Final Project Write Up
COMP4102A

Automotive Safety Suite

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Abstract

The Automotive Safety Suite (ASS) is a collection of safety features which try to solve distracted driving problems using computer vision. The ASS has three main components: Gaze Tracking, Pedestrian Tracking, and Road Sign Tracking. Gaze tracking determines where eyes exist in the driver's camera view and derives gaze in order to determine where it is the driver is looking. Pedestrian Tracking involves trying to identify pedestrains in the application's road view. This component is meant to identify where within the view pedestrians are if they exist. The last component is Road Sign Tracking where using the same road view as Pedestrian Tracking it detects and identifies where within the video frame road signs are if they exist. The main goal is to have a suite of features that work together to avoid distracted driving by notifying the driver whenever their gaze is not within an acceptable range of oncoming road signs or pedestrians.

Contents

1 Introduction

The goal of this project is to create an automotive safety suite using computer vision. Our goals are to create a suite of services to track pedestrians, road signs and stop lights, as well as tracking the driver's eye movements to detect distracted driving. A secondary goal is to make the system highly modular, so new components can be easily added in or create interactions between modules.

2 Background

2.1 Gaze Detection and Tracking

Gaze detection and tracking has many positive implications for driver safety, namely to detect if a driver is distracted or drowsy. The US department of transportation found that in years 2011-2015 an overall 2.5% of fatalities were caused by drowsy driving [4], and for distracted driving in 2018 it was found that 8% of fatalities were distraction-affected [5]. Currently there are a wide variety of well-established and novel techniques for gaze tracking as found by a survey by Chennamma and Xiaohui [2].

2.2 Pedestrian Detection and Tracking

Pedestrian detection and tracking is an important aspect in driver safety. Drivers must be aware when one or more pedestrians are moving around their vehicle as to ensure their safety. Stimpson, Wilson, and Muelleman research into pedestrian fatalities shows that from 2005 to 2010 the fatality rate of 116.1 per 10 billion vehicle miles driven had increased to 168.6 in 2010 [7]. OpenCV includes an implementation of the Histograms of Oriented Gradients (HOG) which can identify a person within an image or video. This creates a basis for identifying pedestrians. The implementation details in terms of human detection are found in this paper[3]

2.3 Road Sign Tracking

Road signs are vital to road safety. Stop sign violations accounted for approximately 70% of all crashes.[6] In addition, in some areas, speed limits are lowered in unexpected areas pose great risk for a driver, even when they're striving to follow the speed limit. While much research into this area is focused on using machine learning, some computer vision exclusive implementation have been studied.[1]

3 Approach

3.1 Gaze Tracking

For our gaze tracking component, we investigated a few different approaches to gaze tracking as documented in the survey of gaze tracking performed by Chennamma and Yuan [2]. As depicted in the survey, the most accurate ways to track gaze is with special hardware, which is typically of the form

1. A wearable headset that has two cameras pointed into the eyes, this provides a very accurate gaze that can be approximated by a gaze vector which can then be correlated to a approximate region with a margin of error. This approach is the most effective, and allows the user to move their heads around and still be effective.

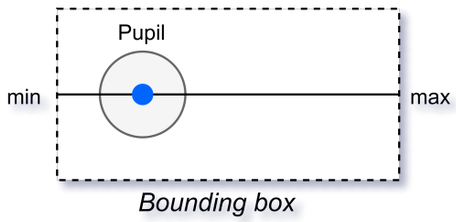
2. Multiple infrared cameras that are mounted at two different locations that use the infrared light to illuminate the pupils. This provides an accurate approach as well, and allows for head movement within a certain range.

3. A single camera can be used to detect pupils (eye tracking); however they can't reliably detect a vector where the eyes are looking. A single camera also does not allow a user to move their head.

Since we are using limited equipment for the ASS suite, we decided to use option (3) and tweak an existing library to derive a form of gaze. We used an reference implementation of Fabian Timm's algorithm [8] which is capable of deriving bounding boxes.

Our eye tracking pipeline functions as follows:

1. Using OpenCV's cascade classifier, we attempt to detect the available faces in the image. For this we are using a pre-trained cascade file that is designed for frontal facing images.
2. If no face is detected, do nothing. Otherwise, we can attempt to find the eyes.
3. Divide the found face into two regions, each region will contain one eye as the face is a fairly centered bounding box. We can derive a relative eye region by partitioning the face with some constant values.
4. Using the eyeLike library [9] (reference implementation of Timm's algorithm), find the center of the eye (pupil).
5. Derive and draw rectangle based on the previously found bounding boxes, place the pupil inside the rectangle.
6. At this we know where the pupil is relative to a bounding box; however, we have not estimated gaze. Thus, we normalize all the values of the eye region and eye center to be relative to the bounding boxes
7. We then consider a one-dimensional plane (a line in the x-axis) which starts at the minimum edge of our bounding box, ends at the maximum edge of the bounding box, and then uses the pupil position as the point on the line. See diagram below



   Between the min and max values is the pupils location, this can be used to derive a percentage as follows (assuming the coordinates have been normalized to min):

$$\frac{pupil.x}{max.x}$$

   This percentage is the percentage to the left or right, where 50% is dead center.

8. We average the percentages between left and right eyes to derive an overall percentage.
9. After some testing, we determined if the eye location is less than 40% the eye is pointed right, if the eye is more than 60% the eye is left, else the eye is centered.
10. We render the findings to the mat, update our application's centralized eyeState value, and return.

3.2 Pedestrian Tracking

Pedestrian tracking is achieved through a single function which takes in a *cv::Mat* object that represents the current frame of the video and returns a custom data structure called *PedTrackingResult*. The function initializes an instance of OpenCV's *HOGDescriptor* object. With the help of OpenCV, this object can be passed a human detection method which can be passed to the *HOGDescriptor*. Once this method is passed to the *HOGDescriptor*, a clone of the original frame is produced. From here, the process of identifying humans in the frame is done by the work of the *HOGDescriptor* using its *detectMultiScale()* function after converting the input frame from four channels to one channel as needed by the function. This function produces a vector of *cv::Rect* objects representing the bounding boxes for human-shaped objects in the frame and the weights associated with these bounding boxes. From here each *cv::Rect* object in the frame is drawn onto the frame with its associated weight. The resulting frame and *cv::Rect* vector is returned to the image pipeline in order to display the frame and to calculate driver attentiveness.

With the returned vector we first calculate the centre of the width for each *cv::Rect* object. We then compare this center pixel against which third of the main video width the bounding box's centre lies in. We then compare the current eye state to this pedestrian object state and see if the driver is looking at the same third. This process is applied to each bounding box until the end of

the list has been reached. Since there are three thirds of the window, if there are an even number of objects detected in each window then we can say that the minimum rate for attentiveness is a third of the total detected pedestrians. This means that if a driver pays attention to third with the most number of pedestrians then the minimum threshold needed for the classification to be passable for driving is $\frac{1}{3}$.

3.3 Road Sign Tracking

The road sign tracking is achieved through a single function which takes in a *cv::Mat* that must be the type "CV_8U4C", and returns a *SignTrackingResult* containing a *cv::Mat* with the rectangles drawn on and a *std::vector<cv::Rect>*.

The road tracking is performed by getting the reds, yellows, and whites within the image. This is done by converting the image to HSV and masking off it's specific value ranges. Then, a canny edge detector is performed on each mask, with a dilation performed on the result to make the edges easier to detect. On the dilated result, *cv::findContours()* is performed to find all continious borders in the image. With the contours and their hierarchy find, the approximate polygonal curves in the image are found, where the edges are then counted. If the edges count match a sign's count in it's respective color, the shape is approved and is included in the return.

The results of the sign tracking could be implemented in the same manner as the pedestrian, but the number of false positives made it a poor addition to detecting alertness.

4 Results

4.1 Gaze Tracking

Our testing results were done with both a laptop web camera, and a higher quality standalone camera. We recommend lower-resolution cameras as it puts less strain on the pipeline's algorithm. Our gaze tracking works under the assumption that the face is parallel to the camera, thus any large head turns will cause erratic results as the pipeline relies on the symmetry of the face to derive bounding boxes for the eyes (the bounding boxes are shown below in white).

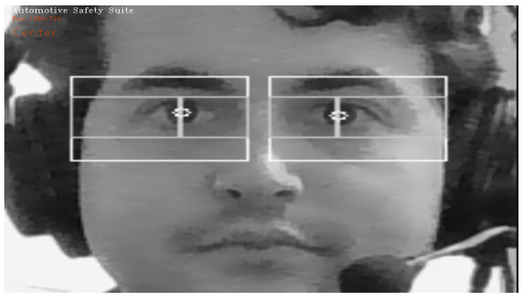


Figure 1: Gaze tracking, straight. In the top lefthand corner of the window is the current eye tracking state

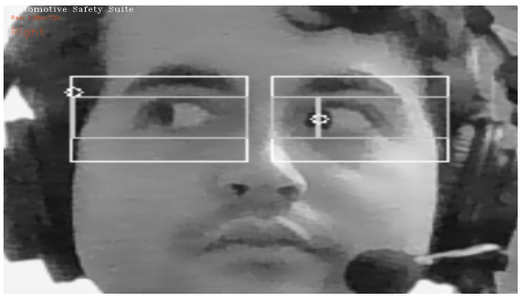
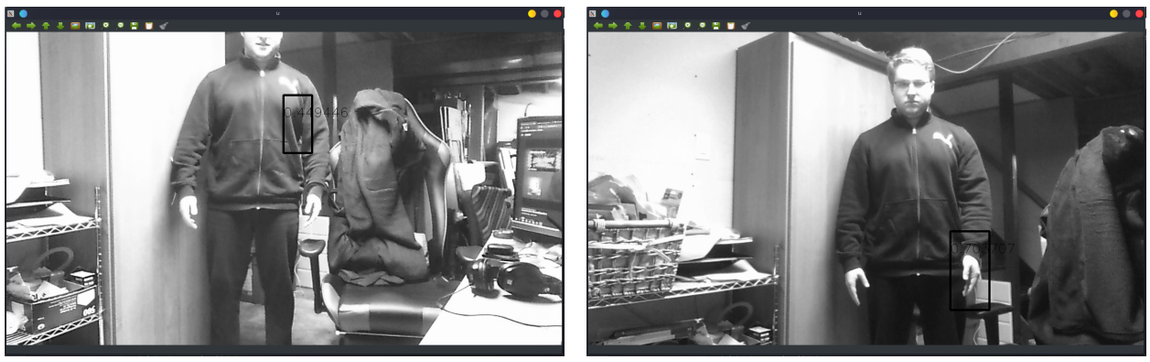


Figure 2: Gaze tracking, right. In this example the left bounding box mistook the dark region of hair as a pupil

Overall the eye tracking is accurate if the person is well lit, however there are anomalies. In 2 Fabian Timm's eye detection algorithm mistook dark hair as being a pupil, as the algorithm favors large regions of difference to determine the pupil (usually the dark pupil is a large contrast to the white of the eye). Other issues with the current eye tracking approach include erratic behavior if the eyes are closed, however a steady state is eventually achieved where the eye state will be set to undefined.

4.2 Pedestrian Tracking

The original testing results when testing with a laptop camera were a little lackluster. For the most part, the use of the HOG descriptor using this wecam resulted in inaccurate readings of human objects within the frame. Mostly it would detect human-like objects in the negative space between objects. An example of this would be when someone was standing reasonably far away from the camera and the HOG descriptor would identify human-shaped objects in the armpits of the subject standing in front of the camera or in the surrounding spaces. Another example is when the subject was standing in front of the camera with their hand turned sideways. This issue arose because the quality of the camera used produced a significant amount of noise in each frame resulting in changes in gradients.



(a) Detected Armpit Error (b) Detected Hand Error

Figure 3: Errors produced using a noisy webcam

Later, testing started to use video files to be more in line with how we wanted to achieve this project. The video used was of a motorcyclist who had a camera attached to their helmet and was riding around while driving by careless pedestrians. When viewing the results of the video file, the accuracy of the HOG descriptor was much more in line with what we had hoped. Most if not all of the pedestrians were identified when within an acceptable range. Whenever the pedestrian tracking component produced a false negative, the cases that generated such errors were those where either a pedestrian was too far from or too close to the camera, and whenever the pedestrian was partially occluded. Both of these conditions are not out of the ordinary since being to close to the camera results in some occlusion since the pedestrian will be partially in frame. When to far away, the gradients in the HOG descriptor become harder to determine if they are human-shaped objects which is normal in nature. Partial occlusion of a pedestrian in the frame is also normal as parts of the gradient data is lost due to occlusion.

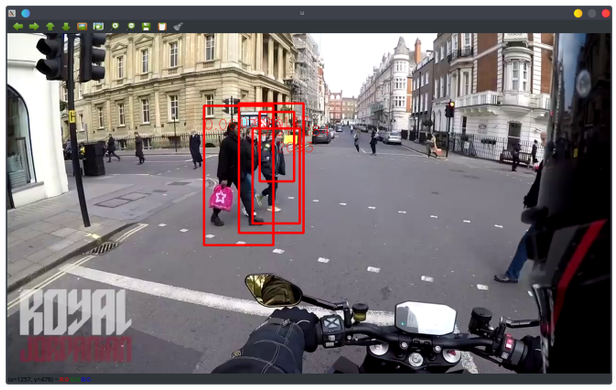
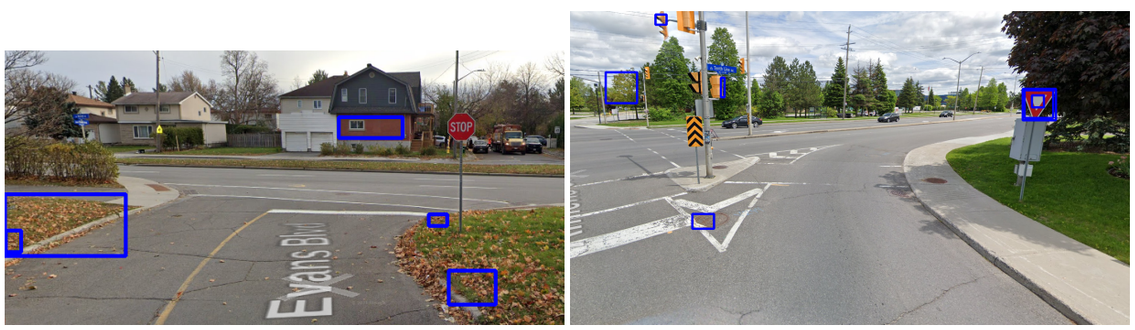


Figure 4: Correct detection in video containing pedestrians

4.3 Road Sign Tracking

The contour edge counting method implemented is very prone to false positives. This is because, for example, any red shape with eight edges would be seen as a stop sign. Additionally, this method is highly dependent on optimal conditions. Were environment or camera inaccuracies to significant offset the color of signs, they would fail to be detected as it's looking for specific color ranges.



(a) The method used is prone to failing to identify signs (b) The edge counting method is prone to false positives

The sign tracking was intitially going to be handled by training an SVM and utilizing a HOG.

This attempt ultimately failed due to the limitations on hand as well as limitations of machine learning. The data sets obtained did not have enough variety for most signs, meaning it would be a poor detector of individual signs. Additionally, the variety of road signs prevented the model from being trained as a single class.

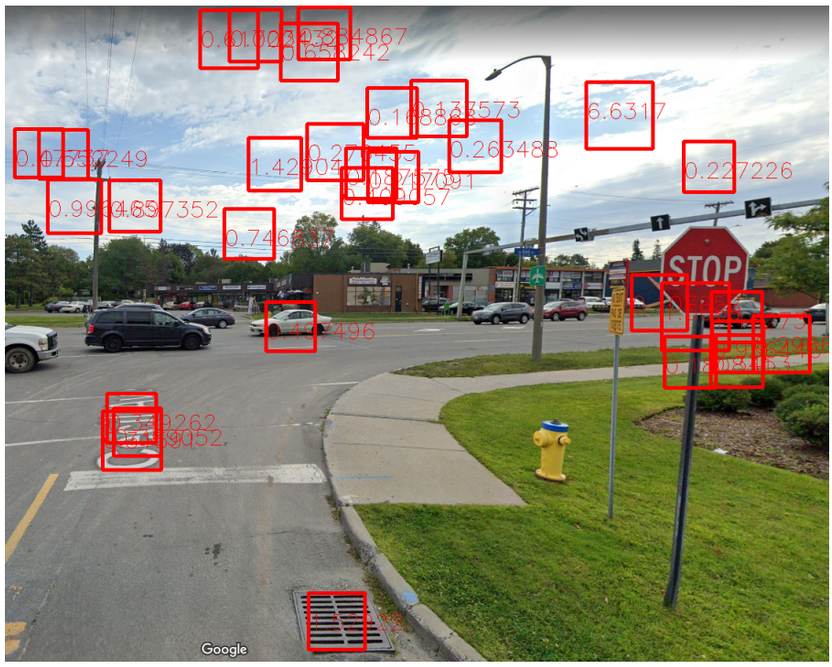


Figure 6: The single-class SVM model was highly inaccurate

As a result of the limitations of SVM and the datasets, the model could not achieve >30% accuracy and ultimately had to be dropped in favor of edge counting.

5 List of Work

5.1 Gaze Tracking

- Conner Bradley

5.2 Pedestrian Tracking

- Christian Belair

5.3 Road Sign Tracking

- Adam Payzant

5.4 GUI Integration

- Conner Bradley
- Christian Belair
- Adam Payzant

5.5 Shared Component Integration

- Conner Bradley
- Christian Belair
- Adam Payzant

6 GitHub Page

https://github.com/ChristianBelair/COMP4102-Project

References

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[2] HR Chennamma and Xiaohui Yuan. A survey on eye-gaze tracking techniques. *arXiv preprint arXiv:1312.6410*, 2013.

[3] N. Dalal and B. Triggs. Histograms of oriented gradients for human detection. 1:886–893 vol. 1, 2005.

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[5] US Department of Transportation. Research note: Distracted driving. *Traffic Safety Facts*, DOT HS 812 926, 2018.

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[7] Jim P. Stimpson, Fernando A. Wilson, and Robert L. Muelleman. Fatalities of pedestrians, bicycle riders, and motorists due to distracted driving motor vehicle crashes in the u.s., 2005–2010. *Public Health Reports*, 128(6):436–442, 2013. PMID: 24179255.

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