Real World Road Platoons and Negative Obstacles

Henry Hexmoor
Southern Illinois University
School of Computing
Carbondale, Il 62901
USA
hexmoor@cs.siu.edu

Khaled Ahmed
Southern Illinois University
School of Computing
Carbondale, Il 62901
USA
kahmed@cs.siu.edu

***Abstract*— the real world road segments contain negative obstacles and hazards as well as congestions that impede free flowing traffic. In addition, real world vehicles are differently equipped and at various roadworthy states. Vehicle platoons are more efficient when the leader selection accounts for actual road conditions and specific attributes of vehicle involved. We propose real world consideration and attributes that represent vehicles and roads in the real world and how to select the most fit platoon leaders. Communication and leader selection methodology is discussed and preliminary results for negative obstacle detection are offered.**

Keywords—platoon, leader selection, negative obstacles, deep learning

I. INTRODUCTION

Platooning is when groups of vehicles travel in close physical proximity in order to minimize aerodynamic drag and prevent frequent accelerations and decelerations in speed. It typically includes sets of multiple vehicles paired together using sensor and communication technologies. At basic levels, adaptive cruise control (ACC) could enable platooning that is our focal interest. More advanced platooning technology controls for both longitudinal ACC and lateral (i.e., automated lane keeping) movements and is considered. There are common communication and operational scenarios that might hinder intended benefits of platooning. Previous research on platoons has assumed idealized road conditions and uniformly capable vehicles, overlooking inherent capabilities and vehicle attributes such as vehicle occupancy levels. Qualifications of vehicles for assuming platoon leadership position role were also not considered. We address these omissions. We have explored decentralized communication and leadership to mitigate shortcomings. There are technological advancements in data collection, management, vehicle communication, and data storage of vehicular platoons [8][9]. Section 2 outlines a revised platoon leader selection. Section 3 highlights communication nuances whereas Section 4 deals with negative obstacles on the road. Concluding remarks are found in section 5.

II. LEADER SELECTION

The Fitness Value (FV) of a vehicle measures a vehicle's capability to deal with situations in real-world environments depicted in Figure 1.

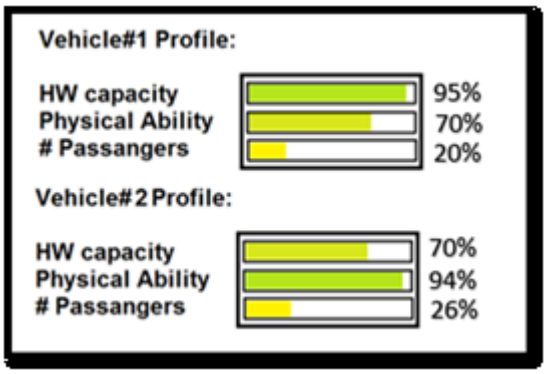

Figure 1. An example of two vehicle profiles

To compute FV, we consider three main components in a Level 5 (i.e., fully autonomous) vehicle. The profile of a vehicle can be seen as 1) Hardware Capability, 2) Physical condition, and 3) number of passengers in the vehicle.

In figure 1, we assume that there are two level 5 vehicles and each with different capability. In order to computer the fitness value, we assume that higher grade hardware such as sensors, cameras, radars, LIDAR, etc. plus better physical conditions such as vehicle driving status, brake pads, lights, etc. would increase the FV, while number of passengers decreases the FV. We assign typical weights to each attribute; e.g.,

- HW Capability = worth 50%
- Physical Ability = worth 25%
- Number of passengers = worth 25%

Fitness Value for vehicle 1 =
$(0.95 \times 0.50) + (0.70 \times 0.25) + (0.20 \times 0.25) = 0.70$

Fitness Value for Vehicle 2 =
$(0.70 \times 0.50) + (0.94 \times 0.25) + (0.26 \times 0.25) = 0.65$

Based on the computed fitness values, vehicle 1 is better fit and will be assigned as the platoon leader.

We have explored three different scenarios and applied each scenario in environments with adverse conditions to determine platoon performance.

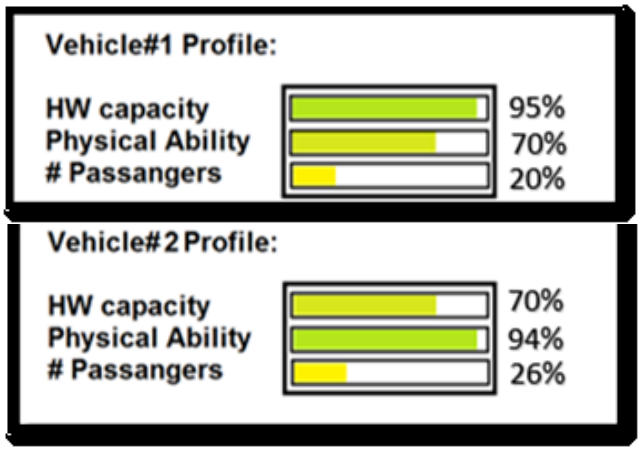

Figure 2. Profiles for two vehicles V1 and V2

A two-mile road segment has been simulated for evaluation. There is a negative obstacle (e.g, a pothole) at 0.25 miles from the start point requiring a lane change. The road becomes slippery at 0.6 mile from the start point requiring a speed reduction of 15 percent (i.e., from 70mpg to 35 mpg). At 1.24 mile from start, there is a pedestrian road crossing requiring a full stop and restart. Maintenance work is blocking the road at 1.45 miles from the start point that requires speed reduction by 15 percent (i.e., from 70mpg to 59.5 mpg) and changing of the lane. At 1.75 mile from the start point, an accident need to be averted by reducing speed down by 50 percent (i.e., 70mpg to 35mpg) and changing lane. A single fully automated level 5 vehicle traveled this road segment; encountered the pothole between 0.23 miles and 0.28 miles from start and changed lane at 69.99mpg. Between 0.58 to 0.59 miles from start, it slowed down for slippery road patch to 59.5 mpg. At 1.19 miles, it stopped at the pedestrian crossing and resumed travel. At 1.5 miles, it slowed for road maintenance at 59.5mpg. Accident at 1.7 miles slowed it down to 35mpg. Travel was completed after a about two-minute duration of 1:59:55.

In another scenario, a group of fully automated vehicles joined a platoon, and the leader of the platoon was fixed as a level 2 (i.e., human driven) truck or bus. The platoon encountered the pothole between 0.21 miles and 0.33 miles from start and changed lane at 69.99mpg. Between 0.60 to 0.61 miles from start, they slowed down for slippery road patch to 59.5 mpg. At 1.19 miles, the platoon stopped at the pedestrian crossing and resumed travel. At 1.39 miles, they slowed down for road maintenance at 59.5mpg. Accident at mile 1.69 slowed them down to 35mpg. Travel was completed after about two-minute duration of 02:04:65. This scenario produced slower travel time than the first scenario. Although the platoon was traveling together, the lack of best leader vehicle reduced travel time.

In yet another scenario, a group of fully automated vehicles formed a platoon and the leader of the platoon was the vehicle with the highest fitness value. The platoon encountered the pothole between 0.22 miles and 0.27 miles from start and changed lane at 69.99mpg. Between 0.57 to 0.58 miles from start, they slowed down for slippery road patch to 59.5 mpg. At 1.18 miles, platoon stopped at the pedestrian crossing and resumed travel. At 1.39 miles, they slowed down for road maintenance at 59.5mpg. Accident at mile 1.69 slowed them down to 35mpg. Travel was completed after about two-minute duration of 1:59:74. This scenario of picking the most vehicle to lead made the platoon behave as a cohesive single vehicle and produced a travel pattern that mimicked a single vehicle characteristic with comparable travel time.

III. COMMUNICATION

Intelligent transportation systems have long advocated for vehicles to connect to the cloud, roadside units, and ambient vehicles. *Cloudlets*, as micro data centers, are slated for use in every vehicle of the platoon [4]. Already, connected vehicles in the vicinity are connected using a *mobile micro cloud* at a road intersection or as parker vehicles. Micro clouds can be used as virtual edge servers that assist traditional cloud and edge servers [8]. This has been reinforced by our recently proposed policies for creating and using vehicular ad hoc clouds [7].

In a platoon, we assume the foremost computational and sensory capable lead vehicle will track platoon members, their attributes and status for providing data and compute services to their impromptu, ad hoc platoon cloud. Vehicles that are most fit can be platoon servers and vehicles with lower fitness value will be collective clients. Once servers are identified and tasks are assigned, the leader will broadcast a table contains the servers and their tasks to all vehicles within a platoon, so that each vehicle may contact a server for needed services. IEEE 802.11p standard is provided by IEEE to support inter-vehicle communication (IVC) and Vehicle-to-Roadside at speeds ranging from 200 to 300 km/h covering communication range of 1000 meters [11][12][13]. If the platoon is longer than 1000 meters, this communication method will be extended by having a vehicle in every 1000 meters serving as a relay, which will carry and forward data from and to neighboring vehicles. In order to most rapidly reach servers, vehicles would need to contact the farthest vehicle that in its **k** nearest vehicle range. Each vehicle can contact **k** number of nearest vehicles that are within reach. Therefore, we modify the k nearest vehicles method to be nth-farthest vehicle of k nearest vehicles.

With nth-farthest vehicle of k nearest vehicle (NFKN), a vehicle will contact the farthest vehicle of the k nearest vehicle until reaching the desired server, and all the farthest vehicle will be relay based where they just carry and forward the data to and from/ clients to and from a server. For example, the vehicle 5 is a client in position 10, and wants to request a service from a server in position 1. The platoon could use a three nearest neighbor method. Therefore, client 5 will would contact the third nearest vehicle (or the first farthest vehicle, which is vehicle in the position 7. Now,

vehicle 7 will check if the desired server is in its three nearest vehicle range. If not, it will repeat the first step and contact the third nearest vehicle (i.e., the first farthest vehicle), which is vehicle 4. Vehicle 4 will find that the desired server is in its range. Hence, it will request the data or the service and carry it back to the requestor using the previous steps. In this example, client 5 uses two relay-based communication to request the service, which are vehicles 7 and 4. Optimal value of k is suggested by the following equation that computes the square root of the platoon length. N is the number of vehicles in the platoon. L is the average length of a vehicle. In addition, d is the distance between vehicles.

$$K = \sqrt{\left(\left(\sum_{i=1}^{N} L_{V_i}\right) + \left(\sum_{i=1}^{N-1} d\right)\right)} \qquad (1)$$

On average, length of a typical vehicle is in the ranger of 3.3 – 4.8 meters. Distance between a pair of platoon vehicles can be kept as short as two meters. The number of vehicles can be 10, 100, 1000, or more. Therefore, using equation 1 we suggest the optimal k to be as inversely proportional to the platoon size as shown in Figure 3.

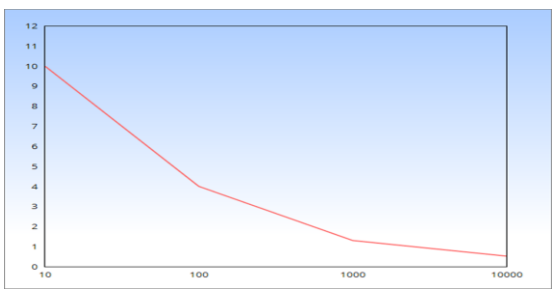

Figure 3. Suggested optimal k

IV. NEGATIVE OBSTACALE DETECTION

One of the most challenging aspects of real-world roads is perception of negative obstacles such as holes, trenches, uneven pavement surfaces, and transitions. Significant percentage of traffic crashes are produced due to roadway environmental factors (mainly by poor pavement conditions). Section II addressed the platoon leader election process that selects the most fit platoon leader. Such as vehicle must possess the highest hardware capabilities such as sensors and cameras and radars, etc. Visual inspections for negative obstacles on the road is discussed next. Image acquisition, preprocessing, and image classification are the primary steps. For image acquisition, the camera would be installed in platoon leader where the distance between the camera and the pavement is about 1.5 m and it has a front facing field of view of 45 degrees. Before training and prediction process, it is required to remove environmental interfaces such as useless background as much as possible. Consequently, image preprocessing operations should be developed as follows.

A. *Preprocesing*

To enhance illumination, we may use simple algorithms such as logarithm spaces [14]. The illumination enhancement formula is shown in equation 2.

$$\log(f'(i,j)) = \delta \log(av(i,j)) + \sigma\left[\log(f(i,j)) - \log(av(i,j))\right] \qquad (2)$$

log(f(i, j)) is the logarithm of the negative value of the image at pixel *(i, j)*; *log(av(i,j))* is the logarithm of the average values of the neighborhood of the image at pixel *(i, j)*. The parameters δ and σ are used to highlight the darker or lighter pixels. Figure 4a shows the original pothole pavement image. Figure 4b shows the illuminated pavement image. To smooth it without losing edge precision and remove random and uniform noises, bilateral filter [15] is used as shown in figure 4c. Figure 4d shows the result of applying Canny edge detector algorithm to pavement images in figure 4c with a previously applied bilateral filter. All the applied preprocessing steps provide a final pavement image with clearly defined pothole in the pavement. In order to extract image features from that final pavement image, projective integrals are used. The integral projections techniques have already been used in problems such as face detection [16]. The projective integral technique calculates the arithmetic mean of a row or column pixels. Consequently, each image is transformed into sum of number of rows and columns data. For example, assume an image 851x572 that means 486,772 data, its projective integral produces 1423 data (851 from horizontal projective integral and 572 from vertical one). Figure 5 shows the results of the horizontal and vertical projective integral of the image in figure 4a. In figure 5, the vertical projective integral, horizontal axis represents each column of the image, and the vertical axis represents the addition of the pixels detected as edges by Canny method in each column. In the horizontal projective integral vertical, axis represents each row of the image. The horizontal axis represents the addition of the pixels of each row that have been detected as edges by Canny method.

B. *Negative obstacle detection and classification*

Object detection and classification are the most fundamental problems in the field of computer vision research [17]. The negative obstacle detection and classification task consists of two parts: detection the negative obstacle and detect localization, obtaining detailed regions of negative obstacle (pothole). The early successful deep networks are based on the sequential architecture [18] launching the basic structure of the convolution neural network (CNN). In this paper we select the VGG16 [19] as the backbone and resized images to 224 x 224. We used SGD o train with wright 0.0001 and a momentum 0.9.

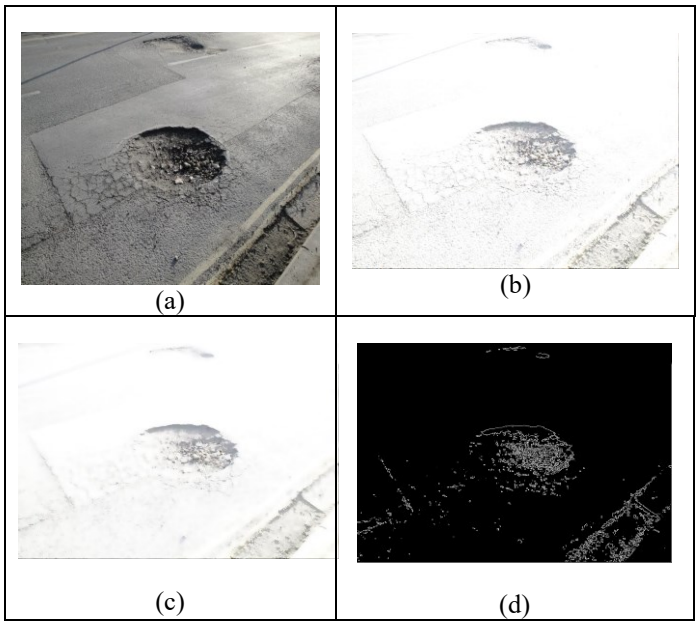

Figure 4. Image Preprocessing

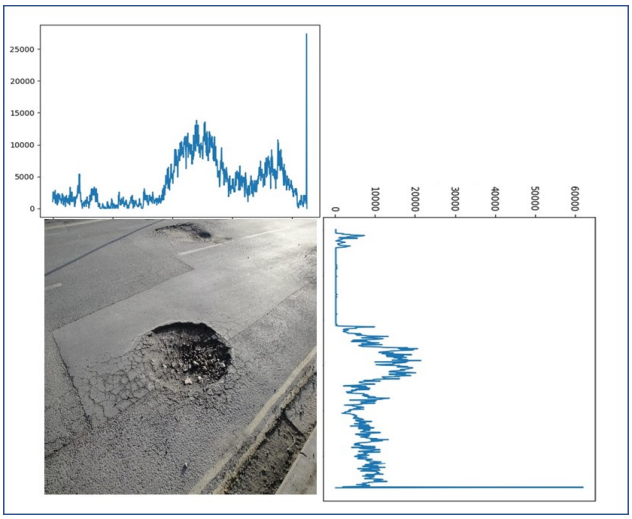

Figure 5. Horizontal and vertical projective integrals.

The performance is evaluated on a dataset of 340 images, 315 images include potholes and 25 images doesn't include potholes. Example of an image includes pothole is shown in figure 4a. To perform detection tasks, we provide annotations saved as XML files that mark the bounding boxes of potholes appearing in each image. Figure 6 shows potholes detection and localization with green ground truth box. Experiments show that the proposed network able to detect negative obstacles (potholes) with accuracy about 94%. Figure 7 shows the training accuracy vs validation accuracy and training loss vs validation loss in 200 epochs. These primary results are significant to detect negative obstacles (potholes) by the platoon leader.

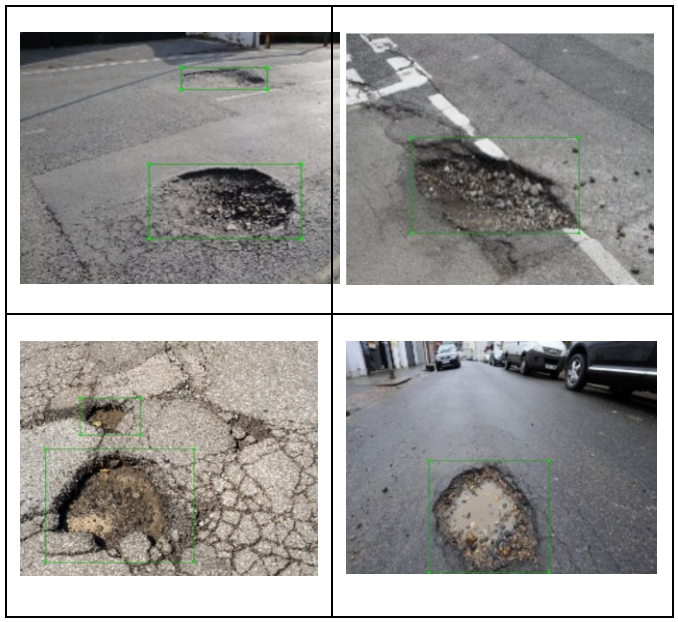

Figure 6. Examples of Potholes detected.

V. CONCLUSIONS

This research has made a case to account for the real world vehicles and the real world road conditions. A simple fitness measure is introduced to eliminate candidates who appear not to be appropriate for the platoon leader position. Vehicles who are more fit can be servers to others in a suggested decentralized communication environment facilitating rapid exchange of data and computing services. The preliminary results show us that in scenarios with no obstacles, the travel time results is 1 minute and 43 seconds. In scenarios that are more realistic there are different travel times that are 1 minute and 59.55 seconds for scenario 4, 1 minute and 4 seconds for scenario 5, and 1 minutes and 59.74 seconds for simulation 6. The outcomes of simulation cannot produce similar reactions to humans. Simulation may be disadvantageous in some cases whereby the programs that are used in simulation have been designed poorly. Decentralized communication among vehicles help avert conflicts and proactively circumvent problems. We discussed communication among vehicles partly for high fitness vehicles to be servers for low fitness vehicles. A nearest neighbor measure is introduced. For the future work, we need to work on assuring the least communication latency and meeting the highest vehicle expectations. This paper has introduced negative obstacle detection and classification process using deep neural networks. The primary results are significant that motivate the authors to elaborate more in proposing a CNN that improves the negative obstacles detection accuracy in real-time.

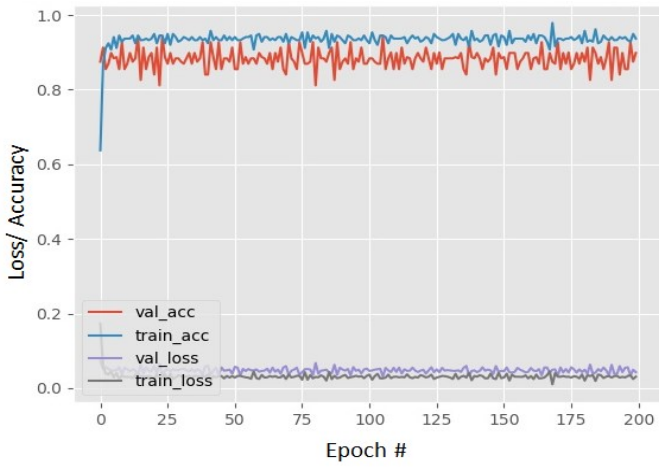

Figure 7. Results: Training accuracy vs Validation accuracy and Training loss vs Validation loss

Acknowledgement

We thank Mr. Abdulzaiz Almuhanna for contributions during his MS studies at SIUC.

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