Autonomous Collision Avoidance System for Collaborative Vehicle Platooning

Category: Autonomous Vehicle Issues

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Automated vehicle platooning is desirable as it decreases fuel usage, improves the flow of traffic, and increases the safety of vehicle platooning. Automated platooning is particularly relevant to tractor-trailers as they travel long distances at high speeds; however, effective collaborative platooning in tractor-trailers is challenging under the operation of human drivers. The goal of this project was to build fully autonomous small-scale vehicles for collaborative platooning to demonstrate the safety benefits of an automated system and address how the system responds to disturbances.

The four features of this project, which aimed to enable collaborative platooning, were lane keeping, obstacle detection and identification, automated object avoidance, and vehicle-to-vehicle communication. Lane keeping is essential to autonomous vehicles as it enables vehicles to navigate without human intervention. Obstacle detection and identification enable vehicles to identify and to classify nearby obstacles by the threat they pose to the vehicle, thereby facilitating an intelligent response to the obstacle. Automated object avoidance describes the decision logic and control algorithm used to navigate a roadway containing obstructions. Finally, vehicle-to-vehicle communication enables the cars to act in unison by communicating maneuvers before the maneuvers are executed. Together, these technologies enabled this project’s primary focus: the effects of disturbances on collaboratively platooning vehicles and the overall safety of the platoon.

The team was a multidisciplinary group of mechanical and computer engineering students, which allowed the skills of each discipline to be leveraged in order to accomplish the project goals. The mechanical engineering group developed two small-scale vehicles, simulated vehicle maneuvers, and designed the vehicle test track. The computer engineering group developed computer vision capabilities using open-source libraries on an embedded platform and developed threat assessment and decision-making logic. Ultimately, the two groups produced two vehicles capable of navigating a winding track, responding to a small set of traffic signs, executing maneuvers simultaneously, and detecting and avoiding obstacles as a platoon. The project successfully demonstrated the importance of vehicle-to-vehicle communication as it drastically improves the platoon’s safety and stability.

Safety Impact

Tractor-trailer trucks in the United States weigh approximately 80,000 lbs. when hauling a fully loaded trailer. Their large weight restricts their maneuverability and braking distance when trucks react to a hazard. Platooning incurs additional risk in the absence of automation because the following vehicles are limited in forward visibility due to the size of the lead vehicle and the reduced distance between trucks, which demands a fast reaction time for the following vehicles.

In the United States, there were 4,067 deaths and 116,000 injuries in automobile accidents involving large trucks in 2015 (nearly 10% of all accidents in the US) [1]. Nearly three-quarters of the people injured in these accidents were occupants of vehicles other than the tractor-trailer truck and approximately a quarter were occupants of the truck itself. According to the United States Department of Transportation, 94% of all automobile accidents are caused by human error [2]. For large trucks, human error caused approximately 3,283 deaths and 109,000 injuries in the United States annually. Our goal was to mitigate human error in order to save lives.

These safety concerns were addressed by developing hardware and software capable of mitigating these risks and making platooning safe. By allowing the following vehicles to communicate with the lead vehicle, the safety risk of the limited line of sight of the following vehicles was mitigated and the lag between each vehicle applying its brakes was reduced. The lead vehicle communicated upcoming obstructions and hazards with the following vehicle as well as the anticipated response. If the lead vehicle braked, it notified the following vehicle allowing for a coordinated stop. Automated steering and braking systems eliminated human error when vehicles avoided obstacles while enabling the vehicles to respond quickly enough for safe platooning.

Economic Incentives

Autonomous platooning technologies not only represent a significant increase in safety, but also represent a significant potential economic value. In the United States, there are 2.7 million Class 8 semi-trucks, each driving an average of 40,000 miles per year [3]. One of the largest costs associated with semi-trucks is the fuel consumed. In the United States, semi-trucks used 28 billion gallons of fuel, which represents 22% of the energy used in the transportation industry in 2015 [4]. At the national average price for a gallon of diesel of 3.078 dollars per gallon, this is a fuel cost of 83 billion dollars a year [5]. Worldwide, a total of 110 billion miles are driven by semi-trucks per year [3]. The goal of platooning is to reduce the fuel consumption of semi-trucks in the platoon by reducing the effects of drag on all vehicles in the platoon.

Research has shown that 63% of the miles driven by trucks in the United States occur at speeds amenable to platooning and 55% of this time there is a truck nearby that could be used to platoon [6]. It has also been found through testing that platooning trucks traveling at 60 mph at a following distance of 13.2 feet experience an average of 10% savings in fuel for the lead vehicle and an average of 17% fuel savings for a middle vehicle due to the decreased aerodynamic drag [6]. Computational fluid dynamics models on truck platooning have confirmed these numbers and have found that the percent savings of fuel for trucks following at 30 feet to be 4.2% for the lead vehicle and 20% for a following vehicle [7]. To further increase the fuel savings due to platooning, the following distance can be decreased and the number of vehicles in the platoon can be increased.

Assuming 63% of all truck driving is done in platoon at a fuel reduction of 5%, over 4 billion dollars of fuel could be saved annually in the United States. This will propagate to a lower cost of goods and benefit all consumers. It will also reduce the carbon emissions of the trucking industry by decreasing the energy necessary to ship goods. Additionally, the reduced rate of traffic accidents represents an economic value of equipment and lives that is difficult to quantify. Trucking is an excellent application of this technology because trucks tend to drive long distances at highway speeds. During highway operation, platooning could be implemented with the use of autonomous technologies to mitigate risk.

Implementation

Our goal for this project was to show that these technologies make platooning safe and effective while responding to disturbances. The technologies required to achieve this were lane keeping, object avoidance, and vehicle-to-vehicle communication. We chose to implement these technologies on modified 1/10 scale RC cars as small-scale vehicles are safe to operate, cheap, and fast to develop.

There were two major steps in our approach to tackling these problems. First, using IPG Automation's CarMaker (a software suite that interfaces with MATLAB/Simulink to develop control algorithms), we simulated autonomous vehicle and platooning functions. Second, after successful simulation, the algorithms were deployed and tuned on small-scale vehicles running on a closed-circuit test track.

Two 1/10 scale RC cars, seen in Figure 1, were modified by adding a Jetson TX2 Developer Kit as an onboard computer. The Jetson interfaced with an electronic speed controller and a steering servo to control the car's steering through an Arduino Mega 2560 that produces pulse width modulation (PWM) signals. For much of the project, a single 1080p wide-angle camera was used for basic lane keeping, platooning, and object avoidance functionality; however, a Zed Mini stereoscopic camera from Stereolabs eventually replaced the single wide-angle camera to give the vehicles depth perception. Figure 2 shows the stereoscopic camera. The ability to produce a depth map allowed the cars to more effectively detect and avoid objects. Each car was equipped with identical hardware to make the development process easier as progress served both vehicles and either vehicle could act as the lead vehicle.

Figure 1. The two 1/10 scale RC cars with hardware modifications featuring the original cameras

Figure 2. One 1/10 scale RC car with hardware modifications featuring a stereoscopic camera

The Jetson provided the computational power for image processing in this project. With the software developed, the vehicles tracked lane lines by looking for a sharp change in contrast in the image taken by the camera. By processing this image, our software could determine the vehicle's position relative to the center of the lane and could control the vehicle's steering servo with a PID controller. Traffic sign recognition was also implemented to allow for reactions to different road signs, which was used to test the platoon's ability to execute simultaneous speed changes. Furthermore, the addition of the stereoscopic cameras allowed the vehicles to determine distances accurately while enabling the vehicles to detect and avoid objects.

There were two main components that enabled vehicle platooning: adaptive cruise control and vehicle-to-vehicle communication. Our adaptive cruise control used computer vision to track the height of the lead vehicle, which is inversely correlated to the horizontal distance between the vehicles. The distance was controlled with a PID controller to allow the vehicles to drive together. Because this system alone resulted in significant oscillations within the platoon, vehicle-to-vehicle communication was implemented to reduce these oscillations. By communicating target and actual speeds over WiFi, the vehicles were able to more finely and accurately maintain the distance of the following vehicle while dampening the oscillations within the platoon.

Finally, object detection was developed to allow for the vehicles to detect and avoid obstacles. The primary tool in achieving this object detection was a Fast You Only Look Once (Fast YOLO) neural network [8]. The YOLO neural network was chosen as it allowed for real-time object detection on our systems without compromising the other processes running on the vehicles. This model was cloned from a GitHub repository maintained by pjreddie [9], which allowed for our team to focus on the decision logic used to avoid detected obstacles rather than on the obstacle detection algorithm itself.

Each frame was passed to the Fast YOLO neural network, which would detect objects and produce bounding coordinates for each detected object. Figure 3 shows the bounding boxes being drawn on the neural network's input images. These objects were then passed to the object detection algorithm, which used the lane lines found by the lane tracking algorithm to determine whether an object posed a threat to the vehicle. If an object was found in only in the vehicle's present lane, the vehicle would change lanes. If both lanes were blocked, the vehicle would stop. In both cases, the behavior was communicated to the following vehicle.

Figure 3. Fast YOLO neural network identifying multiple objects including a stop sign

At the 26th International Technical Conference on The Enhanced Safety of Vehicles' Student Safety Technology Design Competition in Eindhoven, Netherlands, the Fast YOLO neural network failed due to the poor lighting conditions in the conference center. In order to present a fully functional project to the judges, the team rewrote the object detection algorithm to utilize only the depth map. Though this resulted in the vehicles having no knowledge of what the object was, the team felt this was acceptable limitation as it simply resulted in the vehicle being conservative in its object avoidance, particularly as it is rare for striking an object to be an desirable course of action for a vehicle.

This new algorithm was implemented using only the depth map produced by the stereoscopic cameras. The depth map was searched for objects that were within a threshold distance. Lane lines from the lane tracking algorithm were then projected onto the depth map to determine whether these objects fell within the roadway. If the object was within both a threshold distance and within the lane lines, the object was considered a threat to the vehicle. Figure 4 and Figure 5 show the depth map with lane projections (green) and approximations for regions (red) where objects would threaten the vehicle. If objects were found within the threshold distance, then the vehicle examined both lanes. If the object fell only within the current lane, the vehicle would change lanes to avoid the obstacle. If the object fell within both lanes, the vehicle would stop until the object was removed from the path at which point the vehicle would resume driving.

Figure 4. Depth map algorithm identifying an object in the current lane and the left lane available for a lane change

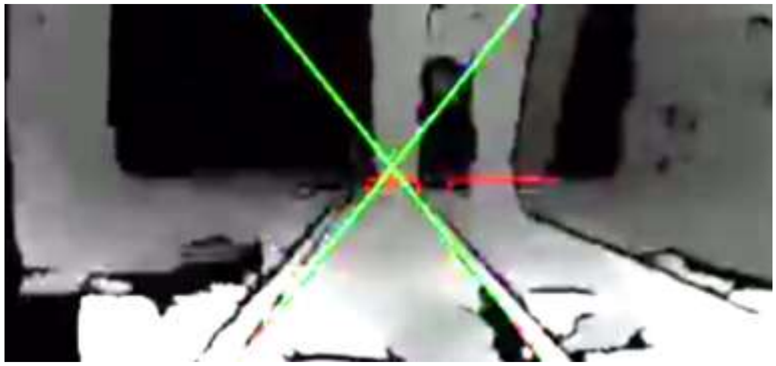

Figure 5. Depth map algorithm detecting a complete roadblock as objects exist in both lanes

Note that the following vehicle never had the ability to detect objects. This was intentional as it demonstrated the importance of the vehicle-to-vehicle communication. Rather than have two independently functioning vehicles, the team felt that having a blind following vehicle emphasized the value of communication between vehicles. Such behavior is expected in the real world as following vehicles will regularly have limited vision due to obstructions from other platooning vehicles.

Given more time, the team would try to utilize both the Fast YOLO neural network and the custom depth map algorithm. By running the depth map algorithm first, computational power would be saved (the custom algorithm is faster than the Fast YOLO neural network); however, detected obstacles would be passed through the neural network to better determine the threat the object poses to the vehicles.

Testing

Before we deployed algorithms on the vehicles, simulations were run in CarMaker to develop and ensure control logic. First, the speed control was developed and tested in simulation. Then steering control logic was developed for lane keeping and object avoidance. These were then implemented in simulation. After this, platooning was simulated by adapting the car's speed controller to keep it a set distance behind the lead vehicle. The lead vehicle would then perform maneuvers such as lane changes and stopping. The following car would mirror these maneuvers in a platoon formation. These simulations were used to create logic that was then implemented on the scale model RC cars. This use of CarMaker by IPG Automation rapidly increased the rate at which we could develop control algorithms before deployment in the hardware.

We performed basic testing procedures to validate the control algorithms and to fix any electrical issues. The motor and steering servo were tested individually with the Jetson. After we tested them on a test stand, a circular test track was assembled to test the lane keeping algorithm. The car demonstrated a good ability to follow a straight path as well as making turns at speed. Lane keeping was further validated by constructing more challenging S-bends, which it has handled successfully.

With the construction of the second car, we tested both an adaptive cruise control system and a platooning system that incorporates vehicle-to-vehicle communication. To test both the adaptive cruise control system and the full platooning system, the cars were run on a closed-loop test track without an S-bend. The cars were also run on an open-loop track with a long straightaway to test the steady state response of the system, as turns introduce impulses to the system and prevent steady state. The rear vehicle tracked of the height of the lead vehicle's battery enclosure and was commanded to keep this height at a steady value of 140 pixels, which corresponds to approximately 1.25 feet between the two vehicles. Note that the height of the battery enclosure is inversely correlated to the distance between vehicles. Figure 6 shows the results of platooning with and without vehicle-to-vehicle communication on the long straightaway, which allowed the cars to reach steady state.

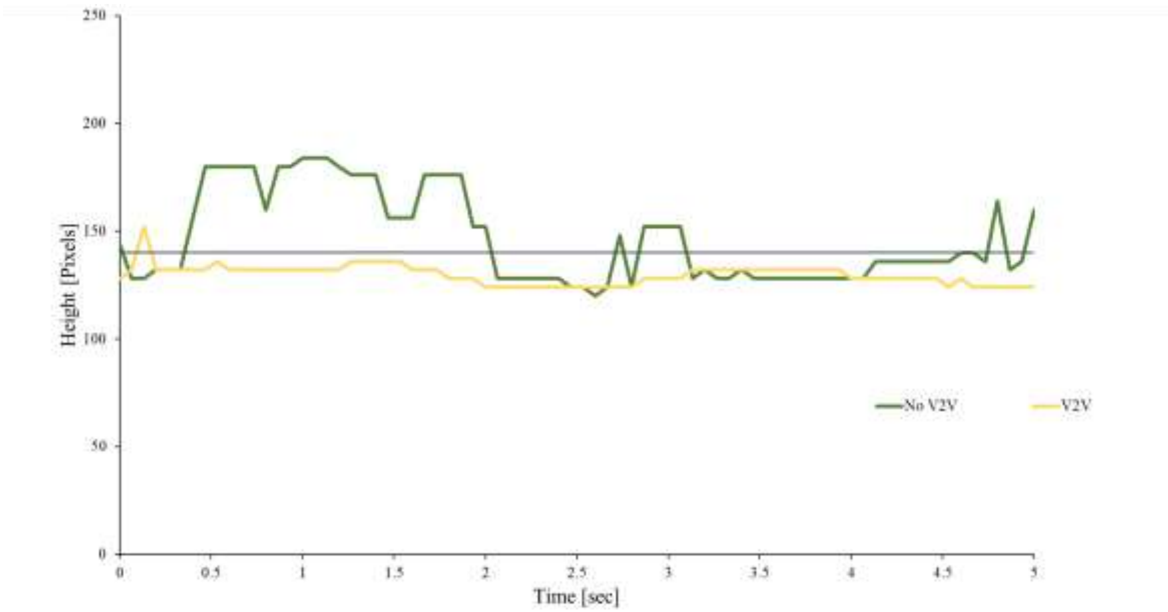

Figure 6. Recorded height (in pixels) of the lead vehicle's battery enclosure, taken at 15 frames per second on a long straightaway (height of battery enclosure is inversely correlated to the distance between vehicles)

Implementing vehicle-to-vehicle communication resulted in significantly fewer oscillations in the following car. In Figure 6, the flat line is the set point in the PID loop. Without communication the following vehicle experiences significant oscillations; however, with the addition of communication, the vehicles approached steady state without the significant oscillations that were previously observed. Note that though Figure 6 shows some oscillations in both trials, much of these oscillations were caused by noise resulting from the physical constraints of the camera system and from road vibrations. The oscillations seen in Figure 6's vehicle-to-vehicle communication trial were barely observable in the actual system while the oscillations seen in Figure 6's trial without communication were easily observed.

For vehicles without communication, the average absolute error from the setpoint is 30 pixels (about 6 inches). With the addition of vehicle-to-vehicle communication, the average absolute error drops to 17 pixels (about 3.5 inches) from the set point of 140 pixels. This is a 43% reduction in the absolute error of the system. The communication not only dampened out oscillations in the platoon, but it also increased the ability of the following vehicle to achieve the desired following distance.

After developing object detection, a single vehicle was tested on the track. Due to time constraints, testing was limited; however, it was observed that the vehicle did a good job avoiding obstacles (most, but not all obstacles were avoided). The addition of a second vehicle posed no new issues as all maneuvers were communicated to the following vehicle, which ensured that the following vehicle did not strike any objects detected by the lead vehicle.

As noted above in the implementation section, the Fast YOLO neural network failed at the competition due to poor lighting conditions we had not anticipated. This failure resulted in the implementation of a new algorithm, which was tested briefly before the competition's judging. The new algorithm demonstrated an improved ability to detect obstacles as the depth map did not require obstacles be within the set of pretrained object classes; however, due to limitations with the depth map's resolution, it was challenging to detect thin obstacles as they could not be resolved in the depth map.

The tests at competition (these tests were demonstrations, which were observed and noted for their successes or failures) consisted of an open road, a single blocked lane (both in the vehicle's current lane and in the neighboring lane), and both lanes being blocked. The vehicles easily traversed open roadway. The vehicles also demonstrated that they could easily pass by an object sitting in the neighboring lane. The test consisting of an object only in the vehicle's lane posed challenges; however, after extensive development, the platoon demonstrated the ability to change lanes when the object was detected. Finally, the most challenging case was when both lanes were blocked. In the most recent version, the vehicle would detect an object in its lane, then try changing lanes, then identify another object in the adjacent lane and stop. This process could be improved in multiple ways with the most immediate solutions being a revised object detection algorithm and by mounting more sensors on the vehicle (a consistent theme throughout the project).

The reliability of the communication within the platoon was observed by debugging any failures during other tests. It quickly became clear that the communication needed improvement as failures in the communication were catastrophic to our system. For example, in one case the lead vehicle detected and avoided an obstacle but the WiFi packet containing the desired platoon behavior was dropped during communication, which resulted in the following vehicle striking the obstructing object. We believe the effects stemming from the failed communication could be lessened or perhaps even eliminated by adding object detection to the following vehicle. Nonetheless, improved communication between the vehicles would certainly be an opportunity for improvement in the project.

The overall system was evaluated on its performance in object avoidance maneuvers and its ability to drive smoothly. The vehicles demonstrated their ability to reliably stay within the lanes while maintaining their platoon formation. Furthermore, the platoon was able to avoid objects despite the following vehicle lacking object detection software. This was possible via the vehicle-to-vehicle communication, which demonstrates the importance of such technology in autonomous vehicles, particularly in the application of platooning.

Impact on Truck Platooning

The successful implementation of the systems in the scope of this project will demonstrate the safety and effectiveness that can be achieved in full-scale truck platooning with similar systems. It will also demonstrate the successful development of decision-making logic for a platoon of vehicles in the face of disturbances. The ability to safely platoon represents a large economic potential in terms of fuel savings, reduced carbon emissions, and increased road safety for trucks and cars.

The implementation of autonomous lane keeping and steering control will make roads safer by removing the error that humans introduce into a system when operating a semi-truck. It also allows a platoon of semi-trucks to respond autonomously to hazards faster than a human-driven platoon. Vehicle-to-vehicle communication allows the platoon to act in unison and safely preserve the platoon by avoiding crashes. We hope our developments and tests on our small-scale RC cars will help advance the field of autonomous vehicles. The implementation of all these technologies in a full-scale system would make platooning a viable way for trucks to travel across the world while saving billions of dollars in fuel and making the roads safer for all drivers.

As a team we would like to recognize our industry sponsors, IPG Automotive and Daimler Trucks North America. They have provided software, financial support, and guidance to our project team and have greatly enabled our success. The team would also like to thank our academic sponsors Professor Charles Birdsong and Professor Bruce DeBruhl for their guidance, motivation, and support through the year. Professor Peter Schuster and Professor Lynne Slivovsky also offered structure and support in our senior project courses throughout the duration of the year. Additionally, the College of Engineering at Cal Poly in addition to the mechanical and computer engineering departments offered financial support and facilities necessary for the project's completion. Finally, in addition to the previously mentioned individuals, other professors, students, and family members provided guidance whenever we needed it.

It is without question that this project could not have been possible without our above supporters.

To them, thank you.

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