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Adaptive Cruise Control Employing Taillight Tracking for a Platoon of Autonomous Vehicles

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ABSTRACT

Traffic congestions in urban cities unwantedly form platoons of vehicles running at low speeds. For vehicles operated by human drivers, reaction to speeding up or down requires some time, thus, increasing travel time. In this study, we present an adaptive cruise control for a group of autonomous vehicles that follow each other. We propose a taillight tracking system by utilizing low-cost dashboard cameras for detecting the position of the lead vehicle and then allow autonomous vehicles to correctly accelerate or decelerate depending on the nature of traffic. This is achieved by detecting the leading vehicle's taillight via linear AND-ing of the the RGB and HSV color model representations. We evaluate the proposed system by employing real captured traffic images and tested by utilizing mobile robots for the platoon of vehicles testing.

Key words: Platoon of vehicles, Adaptive cruise control, Taillight detection, Traffic congestion

1. INTRODUCTION

With the rise in the number of vehicles plying the urban landscape [1], traffic congestion emerges due to the presence of slow-moving vehicles. These slow-moving vehicles in turn frm a vehicular platoon, wherein the movement of each member is dependent on the leader or the first vehicle [2]. Addressing the smooth flow in an intelligent transportation network cannot be solved by simply adding more lanes and roads. While considering the heterogeneity of commercially available vehicles and human driver behaviors, one possible solution is to introduce an adaptive cruise control (ACC) between vehicles to synchronize their movements. ACC not only provides convenience in driving and travelling but also avoids collision and provide safety [3]. This initiative removes or reduces human interventions by introducing an automated vehicle on the road [4].

Previous studies have focused on using RAdio Detection And Ranging (RADAR) and LIght Detection And Ranging (LIDAR) technologies as a means for depth perception that can be employed for ACC. In [5], an index-coding data dissemination based on LIDAR data was implemented to efficiently broadcast on-demand road segment \map data to aid platoons of autonomous vehicles on a road segment in navigating their surroundings. BMW has employed video processing in their driver assistance systems only for detecting lane changing [6]. On the other hand, Isuzu MU-X has implemented a cruise control without the aid of any sensor, but still under the guidance of the human driver, specifically when the distance from a leading vehicle is decreasing [7].

However, majority of the related works in connected vehicles studied the effect of communication delays and wireless connectivity in promoting ACC. Though most research have focused on theoretical and simulation studies, ACC was implemented and empirically tested in a fleet involving six vehicles and evaluated both the communication and sensor areas [8]. The work in [9] tackled the various challenges and solutions in connected vehicles by focusing on the wireless connectivity of each member vehicle of a platoon. In [10], the car-following scenario was modeled by incorporating the stochastic delay presented when an information was sent by leading car. The information flow topology given communication constraints was considered in [11] [12]. Their work designed the cooperative ACC under the failure of communication by relying on the dynamic information available to the platoon of connected vehicles. Individual vehicles were then designed to maintain the string-stability performance of the platoon.

At most, vehicles plying the urban roads have only dashboard cameras installed onto their system which are easily operated and accessed. In this work, we exploit these features to implement an adaptive cruise control for a platoon of connected vehicles. Particularly, we focus on scenarios where vehicles are cruising at low speeds which are experienced during congestion or nearing a traffic light. In this case, overtaking and lane-changing are discouraged. More importantly, a platoon of autonomous vehicles is formed, where trailing cars are following the car directly in front of it. To achieve this, trailing cars can detect the leading car's taillights and base its navigation speed on the detected taillights' sizes. The major contributions of this work are summarized below.

1. A taillight tracking system based on a linear AND operation between the RGB and HSV image representations is developed to detect leading car's taillights while at the same time filtering noises.
2. A robotic testbed has been employed to evaluate the adaptive cruise control based on the taillight tracking algorithm and the car-following model presented in [13].

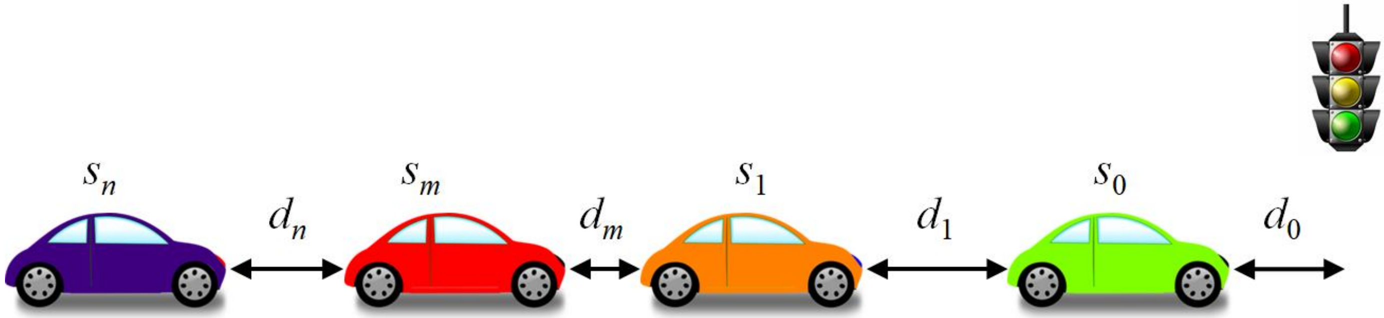

Figure 1: A system of a platoon of connected vehicle. Each member initially has their own speed (s_i) and distance (d_i) with respect to the leading vehicle. The lead car (green) is the only vehicle concerned with its proximity from the traffic light.

This paper is organized as follows: Section 2 presents the problem formulation and the proposed cruise control via taillight detection. Section 3 tackles the experimental results of the proposed adaptive cruise control. Finally, Section 4 concludes the study and gives ideas for future study.

2. PROBLEM FORMULATION, TAILLIGHT DETECTION, AND CRUISE CONTROL

In this section, we present the operation of implementing an adaptive cruise control via taillight tracking.

2.1 Scenario of a Platoon of Autonomous Vehicles

Consider a platoon of autonomous vehicles depicted in Figure 1 on a single lane of an urban road or highway. Multiple lane setups are obtained by superposing multiple single-lane scenarios of Figure 1. The following are the assumptions for developing our proposed adaptive cruise control employing taillight tracking of a lead vehicle and follows the car-following model [13]. Each member vehicle of the platoon:

1. is not allowed to change lane and only has dashboard cameras and proximity sensors as means to monitor its surrounding. Vehicle-to-vehicle communication is also not supported by any member vehicle.
2. can be unique or like the other member vehicle in a platoon. (This addresses the heterogeneity and diversity of car manufacturers.)
3. determines (or maintains) its proximity from the leading car only and not of the trailing car.
4. has a speed that is less than or equal to the speed of its lead car, i.e., $s_n \leq s_m \leq, \ldots, \leq s_1 \leq s_0$.
5. has a distance d_i from its leading car that is greater than or equal to a maintaining distance d_τ.

In Figure 1, the leading autonomous car (green) senses its proximity from a traffic light, represented by d_0, and decides to run at a speed s_0. Given a safe maintaining distance d_τ, trailing orange car monitors the taillights of its leading car, i.e., the green car, to adjust its current speed s_1 while keeping its distance d_1 above or equal d_τ. The other two trailing cars (red and violet) also perform the same operation. Eventually, each trailing member of the platoon will maintain an equal maintaining distance d_i, running at equal speed s_i, i.e., $s_{i=1,\ldots,n} \leq s_0$.

2.2 Taillight Tracking Algorithm

The leading taillights are determined following the block diagram in Figure 2. Images captured by the onboard dashboard cameras are processed in both the RGB and HSV color model representations. Threshold values for each color space are set to initially remove non-red objects, i.e., since red represents the taillights denoting that there is a decrease in the leading car's speed. The binarized RGB and HSV images are then median-filtered to remove "salt and pepper" noises. Finally, the binarized RGB and HSV images are ANDed to determine the location of the red brake light of the leading car. And-ing these images will reveal the location of red objects found in both color space model. Equivalently, the AND-ing process assures that by using two color space models, a red object is really found. The leading car's taillights are finally tracked by locating the white blobs of reasonable size.

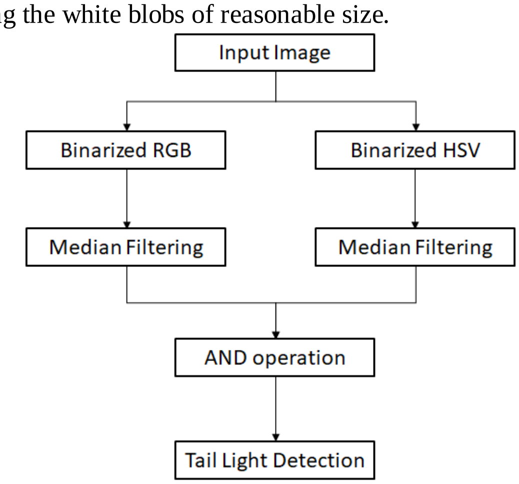

Figure 2: Block diagram for detecting the taillights of a leading car.

2.3 Adaptive Cruise Control via PID control

To implement the adaptive cruise control among the autonomous vehicles in the platoon, a Proportional-Integral-Derivative (PID) controller is employed. PID controllers are very much utilized in linear and nonlinear systems, such as unmanned aerial vehicles [14], process control [15], etc., due to its modularity and robustness to system disturbance and dynamics. The speed and torque control of the vehicle is portrayed in the block diagram shown in Figure 3.

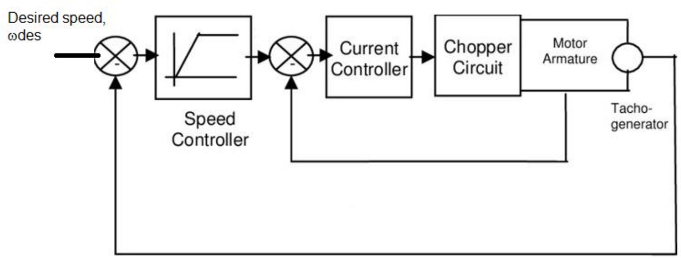

Figure 3: Speed and Torque PID control for a DC motor.

To determine the current vehicular speed, an encoder is installed at the rear wheel. This current speed is compared to the desired speed obtained from the taillight detection algorithm. The analytical derivation of the PID controller values are obtained from [16]. We note that not all mobile robots (mobots) used in the experiments required all PID parameters, i.e., some only use PI controllers.

3. RESULTS AND DISCUSSION

In this section, we present the experimental results of the adaptive cruise control via taillight tracking. An ordinary and low-cost dashboard camera is used to capture real traffic footage. A Raspberry Pi processes the images and provides the appropriate speed (in terms of duty cycle/pulse width) so that a platoon of autonomous vehicles can maintain the leading car's cruising speed while maintaining the threshold distance between two successive vehicles.

3.1 Video Frame Processing for Taillight Detection

A sample frame of the video is taken as shown in Figure 4. In order to track the taillights, the image undergoes color space isolation, binarization, blob detection, and bounding. From the original sample, it is evident that the taillights have a red glow.

Figure 4: Actual sample of a lead vehicle's taillight

There are also unwanted red lights from other sources such as other cars that are not the subject, as well as the red stop light, all of which must be removed or minimized. For color space isolation, the RGB of an instance of a sample image, as well as HSV, is modified. For RGB, red is the signal of interest, and it is subtracted from the RGB intensity signal to yield the image in Figure 5.

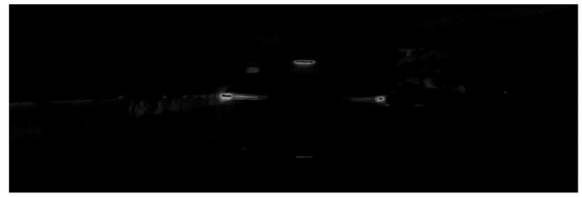

Figure 5: R minus RGB Intensity

For HSV, hue is the signal of interest as shown in Figure 6. For binarization, various threshold values were tested for each case of RGB and HSV, and the threshold value that eliminates the most noise and retains the reddest signals in the image as per visual inspection is chosen. For RGB, most of the red signals were detected but the binarized image was very noisy. Other red signals like the stoplight and other taillights are evidently seen as shown in Figure 7. For HSV, most of the red signals were detected but the binarized image was very noisy as well. Though it is inspected that the orange and yellow signals were completely blocked out as shown in Figure 8.

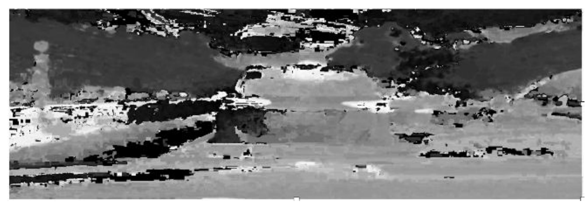

Figure 6 H signal from HSV

Figure 7: Binarized Result from RGB Signal

Figure 8: Binarized Result from HSV Signal

The solution we propose is to take only red-light parts of both the RGB and HSV. This is achieved by passing through an AND gate the binarized outputs of RGB and from HSV in Figure 7 and Figure 8, respectively. The result is shown in Figure 9 and it is noticeable that the bigger blobs are identified as the lead vehicle's taillights.

Figure 9: Output Result for AND of RGB and HSV

Based from the size of the detected taillights (as blobs), the distance is determined and related to the necessary Pulse Width Modulation (PWM) duty cycle that the PID controller needs to output. The relationship between the PWM duty cycle and the pixel distance of the taillights and the actual distance from the taillights is found to be nonlinear, i.e., hyperbolic and is shown in Figure 10. In order to avoid complex and nonlinear calculations, this hyperbolic relationship is translated into a linear equation by utilizing the inverse of the PWM duty cycle, as shown in Figure 11.

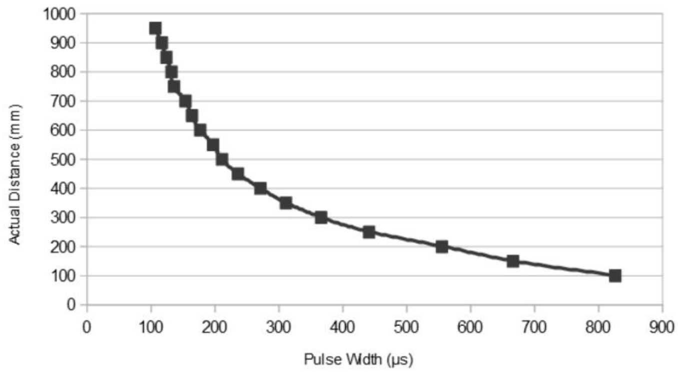

Figure 10: Tail Light Distance Mapping

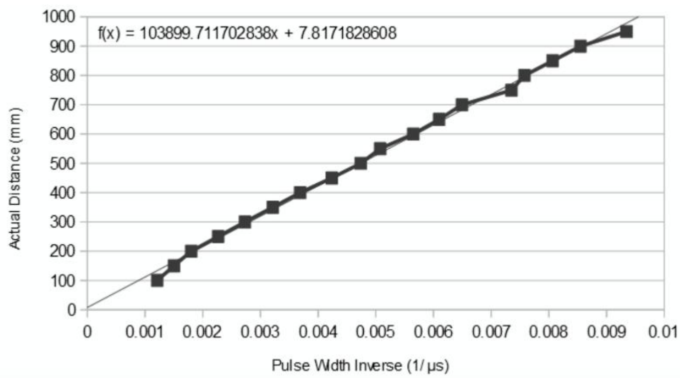

Figure 11: Linear relationship representation of the necessary pulse width to provide the desired distance

3.2 Mobile Robot Testbed for Evaluating Adaptive Cruise Control

The scenario in Figure 1 is evaluated by utilizing four mobile robots shown in Figure 12. The lead and trailing vehicles' speed profiles (green line), derived from [17], and their distances from the traffic light are illustrated in Figure 13, top and bottom locations, respectively. d_τ is set to one meter, which is enough for the driver to see the rear tires of its leading car during congestion and full stop.

In the experiment, initially at time t = 0, trailing cars have detected their respective leading car, therefore, each started to decelerate. The PID controller produces the appropriate duty cycle input to correct the autonomous vehicle's cruising speed. Once the trailing vehicle is in the vicinity of its leading car, the trailing car approximates the speed of the car in front of it. This happens until all members have approximately the same speed value and in turn form a platoon. The decline in speed reveals that the leading car sensed that the traffic light is turning red. This is seen at the time interval of 200 – 400 seconds.

One thing to note is that once the traffic light turns green, each vehicle accelerates to the leading car's speed at a much faster time when compared to scenario when all vehicles are approaching the traffic light. This output is expected since at low speeds, each vehicle is quick to attain the desired speed set by the leading car.

Looking at the distance profile, while the vehicles are approaching the traffic light, the last trailing light is the farthest. The reverse is true when the traffic light turns green, i.e., the last trailing car will be the nearest to the traffic light. But, during this time, all cars are maintaining the same speed and separation between leading and trailing vehicles.

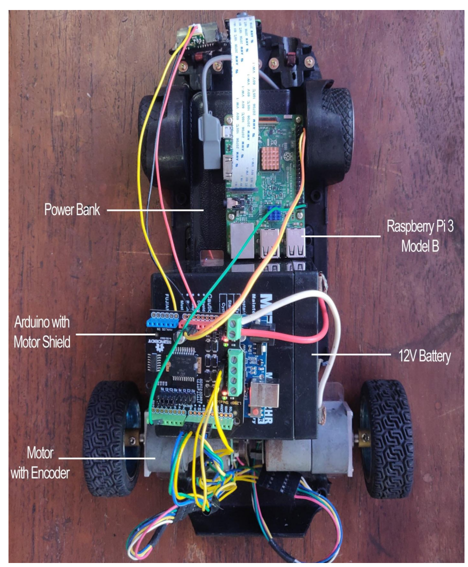

Figure 12: Mobile robot as an autonomous vehicle and member of a platoon.

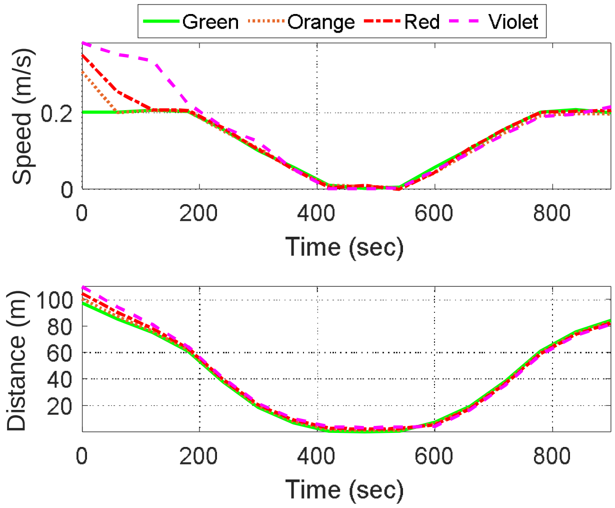

Figure 13: Implementation of an Adaptive Cruise Control based on PID controllers. Speed profile (top) and distance profile (bottom) of all four cars.

To check for the system's latency, three trials were conducted to capture 380, 383, and 382 frames, or equivalently, 0.791s, 0.798s, and 0.795s, respectively. Overall, it takes the taillight detection scheme less than approximately 0.8 seconds to recognize and track the taillights. This fast detection scheme allows the trailing cars to follow their leading cars almost instantly.

4. CONCLUSION AND FUTURE WORK

In this work, an adaptive cruise control for a platoon of autonomous vehicles based on taillight detection tracking has been proposed, tested and evaluated. The taillight detection scheme has employed the linear AND operation between the RGB and HSV color model representations of the captured images from an ordinary dashboard camera. This process ensures that the detected blobs are coming from the leading vehicle's taillights. From the detected blobs, the empirical linear relationship between the taillights and the distance separating the leading and trailing cars is determined and allowed the tuning of the PID parameters. The proposed system is finally tested by employing small mobile robots and results show the complete tracking of leading cars' taillights and the formation of the platoon of autonomous vehicles running at the same speed while maintaining the safe distance between them.

One disadvantage of such taillight tracking being implemented on a platoon of autonomous vehicles is that the trailing cars at the end of the platoon will suffer from too much delay before it can move, especially when there is a long line. To remedy this, we consider in future work the incorporation of vehicle-to-vehicle communication so that delay is mitigated. Another possible solution is to use monitoring road cameras to determine on-road vehicle occlusions [18] and roadside units for data dissemination [19]. Another useful extension of the said taillight tracking system is the incorporation of plate number detection while following the lead car [20]. Finally, the swerving of the lead car can also be detected and correctly identify if the driver is unconscious or not [21].

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