 2023

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Background Information/ Readings

We read several papers to gain knowledge on the VIS4ION system before designing our experiment. The papers include "An inconspicuous, integrated electronic travel aid for visual impairment," "A piezoelectric-based advanced wearable: obstacle avoidance for the visually impaired built into a backpack," and a summary of "Communicating through Touch: Macro Fiber Composites for Tactile Stimulation on the Abdomen." The papers provided an overview of the Electronic Travel Aid (ETA) and its components, such as the computer vision and haptic feedback systems. The VIS4ION system was designed to meet the needs of the visually impaired and consists of a stereo camera and a tactor-equipped belt. The papers on obstacle avoidance and macro fiber composites provided further details on the mechanics of the belt. After testing the prototype for sensory discrimination, a new model was created and experimented on for more efficient relaying of information.

Subsequent papers provided a foundation for our experimental plan. The paper "ASSIST: Evaluating the usability and performance of an indoor navigation assistant for blind and visually impaired people" served as the basis for our design and tested an app for indoor navigation. The paper "A Standardized Obstacle Course for Assessment of Visual Function in Ultra Low Vision and Artificial Vision" helped us design the obstacle course for our experiment and provided metrics for preferred walking speed. We also read "Orientation & Mobility Techniques," which taught us important skills for working with visually impaired individuals. As we are working with visually impaired participants, accessibility factors must be taken into account.

We also took inspiration from the IRB document "Effectiveness of the Commute Booster Application for Navigation of Low-Vision Subjects in Urban Settings" to modify our experiment design according to industry standards. Instead of using blindfolds to simulate visual impairment in healthy participants, we will use VisualEyes Vision Simulator Glasses manufactured by Good-Lite Company, which can simulate a variety of visual impairments. Multiple pairs of glasses could be used together to simulate the desired condition. Examining the relevant ethical criteria in IRB also prompted us to reinforce the obstacles in our experiment with a soft fabric, which could protect the participants from injuries and increase the lifetimes of the obstacles.

Although not relevant to our objectives this semester, we relied on "Eye Tracking Methodology: Theory and Practice" for principles and "Best practices in eye tracking research" for practical guidelines to learn about eye-tracking. We chose the Pupil Invisible eye-tracker by Pupil Labs because it looks like a regular pair of glasses and does not require calibration before usage, which can elicit more natural behavior from the participants. We also consulted "A High-Level Description and Performance Evaluation of Pupil Invisible" by Pupil Labs to understand the advantages and disadvantages of the device, and to strategize methods of data collection and visualization.

To ensure accurate detection and distance measurement of obstacles in the obstacle course, several machine learning algorithms are employed for the VIS4ION system. A monocular depth estimation model is utilized to determine the user's proximity to each obstacle in real-time footage captured by a single camera. The desired outcome is similar to "Consistent Video Depth Estimation" but with increased resolution due to recent algorithmic advancements. In addition, object detection is performed using YOLOv5, the most popular model for this purpose. Ideally, over 500 instances of each obstacle would be available for training to improve detection accuracy. The obstacle course construction has been completed for this semester, and the system will be tested on it in the future.

Meeting Details

General details of discussions, presentations, feedback and comments, and assignments.

There were no whole team meetings this semester due to schedule conflicts.

Sample of notes from a milestone presentation:
Meeting on Apr 24, 2023
Presented Spring 2023 Experimental Design Milestone 2
Experimental design subteam meeting
- If we are to label photos with roboflow, roboflow will claim the copyrights of the photos.
- However, this is not a problem that should be worried.
- Met with Junchi to discuss further steps
- Learned how to submit pictures to the database
- Captured photos of objects from different angles and lighting
- Took pictures of different objects in one frame to allow variance as well as videos to generate more accurate pictures on Roboflow
- Working on submitting and labeling the pictures for accurate identification
- Another problem: Time-consuming to label all pictures

Sample notes from a weekly meeting:
Meeting on Apr 10, 2023
Presented Meeting 04/10/23
Experimental design subteam meeting
- We should start putting together the obstacles on the 12th floor next to the lab.
- Need to determine how much space the courses occupy.
- Also, we need to conduct some stress testing on the obstacles to ensure that they don't fail regular stresses and collisions.
- During the meeting with Feng, we should make sure that the camera is able to recognize the obstacle blocks. If the camera could not identify the object, we could paint them.

Meeting with Junchi (this information is outdated as of now)
- Instead of using the dual camera system, as described in the paper, a cheaper alternative– a monocular camera–is used. This is due to commercial considerations.
- Distance information is now inferred from the size of the bounding boxes, as well as the change in sizes of the bounding boxes between each frame.
- The determination of distance is rule-based, which means the inference algorithms follow an arbitrary parameter, which could be manually adjusted for different applications.
- The YOLO uses pre-trained weights from the coco dataset, which includes 91 objects.

- Training for a new category usually requires 500 images. The bounding boxes of the training data need to be manually labeled, which is very laborious and time-consuming.
- However, we could print images of pre-trained objects onto the obstacles to avoid this hassle.
- For example, we could print an image of a chair onto the tall boxes. So the camera is able to identify the outlines of the obstacles easily.
- This has the added benefit of making the experience more realistic.

Main tasks completed throughout the semester are listed below:

Tasks	**Status**
Research eye-trackers	Completed (Mar 20)
Finalize obstacle designs and construction	Completed (Apr 3)
Meet with Junchi	Completed (Apr 13, 20, 27, & May 4)
Observe obstacle durability and space	Completed (Apr 14)
Acquire images of all obstacles	Completed (Apr 21)
Learn the process of YOLO	Completed (May 1)
Understand how to label individual photos	Completed (May 1)
Create a Roboflow workspace	Completed (May 4)
Upload acquired videos and pictures	Completed (May 10)
Assign and label uploaded content	Completed (May 17)

The above tasks were presented in the following presentations+documents at the weekly meetings:

Experimental Design Spring 2023 Intro
Spring 2023 Experimental Design Milestone 2
Experimental Design Spring 2023 Final Presentation
Protocol Template for Observational Study
R Guide

Course Design Fall 2022 Revised
Obstacle Construction Progress.xlsx

Design of Experiment

The study will measure the effectiveness of the VIS4ION system, a haptic interface device designed to aid visually impaired individuals with obstacle avoidance during urban navigation. Two experiments will be conducted: Experiment 1 for healthy participants wearing visual simulator glasses to simulate visual impairment, and Experiment 2 for visually impaired individuals. The main metrics that will be measured are the number of collisions, distance traveled, and time to traverse the course, which will be used to determine the preferred walking speed of participants.

There are two alternative hypotheses for the study. The first hypothesis is that compared to other existing navigation systems like the white cane, the VIS4ION system will be more intuitive to use and require less training. This will be tested in Experiment 1. The second hypothesis is that the VIS4ION system will instill more safety and confidence in visually impaired individuals during obstacle avoidance tasks due to its ability to identify the position of obstacles in the surroundings. This will be tested in Experiment 2.

Pre- and post-experiment surveys will be given to all participants using the System Usability Scale (SUS) to provide a more reliable and subjective view of their experiences. The questionnaires will vary based on whether the participant is visually impaired or in the control group (wearing visual simulator glasses).

Each experiment will have six trials per participant. The first three trials will be without the use of the VIS4ION system, while the other three trials will be with the system. This will allow researchers to observe the difference in performance with and without the device.

After the trials, data from the computer vision system, accelerometer, and video recordings will be combined to perform tests and analyses to come to a conclusion on the effectiveness of the VIS4ION system. These analyses include unequal-variance t-tests to compare the VIS4ION system's effectiveness as a primary or secondary assistive device, and paired-sample t-tests to track individual participants' performance across different experimental conditions. Chi-squared tests can also be performed on data collected by the pre- and post-experimental surveys to find differences in perception of the product between the two groups. All analyses will be performed using R.

The study aims to improve user experience by providing insights into the effectiveness of the VIS4ION system in aiding visually impaired individuals with obstacle avoidance during urban navigation.

Obstacles Construction & Reinforcement

The experiment incorporated an obstacle course as a crucial element, which was designed with three levels of increasing difficulty. It is worth mentioning that the horizontal obstacles were meticulously built and arranged to observe whether the participants would walk over them. Similarly, obstacles placed at different angles were integrated into the design to assess whether the device guided the participants to walk over them or led them on an alternative optimized path.

Modifications have been made to the obstacle course designs compared to the previous semester, aiming to enhance the consistency of courses within each difficulty level. The difficulty of each obstacle course is determined by the number of turns (T) that participants need to make before reaching the destination, following the methodology used by Nau et al. T values are calculated for all obstacle courses, and the mean and standard deviation of T are computed for each difficulty level. The placement of obstacles in each difficulty level is adjusted until the T values become relatively similar among the courses within that level (see Figure 1). Additionally, tilted obstacles are introduced to heighten the difficulty of Level 3 courses.

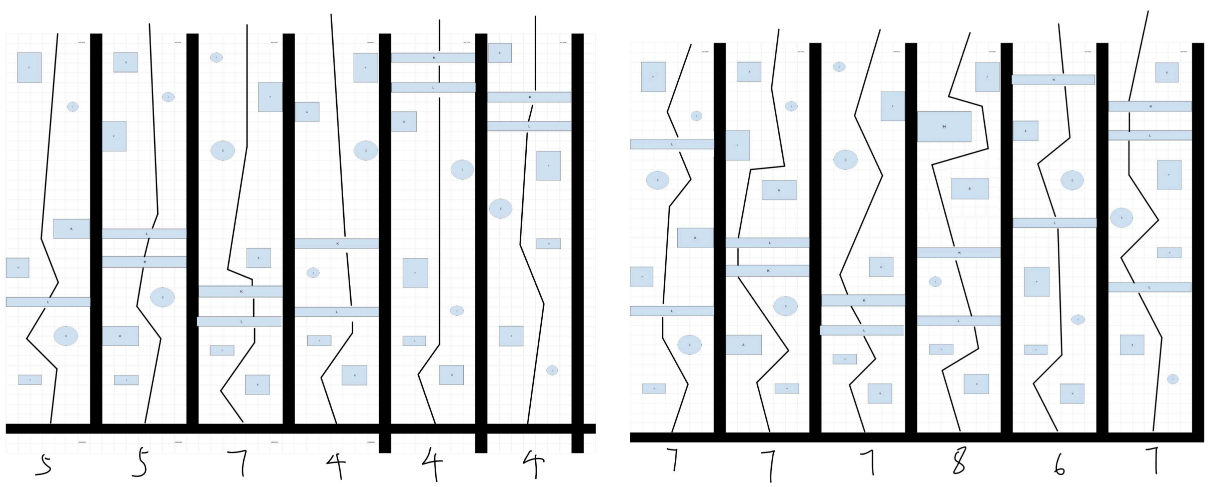

Figure 1: Level 2 Courses Before (left) and After (right) Adjustment with T Labeled

At the end of the semester, we completed all of the obstacle reinforcement and successfully built the trapezoid obstacle. We're facing problems like the instability of some tape and running out of fabric materials. But we overcame the challenges in the end. We found the perfect tape which makes the fabric stick with the obstacles closely. We usually met on Fridays, cut the fabric into pieces, and applied them to every obstacle. Now every obstacle is covered with a cloth-like fabric and ready to use. We also redid the reinforcement for some of the obstacles since the fabric was falling apart.

Object	Cardboard Obstacles	Dimensions	Copies Made	Reinforced?	Method	Styrofoam
A	Block	2x2x3'	3	Yes	Diagonal and Horizontal	Yes
B	Cylinder	2'Dx2'H	2	Yes	Styrofoam	Yes
C	Trapezoid	45"LX 24" WX24	1	Yes	Z Shape	Yes
D	Block	1x2x3'	2	Yes	Diagonal	Yes
F	Block	2x3x3'	1	Yes	Horizontal	Yes
G	Cylinder	1'Dx5'H	1	Yes	Tape	Yes
H	Block	2x2x1'	1	Yes	Horizontal	Yes
I	Block	1x3x5'	1	Yes	Styrofoam	Yes
J	Ball	1' Diameter	2	No	N/A	N/A
K	Beam	2"Lx6'Wx4"H	2	Yes	Tape	Yes
L	Beam	2"Lx6'Wx2"H	2	Yes	Tape	Yes

Table 1: Completed Obstacles

Figure 2: Part of the Reinforced Obstacles

The technique of cross-bracing was used again this semester for building the trapezoid obstacle in order to make the obstacle have greater support.

Figure 3: The Trapezoid Obstacle

Object Detection

An online machine-learning platform, Roboflow, is used for image labeling and model training. It allows a fair allocation of labeling work and customized augmentation of the dataset. Initial data was collected in the form of videos and images. The video footage is converted into images using frame extracting at a rate of 10 pictures per frame, and is combined with ~100 images to create the dataset.

The images were labeled using rectangular bounding boxes according to commonly accepted best practices for object detection models, these practices include aligning the outlines of the objects with the bounding boxes and omitting objects that are obscured by >70%. Four object categories were created; they are “box” for rectangular/cuboidal objects, “long” for slab obstacles (K and L), “cylinder” for cylindrical obstacles (G and B), and “special” for trapezoidal obstacles (C). Up to the writing of the report, 536 images were labeled, and the number of instances from each class is displayed in Figure 4.

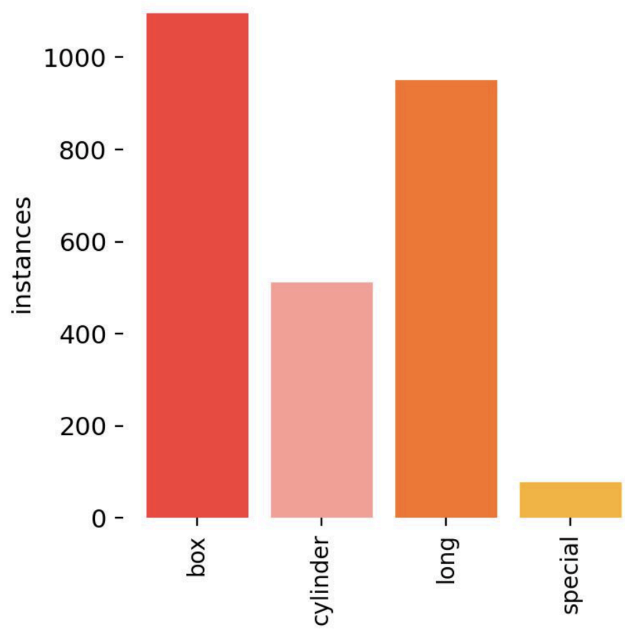

Figure 4: Instances from each Class

The labeled instances were resized and reoriented before being augmented using rotation (Between -45 degrees and +45 degrees, blur (up to 2.5px), and noise (up to 5% of pixels), obtaining the dataset of ~1500 images for training. YOLO-v5 was chosen as the object detection model for its consistency and abundance of supporting literature. The model was trained for 99 epochs with all default parameters, which took around 20 minutes. The confusion matrix of the model is presented in Figure 5, where darker color corresponds to a higher overlap between the two axes.

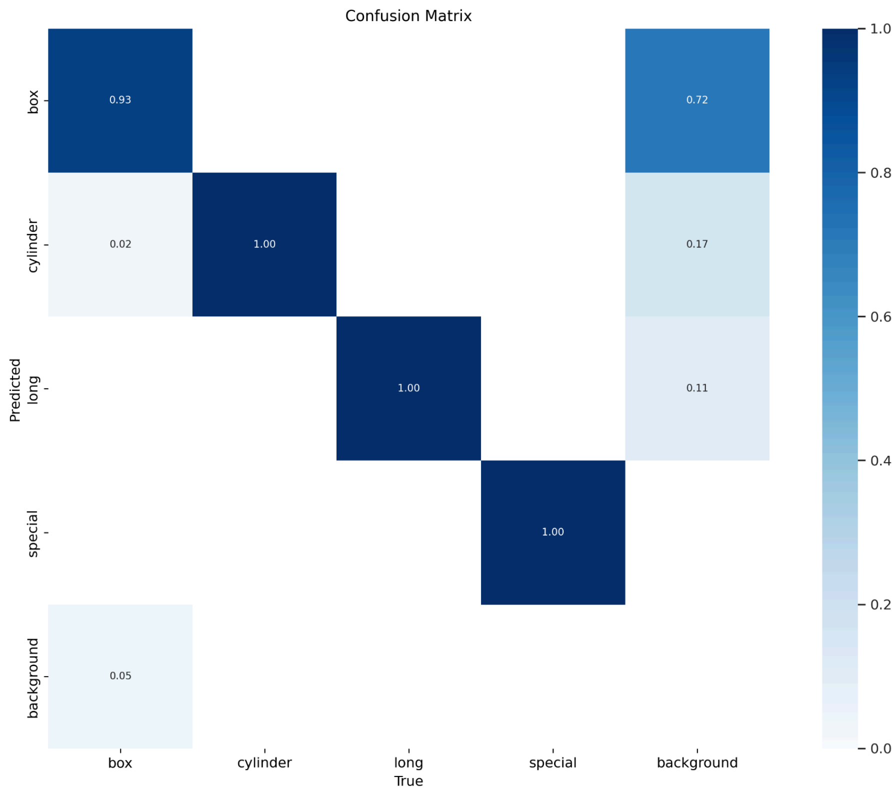

Figure 5: Confusion Matrix of the Trained Model

It can be seen while the model performs well at distinguishing “cylinder”, “long”, and “special” objects, it sometimes confuses objects in the background as boxes. This can be due to the crowded background environment of the images, and the fact that many common office supplies and furniture take the shape of a rectangle. This could be resolved by training with images in a greater variety of lighting environments and on different backgrounds.

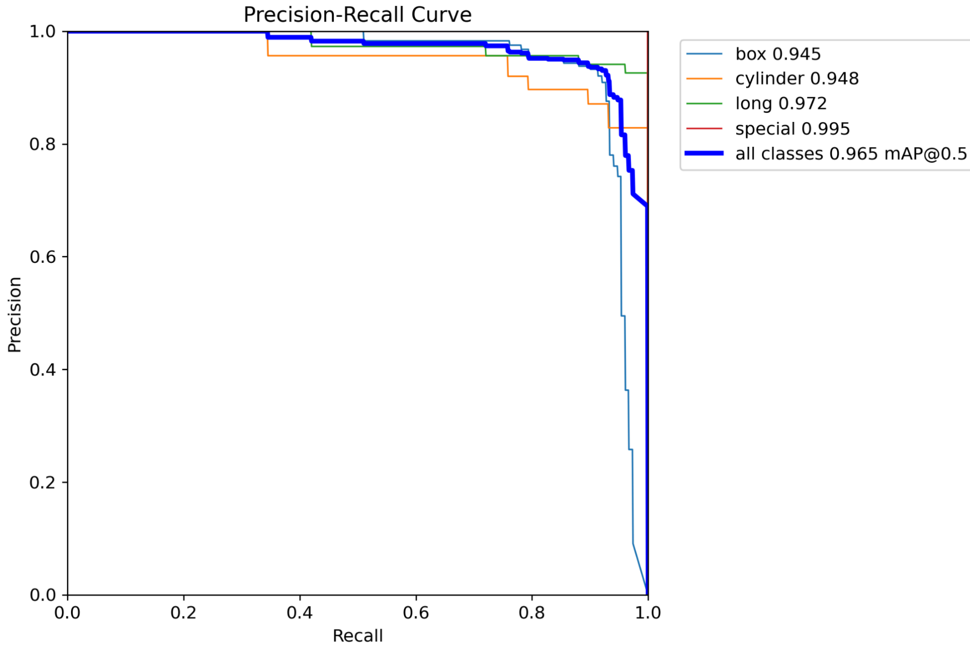

Figure 6: Precision-Recall (PR) Curve

Precision is plotted against recall in Figure 6. Precision and recall are both measurements of model accuracy. However, the two measures are on opposite sides of a scale in the sense that trying to increase precision usually leads to sacrifices in accuracy and vice versa. The PR curve of a perfectly accurate model would form a right angle at the top-right corner. It can be seen that the model is satisfactorily accurate since the curve aligns well with the edge of the plot.

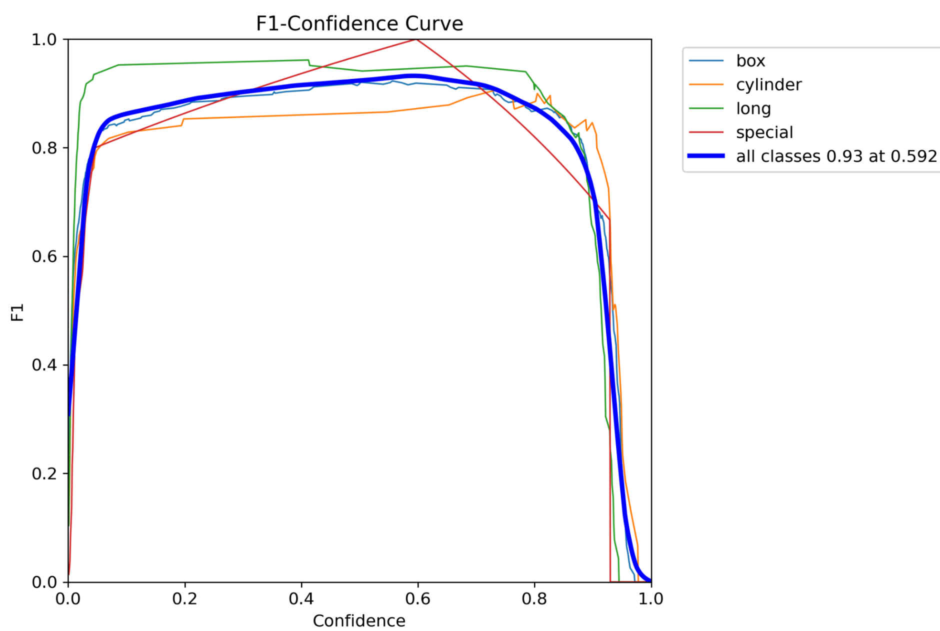

Figure 7: F1 Curve

F1, a metric combining precision and recall, is plotted against confidence in Figure 7. It can be seen that a maximum F1 score is observed at a confidence of 0.593. This means the model performs most well when we set the confidence threshold of acceptance to or above 0.593. The confidence could be tweaked depending on the end-use to achieve the best effect.

A demo of the trained model at work can be found here.

Other Works

No other works were completed during the development of the project.

Obstacle construction and reinforcements were heavily focused on during the beginning of the semester, and after completion, object detection followed. Obstacle construction included building and reinforcing existing objects to withstand the force applied, while also constructing more recent models. The obstacles were constructed using cardboard and wrapped with a cloth-like fabric, which was held together by aluminum foil-like tape.

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Object detection included obtaining pictures of obstacles from various angles and lighting to have a larger pool of data for computer recognition. The pictures included individual obstacles in one frame as well as multiple-shaped obstacles in another frame. Roboflow also allowed videos to be uploaded to obtain further information, therefore, detailed pictures were generated from the videos captured of the obstacles allowing more accurate data recognition.

Future Goals

In order to carry out the experiment to completion, a recruitment process and finding participants for our study is necessary. Next semester, we will design recruiting posters and distribute them in multiple locations. In the long term, we aim to perform as many repetitions as possible after receiving results in order to have as much data as possible to improve the VIS4ION system.

Also, we need to make all the labeling done and put them into the YOLO platform to train the algorithm. We also may need to take more photos or videos for more resources. As the supervisor mentioned in the final presentation, we probably need to put the obstacles under some non-white backgrounds so that they do not conflict with the white fabric on the obstacles. This will lower the possibility of failure and make the training on the YOLO platform more progressive.

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