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DEVELOPING AUTONOMOUS VEHICLES WITH OPTIMAL SENSOR SELECTION, INTEGRATION & CONTROL IMPLEMENTED AT 2018 INTELLIGENT GROUND VEHICLE COMPETITION (IGVC)

Andrew Kosinski
Mechanical Engineer
US Army GVSC GVR
Warren, MI

Kiran Iyengar
Electrical Engineer
US Army GVSC GVR
Warren, MI

Jane Tarakhovsky (Self-Drive Chair, Volvo/Veoneer)
Jerry Lane (GLS&T, IGVC Co-Founder)
KaC Cheok (Oakland University, IGVC Co-Founder)
Bernie Theisen (US Army GVSC GVR, IGVC Co-Chair)
Sami Oweis (Oakland University, Adjunct Professor)

ABSTRACT

The IGVC offers a design experience that is at the very cutting edge of engineering education, with a particular focus in developing engineering control/sensor integration experience for the college student participants. A main challenge area for teams is the proper processing of all the vehicle sensor feeds, optimal integration of the sensor feeds into a world map and the vehicle leveraging that world map to plot a safe course using robust control algorithms. This has been an ongoing challenge throughout the 26 year history of the competition and is a challenge shared with the growing autonomous vehicle industry. High consistency, reliability and redundancy of sensor feeds, accurate sensor fusion and fault-tolerant vehicle controls are critical, as even small misinterpretations can cause catastrophic results, as evidenced by the recent serious vehicle crashes experienced by self-driving companies including Tesla and Uber Optimal control techniques & sensor selection/integration into these autonomous ground vehicles will be the focus of this technical paper.

INTRODUCTION

The IGVC is a college level autonomous unmanned ground vehicle (UGV) competition that encompasses a wide variety of engineering professions – mechanical, electrical, computer engineering and computer science. It requires engineering students from these varied professions to collaborate in order to develop a truly integrated engineering product, a fully autonomous UGV, where optimal control and sensor selection/integration play a large role in competitor's autonomous vehicle performance and operation.

This industry aligned, vehicle control/sensor selection focus of this competition has been further emphasized over the last 3 years, with the third Self-Drive Challenge being carried in 2019, requiring vehicles to perform autonomous, street-legal vehicle road operations including lane keeping, lane switch, merging, avoiding crossing obstacles (simulated pedestrians/vehicles), taxi pickup of passengers, simulated pothole detection, stop and crosswalk lines detection, right/left turn and intersection detection/logic, navigation to GPS waypoints and autonomous parking.

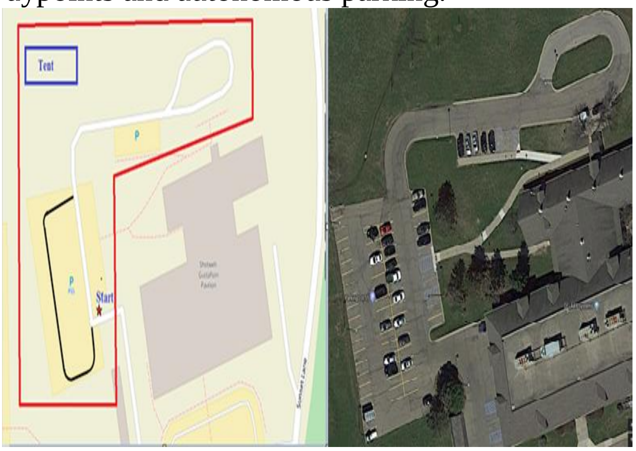

Figure 1. 2018 Self-Drive Challenge course (Oakland University Incubator, 419 Golf View Ln, Rochester, MI 48309).

Adding a further industry relevant emphasis for autonomous vehicles, a new challenge, the Cyber Challenge, is being incorporated in 2019 with the goal to educate & promote knowledge of vehicle cyber security best practices for autonomous, intelligent & smart vehicles. Understanding of the NIST RMF process is a primary objective of this competition and will be given special attention by the judges. Understanding of the NIST RMF process will be demonstrated by a written report describing the process in general, followed by a specific case study using either a provided or novel threat concept applied to a specific vehicle. An oral presentation will be delivered during the IGVC competition and will demonstrate team understanding of the NIST RMF process as well as how it was applied to the choice, design, and implementation of cyber controls for team robots specific to chosen threat scenario.

With regards to general autonomous vehicle control, potential methods of control algorithms that could be applied to military platooning convoys involve path planning and maneuvering command. These are both critical steps in autonomous driving vehicle systems. Path planning is on the rising edge for robotics control, feedback monitoring is the next step of planning and confirmation to command assignment, adding the control to smooth the projected path is state of the art in robotics control, and it has many advantages; such as smooth cornering and curve/ramp handling. Robotics tracking is a noticeable advancement that can be achieved in many ways, by utilizing simulation to report locations and position and orientation. Robotics tracking has undergone noticeable advancements and can be achieved in many ways including a smooth path planning (SPP) that is found with Lyapunov stability and back-stepping control background, as will be more extensively discussed in this technical paper.

Teams are required to document their approach to sensor selection, sensing, processing and vehicle control algorithms in their design report each year which is evaluated by a panel of industry judges with extensive automotive/autonomous vehicle knowledge/experience. Each student team provides a documented design report which will be used as the primary references of this paper. Below is an example of the Host University discussion on sensors and controls. This paper will address other university sensor & control approaches and map the team's performance in the IGVC autonomous driving challenges.

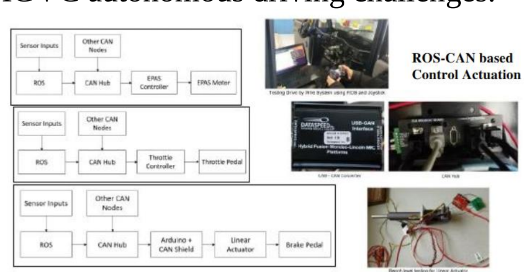

Figure 2. Oakland University's 2018 Self-Drive Vehicle Control Diagram.

Figure 2 explains the high level vehicle control scheme for their 2018 Self-Drive vehicle, which required autonomously operating a street legal Polaris GEM 2 electric vehicle through drive-by-wire modifications to the existing chassis to control vehicle actuation (steering, throttle and brake). An existing Dataspeed Advanced driver-assistance systems (ADAS) kit was used, with the setup of a laptop computer running Robot Operating System (ROS) controlling a CAN hub which then fed commands to control the throttle and to actuate the steering wheel/brake pedal.

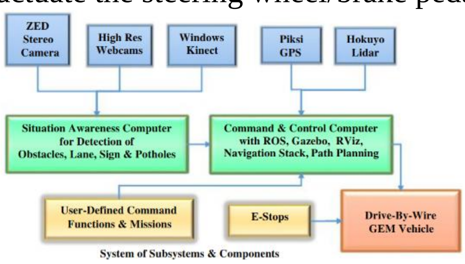

Figure 3. Oakland University's 2018 Self-Drive Vehicle Sensor Functions Diagram.

As shown in Figure 3, sensors used included a ZED stereo camera, webcams, Windows Kinect, GPS and Hokuyo Lidar, utilizing existing ROS packages for processing sensor feeds. The camera and Kinect were used for detection of obstacles, lane marking, signs and potholes, fusing with the GPS/Lidar information for overall vehicle navigation/path planning decisions. This system provides for increased robustness, as multiple sensors are supporting similar autonomous vehicle functions such as obstacle detection, which is critical for the very high reliability demands for autonomous vehicle systems, even at lower speeds (5mph max allowable speed during IGVC competition).

Exact correlation of performance to sensor/control approaches will not be guaranteed due to many other competition factors at time of runs but an overview perspective will be provided together with university references for further collaboration on individual techniques.

Section 1. Vehicle Machine Vision – Sensor Selection/Processing/Integration

Vehicle machine vision is a huge part of a successful autonomous vehicle, as the vehicle is completely on its own while operating in the various relevant applicable environments. As mentioned above, teams normally use mono/stereo cameras and LADAR. Component redundancy is important, even more-so with regards to sensors, with some teams adding multiple cameras for redundancy as well as to increase the sensors' field of view for detection. Teams have also installed planar LADARs on pan-tilt assemblies to allow for 3-D sweeping detection. 3-D sweeping is especially important for detecting negative obstacles, like potholes.

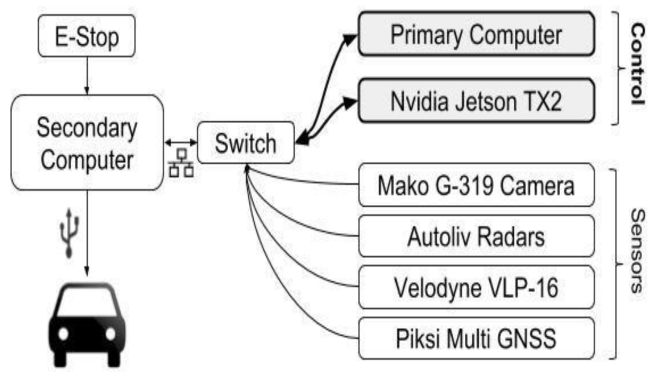

Figure 4. Lawrence Technological University's 2018 Self-Drive vehicle safety/processing/sensor overview schematic.

A significant sensor challenge is not just processing and analyzing a sensor's data feed, but then integrating it with the other vehicle sensors to build a coherent world map of the vehicle's environment. Normally simultaneous localization and mapping (SLAM) algorithms are used for this purpose. SLAM also serves as a good redundancy to the data pulled from the vehicle's high precision differential GPS.

This then immediately ties into requiring robust software coding, building in a comprehensive ruleset to be able to segment out irrelevant data and filter noise, as well as segment and recognize important parts of the world map corresponding to obstacles (barrels, potholes, ramps) and other items of interest (flags, spray painted course boundary lines, etc.). In addition to categorizing these items, there needs to be further logic with regards to flags and spray painted course lines.

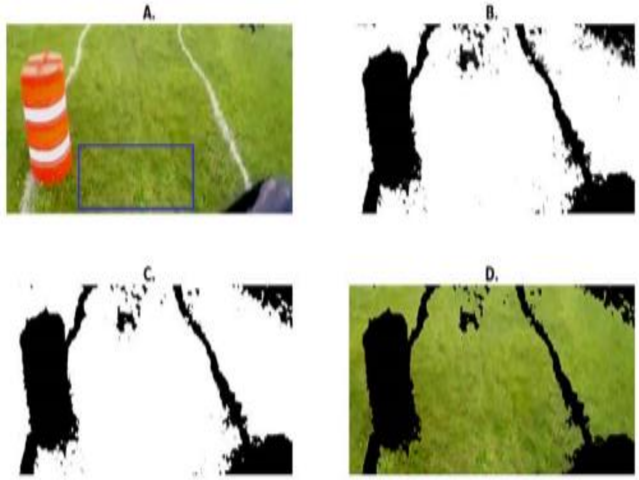

Figure 5. Stony Brook University vehicle camera extracted histogram projection.[1]

The logic for spray painted lines is straightforward, to have the vehicle stay between the two boundary lines. The logic for flags is more involved, requiring the machine vision system to first not only detect the flags, but accurately determine their color (red or blue), and then after knowing the color, program the vehicle to stay to the left of the red flags and to the right of the blue flags.

Sensor noise can become extremely problematic, requiring implementation of additional processing techniques, such as the Oakland University team's application of an Artificial Neural Network (ANN) to assist in the determination of the white course boundary lines. Using self-learning approaches can be very helpful in situations like this, where hard coding white line extraction algorithms that will be applicable in real-life IGVC implementation become challenging. The ANN white line detection process the Oakland University team used is characterized below:

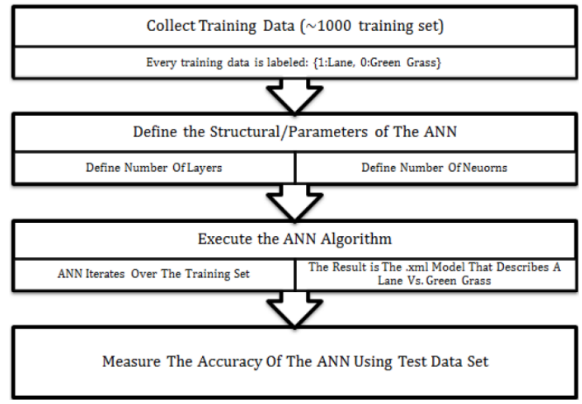

Figure 6. Oakland University Team's ANN White Line Detection Process.[2]

Section 2 Optimal Vehicle Control Through Simulation/Real-Life Testing

Optimizing vehicle control through testing of the vehicle is critical and it can take the form of real-life testing and/or simulation. See below for a mock IGVC course created by the Indian Institute of Technology Bombay team for vehicle testing/evaluation:


Figure 7. Indian Institute of Technology Bombay mock IGVC course.[3]

An obvious advantage control algorithm refinement though the use of simulation over real-life testing is that the vehicle can be worked on while evaluating its (virtual) performance on a computer. An obvious drawback to simulations is that it is only as good as the input data, simplifying assumptions, etc. Another advantage of a simulation is that the (virtual) vehicle can be evaluated many times faster than real-time.

The University of New South Wales (UNSW) team's simulation environment allowed for the simulation to be run up to 5 times faster than real-time and in parallel. The advantages of this can be extreme, assuming wise creation of the simulation environment as a whole and informed determination of the necessary input data, simplifying assumptions, control algorithms, etc., to ensure a highly accurate representation of the real-life vehicle conditions/environment/operations. This can allow for a huge scaling in the amount of vehicle testing within a timeframe, which can greatly improve overall vehicle operation/performance in future real-life testing and at the actual IGVC competition.

Obviously huge amounts of data are generated from these virtual vehicle runs, which then necessitates quick/accurate analysis in order to be useful. For this purpose, the UNSW team developed and incorporated several tools to "automatically analyze and collect statistics regarding the performance in a simulated run of the competition. These statistics, which include average speed, localization error, and proximity to obstacles, allow for quick tuning and verification of parameters to determine which combination of these parameters optimizes the performance of the system as a whole."[4]

The California State University, Northridge (CSUN) team developed their simulation program using LabVIEW. As they state, "The simulation was developed as a method to allow testing of new codes without endangering the vehicle with a previously untested code, which may have bugs that create unsafe conditions for El Toro...Virtual LRF (laser range finder) data is created, while inducing specified levels of Gaussian white noise to more realistically represent the stream of data that would come from the sensors. This allows the vehicle to choose different paths each time it navigates through the simulation. The simulated data gathered by the LRF and compass is passed to the navigation and system integration code, allowing the vehicle to run autonomously."[5]

The Gazebo simulation environment is especially popular with IGVC teams as can be seen below:

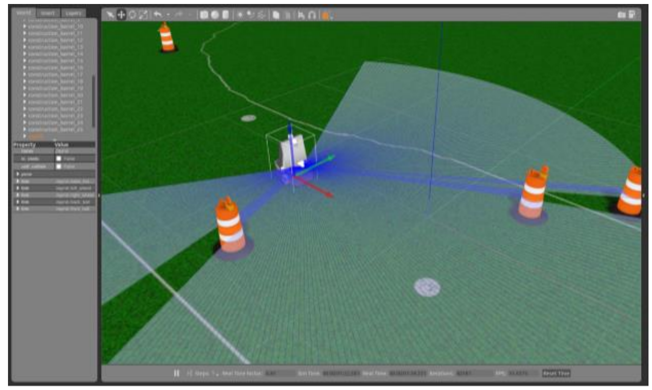

Figure 8. Georgia Institute of Technology Gazebo simulation.[6]

Figure 9. LTU Self-Drive vehicle simulation testing with relevant simulated environment (road signs, lane markings, etc.)[7]

The real-life improvements of a system, such as for these IGVC vehicles, from utilizing effective simulations that feed the optimization of vehicle control algorithms cannot be overstated, especially with the growing virtual toolset for improved simulation, analysis and optimization of real-life system performance. Such toolsets include optimization routines such as neural networks and evolutionary systems, as well as deep learning, which was displayed in a limited, though dramatic degree, with regards to a virtual tool (deep learning computer program AlphaGo) quickly optimizing its performance of the game of GO, as well as the vast improvements demonstrated by later versions of the deep learning software in reduced time periods (AlphaGo Master/Zero). Deep learning has expanded into many fields including speeding up drug analysis/discovery, self-driving vehicle control/behavior optimization, additional "game playing" applications such as OpenAI beating the best Dota 2 team in 2019, artificial general intelligence, etc.

Section 2.1 Smooth Trajectory Platooning Autonomous Vehicle Control Through Simulation/Real-Life Testing

As mentioned earlier, ground vehicle tracking/control has undergone noticeable advancements and can be achieved in many ways including a smooth path planning (SPP) that is found with Lyapunov stability and back-stepping control background, as is further elaborated below.

MATHEMATICAL FORMULATION

2.1.1 System Variables

Some of the important variables to keep in mind are shown below for the formulation of the smooth path planner (SPP).

r = distance from prime vehicle to target vehicle

θ = angle of target direction w.r.t. the joining line

δ = angle of prime direction w.r.t. the joining line

ω = angular speed of prime vehicle

v = forward speed of prime vehicle

δ represents the steering angle for the prime vehicle, and r is the separation distance between the vehicle and the target. Assume that the target is fixed or not moving. For practical implementation purposes, it is noted . that these variables can be determined from a combination of measurements from camera, GPS, IMU, lidar and/or radar.

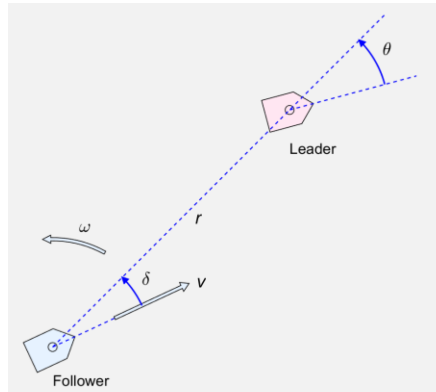

Figure 10. Top view diagram of leader-follower robotic vehicles.

2.1.2 Kinematic Model

Using the kinematics relationship, it can be shown that

$$\begin{bmatrix}\dot{r}\\ \dot{\theta}\end{bmatrix} = \begin{bmatrix}-v\cos\delta\\ \frac{v}{r}\sin\delta\end{bmatrix} \tag{1}$$

Since the target is stationary, it can also be shown that

$$\dot{\delta} = \frac{v}{r}\sin\delta + \omega = \dot{\theta} + \omega \tag{2}$$

As an illustration, the model 1 & 2 and **Error! Reference source not found.**5 represent a robotic vehicle as being driven to a parking space represented by the target if we are able to drive $\theta \to 0$ & $\delta \to 0$. On the other hand they represent a follower robotic vehicle trailing a leader target vehicle if we choose to drive $r \to$a separation distance, $\theta \to 0$& $\delta \to 0$. Or a robotic formation, if we also choose to drive θ & δ to a certain angle. Therefore, controlling the model 1 through 2 is a key to path planning for robotic platooning.

2.1.3 Lyapunov Stability Criterion (LSC)

For the purpose of stability analysis, consider driving $r \to 0$ and $\delta \to 0$. To apply the LSC, use the positive definite function (3) as a Lyapunov candidate

$$V = \frac{1}{2}r^2 + \frac{1}{2}\theta^2 \ > \ 0 \tag{3}$$

where r is a positive separation distance. The LSC states that if the time derivative of V is negative

$$\dot{V} = r\,\dot{r} \ + \ \theta\,\dot{\theta} \ < \ 0 \tag{4}$$

then it is known that $r \to 0$ and $\theta \to 0$. That is, a speed v and ω should be obtained that produces a steering angle δ which results in a distance r and an orientation θ, such that 4 is satisfied.

2.1.4 Desire Vehicle Orientation

A method to satisfy LSC is to set the desired orientation as shown in (5), where is a positive value to be assigned

$$\delta_{des} = \tan^{-1}(-k_1\theta) \tag{5}$$

Since $\theta \in (-\pi, \pi] \subset \Re$, (5) leads to the properties given by (6)

$$-\frac{\pi}{2} < \delta_{des} \le \frac{\pi}{2},$$
$$\cos\delta_{des} \ge 0$$
$$sign(\sin\delta_{des}) = sign(\delta_{des})$$

Drive $\delta \to \delta_{des}$, which results in:

$$\begin{bmatrix} \dot{r} \\ \dot{\theta} \end{bmatrix} \to \begin{bmatrix} -v\ \cos\delta_{des} \\ \dfrac{v}{r}\ \sin\delta_{des} \end{bmatrix}$$

Substituting (7) into (4) and applying (6) lead to

$$\dot{V} \to -r\,v\ \cos\delta_{des}\,r\,\dot{r} \ + \ \theta\frac{v}{r}\ \sin\delta_{des}\ < 0 \tag{8}$$

The Lyapunov function qualified by equations (3) & (8) implies that (1) will be stable if we drive $\delta \to \delta_{des}$.

2.1.5 Steering Command via Back-Stepping Control Scheme

The steering error can be defined as

$$e \ = \ \delta_{des} - \delta \ = \ \tan^{-1}(-k_1\theta) - \ \delta \tag{9}$$

The time derivative of which is given by

$$\begin{aligned} \dot{e} &= \dot{\delta}_{des} - \dot{\delta} \\ &= \frac{-k_1}{1+(k_1\theta)^2}\dot{\theta} - \dot{\theta} - \omega \\ &= -\left(1 + \frac{k_1}{1+(k_1\theta)^2}\right)\frac{v}{r}\sin\delta - \omega \end{aligned} \tag{10}$$

A back-stepping control scheme is then applied to drive the angular speed ω resulting in:

$$\omega_{des} = \left(1 + \frac{k_1}{1+(k_1\theta)^2}\right)\frac{v}{r}\sin\delta + k_2\ \frac{v}{r}e \tag{11}$$

where $k_2 > 0$ is a controller gain to be assigned. As $\omega \to \omega_{des}$, the error dynamics (10)

$$\dot{e} \to -k_2 \frac{v}{r} e \tag{12}$$

which is exponentially stable since $k_2, v \,\&\, r$ are positive values. Equations (5) & (11) form the desired steering command for the Lyapunov-based smooth trajectory-planning (SPP) scheme.

2.2 Steering Actuation and Control

A steering mechanism is required to produce the angular speed ω, which would be controlled by an actuator input u. The dynamics of the steering can be described by

$$\dot{\omega} = -a\,\omega + b\,u \tag{13}$$

where $a \,\&\, b$ are system parameters for the actuation. To drive ω to ω_{des}, a proportional + integral action controller can be implemented given by (14), where $k_p \,\&\, k_i$ are gains to be determined.

$$\varepsilon = \omega_{des} - \omega$$
$$u = k_p \varepsilon + k_i \int \varepsilon \, dt$$

2.3 Overall Scheme at a Glance

Figure 11. Overall smooth path planning (SPP) scheme depicts the smooth path planner (SPP) scheme at a glance, consisting of all the factors described above.

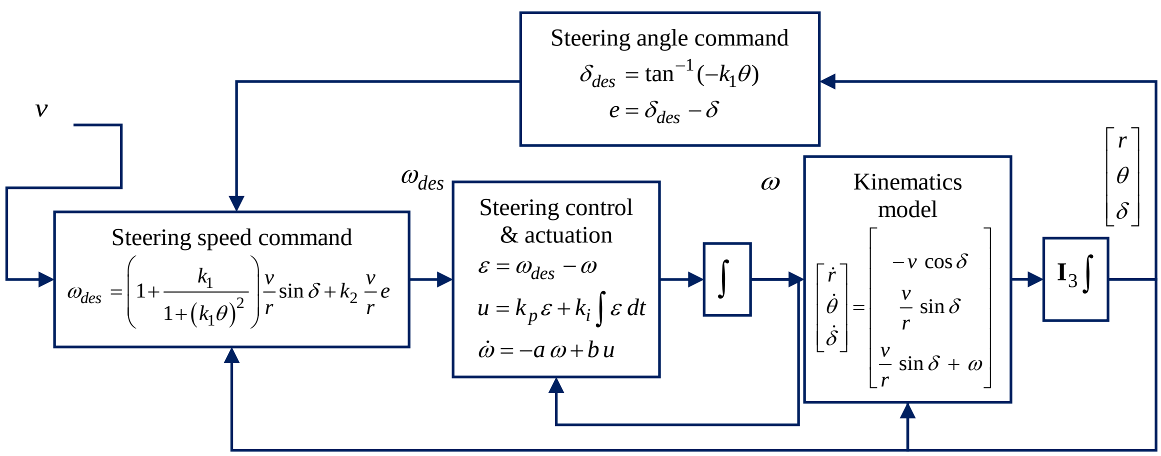

Figure 11. Overall smooth path planning (SPP) scheme

k_1, k_2, k_p & k_i are design parameters whose values are usually determined with the help of simulation. k_1 determines how much reaction should be given to θ, and can range from 0 to 10. k_2 determines how fast δ should approach δ_{des} and ranges from 1 to 5. The choice of k_p & k_i depends on the actuators and are chosen to control the transient behavior the steering speed ω converging to ω_{des}.

2.4 Matlab Visualization of Smooth Path Planner

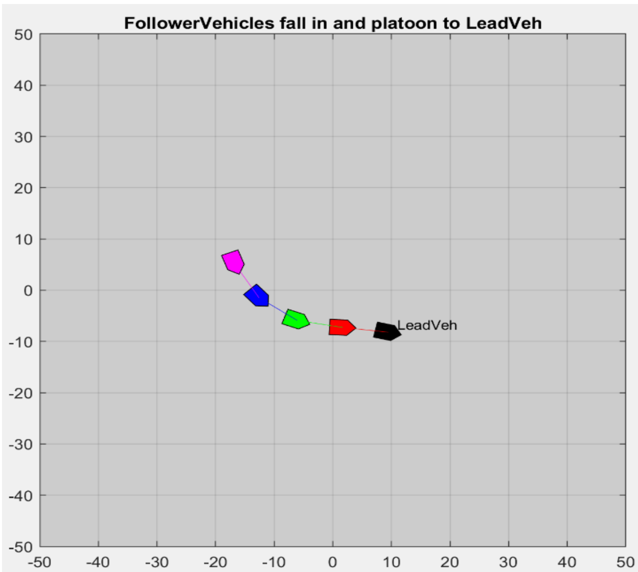

Figure 12: This shows a Matlab animation of SPP used for single file, platooning maneuver. Here, the 2nd vehicle follows the lead vehicle. The 3rd follows the 2nd, etc.

2.5 ROS Gazebo Simulation of Smooth Path Planner

A 3D simulation of leader-follower platooning for multiple Polaris Gem e2 vehicles was implemented using the Robotics Operating System (ROS) Gazebo simulator. Implementation in ROS is being investigated as we are preparing for real-time experimentation of the SPP schemes. Figure shows four follower vehicles led by a lead vehicle swerving through a field, while Figure shows a similar scenario that includes lane following maneuvers.

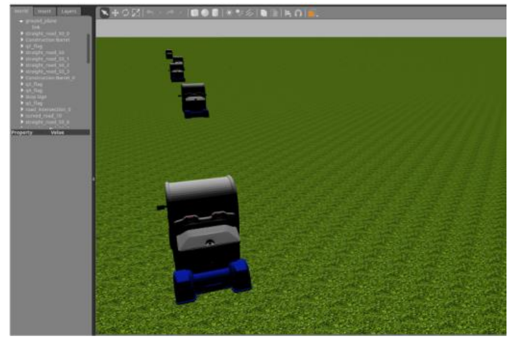

Figure 13. Platooning Polaris Gem e2 vehicles with smooth path planner with a swerving leader

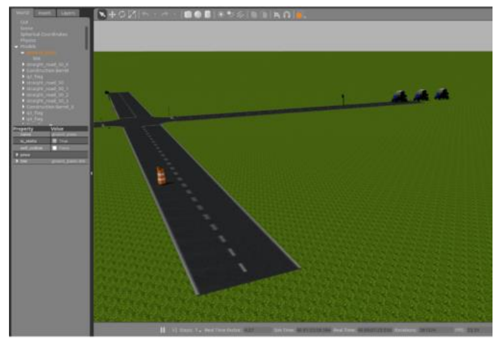

Figure 14. Gazebo simulation of a lead vehicle and two followers performing lane keeping maneuvers with the smooth path planner.

2.6 Smooth Path Planner Future Research

A future aspect is to include the dynamics and control behaviors of the vehicle motion in the SPP analysis. This will take actuation drives, control schemes and processing delays into consideration so there can be a more realistic expectation. This is in process of realizing the SPP on Polaris Gem e2 class vehicles, with multi-sensors, for the 2019 IGVC in the Self-Drive Challenge. Even though the smooth path planner (SPP) was derived using detail analysis involving kinematics model, Lyapunov stability criterion and back-stepping control, its synthesis is relatively simple. This allows the SPP to be readily adapted or switched to work with many car maneuvers and other potential practical applications.

CONCLUSION

The 2018 IGVC was a successful autonomous ground vehicle competition which further developed team capabilities in the very industry/Military relevant engineering skillset areas of optimal sensor selection, integration & control through the creation and evaluation of functional autonomous vehicles capable of real-world navigation. Teams gained valuable engineering experience which will benefit them in their future careers. The refinement of the Self-Drive Challenge proved a success in providing a highly industry/Government relevant street legal vehicle competition which further develops the necessary skills engineers should have in the growing fields of autonomy, AI, machine learning, self-driving vehicles, etc.

REFERENCES

[1] Stony Brook University Design Report. 2016. http://www.igvc.org/design/2016/22.pdf.

[2] Oakland University Design Report. 2015. http://www.igvc.org/design/2015/16.pdf.

[3] Indian Institute of Technology Bombay Design Report. 2017. http://www.igvc.org/design/2017/8.pdf.

[4] University of New South Wales (UNSW) Design Report. 2015. http://www.igvc.org/design/2015/24.pdf.

[5] California State University-Northridge (CSUN) Design Report. 2015. http://www.igvc.org/design/2015/4.pdf.

[6] Georgia Institute of Technology Design Report. 2017. http://www.igvc.org/design/2017/5.pdf.

[7] Lawrence Technological University Research Day 2018 Presentation. 2018. https://www.ltu.edu/provosts_office/research_day.asp

[8] J. Park and B. Kuipers, "A smooth control law for graceful motion of differential wheeled mobile robots in 2d environment," 2011 IEEE International Conference on Robotics and Automation (ICRA), May 2011, pp. 4896-4902. W.-K. Chen, Linear Networks and Systems (Book style). Belmont, CA: Wadsworth, 1993, pp. 123–135.

[9] Olson, Edwin. "A primer on odometry and motor control." (2004).

[10] J. Park and B. Kuipers, Autonomous Person Pacing and Following with Model Predictive Equilibrium Point Control, 2011.

[11] Cheok, KaC, Kiran Iyengar, and Sami Oweis. "Smooth Trajectory Planning for Autonomous Leader-Follower Robots." *Proceedings of 34th International Confer 58 (2019): 301-309.*

[12] P. Foster, Z. Sun, J. Park and B. Kuipers, VisAGGE: Visible Angle Grid for Glass Environments *LIDAR mapping for glass, metal, mirrors, and other non-diffuse surfaces, 2011.

[13] K. Iyengar, "Smooth control path planning and tracking of an autonomous mobile robot in real-time," M.S. thesis, School of Eng. And Computer Sc., Oakland Univ., Rochester, Michigan, USA, Aug. 2015. Accessed on: May. 28, 2018.

[14] Hargadine, Calvin S. Mobile robot navigation and obstacle avoidance in unstructured outdoor environments. Diss. Monterey, California: Naval Postgraduate School, 2017.