SmartCruise: A Highway Driver Assist Technology

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Abstract

Driver fatigue is one of the leading causes for motor vehicle accidents. The rise of automated vehicle technologies and autonomous features, not only significantly reduces the effects of driver fatigue in turn reducing motor vehicle accidents, it also reduces fuel consumption, traffic congestion, travel time, and significantly improves vehicle accessibility for people who are not able to drive a car themselves.

In this thesis, a new highway driver assist technology called SuperCruise is presented. SuperCruise takes over parts of the driving task by controlling the throttle, braking, and steering of the vehicle.

For the longitudinal control of the vehicle, a new Adaptive Cruise Control(ACC) system is introduced which solves the problem of repetitive switching between the two modes of the classic ACC system. To achieve this, a novel switching algorithm is implemented that creates a hysteresis between the two modes by implementing a set of logical comparisons which smoothens the transition between the two modes, and reduces repetitive switching. This results in lower longitudinal acceleration and jerk, ensuring a more comfortable ride.

For the development of the lateral controller which is the Lane Centering Assist(LCA), a Fuzzy Model Predictive Controller(MPC) is developed by implementing fuzzy control logic into the formulation of the MPC. This system automatically tunes the cost function parameters of the optimization algorithm used in MPC to improve the lateral stability of the system based on the current lateral deviation and heading angle error of the vehicle with respect to the desired trajectory.

The longitudinal system is then compared to the classic ACC via three different driving scenarios. Results show significant reduction is the switching between these modes which results in lower longitudinal accelerations and hence an improvement in driver comfort.

The performance of the proposed lateral controller on the other hand, has been evaluated by comparing the path following performance, lateral stability, and driver comfort of the system with two of the well known methods used in literature; Stanley method and classic MPC in three different driving scenarios. Results show that implementation of Fuzzy control logic into the MPC, improves the lateral stability of the system and reduces the unnecessary oscillations in steering which in turn reduces lateral acceleration and increases driver discomfort.

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Declaration of Authorship

I, Shiva Ghasemi Dehkordi, declare that this thesis titled, "SmartCruise: A Highway Driver Assist Technology" and the work presented in it are my own. I confirm that all the following sections are done by me and other works and researches which are used in this thesis are clearly referenced.

- Chapter 1: Introduction
- Chapter 2: Automated Vehicles Technologies (AVT)
- Chapter 3: Advanced Driver Assistance Systems (ADAS)
- Chapter 4: Proposed Driver Assistance System : SmartCruise
- Chapter 5: Simulation and Test Scenarios
- Chapter 6: Results and Analysis
- Chapter 7: Conclusion and Future Work
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List of Abbreviations

AAE	**A**verage **A**bsolute **E**rror
ACC	**A**daptive **C**ruise **C**ontrol
ADAS	**A**dvanced **D**river **A**ssistance **S**ystem
AVT	**A**utomated **V**ehicle **T**echnologies
DC	**D**istance **C**ontrol
DCM	**D**istance **C**ontrol **M**ode
FCM	**F**ollowing **C**ontrol **M**ode
GNN	**G**lobal **N**earest **N**eighbour
GPS	**G**lobal **P**ositioning **S**ystem
IDM	**I**ntelligent **D**river **Model**
LCA	**L**ane **C**entering **A**ssist
LiDAR	**Li**ght **D**etection **A**nd **R**anging
LQR	**L**inear **Q**uadratic **R**egulator
LRR	**L**ong **R**ange **R**adar
MaaS	**M**obility-**as**-**a**-**S**ervice
MPC	**M**odel **P**redictive **C**ontrol
MRR	**M**id- **R**ange **R**adar
NHTSA	**N**ational **H**ighway **T**raffic **S**afety **A**dministration
PID	**P**roportional **I**ntegral **D**erivative

RMS	**R**oot **M**ean **S**quare
SAE	the **S**ociety of **A**utomotive **E**ngineers
SC	**S**peed **C**ontrol
SDM	**S**mart **D**river **Model**
SRR	**S**hort **R**ange **R**adar
VCM	**V**elocity **C**ontrol **M**ode
V2X	**V**ehicle to**(2)** things**(X)** Communication

List of Symbols

A_f	Frontal Area
C_d	Coefficient of Drag
C_g	Center of Gravity
d_{des}	Desired Distance
d_{rel}	Relative Distance
d_{safe}	Safe Distance
e	Lateral Deviation
e_{dist}	Distance Error
e_{speed}	Speed Error
$e_{velocity}$	Velocities Error
F_{aero}	Aerodynamic Force
F_{xf}	Front Tire Force
F_{xr}	Rear Tire Force
J	MPC Cost
K	Controller Gain
K_P	Controller Proportional Gain
K_l	Controller Integral Gain
l_f	Distance Between the Front Axle and the Center of Gravity
l_r	Distance Between the Rear Axle and the Center of Gravity

m	Vehicle Mass
N_p	Prediction Horizon
N_c	Control Horizon
R	Radius of Instantaneous Center of Rotation
R_i	Reference Variable
R_{xf}	Front Rolling Resistance Force
R_{xr}	Rear Rolling Resistance Force
T_{gap}	Time Gap
U	Input Variable
V_{ego}	Ego Velocity
V_{lead}	Lead Velocity
V_{set}	Set Velocity
V_{wind}	Wind Velocity
X_c	X Location of Center of Gravity
X_i	Measured State
X_p	X Location of Closest Point on the Trajectory
Y_c	Y Location of Center of Gravity
Y_p	Y Location of Closest Point on the Trajectory
α - β	Tuning Parameters
δ	Steering Angle
θ	Heading Angle
κ	Speed Tuning Parameter
ρ_{air}	Air Density
ψ	Heading Error
ω	Rotation Rate

Chapter 1

Introduction

1.1 Driver Fatigue: Number One Cause of Motor Vehicle Accidents

Rapid development in communications and robotics technologies have had major impacts on our everyday lifestyle enabling long time ideas such as self-driving cars to come true. Technologies like this, not only aim to increase driver safety by reducing the number of crashes, it also has a significant impact on energy consumption, pollution, congestion and transportation accessibility enabling older people or people with disabilities to freely and easily commute[6].

Most of today's motor vehicles are equipped with features that aim to increase the safety of the driver and ease the task of driving. Automated technologies were initially used to increase the safety of the driver, by adding features such as anti-lock brake systems. As time passed, more advance safety features were added with the aim to reduce car crashes such as blind spot detections and forward collision warning. The continuous evolution of automated vehicle technologies, works towards not only providing greater safety benefits to drivers but also handling a part or the whole task of driving. Some of the main advantages of automated driving systems are discussed below:

Motor Vehicle Fatalities

Motor vehicle fatalities are one of the top non-disease causes of death across the world. A statistical projection of traffic fatalities for 2020, shows an estimate of 38,000 people who have died in motor vehicle crashes in North America alone. Looking at the cause of crashes in these incidents, 90% of the time, the driver has been responsible for the crash, whereas vehicle and environment related causes only take up around 2% each[47].

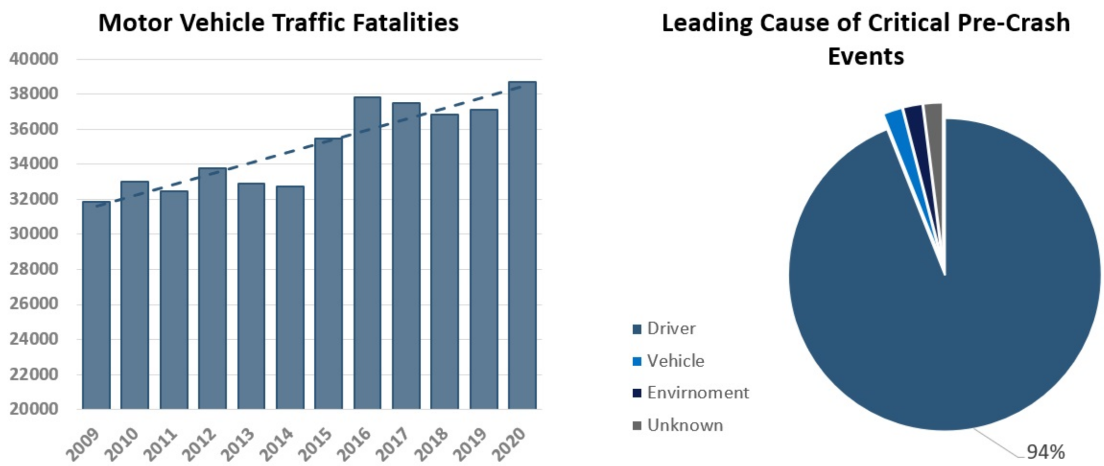

FIGURE 1.1: Statistics of Motor Vehicle Fatalities

Driver fatigue is one of the main causes of human error. A tired driver reacts slower to the changes on the road, makes poor decisions and sometimes drifts away from the lane they are driving in. The biggest effect of driver fatigue is what is called a recognition error which makes up to 42% of human error. Some examples of recognition errors are; the driver not paying full attention, or missing to notice an object surrounding the vehicle. The second biggest category is error in decision making which makes up about 35% of human errors. This includes things such as speeding, missing a red light signal or not following the traffic rules. The rest are dedicated to performance and non performance errors.

As vehicles are more equipped with advanced driver assistance systems, the task of driving is getting easier and safer. Most recent cars are utilizing many new safety technologies that warn the driver or take control in cases where there is a risk of getting into an accident. According to the United States Department of Transportation, the rise of driverless cars will reduce traffic fatalities by 90% [45].

Reduction in Travel Time

The advantages of driverless vehicles does not stop there. According to KPMG, autonomous cars are expected to reduce the "impedance to travel" by 40%[27]. Impedance to travel is defined as a combination of travel time, travel cost and the experience itself. This reduction generates economical benefits and increases productivity of the users [27].

Mobility-as-a-Service (MaaS)

The onset of automated driverless vehicles opens the door to many opportunities that can improve our life quality significantly. Concepts such as Mobility-as-a-Service are founded based on the idea of shifting away from self-owning vehicles towards shared transportation systems that can be booked and are provided as a service [58]. Not only are these systems more accessible and available for everybody, they can also be customized and personalized based on the user's preferences.

MaaS reduces the amount of space that is allocated for parking spots all around the city and also reduces city congestion. This will lead to higher vehicle utilization, lower cost per user and improved transit efficiency. Such a system enables mobility for all citizens equally including those who can not drive a vehicle themselves[42].

Reduction in Fuel Consumption

In general, autonomous vehicles reduce the unnecessary acceleration and brakings and drive smoother than an average human driver, which results in better fuel consumption. Further fuel consumption improvement is possible when enabling other advanced vehicle technology applications such as platooning. Platooning refers to the concept of when multiple vehicles driving at the same speed, with shorter distances between them, leads to reduced air drag and unnecessary jerks, which in turn results in better fuel consumption. James M. Anderson in [23] claims that given the facts mentioned above, autonomous vehicles will improve fuel economy by 4-10%.

As automated technologies and autonomous vehicle features advance, there will be greater safety benefits available for consumers. The automotive industry aims to soon deliver automated driving assistance systems (ADAS) that can handle the whole task of driving. With all the ongoing improvements in ADAS technologies, we are getting closer and closer to our long time goal of having congestion-free and accident-free roads.

1.2 Thesis Contribution

Highway assist technologies have been a popular topic of research over the past decade. These features take over parts of the driving task, and significantly improve driver experience by reducing driver fatigue. In terms of vehicle control, longitudinal controllers are in charge of throttle and braking of the system, and the lateral controllers control the steering of the vehicle ensuring that it remains in the center of the lane it's traveling in.

Adaptive Cruise Control(ACC) is a longitudinal controller that automatically adjusts the speed of the vehicle to maintain a safe distance with the vehicle in front of it. Adaptive Cruise Control works primarily on two modes, Velocity Control Mode (VCM) and Distance Control Mode (DCM). Most common methods available in the literature switch between these two modes once the vehicle approaches another vehicle and the distance falls below a certain threshold. The limitation of this switching method is that in certain scenarios where the relative distance between the two vehicles is very close to the threshold, the system keeps switching between the VCM and DCM modes causing unnecessary longitudinal jerk. This repetitive switching reduces driver comfort significantly.

Lane Centering Assist (LCA) on the other hand, is a lateral controller that proactively keeps the vehicle in the center of the lane by automatically adjusting the steering given the lane information it receives from the sensors. Regarding the LCA technology, there are many path tracking techniques available in the literature. Two of the most common ones are the Stanley controller and the Model Predictive Controller (MPC). While these two controllers work sufficiently under certain driving scenarios, each have their own limitations which create instability in the system in higher speeds.

In this project, a new highway assist technology is proposed called, Super-Cruise. This feature takes over part of the driving task by combining Adaptive Cruise Control and Lane Centering Assist technologies. The proposed longitudinal system introduces a new switching method that eliminates the problem of repetitive switching, and for the lateral controller an improved Fuzzy MPC is introduced to increase system stability. In this work, the new switching method, the path tracking performance and lateral stability of the proposed longitudinal and lateral controllers are investigated.

To evaluate the proposed system, a vehicle model has been developed in MATLAB SIMULINK. Both longitudinal and lateral controllers are modeled to take over the throttle, braking, and steering of the vehicle. Six driving scenarios have been designed in Driving Scenario Designer App to evaluate the performance of the proposed system and compare the results with most common state of the art methods to evaluate system performance, stability and driver comfort.

1.3 Thesis Outline

Chapter two goes over the history of automated vehicle technologies, SAE levels of autonomy, current automated vehicle developments, and common sensing technologies used in automated vehicles. Common ADAS features, including ACC and LCA are further discussed in detail in chapter three. This chapter goes over the fundamentals of each technology, and the common methods used in the literature.

Chapter four breaks down the proposed system. The theory behind the longitudinal and the lateral control development process is discussed in detail and the formulation of the system is outlined. The sensors used, and the detail of the test scenarios designed is discussed in chapter five. This chapter covers details of each test set up as well as the evaluation metrics used for each test. The performance of the proposed SmartCruise is evaluated and compared to the baseline controllers in chapter six.

Chapter 2

Automated Vehicle Technologies (AVT)

2.1 Overview of AVT and Its Applications

2.1.1 The 100-Year History of Autonomous Vehicles

The first attempt towards driverless vehicles goes back as early as 1920s[31]. About 20 years later in 1939 at Futurama which was an exhibit at the New York's World fair, General Motors presented the idea of free-flowing highways filled with self-driving cars and trucks[55]. By 1960s, many early prototypes of self driving cars was presented by different organizations. This was the beginning of the introduction of cameras and vision sensors to these systems for better navigation. however, the cost associated with these vehicles was very high thus making it impractical to develop these cars for public use[46]. Soon after, computational techniques improved significantly, allowing these technologies to enter a new stage.

By late 1980s, Ernst Dickmanns, a professor at Bundeswher University collaborated with Mercedes Benz to launch a vision-guided robotic van. His work formed the basis of modern control strategies and added momentum to the development of driverless vehicles [57].

By early 2000s, not only many car manufacturing companies were interested in conducting research on this topic, but many governmental organization started funding research on automated transportation means. As an example, the US government funded three military efforts to design driverless ground vehicles that would navigate miles avoiding obstacles such as rocks and trees[12].

In March 2015, Tesla announced that they are introducing a new ADAS technology called “Autopilot” with high automation capabilities such as traffic-aware cruise control, auto lane change and auto park.

Public demand for advanced driver-assistance systems (ADAS)—which help with monitoring, warning, braking, and steering tasks in driving—is increasing year by year and this has introduced evident competition amongst all car manufacturers. As a result of this competitiveness, most car manufacturers have dedicated significant amount of resources to developing commercial level autonomous vehicles to be accessible by the general public [16].

2.1.2 Levels of Autonomy

As a part of the development effort, society of automotive engineers (SAE) and National Highway Traffic Safety Administration (NHTSA) have published definitions for different levels of automation to provide a standard and basis for communication on this topic. This categorization has been based on the functional aspect of the technology as well as the level of involvement of the driver. These two organizations have divided the levels of autonomy to six levels going from zero automation at level 0 to full automation at level 5 [34],[41].

It should be noted that active safety and crash avoidance features may be included in any of these six levels as they are excluded from the scope of this autonomy categorisation. This is because these tasks are not identified as part of active driving task. These features include automated emergency braking, and certain driver assistance systems such as lane departure warning[41].

These levels are differentiated mainly by the degree of association of the driver in performing the active dynamic driving tasks such as accelerating/ decelerating, steering and changing lanes and the level of supervision required from the driver. From a driver's perspective, there is a significant distinction between level 2 and level 3 of autonomy where the human driver does perform part of the driving task in level two, however, in level three the system is in charge of performing the entire driving task.

A brief overview of all the automation levels and their definitions along with example technologies have been provided in the Table 2.1 below.

TABLE 2.1: Levels of Autonomy

Level	Name	Description	Execution of Acc/Decc and Steering	Monitoring the Envirnoment	Example
0	No Automation	The driver is in charge of all driving tasks	Driver	Driver	Blind Spot Detection Lane Departure Warning
1	Function Specific Automation (Driver Assistant)	An advanced driver assistance system is available on the vehicle,and it is capable of assisting the driver by either steering or braking/accelerating separately. Driver is still in charge of supervising and driving of the vehicle.	Driver and The system	Driver	Lane Centering Adaptive Cruise Control
2	Combined Function Automation	The execution of steering and Acc/Decc can be done by the system simultaneously under some circumstances. With the expectation that the driver is monitoring the environment and is performing all the remaining aspects of the driving.	System	Driver	Lane Centering Adaptive Cruise Control
3	Limited Self-driving Automation (Conditional Automation)	The vehicle is capable of executing all aspects of dynamic driving under certain circumstances with the expectation that the driver is ready to take control at any time when the system requests.	System	Driver	Traffic Jam Chauffeur
4	High Automation	The vehicle performs all aspects of driving in certain conditions while also monitoring the driving environment with no expectations from the driver to intervene. This Feature is limited to certain locations/ conditions.	System	System	Local Driver-less Taxi
5	Full Automation	The driving task is performed by the system at all times under any environmental conditions. The driver is just a passenger. This feature can be activated in all conditions.	System	System	Fully Autonomous Vehicle

2.1.3 Automated Vehicle Developments

As auto industry enters a new era of research and development, more companies and organization are dedicating time to developing AVT features. Some of the unique state of the art projects that have been going on over the past few decades will be discussed in this section.

Public transit in Europe : CityMobil2

CityMobil2 is a follow-up of a series of projects that have been funded by the European commission. The aim of this project is to improve mobility of citizens by adding small, lightweight automated public transit vehicles. Another benefit of this project is the fact that using these transit systems is increasing the awareness and trust of people to fully automated transportation systems[3].Currently there are 7 demonstration sites across Europe and this number is increasing year by year.

General Motors SuperCruise

General Motors SuperCruise is a new hands-free driver assistance technology that GM has developed. This system uses sensors such as LiDAR, radars, cameras, GPS and V2V communication to navigate through the highway. This system is considered to be a level 2 automated system and it actively accelerate/decelerates the car and it also steers the vehicle to keep the vehicle centered in its lane[32]. This feature requires the complete supervision of the driver since it will perform many driving tasks such as making turns, steering through construction zones, entering or exiting the highway, and many more[44]. SuperCruise is also equipped with a lane change on demand feature, in which when activated and safe to change a lane, the driver can request a lane change by activating the turn signal in the direction of the desired lane change[44].

Volvo DriveMe

This system is considered to be a level 4 system and can only be enabled on certain certified highways. Once the system is active, the drivers can completely disengage from actively driving. This system uses cameras, Lidar, Radar, Sonar and digital maps to enable lane centering, adaptive cruise control and stop and go highway traffic[32]. There is a redundancy in sensors used for this system, however, this has been intentionally done to ensure safety of the vehicle in case one of the systems fail. This system heavily relies on digital maps and needs access to the cloud for that information. The vehicle is also equipped with a constant V2I communication and receives constant information about the weather and on going constructions.

Google Self-Driving Car

Google began its development on self-driving cars back in 2008. These vehicles use LiDAR, multiple cameras, LRR, SRR, and GPS. Google self driving cars have been on public roads in Mountain view, California, Texas and many other cities and have driven more than 1.3 miles in full auto mode. Google uses detailed maps to precisely localize the location of the vehicle on the street using GPS, and comparing sensor map data with previously collected data from the same street[36]. This allows the system to differentiate between stationary obstacles that are part of the street and pedestrians and choose obstacles of interest to make decisions based up on[10]. The system is also programmed to interpret common road signs and behaviours and makes control decisions accordingly. It also uses predetermined motion descriptors that are programmed into the system to help categorize objects and distinguish pedestrians and bicycles from other motor vehicles[1].

2.2 Common Sensing Technologies

Perception by definition, is the sensory experience of the world. For a vehicle to be able to navigate through the world and identify objects around, it first needs to perceive its surrounding. In an automated vehicle, this is done using a combination of high-tech sensors such as radars and cameras to comprehend and understand the environment around the vehicle. The information received by these sensors is then interpreted in a process called sensor fusion. Sensor fusion makes it possible to use various sensors with different capabilities, in order to accurately and reliably detect objects such as cars, pedestrian and cyclists. This also provides some level of redundancy since objects will be detected by multiple of these sensors at the same time. This greatly improves the safety of the system against any possible sensor malfunction or system failure. Perception is the key to any driver assistance and safety system.

In the following, an overview of common sensing technologies used in AVT applications are presented. Automated vehicles often combine a few of these sensors together all around the vehicle, in order to provide an overlapping coverage between the sensors. This way one can take advantage of different strengths of all the sensors in different scenarios at the same time.

2.2.1 Radars

Radars use radio waves to determine the position information of an object and thus are commonly used in many different fields. In passive radars, these waves will be reflected back to the transmitting radar when there's an object in its field of view. These high-resolution sensors use the reflected waves that are striking back from an object to calculate the distance and the velocity of objects around them using the Doppler effect.

In the vehicle industry, radars can be classified into three main categories: Short-Range Radar (SRR), Mid-Range Radars(MRR) and Long-Range Radar(LRR). Long range radars are often placed in the front bumper of the vehicle for detection of objects in the path of the vehicle. Some of common ADAS technologies that mainly rely on a front radar are: Adaptive Cruise Control(ACC) and forward collision warning[9]. These sensors can have a detection range of up to 250m, however, their horizontal filed of view is mostly limited to 8-20°[9],[29].

Mid-Range Radars on the other hand have a wider horizontal field of view of about 20°[10] however their detection range on average is limited to 150m. These sensors can be used in conjunction with the LRRs for technologies such as ACC and automatic emergency breaking. They also have a wider field of view of up to 80°at close-range which helps with pedestrian detection [10].

Short-Range Radars are mainly used as corner radars all around the vehicle. These sensors have a wide detection angle, and they detect objects and pedestrians quickly and accurately. In addition to the position of the object, these sensors provide the relative speed and direction of motion [8]. SRR sensors are commonly utilized for monitoring the area behind and around the vehicle and can be used in systems such as blind spot detection, Rear cross traffic alert, lane change assist and many more. Figure 2.1 below shows a very common radar setup that is used in many modern vehicles.

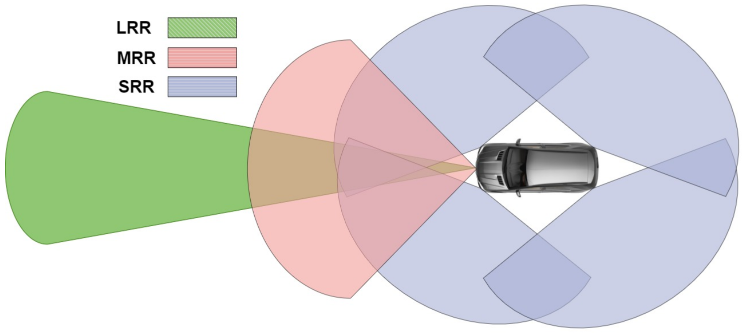

FIGURE 2.1: Most Common Radar Layout in Modern Vehicles

Since radars work with electromagnetic waves, they can work under any weather condition. This is a major advantage of radars in comparison with many other sensors that get affected by lighting, rain or fog. Another advantage of the radars is their high longitudinal accuracy. They are also very accurate in differentiating stationary vs moving targets. They are relatively cheaper compared to other object detection sensors. However, radars do not have a high resolution at range. In addition, they are prone to getting saturated if a large object is close to the transmitter. Another limitation of radars is the fact that they can not accurately differentiate between moving obstacles such as cars, trucks, and etc [2].

2.2.2 Ultrasonic Sensors

Ultra sonic sensors have been used in vehicles to detect objects close to the car for many years now. These sensors emit acoustic pulses, and the return of these pulses is then measured by a control unit which will calculate the distance of the object from the vehicle. As shown in Figure 2.2, these sensors are commonly placed in the front and rear bumper of the vehicle to compliment other sensors used in the vehicle to get a full picture of the immediate environment around the vehicle [59].

Ultrasonic sensors can be commonly found in vehicles equipped with features such as parking assist, rear collision warning and blind spot detection. In the recent years, there has been more interest in use of ultrasonic sensors for technologies such as connected vehicles to analyze the condition around the vehicle for higher levels of autonomy[5].

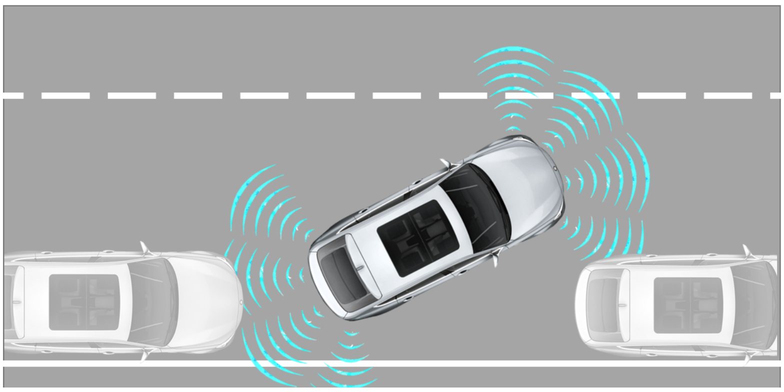

FIGURE 2.2: Ultrasonic Sensors in AVT Vehicles

A few advantages of these sensors that is worth mentioning is their low cost. They are also not sensitive to lighting and are not affected by the color of the object. However, a few limitations of these sensors, is that since they work on basis of reflection of sound waves, their range can be affected in extreme weather conditions. They also may not detect small, narrow objects such as a narrow pole which is not sufficiently large enough to reflect the ultrasonic waves[19].

2.2.3 Cameras

Cameras have been used in many applications as the mean to create a visual representation of the surrounding. Cameras have high precision, and they are very good at classifying specific objects such as pedestrians and vehicles. With the help of machine learning, they are also heavily used to detect road signs and other objects on the road such as construction cones.

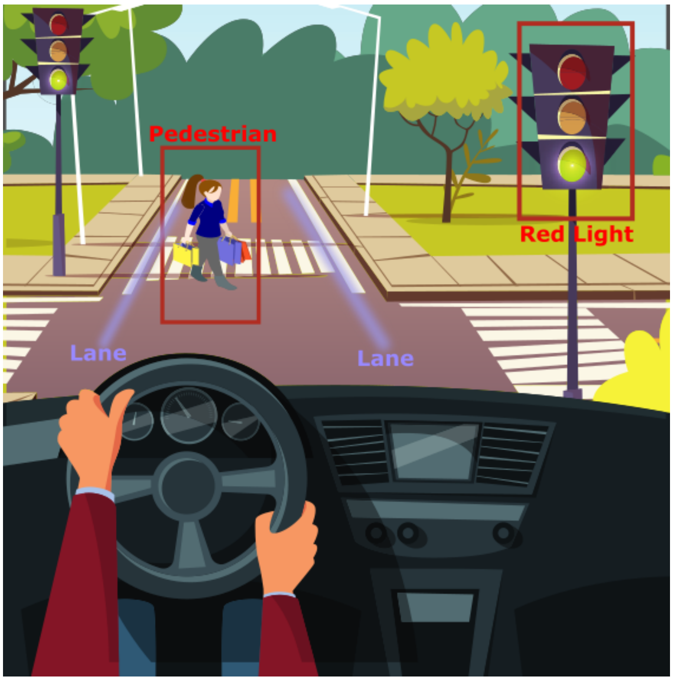

FIGURE 2.3: Applications of Cameras in AVT

In addition, using computer vision and image processing, lane detection is also done by cameras which is used in lateral ADAS features. This is a unique element that distinguished cameras from other sensors.

However, cameras have poor ability to adapt to different lighting conditions and operate under severe weather conditions. They also often have a wide field of view, but a shorter range compared to sensors such as LiDARs and Radars.

Using cameras in combination with other sensors helps the autonomous system to gain a better understanding of its surrounding and be able to interpret the situation it is in. This diversity between sensors and the redundancy in detection will verify that the detections are accurate and reliable.

Almost all vehicles with ADAS features are equipped with at least one camera in the front and one in the rear. More advanced vehicles with higher level of autonomy often have cameras placed on every side of the vehicle: front, rear, left, and right to create a 360-degree view of their environment. Work is being done to implement stereo vision for self-driving cars by using two cameras in order to get a better estimate of the depth of all objects around the vehicle for a better motion planning [18][39].

2.2.4 LiDAR

LiDAR, "Light Detection and Ranging" is a sensing technology that uses laser beams to create a 3D visualization and understanding of the surrounding environment as shown in Figure 2.4.

A LiDAR system is an active system, meaning the system itself generates the source light and emits it to the surrounding. By receiving the beams that have been reflected back by obstacles such as trees and buildings, LiDAR measures the time it takes for the beam to travel back to the sensor, and uses this information to calculate the distance traveled by the beam [53]. This is known as 'Time of Flight' measurements.

FIGURE 2.4: LiDAR

LiDARs work in a similar way to Radars and Ultrasonic sensors in the way they all emit a source of energy and receive back the reflections. However, They have different strengths and weaknesses. For example, Ultra sonic sensors have a very short range and Radars generally have a limited lateral resolution depending on the size of the sensor, several meters at a distance of 100meters. In comparison, LiDARs have a high level of accuracy for 3D mapping with a resolution of a few centimeters at a distance of 100meters. As a result, each sensor is used for a particular application in collaboration with each other. While Radars are usually used for collision avoidance, LiDARs are often used for contour mapping, localization and navigation through the environment[60].

In Automated Vehicle Technologies, LiDARs act as a vehicle's eyes to always assess the surrounding in all directions in real-time. This 3-D visualization of the environment, helps identify all sorts of objects around the vehicle whether stationary or moving. Although LiDAR sensors are enabling many application in ADAS systems, there are some downsides to these sensors. As an example, LiDAR sensors are more expensive than camera and radars systems. On the other hand, LiDAR data is receiving in a point cloud form which lacks color and texture which requires high levels of post processing and analysis. In addition, their performance will significantly degrade during heavy rain, or cloudy weather[13].

LiDARs have many applications in industry. They are heavily used in geography, agriculture, contour mapping, autonomous vehicles and many more. With the ongoing improvements in these systems and rapid development of ADAS technologies, LiDARs have become a key element in an autonomous vehicle.

2.2.5 Vehicle to X communication (V2X)

Vehicle to X communication(V2X) stands to for 'vehicle to everything' which refers to a wireless technology that allows exchange of data between the vehicle and any entity in its surrounding that may affect the vehicle. The main purpose of this technology is to improve road safety, traffic, and energy consumption. As shown in Figure 2.5, this system has several components, including vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), vehicle-to-pedestrian (V2P), vehicle-to-network (V2N) communications and more.

By integration of these systems into the infrastructure, vehicles can receive critical information about the vehicles around them, nearby accidents, road condition, traffic light, emergency vehicles approaching and more.

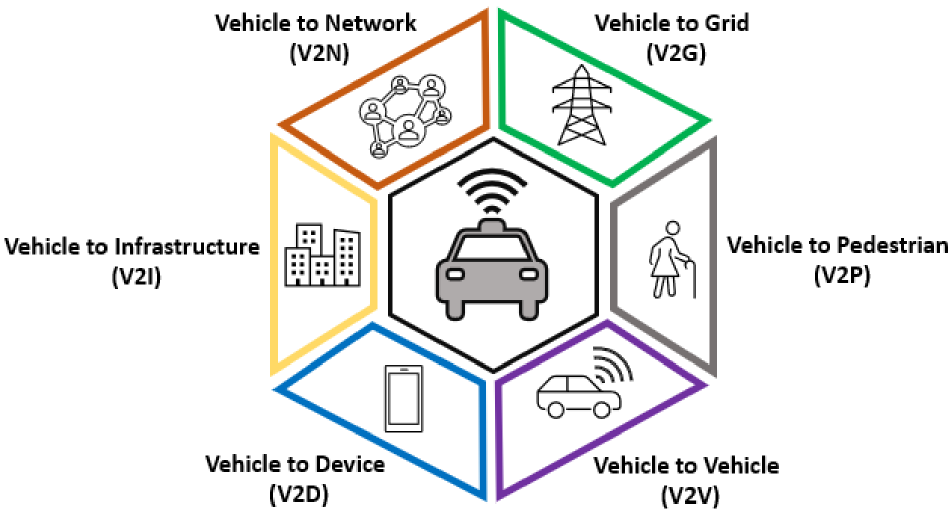

FIGURE 2.5: Components of V2X

In a city equipped with V2X communication,Figure 2.6,vehicles talk to other vehicles, to infrastructure, and pedestrian. This enables many different use cases and applications. One of the major projects and early applications of this is the development of a smart intersection, which is an intersection equipped with not only V2X system, but also cameras and other sensors. Much research is being conducted on using smart intersections to improve road congestion, and minimize accidents by informing the vehicle of upcoming accidents and dangers well in advance which in return also results in reduction of fuel consumption and environmental costs[52].

Another application of this is the development of cooperative and coordinated maneuvers. Platooning, which is by definition the phenomena of driving a group of motor vehicles together uses V2V communication to match the speed of following vehicles to the speed of the proceeding vehicle.

FIGURE 2.6: The Idea of a City Equipped with V2X

Using this technology vehicles can match their speed and react to accelerations and deceleration's of the vehicles in front of them much quicker than a normal driver. This will greatly reduce the lag in reaction time and wind drag. It also impacts traffic flow and increases energy efficiency of vehicles especially in the case of trucks that travel a long way [3]. The idea of cooperation of vehicles doesn't stop at platooning, many research is being conducted on implementation of V2V communication between vehicles on highways and city for driver assistance system applications since V2V reduces the reaction time of the vehicle significantly. With the current reactive systems available in automated vehicles, the reaction time of the perception system is considerably higher than the case of V2V communications. Utilizing this can reduce multi-car rear collisions significantly.

Applications of V2X are increasing day by day. One of the main sectors that is focusing on taking advantage of this technology is the automated vehicles industry. For the car manufacturing companies, enabling V2X communication is a big milestone towards the implementation of self-driving cars.

2.2.6 Global Positioning System (GPS)

GPS is a U.S. owned space-based navigation system that consists of a group of approximately thirty satellites flying around the earth. They are spaced such that between four to eight of them are high above any site on earth at each point in time. Each of these satellites broadcasts a radio signal that travels through space at the speed of light and provides their location, status and precise time. Once a receiver on earth receives the signal, it can calculate its distance from the satellite using the time difference between the moment signal was sent and the time it was received.

Figure 2.7: Global Positioning System

A GPS receiver on earth can calculate its exact location on earth upon receiving unobstructed signal from at least four GPS satellites in space.

Even though this system is highly advanced, it can only calculate the position of a receiver with accuracy of roughly 5m due to limitations that are associated with noise, disturbances, atomic clock drift, and etc [20].

This technology has been used by both military and civilians. In the military, these systems are used to navigate soldiers throughout missions, track targets, used for guidance and targeting of missiles, and many more. As an example of civilian applications of GPS, all aircrafts are equipped with GPS systems. Which is used to locate the plane as well as continuously position it on a computer map for tracking purposes. Other civilian uses of GPS that can be mentioned are robotics, sports as well as personal cell phones [56]. GPS is also used in almost all vehicles for automotive car guidance and navigation. When implementing an ADAS feature, it is required to identify the location of the vehicle at each point in time. This is done by utilizing GPS technology. Intensive research is being done on improvement of the accuracy of the GPS by fusing GPS information with other localizing technologies and other sensors in the vehicle [25]. This fusion will significantly increase the accuracy and robustness of the positioning of this system and enables further development in autonomous features with higher levels of autonomy.

Chapter 3

Advanced Driver Assistance Systems (ADAS)

The basic principle behind the operation of ADAS features can be divided into three modules: Environmental perception and processing, control module and decision making, implementation and actuator module. As mentioned in the previous section, the system needs to first obtain a sufficient understanding of the surrounding vehicles through sensors on the vehicle. There are many different types of sensors available for use in automated vehicles.
Given the perception information and the knowledge of the vehicle operating status, the control module then plans and makes decision on the action that the vehicle must take. This is done in the vehicle's computing system.

This decision will then be implemented using the actuators in the vehicle while receiving feedback from the sensors. Depending on the level of automation of the system, the automated feature can be anything from a light on the dashboard, to fully automated acceleration and steering.

3.1 Common ADAS Features

Early stages of ADAS features were mostly based on passive components and mainly were aiming to warn and assist the driver in case of emergency or danger. Examples of those features are Blind Spot Detection or Forward Collision Warning. As technology improved, more complex systems were introduced. These features are focusing on taking on part or all of the driving task to improve the driver comfort and safety. These features can be subdivided in two main categories: longitudinal control features and lateral control features. By definition, longitudinal control is referring to "any control system that controls the longitudinal motion of the vehicle, for example, its longitudinal velocity, acceleration or its longitudinal distance from another preceding vehicle in the same lane on the highway" [37]. Lateral control features on the other hand are features that are related to the lateral control and safety of the vehicle. Which can be done by controlling the steering of the car.

Below in Table 4.2, a list of some of the well-known features available on the market can be found.

TABLE 3.1: Common State of the Art ADAS Features

Longitudinal Control Features	Lateral Control Features
Classic Cruise Control	Blind Spot Detection
Forward Collision Warning	Lane Departure Warning
Adaptive cruise Control	Lane Centering Assist
Stop/Go Traffic Assist	Lane Change on Demand

In the table above, features of each category have been ranked from the oldest and most simple, to the newer and more complicated features. The idea of classic cruise control, as an example, was first introduced in 1900s. Cruise control, actively maintains the vehicle speed by taking over the throttle of the car. This system however, did not use any vision sensor. Development of forward collision warning started around 1950s. This system which is designed to reduce or prevent a collision, monitors the speed of the vehicle and the vehicle in front of it and the distance between them using a radar sensor, and warns the driver if the two vehicles get too close to each other. Adaptive cruise control (ACC), can be found in most cars manufactured after 2017. This feature is an advanced version of the classic cruise control with the difference that it uses sensors such as radars and cameras, to detect a vehicle in front of the car, and automatically brakes in case the two cars get close to each other while following the lead vehicle. Early ACC features were only to be used on highways and would disengage once the vehicle has been brought to full stop. Few years later a more advance ACC was developed, called Stop/Go ACC or traffic assist. This feature is very similar to ACC, with the difference that it has been tuned for lower speeds and urban driving and traffic. Once the vehicle comes to a full stop in traffic jam, the system remains engaged and is ready to follow the vehicle in front of it once it moves.

One of the earliest lateral features developed was the blind spot detection. Blind spot detection systems were first introduced in late 2000s. When the system detects a vehicle driving in an adjacent lane approaching the rear of the driver's vehicle - a common blind spot area, it notifies the driver with an indication which can be a light on the mirror, or a beeping alert or sometimes in more recent vehicles the steering wheel might also shake. Lane departure warning, is designed to help the driver avoid crashes due to drifting or departing from the lane. However it does not take over the active steering of the car. Lane centering on the other hand, is currently the highest level of lane monitoring technology. This system proactively keeps the vehicle centered within the lane it is traveling in. It utilizes automatic steering functionality to make constant adjustments based on road marking information it receives from the front camera. And lastly, the most recent feature which is being added to some cars, is Lane change on demand. This system is used on highways and with request of the driver the vehicle will evaluate the surrounding of the car and when it confirms that the request is acceptable, it will automatically execute a safe lane change.

As discussed above, there has been many longitudinal and lateral ADAS features developed over the past few decades. In the following section, we will dive deeper into two of these features.

3.2 Adaptive Cruise Control

Over the past decade, various approaches have been proposed to simulate human driver behavior. Adaptive Cruise Control (ACC) is a longitudinal driver assistance system that adjusts the vehicle speed automatically to maintain a desired distance set by the driver with the vehicle ahead. This said, this system will attempt to minimize the amount of sudden and unnecessary braking and accelerations applied and therefore enhances the driving comfort and improves the fuel consumption of the vehicle. This is done by having at least two modes of control as shown in Figure 3.1 below. Velocity Control Mode(VCM) and Distance Control

Mode(DCM). VCM is technically the classical cruise control that has been available on vehicles since 1940s. In this mode the vehicle attempts to maintain a "set speed" selected by the driver assuming there is no vehicle in front of it. DCM on the other, aims to adjust its speed in order to maintain a desired distance with the vehicle in front of it. This distance is set by the driver as a function of time gap. Time gap is defined as the time it takes for the ego vehicle to reach the location of the lead vehicle, assuming that the lead vehicle suddenly goes into a full stop.

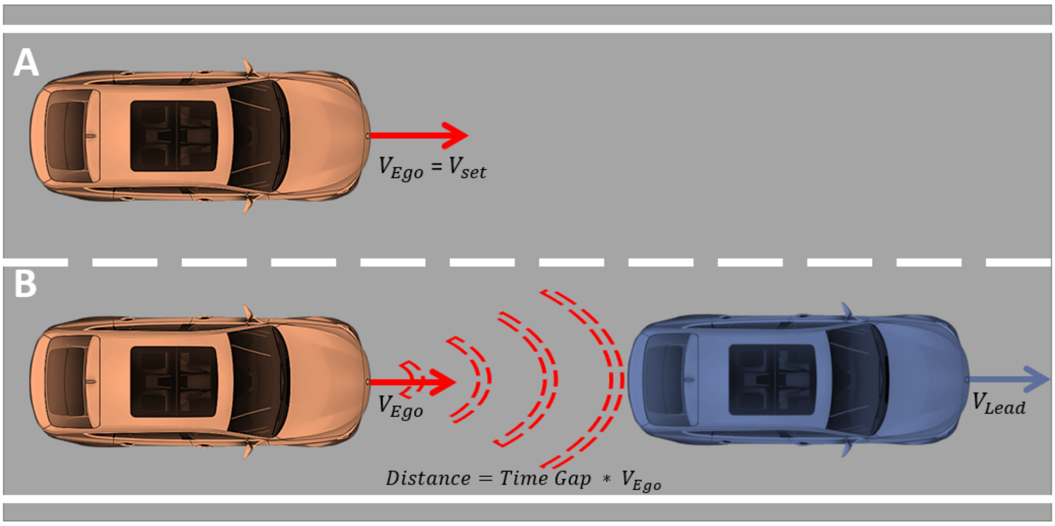

FIGURE 3.1: ACC Modes - A: Velocity Control Mode , B: Distance Control Mode

Research has shown that PI controllers are sufficient enough for VCM. For DCM however, Various types of control methods have been widely reviewed by the researchers.

While some of these categories focus on most accurately simulating the normal manual car-following behavior of an actual driver, others focus on predicting the best motion profile for the vehicle to improve comfort while maintaining a safe distance with the leading vehicle.

Some preliminary work was carried out in the early 2000s by Treiber et al [48]. In his paper, Treiber et al proposes a human driver model named Intelligent Driver Model (IDM) [48]. IDM provides a sensible model by capturing different congestion dynamics. However, IDM has unrealistic behavior in cut-in situations and hence is it unstable under traffic conditions. In [30] however, Chaoru Lu suggests an adaptive cruise control named Smart Driver Model (SDM) to address the instability of IDM under various traffic conditions in order to stabilize the homogeneous traffic flow in a city. Chaoru Lu [30] measures vehicle speed, gap and the relative speed of the preceding vehicle using on-board sensors. However, SDM inherits the acceleration maneuver of IDM which has a predefined formula for values of acceleration and braking of the vehicle. Following a set of predefined acceleration and deceleration values for all the driving scenarios may result in a suboptimal speed profile and unnecessary acceleration and braking maneuvers thus a decrease in driving comfort in some cases [33].

Many attempts have been made in recent years [Nunen 2017, Lin 2017, Bertoni 2017, Firoozi 2018] with the purpose of implementing different Model Predictive Controls (MPC) into ACC. however, The constraints they use to formulate their MPC significantly vary among different works as some aim to ensure high performance and robustness in terms of stability while others focus on energy-efficiency and fuel consumption.

Nunen E. [49] developed a method called Cooperative Adaptive Cruise Control

(CACC) with the usage of Vehicle-to-Vehicle (V2V) communication in a feed-forward manner using an MPC. In his work, Nunen focuses on improving the robustness and performance of the CACC control in the presence of intermittent packet losses just in case the V2V communication momentarily fails.

Xiaohai Lin [28] and Bertoni [7] on the other hand, focus on using Model Predictive Control (MPC) approach to smoothen the velocity profile of the vehicle such that unnecessary acceleration and braking maneuvers are minimized based on the environmental conditions. They both argue that their models will significantly decrease the energy consumption of an electric vehicle [49][7] . Lin's method, however, only relies on receiving data about the lead vehicle by radars and cameras and does not consider other possible more advanced ways of receiving data such as V2V communications. This limitation has been tackled by Bertoni as his method allows for Vehicle-to-Vehicle communications as well [7] . In a more recent study, Firoozi [17] investigates the possibility of using road grade information in the MPC framework to optimize comfort, safety, and energy efficiency of the ACC system. Many other methods have also been tested to improve the stability of the system by altering the desired distance of the controller.

While most controllers use a constant time gap set by the driver to calculate the desired distance, [51] attempts to adjust the spacing between the vehicle and the lead vehicle based on a variable time gap instead and it shows to improve the stability of the system as well as the traffic flow. Gain scheduling is also one of the common methods used in distance control since a set of acceleration and breaking control commands that result in a smooth maneuver in high speed drives might cause excessive jerk in lower speeds [38].

While these methods are successful in theory, they often result in repetitive throttle switching in real life implementations. To tackle this, most methods in literature create a hysteresis between the two modes to avoid unnecessary switching. In this project a new switching method has been implemented in conjunction with an addition of a new control mode using PID controllers which improves driver comfort and avoids unnecessary vehicle jerks due to sudden switching between the two modes of the system.

3.3 Lane Centering Assist

Since one of the main causes of motor vehicle accidents is departure from the driving lane, the goal to develop a feature that takes care of the active task of steering has been of the main interests of researchers for decades.

Early work in the area of lateral control begun with development of warnings and passive assists such as Lane Departure Warning or Lane Keep Assist. These features which represent the same concept, alert the driver once the vehicle is close to the line and is about the exit the lane it is driving in. While these feature have been very effective in reducing lateral accidents that are due to lack of attention from the driver, they do not take away from the task of driving that can cause driver fatigue in the first place.

Lane Centering Assist (LCA) which is currently one of the highest levels of lateral control technologies, proactively and automatically steers the vehicle to follow the path or the lane that vehicle is in. This feature that has been better illustrated in Figure 3.2 below, uses the lane information received and processed by the cameras and other sensors on the vehicle, to calculate the best path it should take. It then automatically steers the vehicle to follow the path.

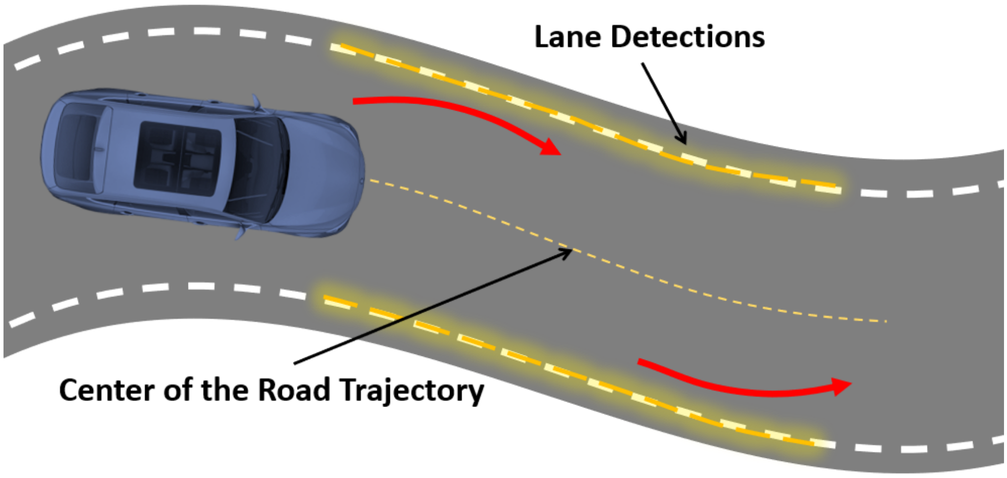

FIGURE 3.2: Lane Centering Assist

Previous work on this topic investigates various approaches. As an example, one of the commonly used controllers for path tracking is the Proportional-Integral-Derivative (PID) controller. This controller is very easy to implement with minimal computational power needed. However, this method has its limitation in the sense that it can not adapt to various environments and different maneuvers. For this reason, much work has been done on developing adaptive methods, which will compensate for the limitations of PID.

Zhao et [63], investigates the development of an adaptive PID controller to follow a predefined path. His controller takes in lateral error with the aim to minimize this error throughout the drive as much as possible.

Another category of lateral controllers, is the geometric controller which tracks a reference path using the information about the vehicle kinematics. This method ignores the dynamics of the vehicle, and instead assumes a no-slip condition. The most common geometric path-following methods are Pure Pursuit method and Stanley method. In his thesis, Jarrod Snider [43] implements and compares these two common geometric path tracking methods and concludes that both methods work well under known paths and circumstances, however, due to the lack of dynamic inputs in the controller formulation, both have significantly poor performance in higher speeds or unknown curvy paths.

Stanley method has shown to work slightly better than Pure Pursuit in different scenarios since it takes into account both the lateral error and the heading error and it therefore has been more researched on. In [35], Oliver works with Stanley method to develop a lane keeping algorithm. By tuning the constant gain in the formulation of Stanley, he presents the improved performance of Stanley compared to a linear controller. Amer NH [4] takes a slightly different approach and introduces an adaptive Stanley in combination with a fuzzy supervisory controller. This way the controller gains are adapted to the maneuver and the vehicle speed automatically. This method shows a better performance compared to the Stanley alone, however, since the adaptive characteristics of the controller comes from prior knowledge of tests conducted in certain environments, it does not perform as well in new paths and severe maneuvers that controller has not been previously exposed to.

Another method that has gained popularity in this area of research is Model Predictive Control(MPC). MPC which by nature is a control method that predicts the future state of the system, and tunes the control input accordingly to reduce the total error, has been used on many dynamic systems. In his article Yan Ding [15], discusses three methods of path following: Pure Pursuit, Stanley and Basic

MPC. By comparing the three controllers theoretically and then in simulation, he goes over the advantages and disadvantages of each model. While Stanley and Pure Pursuit have their own limitations since they are only based on the kinematic model of the vehicle, MPC takes advantage of the dynamic plant model embedded in it, and reduced the lateral error significant. However, he presents the disadvantages of MPC as being computationally expensive. He also points out that in some scenarios, the MPC controller perform unsteadily and the steering was shown to be jerky. In [50], Vivek compares Stanley, Linear Quadratic Regulator (LQR) and MPC. He evaluates the three controllers in MATLAB and IPG CarMaker simulation software. By defining the parameters of interest as the lateral error and the input steering angle, the controllers are optimized and the results are compared based on their Integral Absolute Error. Results show that MPC has the least amount of lateral error and it also has the lowest maximum steering angle which is a representation of drivability and comfort of the system. Both Stanley and LQR have very similar lateral error, with the difference that LQR shows to have a better performance in the drivability criteria.

In summary, most of the methods discussed above attempt to develop a controller that can adapt to different maneuvers and speeds while minimizing the lateral error throughout the drive. While Stanley and Pure Pursuit lack the ability to predict the future or take advantage of the dynamic characteristics of the vehicle, they do a good job in outputting a steering input value for the current state of the car assuming the curvature of the road does not change significantly and the speed of the vehicle is not too high. The problem of only taking into account one reference point in time can be overcome by use of predictive controllers such as MPC. MPC is a strong tool used for optimal control. The predictive nature of MPC, allows for the controller to adjust its input in advance and incorporate future information into control formulation to improve its performance. In addition, the ability of this method to satisfying multiple control or performance constraints, makes it a suitable choice for developing lateral control. There are multiple constraints associated with development of a lateral control system for a vehicle. As an example, there are constraints due to physical limitation of a car and there is a minimum and maximum for the steering angle value that is achievable in real life, as well as the rate of change of steering angle.

However, the most common formulation of MPC found in literature which takes into account the lateral deviation of the vehicle from the reference trajectory and the steering angle as the controller input, lacks stability and does not perform well in extreme driving scenario. The controller is unstable and often oscillates in situations where the vehicle is far from the target trajectory which reduces driver comfort. This is mainly due to the fact that the controller has a constant set of parameters and gains for all lateral and heading error values and it does not adapt its cost function accordingly. For this reason, in this project, a new lateral control method has been designed and implemented, which is based on fuzzy adaptive control. In this method, using fuzzy logic control, the weight parameters in MPC can be adjusted in the cost function based on location and orientation of the vehicle with respect to the trajectory. This proposed method improves performance of the system in tracking accuracy and significantly reduces unnecessary oscillations which in return improves driver comfort.

Chapter 4

Proposed Driver Assistance System : SmartCruise

This chapter goes over the proposed highway assist technology. This feature consists of two main controllers as shown in Figure 4.1. A longitudinal controller, which contains the adaptive cruise control algorithm, is in charge of the longitudinal control of the vehicle. This is done by manipulating the acceleration and braking inputs. A lateral controller, which contains the lane centering algorithm, is in charge of lateral control of the vehicle by manipulating the steering angle input.

The full model has been developed in MATLAB SIMULINK. The vehicle plant model consists of the kinematic and dynamics model of the vehicle, and takes the outputs of the two controllers and uses them as actuator inputs to the vehicle model. The output of the vehicle model is information about the state of the vehicle, including longitudinal and lateral speed, longitudinal and lateral acceleration, yaw rate and much more. This information is fed back to the controllers as feedback and is used for decision making and further control calculations.

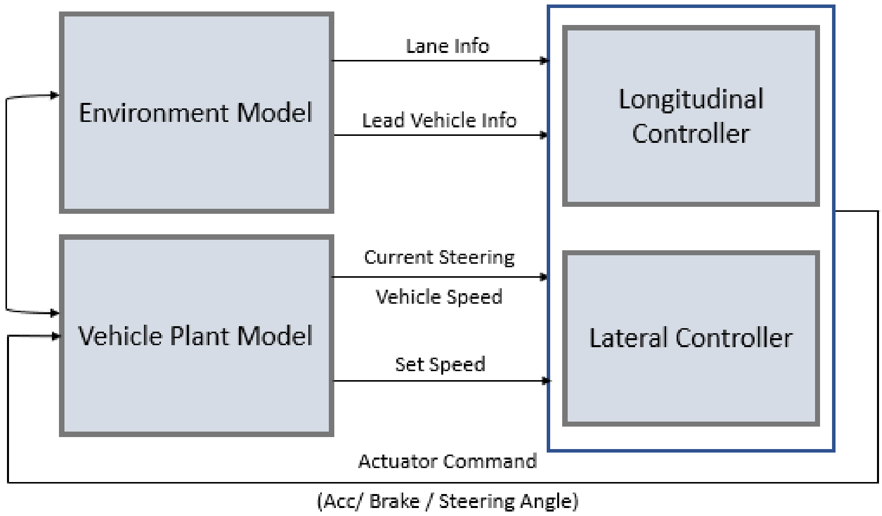

FIGURE 4.1: Motor Vehicle Traffic Fatalities Statistics

Parallel to the vehicle plant model, there is the environment model. The environment model consists of the driving scenario that has been built in the driving scenario designer app in MATLAB. This block models the vehicle and the environment in the world coordinate system, and provides information about the surroundings of the vehicle given the current state of the vehicle. This subsystem also includes the sensor models of the sensors mounted on the vehicle, and takes care of the sensor fusion and tracking algorithms that are applied on the detections of these sensors. This subsystem provides information about the lead vehicle detected and the information about the lane the vehicle is driving in, and passes this information onto the main controller. The environment model is discussed in more detail in the next chapter.

As discussed before, ACC is a driver assist system that maintains a certain distance with the vehicle in front of it, while also following a set speed set by the driver.To achieve this, ACC commonly has two modes. Distance Control Mode (DCM) and Velocity Control Mode (VCM) which are the methods present in classical cruise control. ACC has been researched on for a very long time, and a PID controller has proven to be sufficient for the longitudinal control purposes of the vehicle including both VCM and DCM to ensure safety and sufficient performance[24]. The main difference between different controllers designed however, is the number of control modes they introduce and the way they switch between these modes. Some calculate the acceleration output of both VCM and DCM control modes and apply the minimum of the two [40]. While this method is simple to implement, the result is very jerky since the transition between different acceleration inputs is not controlled and smooth. Other methods, introduce additional modes such as speed matching mode.

Systems containing the two most common control modes, VCM and DCM theoretically work well. However, in real scenarios, repetitive switching happens between these two modes [62][61]. As the vehicle approaches the lead vehicle in front of it, at the desired distance, the system switches back and forth between the two modes which increases jerk and reduces drive comfort. For that purpose, in this project an alternative approach is taken in which a new switching method has been developed that is inspired by the work of Kadir [24], For both controller modes, the most common controllers have been implemented in SIMULINK which are based on PID controllers. The performance of this controller is then evaluated in SIMULINK using Driving Scenario Designer Simulation system. The detail of the system is better described in the next section.

Lane centering assist on the other hand, is a lateral feature that proactively steers the vehicle to ensure it stays in the center of the lane it is traveling in. As mentioned in the previous chapter, there are many methods in the literature that attempt to implement this path following feature, while ensuring the system remains stable and the ride is comfortable.

Geometrical methods such as Stanley which calculate the required steering based on the kinematics of the vehicle and its relative location to the desired path, work sufficiently at lower speeds. However, in cases of higher speed or large lateral deviation from the center of the lane, these systems suffer from instability. A good path tracking controller, as a multi-constraint optimization problem, needs to not only aim to minimize the lateral error but also take into account the comfort constraint and the mechanical and electrical constraints of the system.

Model predictive Controller (MPC), predicts the future state of the vehicle and the path it is traveling on, establishes a multi-variable cost function given all the constraints, and attempts to minimize this cost function with respect to the constraints of interest and the control input.

While the performance of a model predictive controller can prevent the stability and comfort issue and can ensure high tracking accuracy, the fixed gain factors in the cost function of the MPC reduce the adaptivity of the system. In the proposed MPC, this problem is solved by adjusting the weight factors of the cost function to control the accuracy of the path following. Using fuzzy control logic, given the lateral deviation and the heading angle error at each point in time, a set of optimized cost function weight factors are calculated and selected, and the MPC optimizes the system based on these new factors.

In the next two sections the formulation and control laws behind both longitudinal and lateral controllers are presented.

4.1 Longitudinal Control Development

For this project, the main longitudinal model contains two main controllers as shown in Figure 4.2. First is the system plant model, which consists of the vehicle dynamics, and the second controller is longitudinal controller subsystem, which contains the adaptive cruise control. While the vehicle dynamics sub-system attempts to mimic a real vehicle behaviour and respond accordingly to acceleration and braking inputs, the longitudinal controller block receives the information about the surrounding and the lead vehicle in front the ego vehicle in order to calculate the required actuator input (Throttle or brake).

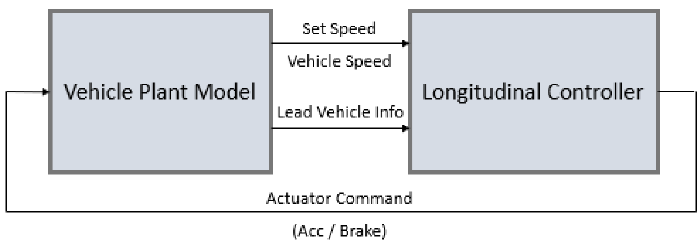

FIGURE 4.2: Longitudinal System Structure

To best model the behaviour of the vehicle and then develop a controller for it, we must first understand the dynamics of the vehicle that affect its motion. Therefore, the next section goes over the dynamics of the vehicle modeled and all the forces applied to it. Following that the development process of the longitudinal control system along with the Adaptive Cruise Control development is explained in detail.

4.1.1 Vehicle Dynamics Model

The vehicle model was made in MATLAB SIMULINK using a vehicle dynamics block set. This block follows the vehicle dynamics law as shown in Figure 4.3 below. This figure represents a typical vehicle longitudinal motion on an inclined road. The forces acting on the vehicle are the front and rear tire forces F_{xf} and F_{xr}, the aerodynamic forces F_{aero} and the rolling resistance forces R_{xf} and R_{xr} . There is also the force due to gravity which will act on the center of gravity of the vehicle.

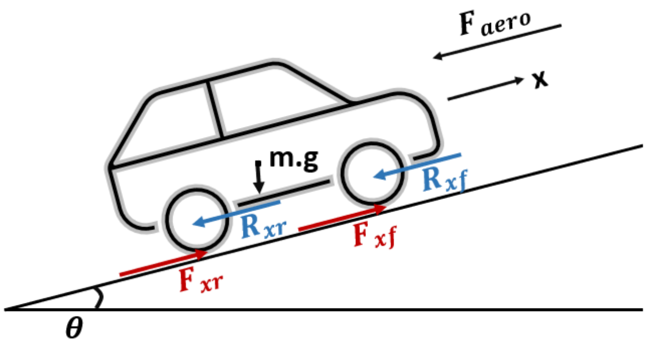

FIGURE 4.3: Longitudinal Vehicle Model

Based on Newton's second law, the equation of the motion of the vehicle can be written as:

$$m\ddot{x} = F_{xf} + F_{xr} - F_{aero} - R_{xf} - R_{xr} - mgsin(\theta) \tag{4.1}$$

Let F_x be total longitudinal tire forces : $F_x = F_{xf} + F_{xr}$ and R_x be the total rolling resistance: $R_x = R_{xf} + R_{xr}$, and assuming θ is a small angle: sin(θ)= θ, Equation 4.1 can be simplified to:

$$m\ddot{x} = F_x - F_{aero} - R_x - mg\theta \tag{4.2}$$

Where given a fixed vehicle shape and standard atmospheric pressure,F_{aero} can be calculated as:

$$F_{aero} = \frac{1}{2}\rho C_d A_f (V_x + V_{wind})^2 \tag{4.3}$$

Atmosphere conditions and temperature affect air density and in return can significantly affect the aerodynamic drag. Following ISA standards, the pressure and temperature of the environment vehicle is running in is assumed to be sea level pressure (101 KPa) and temperature (288K) . The frontal Area A_f, is defined as 80% of the area calculated from the vehicles width and height for a passenger car [50]. The aerodynamic drag coefficient also, can be estimated to be 0.3 since on average, drag coefficient of a car is between 0.25-0.35 [54].

Rolling resistance can be approximated using the formula below:

$$R_x \approx (\mu_1 + \mu_2 V_x) mgcos(\theta) \tag{4.4}$$

Where μ_1 and μ_2 are the rolling coefficients and are set to 0.006 and 0.0001 respectively.

The inputs to the vehicle block are the steering angle in radians and the front and rear forces on the vehicle axle which represents the propulsion force created by the power train in Newtons which will be a function of acceleration and brake command. A summary of parameter values used in the vehicle dynamic block can be found in the table below:

TABLE 4.1: Parameters Used in the Vehicle Dynamic Model

Parameter	Description	Unit	Value
m	Vehicle Mass	Kg	1700
ρ	Air Density	$\frac{Kg}{m^3}$	1.22
C_d	Coefficient of Drag	-	0.3
A_f	Frontal Area	m^2	2.75
θ	Road Grade	rad	0
V_{wind}	Speed of wind	$\frac{m}{s}$	0
μ_1	Rolling Coefficient 1	-	0.006
μ_2	Rolling Coefficiant 2	-	0.0001

4.1.2 Basic Adaptive Cruise Control

In basic ACC, there are two operating modes. The Velocity Control Mode (VCM) and the Distance Control Mode (DCM) . The VCM, which is the classic cruise control, maintains the speed of the vehicle, so called the ego vehicle, at a set speed that has been set by the driver. DCM on the other hand follows the vehicle in front of the ego vehicle, the lead vehicle, while maintaining a safe distance. As mentioned before, a PI controller is used to control these systems.

For the VCM mode, the velocity error ($e_{velocity}$) can be defined as the error between the vehicle speed and the set speed set by the driver as defined in equation

4.5.

$$e_{velocity} = V_{set} - V_{ego} \tag{4.5}$$

Therefore, the control law for the VCM can be formulated as:

$$Acceleration_{Req} = \dot{V} = -K_{P(vcm)}(e_{velocity}) - K_{I(vcm)}(\int e_{velocity}\, dt) \tag{4.6}$$

Where V is the vehicle speed and V_{set} is the set speed. K_P and K_I are the PI controller gains.

The DCM on the other hand has a more complicated system. DCM uses the time gap, T_{gap}, set by driver to calculated a desired distance as shown below:

$$d_{des} = T_{gap} * V + d_{safe} \tag{4.7}$$

Where d_{safe} is called a safe distance. Safe distance is a constant value added to this equation to increase safety and guarantee a sufficient distance between vehicles even at vehicle velocities close to zero. Common values of safe distance can be found in safety standard documentations. It usually is set to be around twice to three times an average vehicle length [26].

The distance error, e_{dist} can be defined as:

$$e_{dist} = d_{des} - d_{rel} \tag{4.8}$$

Where d_{rel} is the relative distance between the ego vehicle and the lead vehicle in front of it. This information will be collected by the sensors on the vehicle and will be processed and provided to the longitudinal controller by the sensor fusion and tracking algorithm. Given the time gap set by the driver, and the distance error calculated using the equation 4.8, the DCM controller can be formulated as:

$$Acceleration_{Req} = \dot{V} = K_{P(dcm)}(e_{dist}) + K_{I(dcm)}(\int e_{dist}\, dt) \tag{4.9}$$

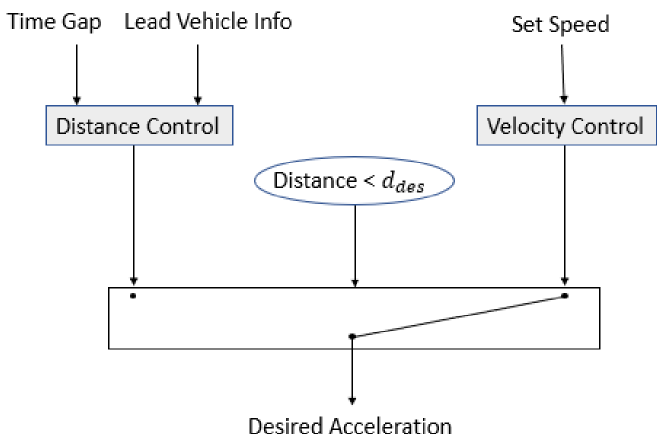

Figure 4.4: Basic ACC Upper Level Controller

The most common switching algorithm used in literature and here in the basic ACC controller, compares the distance between the lead vehicle and the ego vehicle to the desired distance and switches to DCM if the relative distance to the lead vehicle is smaller than the desired distance as shown in Figure 4.4 above. For the purposes of this project, the following parameter values were used in the VCM and DCM controller:

TABLE 4.2: PID Gains in VCM and DCM

Controller	VCM		DCM	
Parameter	$K_{P(vcm)}$	$K_{I(vcm)}$	$K_{P(vcm)}$	$K_{I(dcm)}$
Description	Proportional Gain	Integral Gain	Proportional Gain	Integral Gain
Value	0.075	0.00001	0.5	0

4.1.3 Adaptive Switching ACC

Although the previous controller proves to work well in adjusting vehicle speed to maintain a sufficient distance with the lead vehicle at all times, in practice, the basic switching method is not feasible. For instances where the distance controller overshoots even for a brief period, the system switches back to the VCM mode which results in higher acceleration and therefore the car speeds up and approaches the lead vehicle again, resulting in the controller to switch back to the DCM mode. This repetitive switching behaviour reduces the driver comfort and results in a jerky ride.

The proposed controller has a few advantages over the above system. Firstly, a new controller called a Following Control Mode(FCM), replaces the previously mentioned DCM. This controller consists of two smaller controllers as shown in Figure 4.5. One that attempts to keep the distance with the lead vehicle as close to the desired distance as possible(DC), and the second controller which attempts to match the speed of the vehicle to the speed of the lead vehicle, called the speed control(SC).

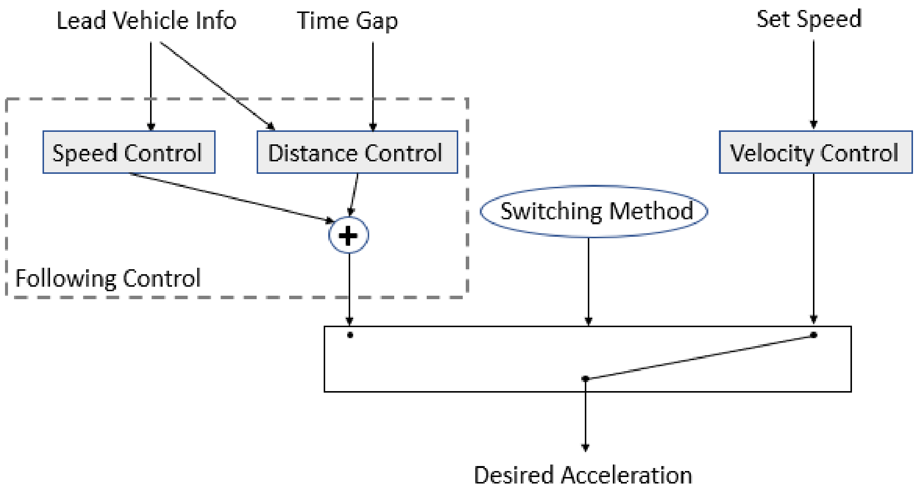

FIGURE 4.5: Adaptive Switching ACC Upper Level Controller

Addition of the SC controller into the old DCM, reduces the unnecessary accelerations and brakings. By matching the ego vehicle speed to the lead vehicle speed during the following mode, variations in the distance error is minimized. Therefore, once an acceptable distance is achieved, it is easier to maintain it by matching the vehicle speeds rather than modifying the vehicle speed only based on the distance error.

The formulation of the velocity controller and the distance controller are identical to the previous ACC mentioned and follow equations 4.6 and 4.9. The speed controller is also very similar to the previous controllers and can be formulated as:

$$e_{speed} = V_{lead} - V_{ego} \tag{4.10}$$

$$Acceleration_{Req} = \dot{V} = -K_{P(scm)}(e_{speed}) - K_{I(scm)}(\int e_{speed}\, dt) \tag{4.11}$$

Where e_{speed} is the difference between the lead vehicle speed and the ego vehicle speed. K_P and K_I are PID gains.
Another advantage of the proposed controller is its switching method. While repetitive switching is a problem in the basic ACC controller mentioned in the previous section, this controller solves that issue by introducing a new switching technique. In the switching algorithm, Figure 4.6, in order for the controller to switch from the VCM to the FCM, one of two things must happen:

1) The distance between the lead vehicle and the ego vehicle falls below the desired distance :

$$d_{des} > d_{rel} \tag{4.12}$$

2) The speed of the lead vehicle is considerably lesser than the set speed, even though it is much further than the desired distance:

$$\kappa * V_{set} > V_{lead} \tag{4.13}$$

And for the controller to switch back to the VCM, one of the following conditions must be satisfied:

1) The distance between the lead vehicle and the ego vehicle increases much more than the desired distance :

$$\alpha * d_{des} < d_{rel} \tag{4.14}$$

2) The speed of the ego vehicle while following the lead vehicle goes noticeably higher than the set speed:

$$\beta * V_{set} < V_{ego} \tag{4.15}$$

κ,α and β are all tuning parameters which can be adjusted based on application and it controls the frequency of the switching.

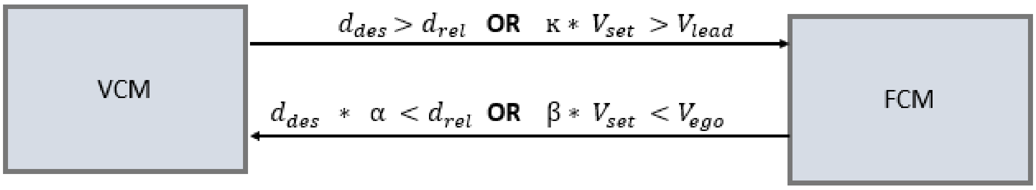

FIGURE 4.6: Adaptive Switching : Switching Conditions

The addition of the second switching condition 4.13, allows the ego vehicle to slow down ahead of time when there is a lead vehicle further away that has a significantly lower speed. This avoids any unnecessary acceleration prior to approaching the lead vehicle and consequently the braking required to slow down to maintain a safe distance. This modification to the switching criteria significantly increases the drive comfort and smoothens the ride and the result of such difference is better presented in the simulation.

Condition 4.14, adds a hysteresis effect to the controller which regulates the frequency of the switching. Note that the desired distance is not modified throughout this processed. Instead, the criteria for switching that is based on the desired distance is adapted to the situation to prevent unnecessary change in controller mode. This might result in the ego vehicle driving faster than set speed to maintain the distance. To prevent this from happening, condition 4.15 is introduced which will add a comparison between the ego vehicle speed and the set speed to ensure that the ego vehicle will not go faster than the set speed and in a scenario where the lead vehicle is driving noticeably faster than the set speed, the controller will switch back to VCM.

Tables 4.3 and 4.4, outline the parameter values used in the adaptive switching ACC controller:

TABLE 4.3: PID Gains Used in SCM

Controller	SCM	
Parameter	$K_{P(scm)}$	$K_{I(scm)}$
Description	Proportional Gain	Integral Gain
Value	0.002	0

TABLE 4.4: Parameters Used in the Switching Method

Parameter	κ	α	β
Value	0.9	1.5	1.2

4.2 Lateral Control Development

The lateral control model contains two main controllers as shown in Figure 4.7 below. Same as longitudinal control mode, the vehicle plant model which consists of the vehicle dynamics mimics the real life characteristics of the vehicle according to the steering control input it receives. It then updates the vehicle states given the control input received and calculates the new location, speed and yaw angle of the vehicle and passes this information to the lateral controller as a feedback.

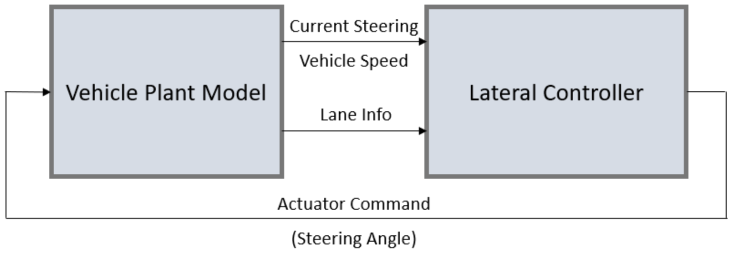

Figure 4.7: Lateral System Structure

Path tracking is very dependent on the vehicle model. Therefore, to best estimate the steering angle input required to minimize the lateral deviation from the trajectory, the lateral controller first models the dynamics of the vehicle and calculates the steering input required based on that. There exist many different vehicle models used for different applications. The bicycle model is a simple and effective vehicle model commonly used for lateral control systems.

In the next few sections, the kinematic bicycle model, Stanley controller, Model Predictive Controller, and the proposed adaptive MPC are discussed in more detail.

4.2.1 Kinematic Bicycle Model

For the vehicle dynamics model and development of a prediction model, the kinematic bicycle model is used. This model has long been well-known as a suitable control-oriented model for representing a vehicle.

There are certain assumptions made in a bicycle model. Firstly, the left and right wheel of the vehicle are lumped into one wheel as shown in Figure 4.8 below.

Tires are also considered to have constant normal load and no slip angle at the wheels in this model. and lastly, the vehicle is assumed to have planar motion, meaning the only coordinates describing the motion of the vehicle in the world coordinate system are x_c, y_c and θ. Where x and y are the inertial coordinates of the location of the center of gravity, and θ is the heading angle of the vehicle.

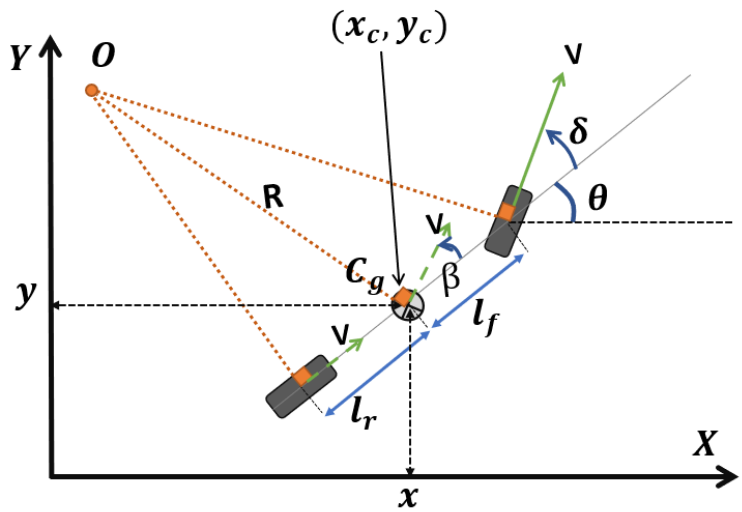

FIGURE 4.8: Lane Centering Assist

In such a model, the steering angle for the front wheels is represented by δ. The rear wheels are assumed to be always straight and can not be steered. The center of gravity of the vehicle C_g is assumed to be l_f meters apart from the front axle, and l_r from rear. Therefore, the total wheelbase of the vehicle is $L = l_r + l_f$.

Instantaneous center of rotation of the vehicle, point O, is the point where at an instant in time, the vehicle is rotating about. Meaning, the velocity of all three points on the vehicle, front axle, center of gravity and the rear axle are all perpendicular to the line connecting the center of rotation to them. Because of the no slip condition, we can introduce ω as the rotation rate of the bicycle as:

$$\dot{\theta} = \omega = \frac{v}{R} \tag{4.16}$$

Where R is the radius of the instantaneously center of rotation. Using the concept of instantaneous center of rotation, the vehicle's equations of motion in an absolute inertial frame with respect to its center of gravity can be represented by the following state equations:

$$\dot{x}_c = v * cos(\theta + \beta) \tag{4.17}$$

$$\dot{y}_c = v * sin(\theta + \beta) \tag{4.18}$$

$$\dot{\theta} = \omega = \frac{v * cos(\beta) * tan(\delta)}{L} \tag{4.19}$$

$$\beta = tan^{-1}(\frac{l_r * tan(\delta)}{L}) \tag{4.20}$$

Using equations above, the vehicle's motion can be estimated. By inputting the steering angle rate and vehicle velocity into the system above,the new heading and position of the vehicle can be calculated using the state space representation below:

$$\begin{bmatrix} \dot{x}_c \\ \dot{y}c \\ \dot{\theta} \\ \dot{\delta} \end{bmatrix} = \begin{bmatrix} cos(\theta + \beta) \\ sin(\theta + \beta) \\ cos(\beta)tan(\delta)/L \\ 0 \end{bmatrix} v + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} \psi \tag{4.21}$$

Using this model, the yaw angle and position of the vehicle in the global coordinate system can be calculated at each point in time.

4.2.2 Basic Stanley Controller

As mentioned in the previous chapter, the Stanley lateral controller is one of the most commonly used geometrical controllers for lateral control. This method computes the steering angle command, in radians, to adjust the current position of the vehicle such that the lateral error and heading error between the vehicle and the reference path is minimized. This controller only takes into account the kinematic characteristics of the vehicle, which is the bicycle model as described in the previous section.

The formulation of Stanley is better represented in the figure 4.9 below. In this method, the front axle of the vehicle is used as the reference point. Lateral error, e is defined as the shortest distance from the front axle of the vehicle to the trajectory path. and the heading error ψ is defined as the difference between the heading of the vehicle and heading of the trajectory at the point of the shortest distance as shown in equations 4.22, 4.23 below.

$$e = \sqrt{(X - X_p)^2 - (Y - Y_p)^2} \tag{4.22}$$

$$\psi = \psi_{trajectory} - \psi_{vehicle} \tag{4.23}$$

Heading error is a measurement of how well the vehicle is aligned and moving along the trajectory path while lateral error is a measurement of how far the vehicle is from the center of the lane. The relative location and heading of the vehicle at any point in time with respect to the desired path, i.e. center of the lane, can be described using these two parameters.

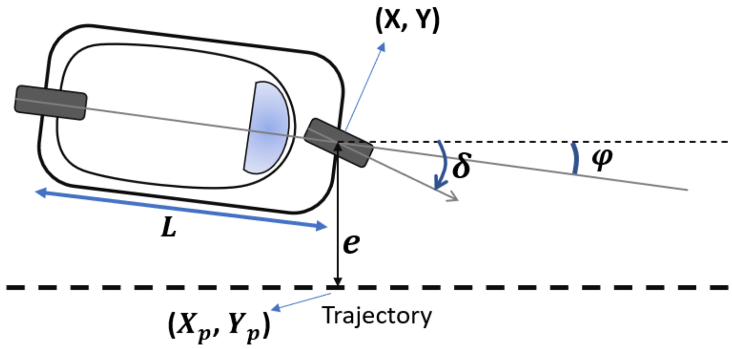

FIGURE 4.9: Stanley Controller

As mentioned above, Stanley is formulated based on three concepts. One, is to eliminate the heading error $\psi(t)$ Secondly, it aims to eliminate the cross-track error $e(t)$ by calculating the steering angle required to drive the vehicle to the trajectory. and Lastly, it obeys the physical constraints of the vehicle and maintains the steering angle between the limits at all times.

Given the model above and putting the three Stanley concepts together, the basic Stanley controller is formulated as:

$$\delta(t) = \begin{cases} \psi(t) + arctan(\frac{ke(t)}{V(t)}) & |\psi + arctan(\frac{ke(t)}{V(t)})| < \delta(max) \\ \delta(max) & \psi + arctan(\frac{ke(t)}{V(t)}) \geq \delta(max) \\ -\delta(max) & \psi + arctan(\frac{ke(t)}{V(t)}) \leq -\delta(max) \end{cases} \tag{4.24}$$

Where k is the controller gain and $\delta(\text{max})$ is the maximum steering of the vehicle which is a physical constraint.

Using equation 4.24 at each point in time, given the information about the trajectory and the location of the vehicle, a steering angle control input is calculated to reduce the lateral and heading error. Huffman in [21] demonstrated that this system is globally asymptotically stable with linear or exponential convergence.

Stanley controller is an effective controller, since it considers both the cross-track error and the heading error. In a scenario where the vehicle heading error is large but the cross-track error is small, the output steering will also be large resulting in the vehicle's orientation adjusting to the path. In a second scenario where the heading error is negligible but the cross-track error is large, $arctan(\frac{ke(t)}{V(t)}) \approx \frac{\pi}{2}$, again the controller adjusts the steering angle such that the vehicle will drive towards the center of the lane.

4.2.3 Model Predictive Controller (MPC)

Model Predictive Control(MPC), is an advanced control method which at each point in time predicts the process output over a finite predictive horizon based on the current state of the system and the system inputs. These predicted state variables are then compared with the corresponding reference variables using the cost function which is developed based on the system constraints. and finally, MPC calculates a control input sequence by optimizing the cost function for the relatively short time horizon in the future [t-t+T]. It then takes the first control action and applies it to the system and repeats all the steps above again.

MPC is formulated based on the mathematical state-space model of a system and this model is used to predict the state variable of the system throughout the prediction horizon. Considering a multiple input output system, the state space model is represented as:

$$X(k+1) = AX(k) + B\Delta u(k) \tag{4.25}$$

$$Y(k) = CX(k) \tag{4.26}$$

Where u(k) is the manipulated input variable, or control input. Y(k) is the process output at time (k). X(k) is the state variable Vector at time k. A, B and C are the state matrices. Prediction horizon (N_p) is the length of the prediction and optimization window.

As mentioned before, the optimization goal of MPC is to develop an optimization algorithm and minimize the cost function J over the receding horizon. The most common formulation of a cost function is a quadratic cost function which is given by:

$$J = \sum_{n=1}^{N} (Q_x (R_i - X_i)^2 + Q_u \Delta u_i^2) \tag{4.27}$$

Where X_i is the measured state, R_i is the reference variable, u_i is the manipulated variable or control input, and Q_x and Q_u are the weighing coefficients penalizing the cost function.

By predicting the state of the system over the prediction horizon using the prediction model and optimizing the cost function for that horizon , the optimal control input for next sample time is calculated. The following sections go over the dynamic vehicle model that is used as the prediction model, the cost function and the complete formulation of MPC for the development of LCA.

A. Dynamics of the Bicycle Model

To best model the lateral characteristics of the vehicle and formulate the prediction model, the kinematic bicycle model is extended to a dynamic model by relaxing the no slip condition and force as shown in Figure 4.10. To begin modeling the lateral dynamics of the vehicle, the following assumptions are made: first, the forward longitudinal velocity of the vehicle is assumed to be constant. This is done by decoupling the longitudinal and lateral dynamics of the vehicle which has been done throughout this project. Secondly, same as the kinematic bicycle model, the front right and left wheels of the vehicle are assumed to be lumped together into a single wheel and same with the rear wheels. And finally, other non-linear aspects of the system such as external forces acting on the vehicle, suspension movements, and road inclinations are all considered to be negligible and are not accounted for in the formulation on this model.

For this model, the center of gravity of the vehicle is assumed to be the reference point to simplify the formulation. The lateral dynamics of the vehicle can be formulated as equation 4.28 below, with only forces affecting the vehicle dynamics being the front and rear tire forces.

$$mV(\dot{\beta} + \dot{\psi}) = F_{yf} + F_{yr} \tag{4.28}$$

Where F_{yf} and F_{yr} are the front and rear tire forces, m is vehicle mass, V is vehicle velocity and $\dot{\beta}$ and $\dot{\psi}$ are the side slip angle and yaw rate respectively.
For the angular acceleration, $\ddot{\psi}$, the moments caused by the tire forces act in opposite direction and create the following equation:

$$I_z\ddot{\psi} = l_f F_{yf} - l_r F_{yr} \tag{4.29}$$

Where I_z denotes the yaw inertia.

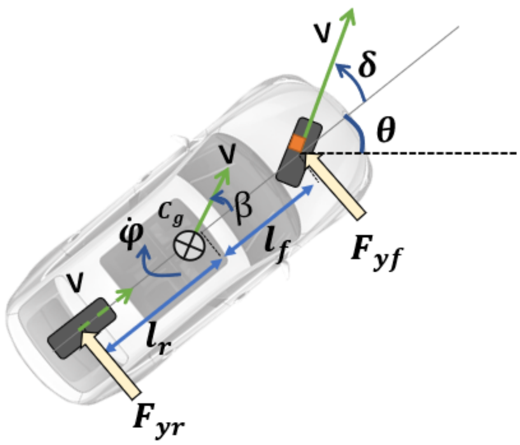

FIGURE 4.10: Lateral Dynamics of Bicycle Model

As mentioned above, the only forces acting on the vehicle are assumed to be the tire forces. Thus it's essential to choose a tire model that models the system accurately. Tire models tend to be nonlinear and complicated. However, for normal driving conditions and small tire slip angles, the tire model can be approximated as a linear function of the slip angle as follow:

$$F_{yf} = C_f \alpha_f = C_f(\delta - -\frac{l_f \dot{\psi}}{V}) \tag{4.30}$$

$$F_{yr} = C_r \alpha_r = C_r(- + \frac{l_r \dot{\psi}}{V}) \tag{4.31}$$

Where α_f and α_r are the front and read tire slip angles. and C_r and Cf are the cornering stiffness of the front and rear tires. Cornering stiffness is defined by the resistance of a tire to deformation while the vehicle corners.

Substituting the tire model into equations 4.28 and 4.29, assuming the state vector is $X_{lat} = [y \; \dot{y} \; \theta \; \psi]^T$, $\psi = \dot{\theta}$, and $u = \delta$ the lateral dynamics system can be represented in standard state space form as follows:

$$\dot{X} = AX + Bu \tag{4.32}$$

$$Y = CX \tag{4.33}$$

Where:

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & \frac{2C_f+2C_r}{mV_x} & 0 & -V_x - \frac{2C_f l_f - 2C_r l_r}{mV_x} \\ 0 & 0 & 0 & 1 \\ 0 & -\frac{2l_f C_f - 2l_r C_r}{I_z V_x} & 0 & -\frac{2l_f^2 C_f + 2C_r l_r^2}{I_z V_x} \end{bmatrix} \tag{4.34}$$

$$B = \begin{bmatrix} 0 & \frac{2C_f+2C_r}{mV_x} & 0 & -V_x - \frac{2C_f l_f - 2C_r l_r}{mV_x} \end{bmatrix}^T \tag{4.35}$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{4.36}$$

and

$$Y = \begin{bmatrix} y \\ \psi \end{bmatrix} \tag{4.37}$$

B. The Prediction Model

The model formulated in the previous section is the continuous dynamics model of the vehicle. In the prediction model of MPC, the future states of the vehicle is predicted throughout a specific prediction horizon using the discretized version of

the model described in the previous section. This prediction model is then used to calculate the control input in the next moment by minimizing the cost function that will be described further in the next section under various constraints.
To best model the behaviour of the car and the mechanical constraints that exist in the steering of the vehicle, a new discretized state space expression is established based on equations 4.32 and 4.33 in which the control input in chosen to be $\Delta\delta$ and is presented as follows:

$$\tilde{X}(k+1) = \tilde{A}_k \tilde{X}(k) + \tilde{B}_k \Delta u(k) \tag{4.38}$$

$$\tilde{Y}(k+1) = \tilde{C}_k \tilde{X}(k) \tag{4.39}$$

Where:

$$\begin{cases} \tilde{X}_k = \begin{bmatrix} X(k) \\ u(k-1) \end{bmatrix}, & \Delta u(k) = u(k) - u(k-1) \\ \tilde{A}_k = \begin{bmatrix} A_k & B_k \\ 0_{1x6} & I \end{bmatrix}, & \tilde{B}_k = \begin{bmatrix} B_k \\ I \end{bmatrix} \\ \tilde{C}_k = \begin{bmatrix} C_k & 0 \end{bmatrix}, & \tilde{Y}_(k) = Y(k) \end{cases} \tag{4.40}$$

The prediction horizon and the control horizon of the controller are N_p and N_c and are set to be 10 and 1 respectively. Meaning the control input is assumed to be held constant throughout the prediction horizon.

$$\Delta\tilde{U}_{Predicted}(k) = \begin{bmatrix} \Delta\tilde{u}_(k) \\ \Delta\tilde{u}_(k+1) \\ \vdots \\ \Delta\tilde{u}_(k+N_c) \end{bmatrix} \tag{4.41}$$

At each moment in time, assuming the current state of the system is represented by $\tilde{X}_k$ and k>0, the future vehicle states can be presented as:

$$\tilde{Y}_{Predicted}(k) = \begin{bmatrix} \tilde{Y}_(k) \\ \tilde{Y}_(k+1) \\ \vdots \\ \tilde{Y}_(k+N_p) \end{bmatrix} \tag{4.42}$$

Where $\tilde{Y}_{Predicted}(k)$ is the predicted output over the prediction horizon N_p and it can be derived by combining Equations 4.38 - 4.42:

$$\tilde{Y}_{Predicted}(k) = \Psi\tilde{X}(k) + \Theta\Delta U_{Predicted}(k) \tag{4.43}$$

Where:

$$\begin{cases} \Psi = \begin{bmatrix} \tilde{C}\tilde{A} \\ \tilde{C}\tilde{A}^2 \\ \vdots \\ \tilde{C}\tilde{A}^{N_p} \end{bmatrix}, \quad \Theta = \begin{bmatrix} \tilde{C}\tilde{B} & 0 & 0 & \dots & 0 \\ \tilde{C}\tilde{A}\tilde{B} & \tilde{C}\tilde{B} & 0 & \dots & 0 \\ \tilde{C}\tilde{A}^2\tilde{B} & \tilde{C}\tilde{A}\tilde{B} & \tilde{C}\tilde{B} & \dots & 0 \\ \vdots & & \ddots & & \\ \tilde{C}\tilde{A}^{N_p-1}\tilde{B} & & \dots & & \tilde{C}\tilde{A}^{N_p-N_c}\tilde{B} \end{bmatrix} \end{cases} \tag{4.44}$$

C. Cost Function

The benefit of MPC over other methods is that MPC finds the optimal control input over the horizon that will minimize the error between the reference values and the output vehicle state values. This is done by minimizing the cost function. To ensure the optimal solution follows the trajectory accurately and obtains lateral stability and ensures driver comfort, the cost function can be constructed as follows:

$$J = \sum_{n=1}^{N}(Q_y e_i^2 + Q_\psi \psi_i^2 + Q_\delta \Delta u_i^2) \tag{4.45}$$

Where Q_y, Q_ψ and Q_δ are the constant weighting factors of the controller and e_i and ψ_i are the lateral error and the heading error respectively and can be calculated using the equations 4.22 and 4.23, and Δu_i is the change in the steering angle input.

The constraints of this problem are shown below:

$$\Delta U_{min} \leq \Delta u_i \leq \Delta U_{max} \tag{4.46}$$

$$U_{min} \leq u_i \leq U_{max} \tag{4.47}$$

In these set of constraints, ΔU_{min} and ΔU_{max} are the minimum and maximum feasible angular increment of the front wheel, and U_{min} and U_{max} are the minimum and maximum steering angle.

For the optimization of the cost function, a finite horizon optimal control method is used in which a range of steering wheel inputs are chosen, and the predicted state output for each of these steering angle inputs is estimated and the cost function is calculated for each of these control inputs. Then the control input that results in the lowest cost is chosen as the optimal control. With steering angle inputs ranged from [-0.3, 0.3] rad, and increments of 0.005, the optimal control input vector is:

$$\Delta U^*(k) = [\Delta u^*(k), \Delta u^*(k+1), ..., \Delta u^*(k+N_c-1)] \tag{4.48}$$

Since $N_c = 1$ for this project, $\Delta U^*(k) = \Delta u^*(k)$. Therefore, the front wheel steering angle input is $u(k) = u(k-1) + \Delta u^*(k)$ which will be the input to the vehicle plant model.

The overall upper level architecture of the MPC system can be seen in Figure 4.11 below:

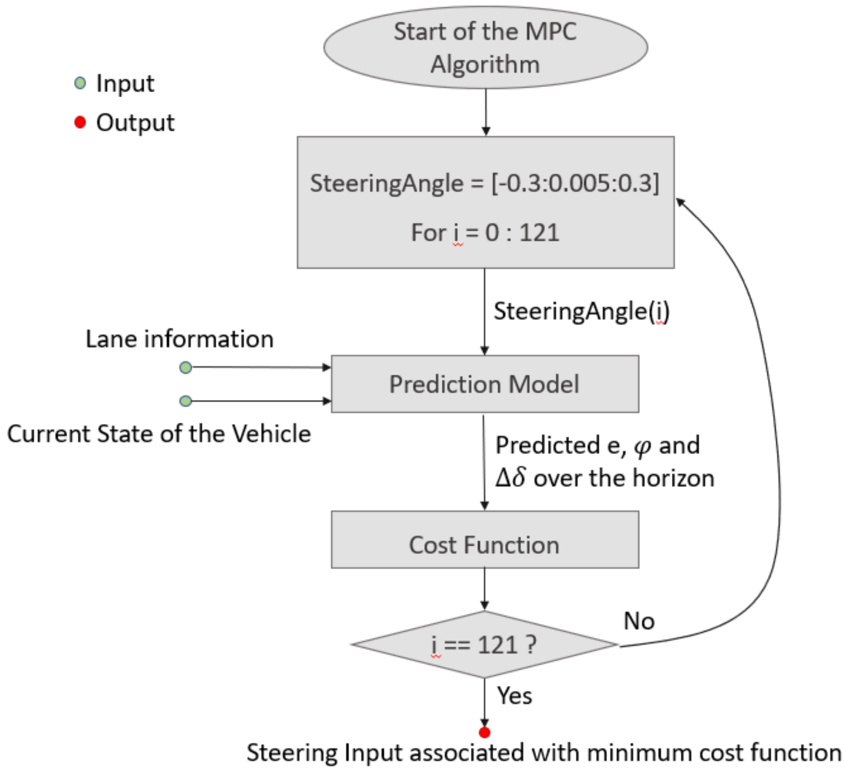

FIGURE 4.11: Upper Level MPC Architecture

4.2.4 Adaptive MPC

As mentioned in the previous chapter, while Stanley and classic MPC methods both perform decently in lane centering assist applications, they both suffer from performance limitations that decrease tracking accuracy and ride comfort in certain scenarios.

Stanley suffers from lack of prediction, since it calculates the steering angle input required only based on the information about the current state of the vehicle and the trajectory. Classic MPC on the other hand, suffers from lack of adaptability to different maneuvers and tracking scenarios which stems from the fact that the cost function gains are tuned to a limited number of scenarios.

The improved adaptive MPC proposed in this work is based on fuzzy control. This method guarantees improved accuracy in tracking and performance since it will automatically adjust the gains of the cost function based on the current state of the vehicle and the lateral error and the heading error. This in return, penalized lateral error, heading error and the change in the steering input differently in different scenarios.

Fuzzy control system is based on fuzzy logic and is widely used in the field of control. This system mimics human behaviour and embeds the knowledge and key elements of human thinking into decision making. Fuzzy logic controller can be divided into three steps as shown in Figure 4.12: fuzzification, inference and defuzzification. In the first step or fuzzification, crisp inputs with specific values are fuzzified into fuzzy variables with a certain degree of membership. Next, the fuzzy logic rules are applied to these fuzzy variables through the inference step and lastly, these outputs will be converted into crisp specific outputs in the process of defuzzification.

FIGURE 4.12: Fuzzy Logic Flow Chart

In the fuzzy controller designed, the two fuzzy input variables are the lateral position error and the heading angle error. These inputs are both fuzzified into five fuzzy sets: NB (Negative Big), NS (Negative Small), ZO (Zero), PS (Positive Small), and PB (Positive Big) using the membership functions 4.13 and 4.14.

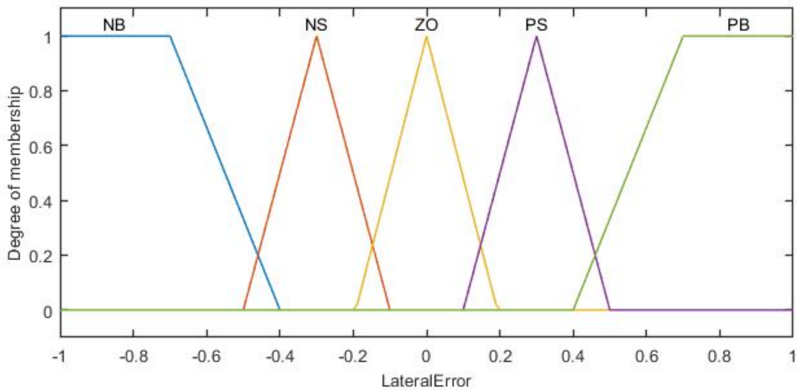

FIGURE 4.13: The membership function of lateral error e

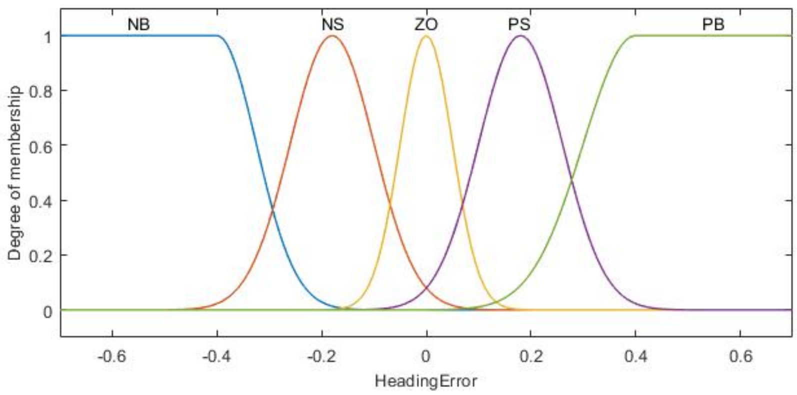

FIGURE 4.14: The membership function of heading error ψ

The fuzzified values are then passed through the inference which implements the fuzzy rules presented in tables below to these fuzzy variables:

Table 4.5: Fuzzy rules of weight on Lateral Error e

	e_y					
e_ψ		NB	NS	ZO	PS	PB
	NB	ZO	PS	PM	PS	ZO
	NS	PS	PS	PM	PS	ZO
	ZO	PS	PM	PB	PM	PS
	PS	ZO	PS	PM	PS	ZO
	Pb	ZO	PS	PM	PS	ZO

Table 4.6: Fuzzy rules of weight on Heading Error ψ

	e_y					
e_ψ		NB	NS	ZO	PS	PB
	NB	PB	PM	PS	PS	ZO
	NS	PM	PS	ZO	PS	ZO
	ZO	PS	ZO	ZO	PM	PM
	PS	PM	PS	ZO	PS	ZO
	PB	PB	PM	PS	PS	ZO

Table 4.7: Fuzzy rules of weight on Delta Steering $\Delta\delta$

	e_y					
e_ψ		NB	NS	ZO	PS	PB
	NB	PM	PS	ZO	PS	PM
	NS	PB	PM	PS	PM	PB
	ZO	PB	PM	PS	PM	PB
	PB	PB	PM	PS	PM	PB
	PM	PM	PS	ZO	PS	PM

These rules are representations of the relationship between the inputs and the outputs based on the experience and intuitions that a driver would have while taking into account both driver comfort and tracking accuracy of the system. The output of these rules, are categorized into four groups of: ZO (Zero), Positive Small (PS), Positive Medium (PM), Positive Big (PB). These output variables are then defuzzified through the membership function represented in Figure 4.15 below using centroid defuzzification method.

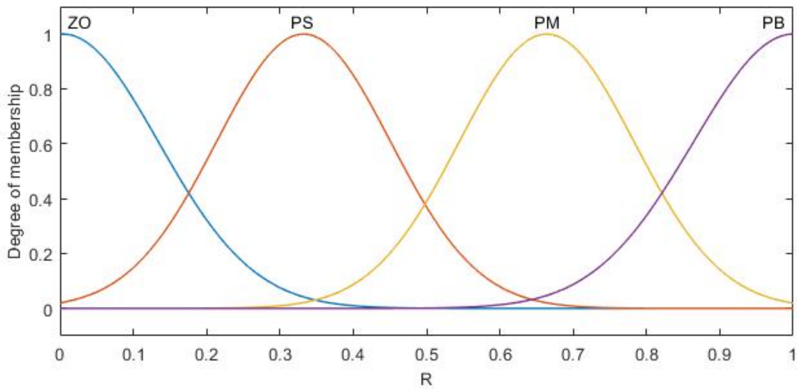

FIGURE 4.15: The membership function of the outputs

Outputs of this defuzzification are r_{Q_y}, r_{Q_ψ} and r_{Q_δ} which represent the ratio of cost function weight factors with respect to their maximum values. Meaning, the outputs of the fuzzy logic system are used in the formulas below to give us the final cost function gain values:

$$\begin{cases} \tilde{Q}_y = r_{Q_y} * Q_{y,max} \\ \tilde{Q}_\psi = r_{Q_\psi} * Q_{\psi,max} \\ \tilde{Q}_\delta = r_{Q_\delta} * Q_{\delta,max} \end{cases} \tag{4.49}$$

Where $\tilde{Q}_y$, $\tilde{Q}_\psi$ and $\tilde{Q}_\delta$ are the adaptive cost function weighting factors, r_{Q_y}, r_{Q_ψ} and r_{Q_δ} are the outputs of the fuzzy controller, and $Q_{y,max}$, $Q_{\psi,max}$, and $Q_{\delta,max}$ are the maximum weight factors. The adaptive cost function weighing factors $\tilde{Q}_y$, $\tilde{Q}_\psi$ and $\tilde{Q}_\delta$ are then passed on to the MPC controller for the implementation of the optimization algorithm.

Below in Figures 4.16-4.18, the response surface of all three parameters are plotted. These plots show the relationship between the system outputs and the inputs given the fuzzy rules.

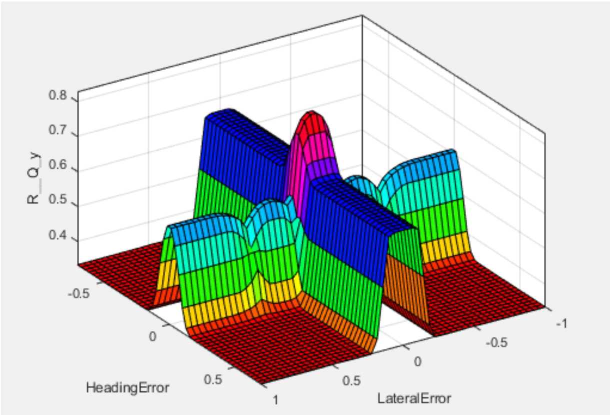

FIGURE 4.16: Response Surface of r_{Q_y}

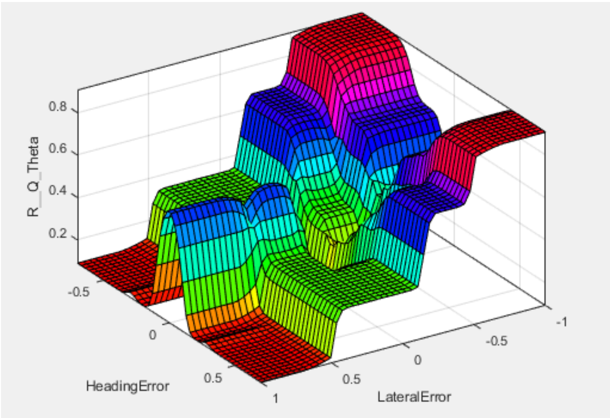

FIGURE 4.17: Response Surface of r_{Q_ψ}

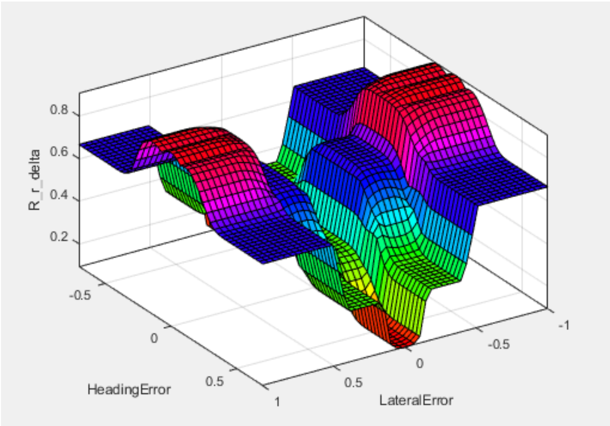

FIGURE 4.18: Response Surface of r_{Q_δ}

Through the method described in this section, at each instance of time, the system will adapt the cost function gain to the relative location of the vehicle to the reference trajectory.

As an example, if the vehicle is far from the center of the lane but aligned with the heading of the path, the weight factor on the lateral error will be increased to ensure the vehicle will be brought back to the center of the lane smoothly. At the same time, the weight factor on the steering wheel input will also be increased to ensure ride comfort and avoid aggressive steering.

Chapter 5

Simulation and Test Scenarios

Based on the methodology explained in the previous chapter, the vehicle model has been designed in MATLAB SIMULINK. The longitudinal and lateral controls are also created to control the vehicle plant model as shown in Figure 4.1.

Driving Scenario Designer app in MATLAB, allows for design of synthetic driving scenarios for testing of different autonomous features.The application allows the user to create roads and actor models, which can be vehicles, trucks, bicycles or pedestrians. It also allows the configuring of different sensors on the ego vehicle to best mimic the real life test scenario.

For the purposes of this project, the following sensor configuration has been designed as shown in Figure 5.1. The ego vehicle is equipped with a front facing long range radar (LRR) placed on the front windshield. The radar has a field of view of 20 ° and a maximum detection range of 150m. This radar detects obstacles such as vehicle and pedestrians that are in the path of the vehicle.

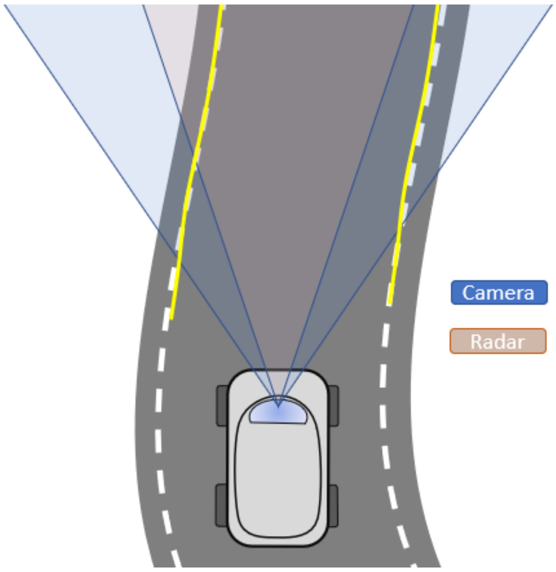

FIGURE 5.1: Vehicle Sensor Architecture

The vehicle is also equipped with a front facing camera. The field of view of the camera is 38 ° and range of the camera is 150m. The camera will create vision detections of obstacles in front of the vehicle as well as lane detections.

The sensor detections received from both sensors are then processed in a sensor fusion and tracking controller as shown in Figure 5.2. Both sensor fusion and the tracking controller are taken from the SIMULINK library. The clustering block, clusters all the detections received if they are within a certain distance from each other. The tracking algorithm on the other hand, initializes, predicts and confirms moving objects. This tracker accepts the clusters and detections from all sensors, and assigns the detections to a track using global nearest neighbor(GNN) method. The lead vehicle is then selected based on these tracks. This controller also provides the relative distance and velocity of the lead vehicle as well as information about the lanes detected.

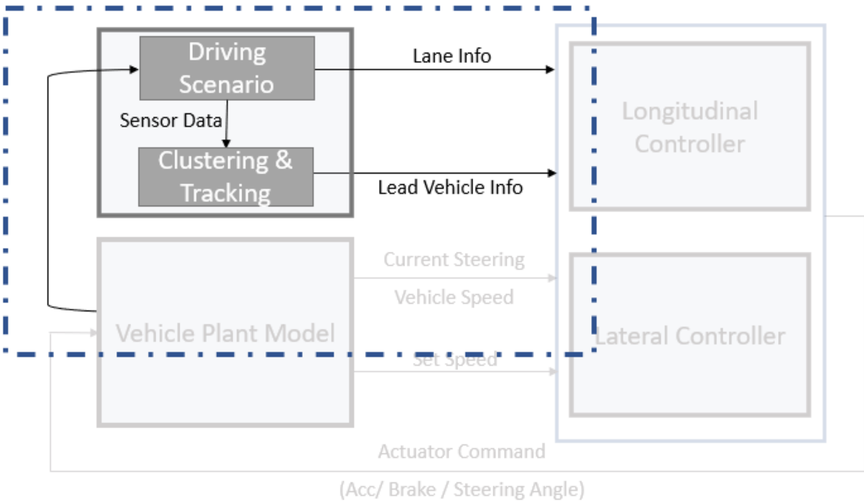

FIGURE 5.2: Inside the Environment Plant Model

Both longitudinal and lateral controllers will then receive the required data and calculate the next control input required for acceleration/deceleration and steering of the vehicle. Since based on the assumptions made throughout the modeling of the system the longitudinal and lateral motion and controller of the system work independently, they have been evaluated and tested separately as well.

Throughout the following sections, the evaluation process of both controllers has been explained in detail.

5.1 Longitudinal Control Evaluation

5.1.1 Test Setup

For the evaluation of the longitudinal controller, three driving scenarios have been simulated and tested. To separate longitudinal control evaluation from the lateral control evaluation, all tests assume a straight road with no road grade.

In the first Scenario, the ego vehicle is travelling at 20 $\frac{m}{s}$. There is a lead vehicle traveling also at the same speed 50m ahead of the ego vehicle. After about 12s, the lead vehicle fairly aggressively slows down to a full stop. The simulation setup can be seen in Figure 5.3. In this scenario, the stability of the switching method of both controllers at the boundary is evaluated as well as the reaction of the system to a sudden stop of the lead vehicle.

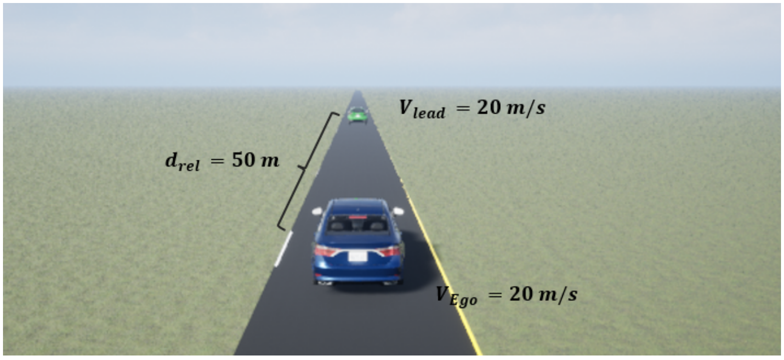

FIGURE 5.3: First Longitudinal Driving Scenario

In the second scenario, the ego vehicle is traveling at 20 $\frac{m}{s}$. This time a lead vehicle is traveling much further in the same line, at a speed of 16 $\frac{m}{s}$. In this scenario, the response of the controller as it approaches a much slower vehicle is evaluated.

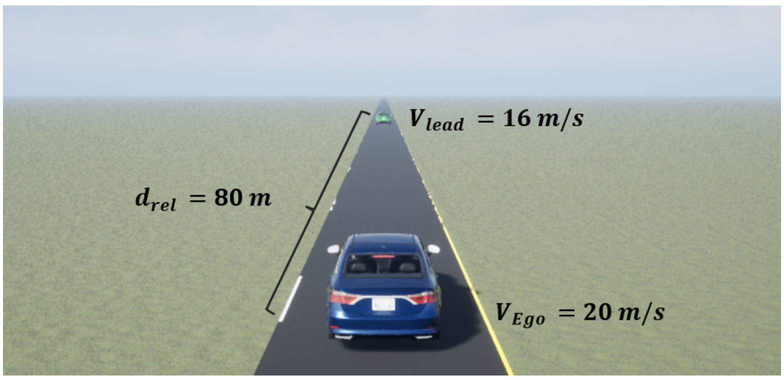

FIGURE 5.4: Second Longitudinal Driving Scenario

As for the third and final longitudinal driving scenario, the case of an aggressive cut in is evaluated. The ego vehicle is assumed to be driving at 20 $\frac{m}{s}$. A vehicle in the adjacent lane is also traveling at the same speed slightly ahead of the ego vehicle. After a few seconds, the second vehicle changes lane and cuts in front of the ego vehicle. This not only evaluates how accurately and quickly the system detects the lead vehicle, it also evaluates the reaction of the system to evaluate how aggressive and jerky the response is.

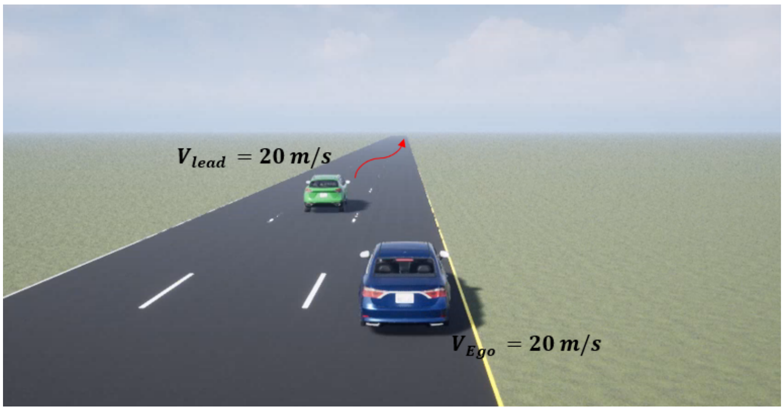

FIGURE 5.5: Third Longitudinal Driving Scenario

5.1.2 Evaluation Metrics

To best compare the two controllers, a few criteria have been set. The performance of the system during the distance following mode can be evaluated by looking at the distance error throughout the ride. In addition to the distance error, the velocity error is also of interest in this project since the modified ACC includes a third controller that aims to minimize that error. There are other factors that are also representations of the performance of the system.

As mentioned before, the main disadvantage of the basic ACC is its switching method. The repetitive switching between the two control modes, creates unnecessary jerk and decreases driver comfort. By comparing the number of times each system has switched between the two controllers amongst all scenarios, we can assess the two switching algorithms.

In addition, increasing driver comfort is one of the main goals of this project. Driver comfort is best measured by Longitudinal acceleration throughout the ride. Excessive acceleration not only decreases driver comfort, but it also significantly impacts the safety of the driver.

To better standardize and control this, a set of acceleration criteria has been put in place that separates the value of longitudinal acceleration and categorizes it into three categories of normal driving, aggressive driving, and extremely aggressive driving[22]. While specific maneuvers and emergency responses of a vehicle might involve aggressive acceleration or braking, the aim in designing an autonomous feature is to minimize the aggressive maneuvers as much as possible while maintaining the safety of the ride. Figure 5.6 shows a summary of the longitudinal acceleration criteria. These values might slightly vary in different applications, but they are all within a very common range. The acceleration threshold for comfortable normal driving is 0-1.47 $\frac{m}{s^2}$. Acceleration values ranging between 0.9-3.07$\frac{m}{s^3}$ are considered to be aggressive accelerations. That being said, the threshold for aggressive braking is higher. Aggressive braking is categorized as any acceleration between -5.06 - -2 $\frac{m}{s^2}$ [22] .

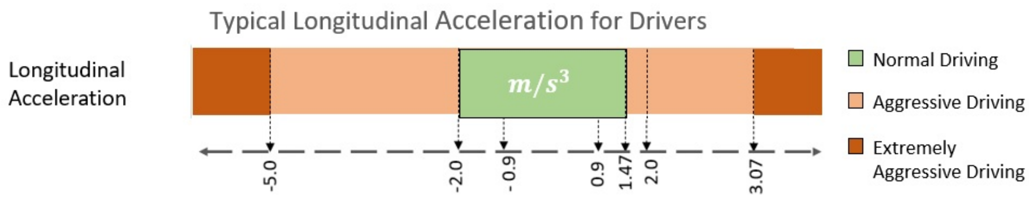

FIGURE 5.6: Range of Acceptable Longitudinal Acceleration Values

To evaluate driver comfort, the longitudinal acceleration and jerk of the two controllers is compared for all three test scenarios to ensure it stays within the acceptable limit. The root mean square error of these values are also compared to evaluate the level of aggressiveness of the ride using the formula below.

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} \tag{5.1}$$

Where n is the number of data measurements and x_i is data at each sample point.

5.2 Lateral Control Evaluation

5.2.1 Test Setup

For the evaluation of the lateral controller also, three driving scenarios were designed to assess the performance of the system in three different maneuvers. Since the evaluation of the lateral and longitudinal controller has been separated, throughout all three lateral scenarios the assumption is that the vehicle has a constant speed of $20\frac{m}{s}$ and the road grade is zero.

The three main challenges lateral controllers face is large lateral deviation from the center of the road, tight curves with high speed, and driving through S shaped curvy roads. To evaluate the system performance in all these challenging maneuvers, the test scenarios have been built based on these cases.

The first driving scenario is a straight road as shown in Figure 5.7 below. The vehicle is traveling at the constant speed of $20\frac{m}{s}$, however the vehicle's initial lateral deviation from the center of the road is 0.8m. This scenario assesses the stability of the system against large lateral deviations.

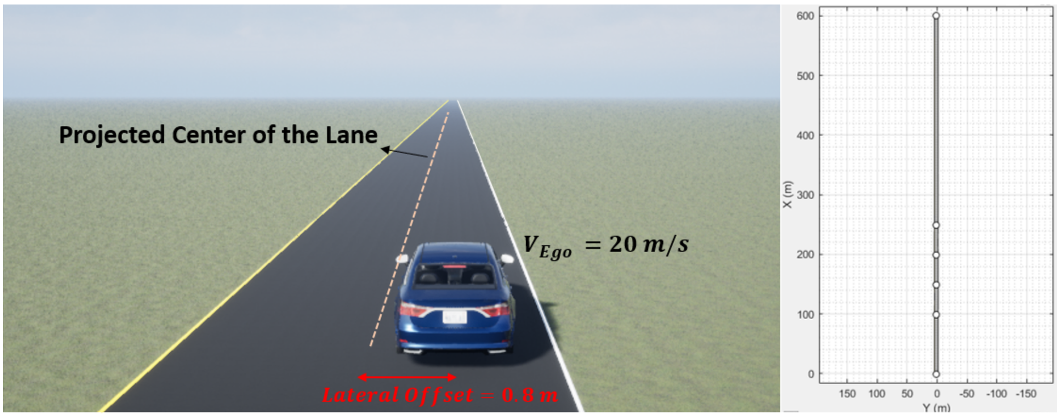

FIGURE 5.7: First Lateral Driving Scenario

Second scenario is a tight highway curve. Based on [14], the minimum radius of curvature of a highway can be calculated using the formula below:

$$R_{min} = \frac{V^2}{15(0.01 * e_{max} + f)} \tag{5.2}$$

Where e is the pavement superelevation, f is the coefficient of side friction force between the vehicle tire and the road pavement, V is vehicle speed, and R is the radius of the curve.

The minimum radius of curvature a given highway can have is determined by the limiting values of f and e which can be found in [11]. Assuming e_{max}=0.06, and f_{max}=0.140 with a vehicle speed of $20\frac{m}{s}$, the minimum radius of the curve can be 190.5m . Therefore, for the second scenario, the vehicle is traveling at the speed of $20\frac{m}{s}$ entering a curved road with a radius of 200m as shown in Figure 5.8 below.

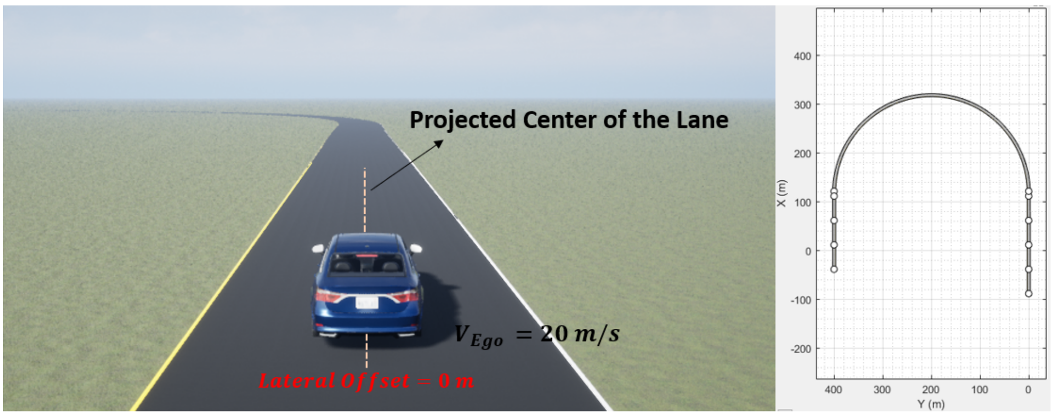

FIGURE 5.8: Second Lateral Driving Scenario

The third scenario is a S shape road with two curves that have a minimum radius of curvature of 200m and the vehicle speed is the same as before which is $20\frac{m}{s}$ and there is assumed to be no road grade.

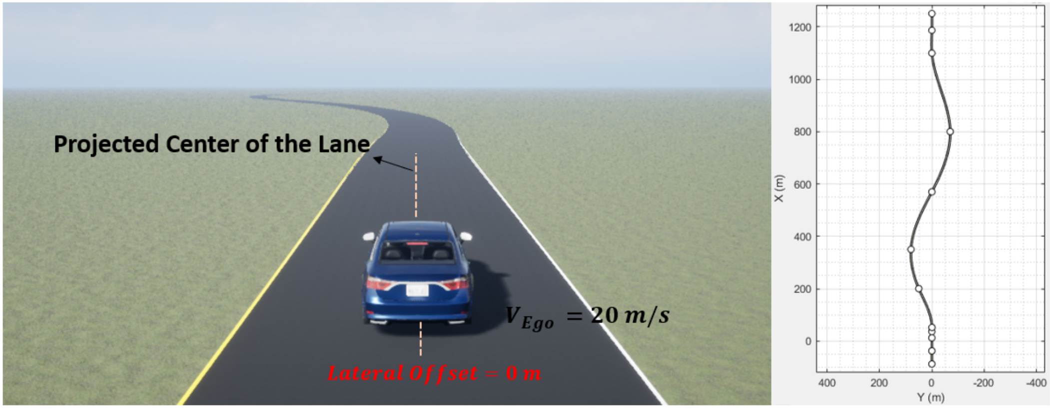

FIGURE 5.9: Third Lateral Driving Scenario

5.2.2 Evaluation Metrics

The Evaluation of the lateral controller is done by looking at the following factors: tracking performance, front wheel angle, lateral dynamic stability, and driver comfort.

Tracking performance can be evaluated by measuring the lateral error which is defined as the lateral position of the vehicle with respect to the projected center of the lane. This evaluation is done by comparing the mean of the error and the average absolute error(AAE) for the lateral error in different test scenarios between the three controllers. AAE can be calculated using the formula below:

$$AAE = \frac{1}{n} \sum\nolimits_{i=1}^{n} |e_{lateral}(i)| \tag{5.3}$$

Front wheel angle on the other hand, which is a function of the steering angle input, is a measure of the control input required throughout the ride. Lateral dynamic stability can be evaluated by looking at the reaction of the controller to the extreme driving scenarios which have been designed using the front wheel angle.

The noticeable improvement in the stability of the system is one of the main advantages of the new MPC controller. This can be seen by the reduction in oscillations in control input and the overall performance of the system.

The last evaluation metric is the driver comfort. This can be characterized by the lateral acceleration throughout the ride. To better standardize and control this, a set of acceleration criteria has been put in place that categorizes the driving style into three categories of normal driving, aggressive driving, and extremely aggressive driving[22]. While specific maneuvers and emergency responses of a vehicle might involve aggressive steering and therefore a more aggressive lateral acceleration, the aim in designing an autonomous feature is to minimize the aggressive maneuvers as much as possible while maintaining the safety of the ride. Figure 5.10 shows a summary of the lateral acceleration. These values might slightly vary in different applications, but they are all within a very common range.

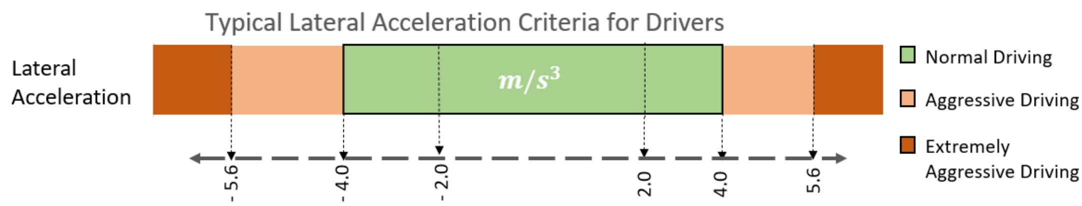

FIGURE 5.10: Range of Acceptable Lateral Acceleration Values

Chapter 6

Results and Analysis

6.1 Longitudinal Controller

6.1.1 First Scenario

As mentioned in the previous section, by looking at the relative speed and distance of the ego vehicle and the lead vehicle, the overall performance of the controllers in VCM and DCM modes can be observed.

As shown in Figure 6.1, in this scenario both vehicles are driving at a speed of $20\frac{m}{s}$ for about 13s before the lead vehicle aggressively slows down to a full stop. Figure 6.2 shows the relative distance between the two vehicles, the desired, and the safe distance. Both controllers show sufficient performance following the desired distance while slowing down to a full stop.

The main disadvantage of the classic ACC method is its switching method. As discussed before, when the distance error between the actual relative distance and the desired distance is close to zero, the classic ACC tends to switch back and forth between the VCM and DCM mode. This can be clearly observed in Figure 6.3 throughout the first 10 seconds of the test. When the vehicle switches to VCM mode from DCM mode, it tends to accelerate the vehicle to match the vehicle speed to the set speed. This reduces the relative distance between the ego and lead vehicle and forces the ACC back to DCM mode. This excessive switching between the two controller modes can best be visualized in Figure 6.3.

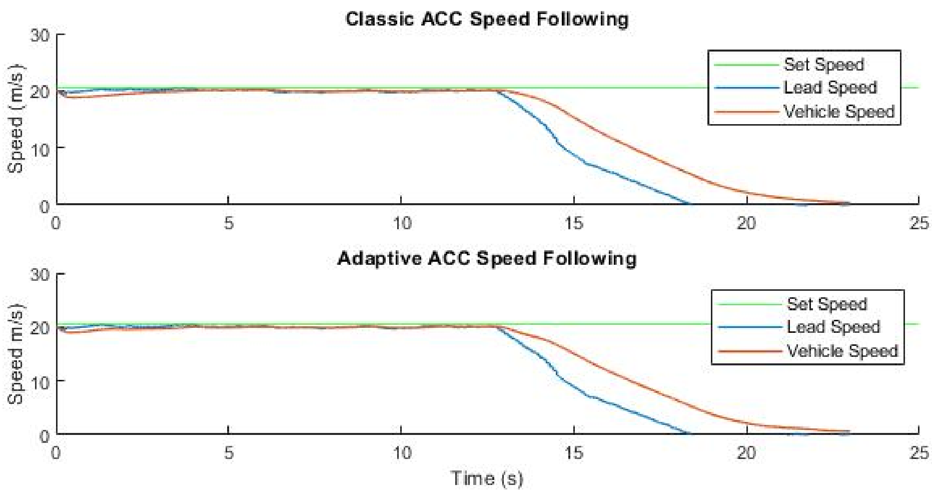

FIGURE 6.1: Scenario 1 - Speed Profile

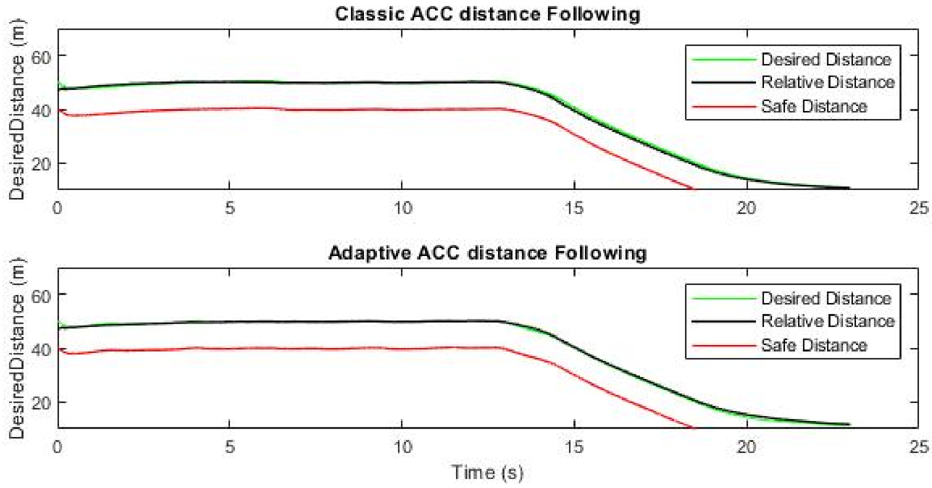

Figure 6.2: Scenario 1 - Distance Following

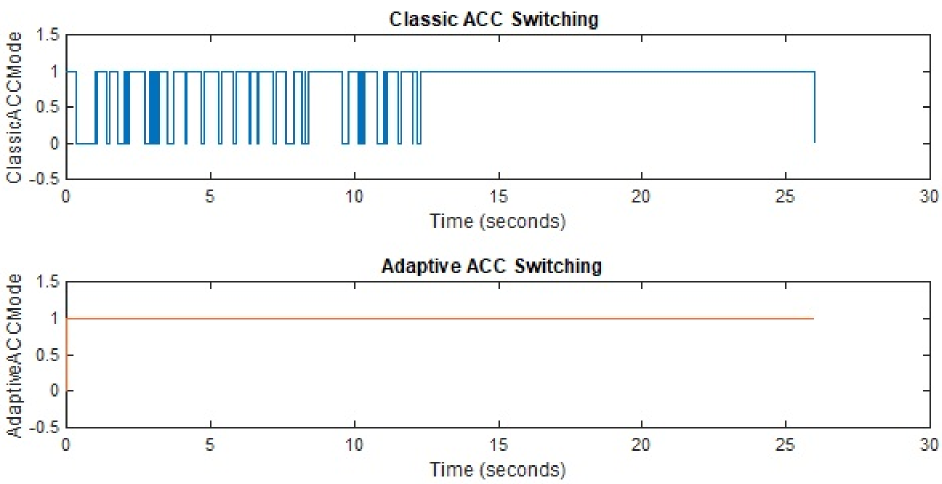

Figure 6.3: Scenario 1 - Switching between VCM (0) and DCM(1)

One of the other evaluation metrics mentioned in the previous chapter is the ride comfort. As mentioned before, ride comfort can be evaluated based on the longitudinal acceleration experienced by the driver throughout the ride. Based on the standards available, the longitudinal acceleration values are divided into three categories of comfortable acceleration, aggressive acceleration, and extremely aggressive acceleration. Figure 6.4, present the longitudinal acceleration of the ride with each of the controllers. The green and red horizontal lines mark the boundaries between different acceleration categories described above. As we can see throughout the first 10 seconds of the ride, the classic ACC has a jerky acceleration profile which is due to the excessive switching between the VCM and DCM mode.

Figure 6.5, plots the bar graph of the RMSE error of acceleration and jerk between the two controllers. Results indicate reduction in longitudinal acceleration throughout the ride which improves driver comfort.

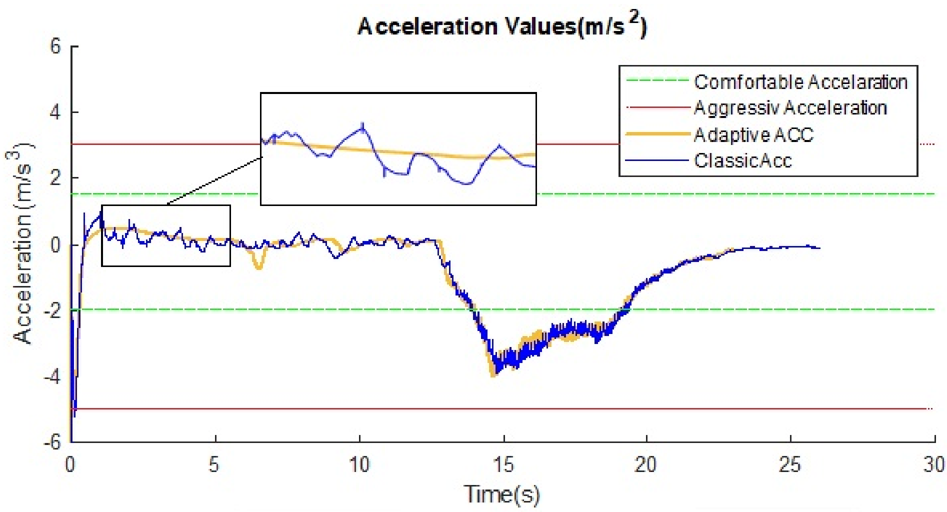

FIGURE 6.4: Scenario 1 - Longitudinal Acceleration Evaluation

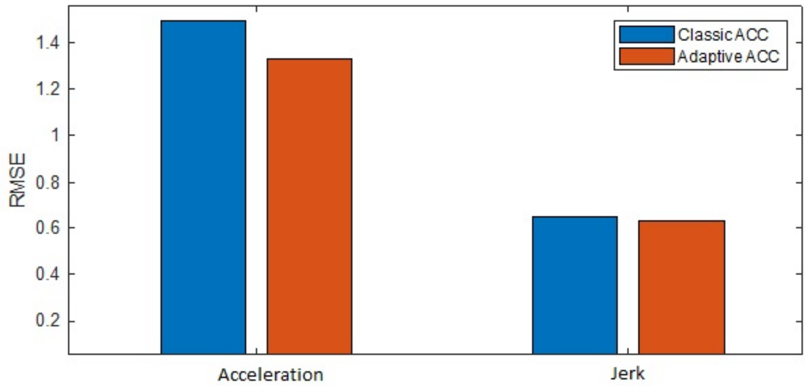

FIGURE 6.5: Scenario 1 - Longitudinal Acceleration and Jerk RMSE Evaluation

6.1.2 Second Scenario

In the second scenario, the ego vehicle is driving at 20 $\frac{m}{s}$ while approaching a slow lead vehicle driving at $16\frac{m}{s}$ much further away. In classic control, switching between VCM and DCM happens once the lead vehicle is closer than the desired distance. Upon the switching, the DCM aims to maintain the relative distance between the ego vehicle and the lead vehicle close to the desired distance. While this switching method works theoretically, in a case like this one where the lead vehicle is driving at significantly lower speed, the transition between the VCM and the DCM will be harsh and once the lead vehicle is detected, the ego vehicle will brake to maintain the desired distance.

However, the Adaptive ACC proposed in this project has the condition of entering the DCM earlier if there is a lead vehicle detected further away that is driving significantly slower. This will in return create a smoother velocity profile and it will give the ego vehicle more time to slow down and match the speed of the lead vehicle.

This phenomena can be better observed in Figures 6.6 and 6.7. While in the classic ACC the ego vehicle goes from $20\frac{m}{s}$ to $16\frac{m}{s}$ within 5 seconds, the adaptive enters the DCM mode much earlier and therefore has a smoother velocity profile and decreases the vehicle speed from $20\frac{m}{s}$ to $16\frac{m}{s}$ within 15 seconds.

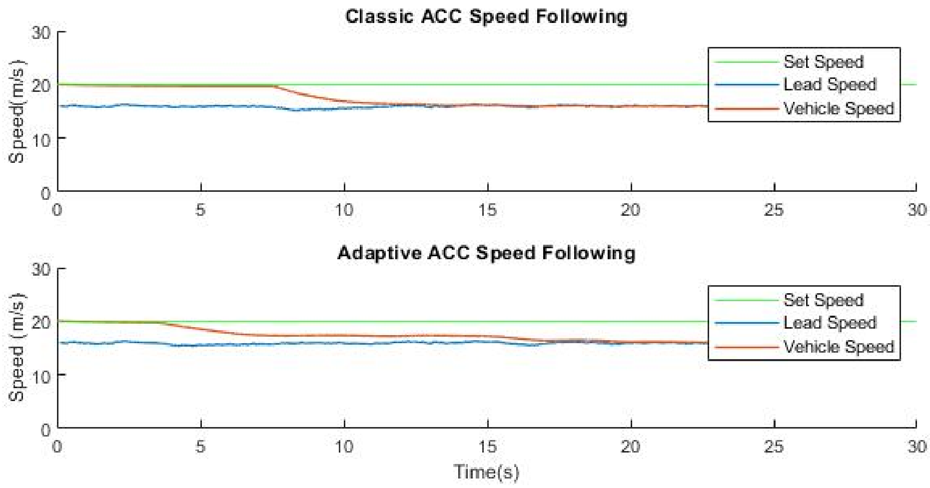

Figure 6.6: Scenario 2 - Speed Profile

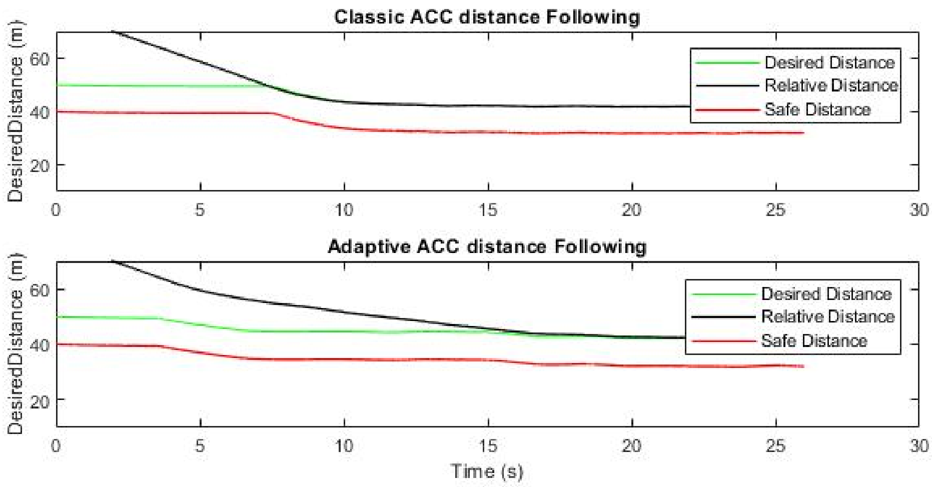

FIGURE 6.7: Scenario 2 - Distance Following

Figure 6.8, shows the frequency of the switching between the two modes of ACC amongst the two controllers. It's seen that the adaptive ACC is entering the DCM mode much earlier than the classic ACC. Besides, repetitive switching occurs between the VCM and DCM in the classic ACC when the error between the relative distance and the desired distance reaches zero.

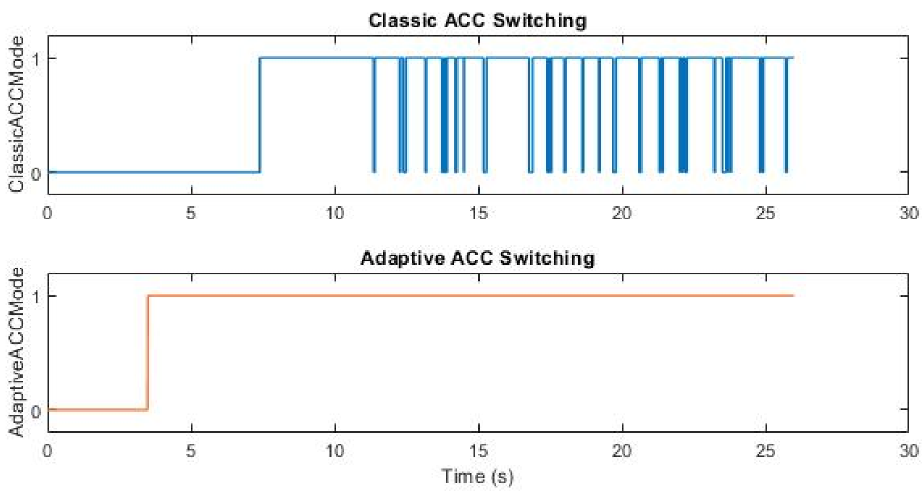

FIGURE 6.8: Scenario 2 - Switching between VCM(0) and DCM(1)

Last but not least, the driver comfort of this scenario is evaluated by looking at the longitudinal acceleration throughout the ride. As mentioned above, the fact that adaptive ACC switches to DCM earlier than the classic ACC increases driver comfort and decreases the intensity of the brake upon reaching the lead vehicle. This is mostly visible in Figure 6.9 below around seconds 5-10 which is when each controller switches to the DCM mode.

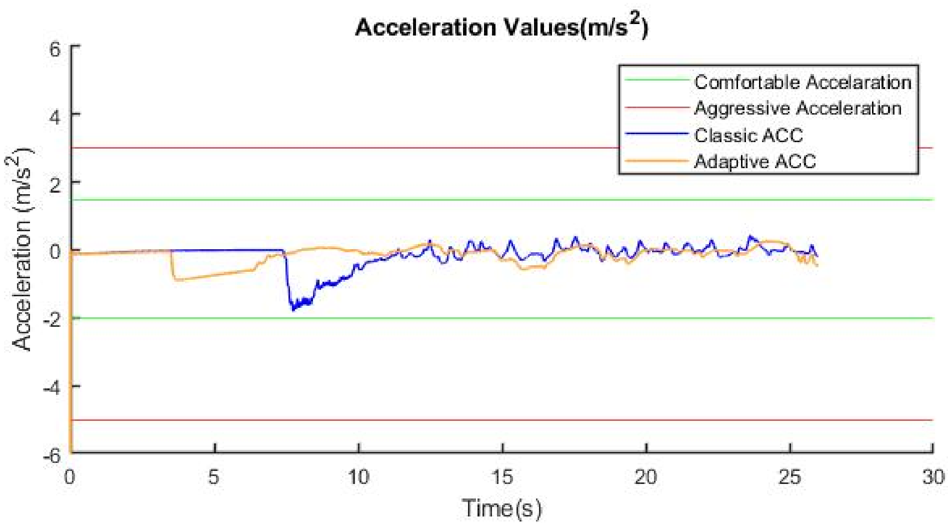

FIGURE 6.9: Scenario 2 - Longitudinal Acceleration Evaluation

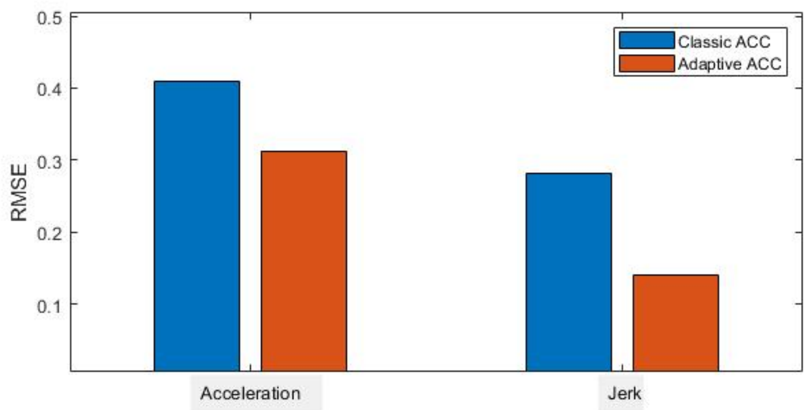

FIGURE 6.10: Scenario 2 - Longitudinal Acceleration and Jerk RMSE Evaluation

The RMSE errors for acceleration and jerk of each of these controllers for this scenario can be seen in Figure 6.10. There is noticeable improvement in driver comfort dues to the reduction of longitudinal acceleration in the adaptive ACC.

6.1.3 Third Scenario

In this scenario, the response of the system to an aggressive cut in is evaluated. The response of the two controllers are quite different in this scenario. The classic ACC applies an aggressive braking when the lead vehicle cuts in front of the ego vehicle. while this ensures the relative distance remains above the desired distance, the aggressive braking creates discomfort.

Figures 6.11, 6.12 present the performance of these controllers in VCM and DCM mode. While both controllers perform adequately, the response of the adaptive controller creates a smoother velocity profile and less longitudinal acceleration.

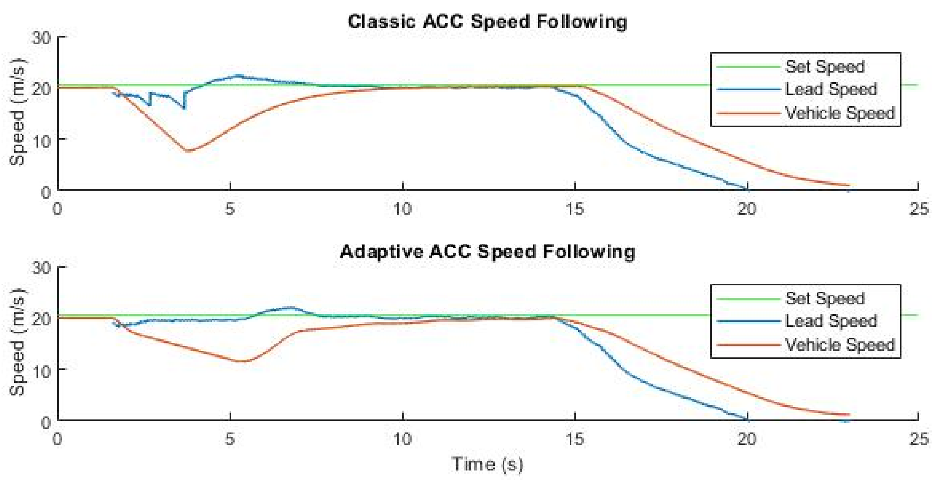

FIGURE 6.11: Scenario 3 - Speed Profile

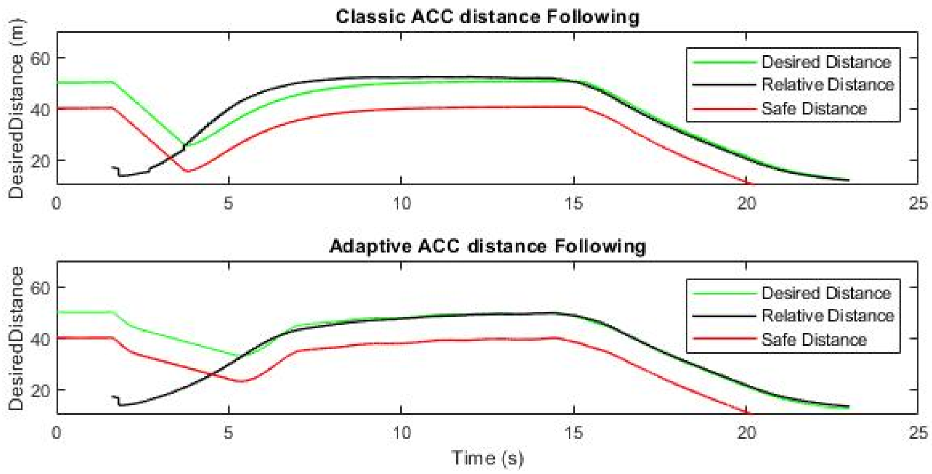

FIGURE 6.12: Scenario 3 - Distance Following

The excessive braking of the classic ACC increases the distance between the lead vehicle and the ego vehicle enough to switch the ACC mode back to VCM. The jerk caused by the aggressive braking followed by an aggressive acceleration creates a significant discomfort for the driver. This behaviour of the classic ACC can be seen in Figure 6.14 below.

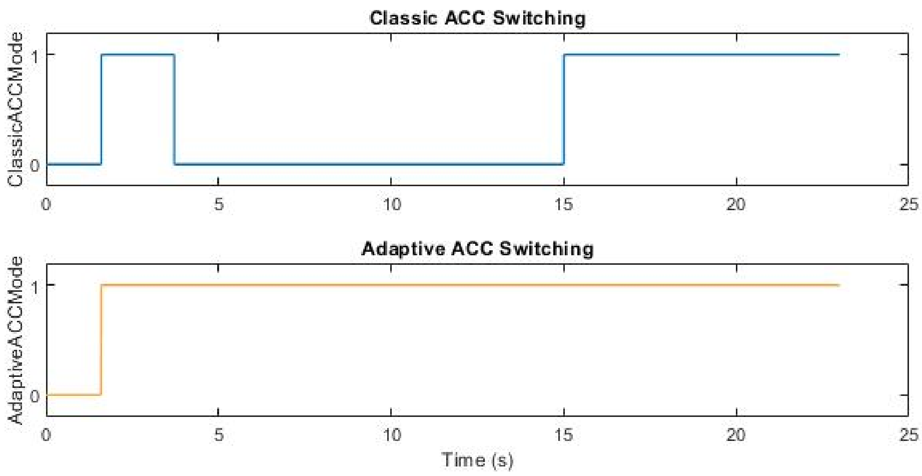

FIGURE 6.13: Scenario 3 - Switching between VCM(0) and DCM(1)

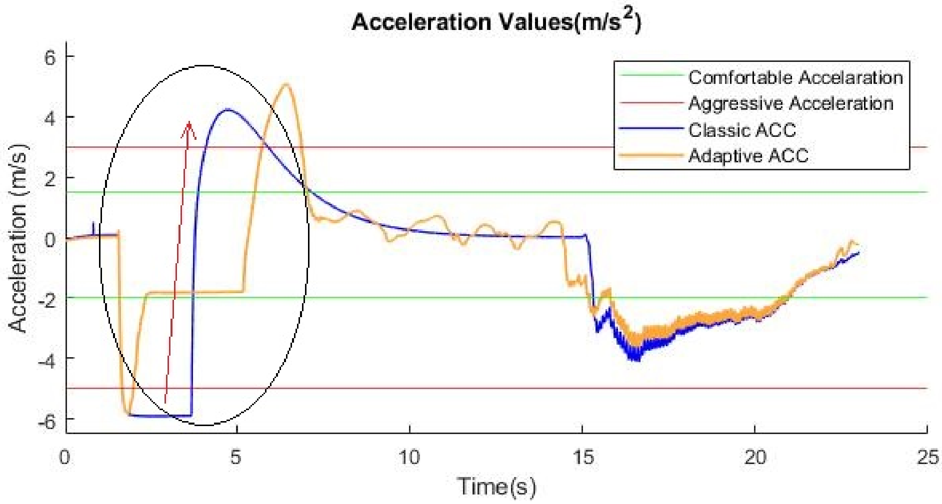

FIGURE 6.14: Scenario 3 - Longitudinal Acceleration Evaluation

The RMSE error associated with the longitudinal acceleration and jerk of both controllers, confirms the above conclusions. The adaptive ACC has improved the driver comfort compared to the classic ACC in scenario 3.

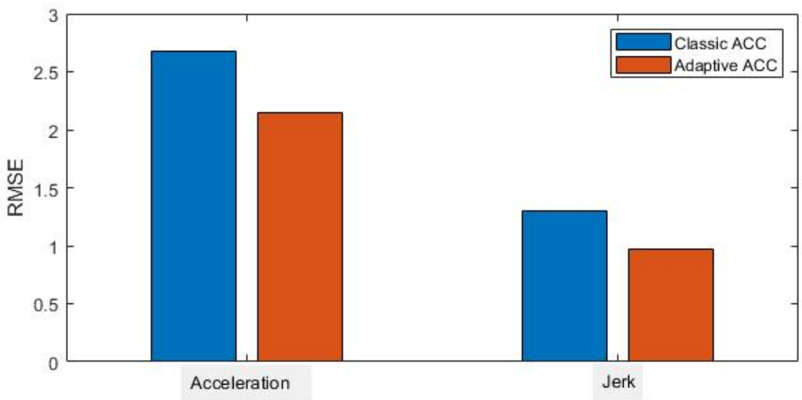

FIGURE 6.15: Scenario 3 - Longitudinal Acceleration and Jerk RMSE Evaluation

6.2 Lateral Controller

In the development of the lateral controller for lane centering applications, the aim is to design a system that remains stable and performs adequately under different maneuvers. Stanley and MPC each have their limitations. While their performance is good in some driving scenarios, they lack stability in others. The test scenarios designed for the evaluation of the lateral controller, covers all these different edge cases to ensure the proposed controller in fact improves path tracking and drive quality performance of the LCA system.

6.2.1 First Scenario

In the first scenario the stability of the system is evaluated under large lateral deviation. This is a major weakness of the Stanley method since the system does not have any predictive factor in it, the controller simply attempts to eliminate this lateral error. This reaction results in major overshoot which pushes the vehicle out to the other side of the lane. This Oscillation can be observed in Figure 6.16 below. While MPC has similar behaviour in the case of major lateral error, the predictive nature of this controller reduces the overshoot and therefore the oscillation.

The Fuzzy MPC in contrast, does not oscillate as much and smoothly brings the vehicle back to the center of the lane. The fact that cost function gains of the adaptive MPC are adjusted to the relative position of the vehicle to the path, ensures stability. The steering angle request of each controller can be observed in Figure 6.17 below.

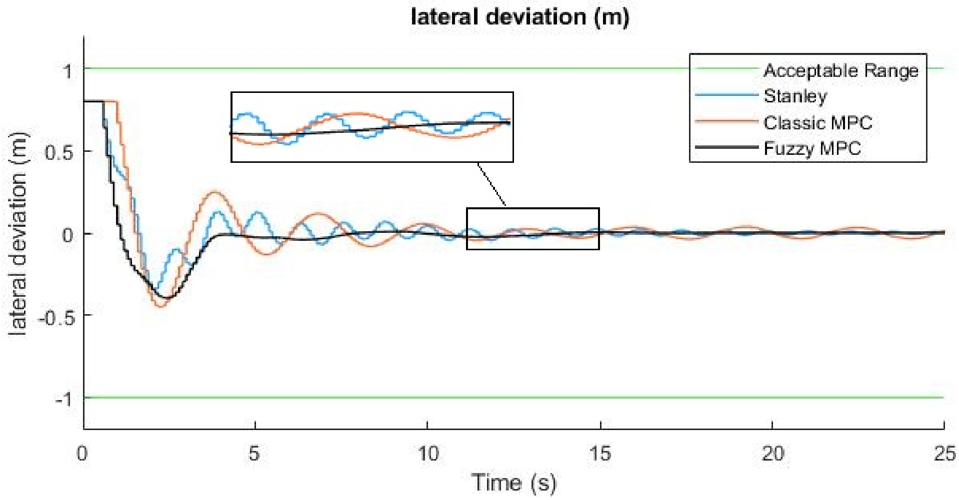

FIGURE 6.16: Scenario 1 - Lateral Offset

While in the beginning of the test the Fuzzy MPC controller requests a big steering angle input to bring the vehicle closer to the center, as the vehicle gets closer to the center, the controller prioritized the heading angle error between the vehicle and the road to ensure the vehicle approaches the center of the lane slowly and smoothly.

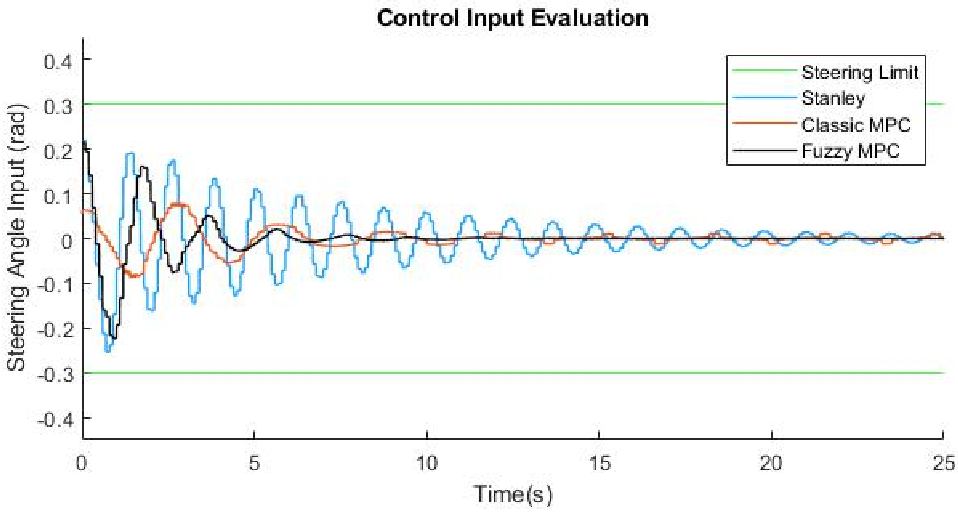

FIGURE 6.17: Scenario 1 - Steering Angle Input

Lateral stability not only is hand in hand with the path tracking performance, it also impacts the drive quality. As mentioned in the previous chapter, lateral acceleration is a measure of driver comfort throughout a ride. Figure 6.18 below, presents the lateral acceleration caused by each controller. The resulting lateral acceleration demonstrates the improvement in driver comfort that Fuzzy MPC provides compared to Stanley and Classic MPC.

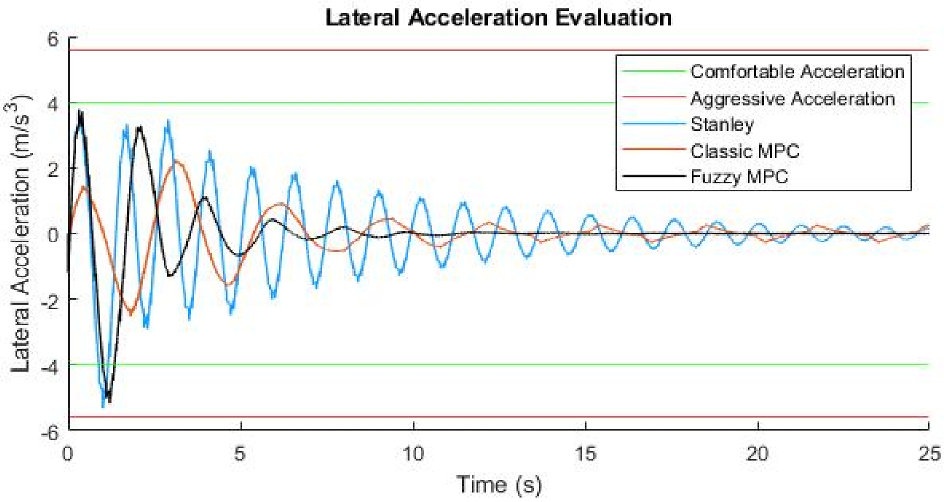

FIGURE 6.18: Scenario 1 - Lateral Acceleration

Figure 6.19 below, shows the mean and average absolute error for lateral deviation and lateral acceleration. It's important to note that to better interpret the performance of each controller, one must look at all these factors at the same time. While the mean of the lateral deviation can demonstrate an overall overview of the path tracking performance of each controller, one can not conclude improvement in performance without looking at the average absolute error since the oscillations are not well represented in the mean calculation. Same goes with the lateral acceleration.

Together, the results suggest a significant improvement in the performance of the controller under large lateral deviation. The Fuzzy MPC controller reaches lateral stability much faster with less lateral acceleration resulting in a more comfortable ride.

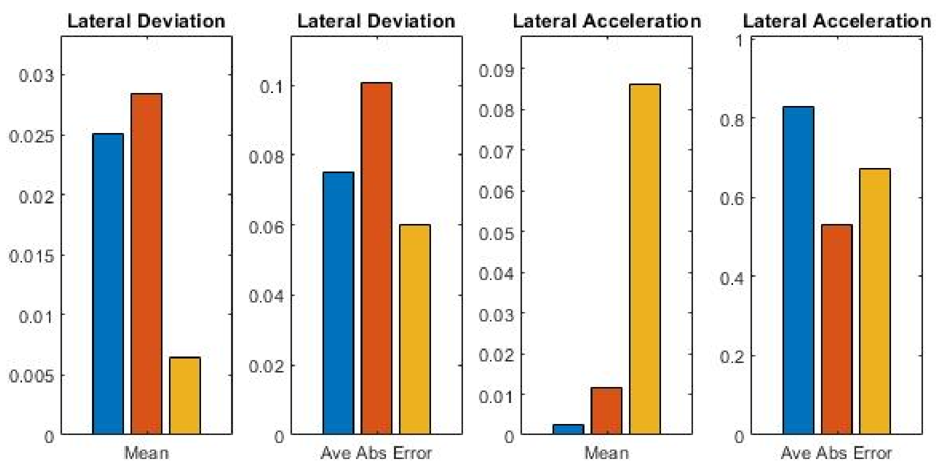

FIGURE 6.19: Scenario 1 - RMSE Error

6.2.2 Second Scenario

The second scenario involves a curved toad with a small radius of curvature. Since the Stanley controller is based on the current instance in time, the controller finds a balance between the heading error and the lateral error term. While the system is steady when faced with a tight curve, it suffers from a large steady state lateral offset error.

MPC on the other hand constantly attempts to reduce this steady state error which in turn creates an oscillation in the system. Fuzzy MPC however, has the least steady state error throughout the curve while it also has the minimum amount of oscillation. The response of all three controllers can be seen in Figures 6.20 and 6.21.

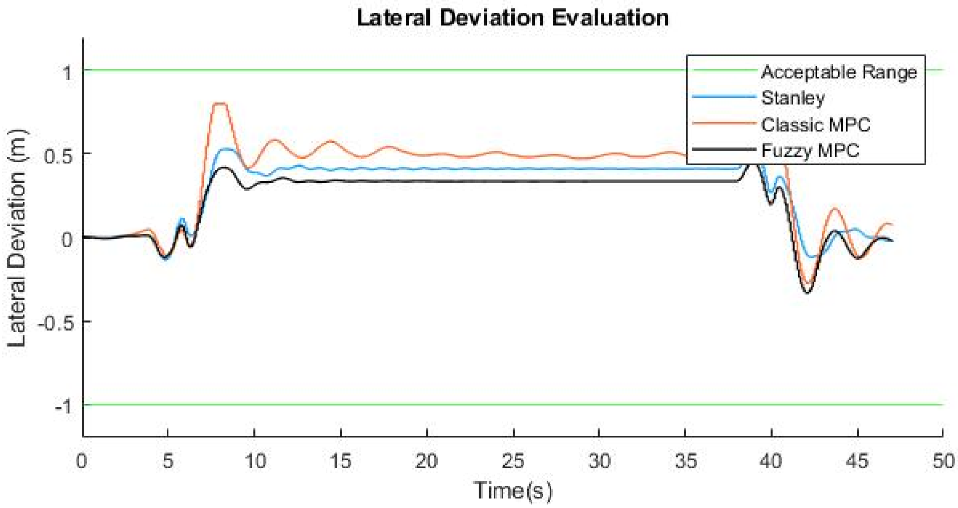

FIGURE 6.20: Scenario 2 - Lateral Offset

This Oscillation can be seen in Figure below. While Fuzzy MPC reaches stability, Stanley and MPC experience oscillations throughout the curve. The adaptability of the Fuzzy MPC controller creates a smoother steering.

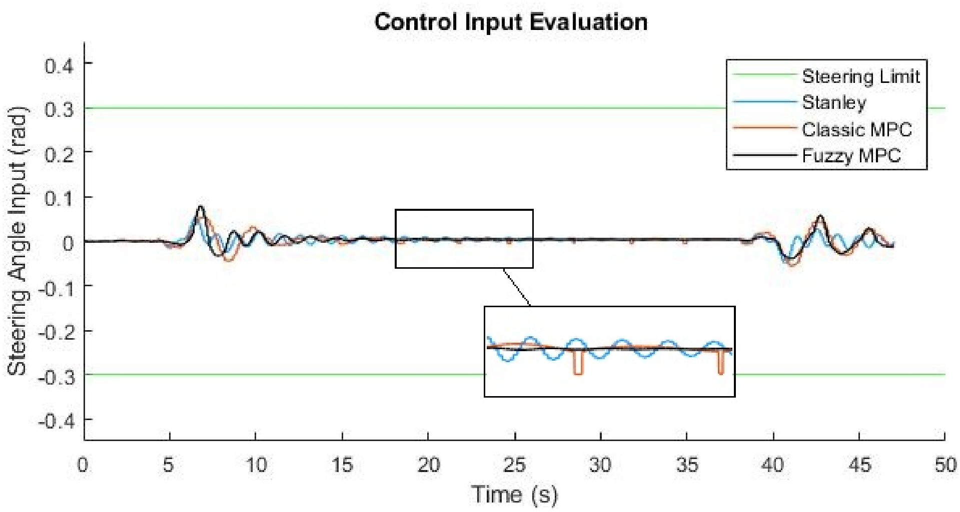

FIGURE 6.21: Scenario 2 - Steering Angle Input

Figure 6.22 below evaluates the driver comfort throughout this test. While all acceleration values for all three controllers remain within the comfortable acceleration boundaries, the oscillations cause discomfort.

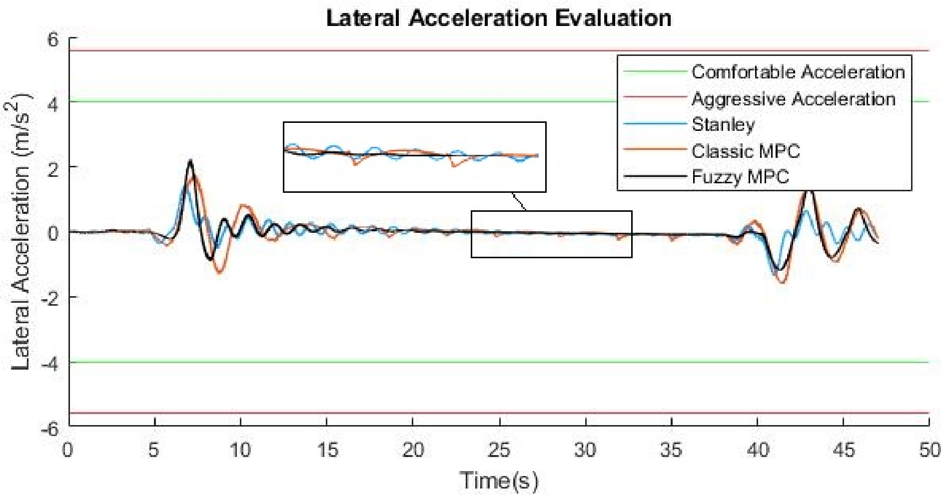

FIGURE 6.22: Scenario 2 - Lateral Acceleration

Looking at the mean and average absolute error values shown in Figure 6.23, the difference in the lateral deviation and lateral acceleration of the controllers is more prominent.

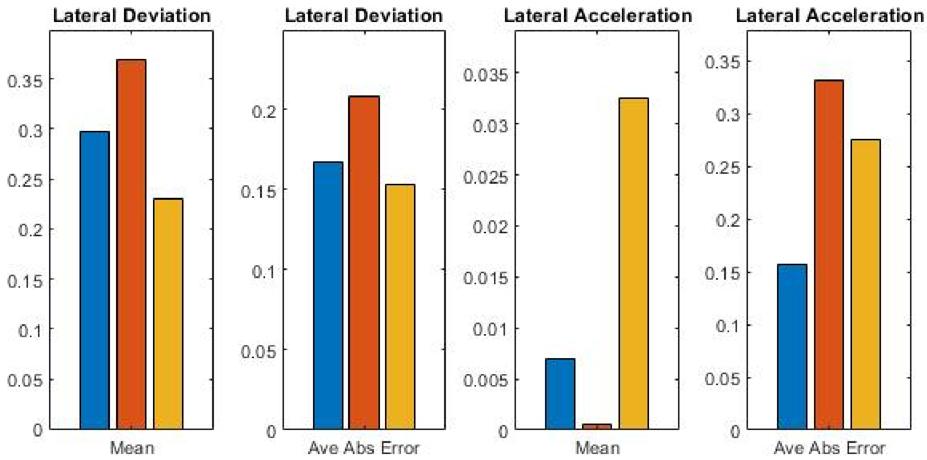

FIGURE 6.23: Scenario 2 - RMSE Error

Lateral deviation of Fuzzy MPC is noticeably lower and hence path tracking performance of the system is better. Looking at the Acceleration mean and absolute error, it can be noticed that on average, Fuzzy MPC has higher acceleration values. This is due to the extra steering that this system has applied to maintain the vehicle closer to the center of the lane. Looking at Figure 6.23 and 6.21 together, one can conclude that even though the magnitude of the steering input applied by the Fuzzy MPC is higher, since the oscillations are minimized throughout the ride, the overall driver comfort is better in Fuzzy MPC.

6.2.3 Third Scenario

The third scenario is an S shaped road. Figure 6.24 presents the lateral deviation of each controller throughout the test. Stanley and Classic MPC controllers both have the larger lateral deviations.

Figure 6.25, shows the control input or steering angle request throughout the ride. Similar to the last two scenarios, Stanley and Classic MPC tend to oscillate more.

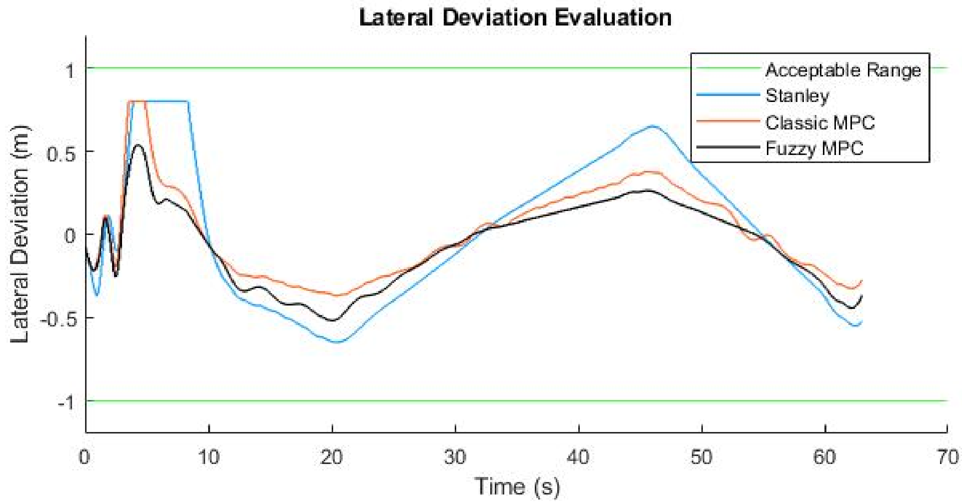

FIGURE 6.24: Scenario 3 - Lateral Offset

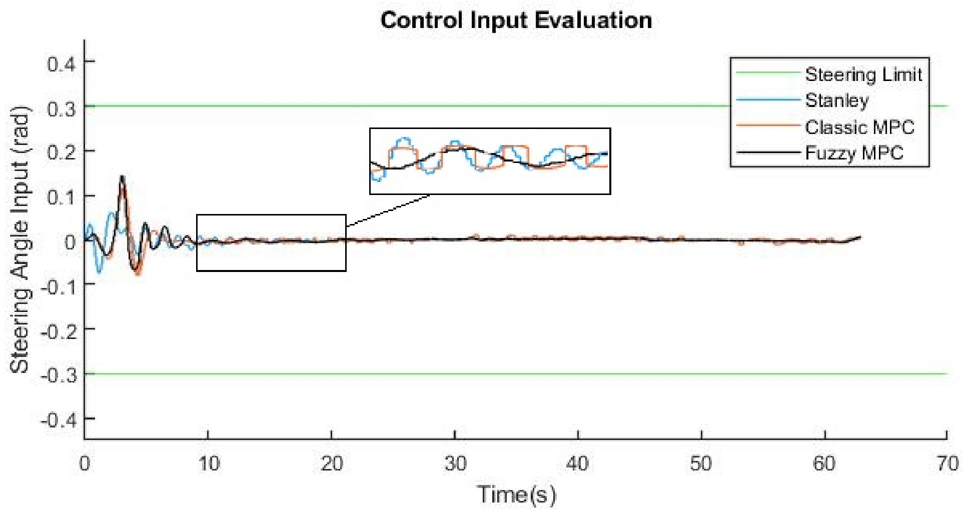

FIGURE 6.25: Scenario 3 - Steering Angle Input

Looking at the lateral acceleration in Figure 6.26, Stanley has lower maximum acceleration compared to other two controllers. However, all three controllers remain within the comfortable lateral acceleration boundaries. Additionally, it's apparent that Classic MPC oscillates more while the other two controllers reach stability faster.

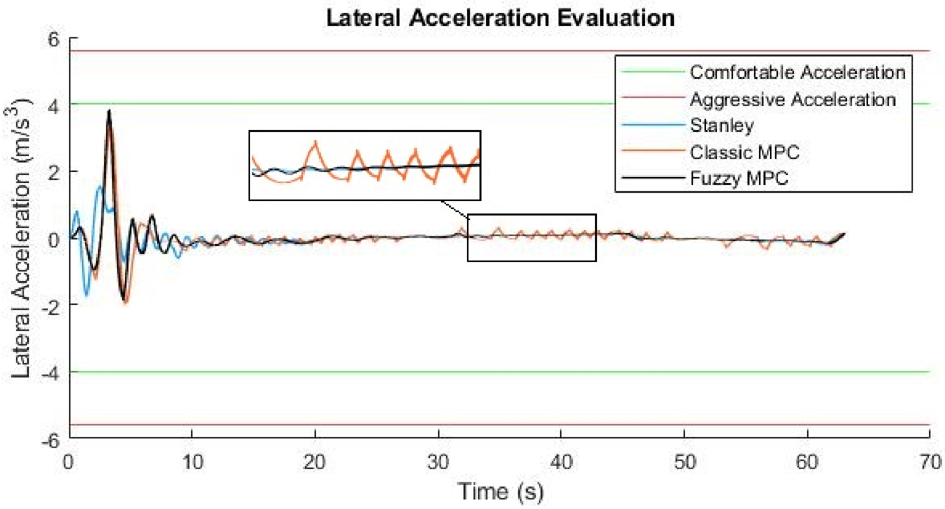

FIGURE 6.26: Scenario 3 - Lateral Acceleration

Looking at the mean and average absolute error of this scenario in Figure 6.27, the mean of lateral deviation of the Fuzzy MPC seems to be higher than the other two. However, looking at the average absolute error and the lateral deviation itself which is plotted in Figure 6.24, one can conclude that Fuzzy MPC has a better performance in path tracking since it remains closer to center of the lane at all times.

On the other hand, while the mean of the lateral acceleration of the Fuzzy MPc tends to be lower, its average absolute error is higher. This indicated that even though lateral acceleration of the Fuzzy MPC is significantly lower than the Classic MPC, it is higher than the lateral acceleration of the Stanley controller.

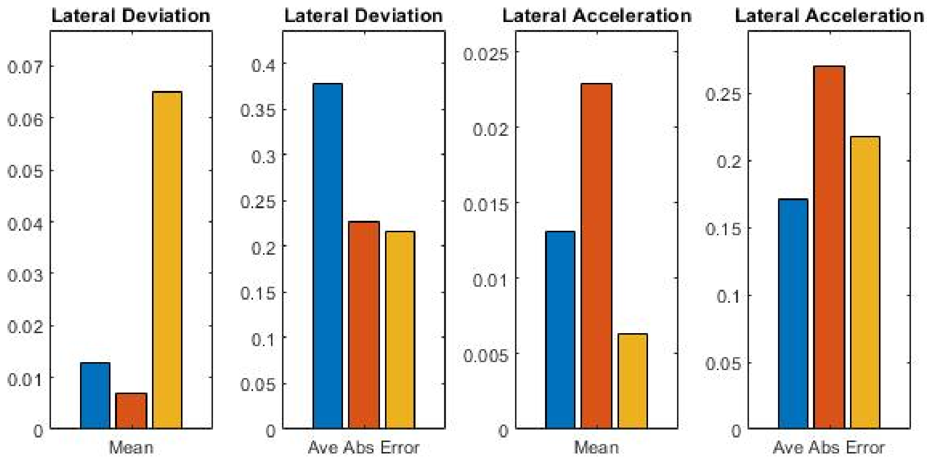

FIGURE 6.27: Scenario 3 - RMSE Error

As proposed, given the results above Fuzzy MPC can cover a better driving comfort performance while improving the path tracking accuracy. This proposed controller guarantees lateral stability under different conditions and throughout the whole process of tracking.

Chapter 7

Conclusion and Future Work

Motor vehicle fatalities are one of the top unnatural causes of death across the world. Advanced vehicle assistance technologies not only aim to increase driver safety by reducing the number of crashes, they also have significant impacts on energy consumption, pollution, congestion and transportation accessibility enabling older people or people with disabilities to also freely and easily commute[6].

In this project, a new Advanced Driver Assistance System(ADAS) called SmartCruise is introduced. This system is a combination of two ADAS technologies: Adaptive Cruise Control (ACC) which controls the longitudinal motion of the vehicle and Lane Centering Assist (LCA) which handles the lateral motion of the vehicle.

ACC is a driver assist system that adjusts the speed of the vehicle to maintain a certain distance with the vehicle in front of it, while also following a set speed assigned by the driver. To achieve this, classic ACC systems have two modes: Distance Control Mode (DCM), and Velocity Control Mode (VCM) which is the classical cruise control.

An improved adaptive switching ACC is presented for the longitudinal controller of the system. The proposed controller has a few advantages over the classic ACC systems. Firstly, a new controller called a Following Control Mode (FCM), replaces the previously mentioned DCM. FCM combines two smaller controllers that aim to not only maintain the distance between the vehicle and the lead vehicle close to the desired distance, but also match the speed of two vehicles in order to improve the distance-following performance. Additionally, a new switching method is implemented in the Adaptive switching ACC controller which reduces frequent switching between the VCM and FCM modes and hence reduces longitudinal jerk and increases driver comfort. The proposed Adaptive switching ACC system is evaluated under three different driving scenarios and the results of this controller are evaluated against the performance of the classic ACC by comparing vehicle following capabilities and driver comfort.

For the lateral system, a Fuzzy Model Predictive controller (MPC) has been presented. This controller predicts the future state of the vehicle and the path, and finds the optimized control input that minimizes the lateral offset and heading error of the vehicle with the trajectory. A fuzzy control logic is applied to this controller which allows for the cost function weights to automatically change. While Stanley and classic MPC both have constant gains regardless of the relative position of the vehicle to the trajectory, Fuzzy MPC adapts cost function weight factors of the system to the current state of the vehicle to ensure stability and improve the performance. Same as the longitudinal controller, the performance of the lateral controller is evaluated under three different simulation tests. Simulation results of the proposed controller are then compared with classic MPC, and the Stanley controller to verify lateral stability of the system along with the driver comfort.

The effectiveness of the proposed system for both the longitudinal and lateral controllers are evaluated via MATLAB SIMULINK Driving Scenario Designer app. All six driving scenarios are designed and tested using this application. Based on the simulation results of both longitudinal and lateral controllers, the following conclusions are drawn:

Adaptive Switching ACC

- The proposed adaptive switching ACC solves the repetitive switching problem of Classic ACC
- The addition of FCM, improves the transition between the VCM and DCM resulting in less aggressive acceleration and braking and hence a more comfortable ride
- The tracking performance of the system is good and the relative distance between the vehicle and the lead vehicle always remains within 1 meter of the desired distance, unless the vehicle is operating in the VCM mode or is in transition between the two modes

Fuzzy MPC

- Fuzzy MPC improves tracking accuracy compared to classic MPC and Stanley controller
- The proposed controller ensures lateral stability when responding to a large lateral offset

- The control input of the system remains within the boundaries of comfortable steering throughout all scenarios

Future research in this area can address the following two topics:

1. There are certain assumptions made throughout the kinematic and dynamic modeling of the vehicle. While these assumptions simplify the model formulation, they result in modeling inaccuracies. One of the assumptions worth investigating is the assumption of constant longitudinal velocity throughout the lateral modeling of the vehicle. This assumption increases inaccuracies when the vehicle is driving on a curved path. Another major assumption is the linearization of the dynamic model of the vehicle by ignoring the non-linear factors such as non-linear forces acting on the vehicle and suspension forces.

   It's worth noting that such assumptions significantly reduce computational cost of the system, which is a limiting factor in formulation of MPC. However, the impact of such simplifications must not be overlooked and is worth investigating.

2. Moreover, in the formulation of the Fuzzy control logic inference, the current fuzzy rule combination has been selected by trial and error. While the selected set of rules improve the performance of the system, it might not be the most optimal. In future work, an optimization algorithm such as a genetic algorithm or a pattern search algorithm can be applied to the fuzzy rule selection to find the most optimal set of rules.

References

[1] Evan Ackerman. Google's Autonomous Car Takes To The Streets. *IEEE Spectrum* (2010).

[2] Admin. LiDAR and RADAR Information (2019).

[3] Adriano Alessandrini. *CityMobil2: Challenges and Opportunities of Fully Automated Mobility*.

[4] Hudha K Amer NH. Adaptive modified Stanley controller with fuzzy supervisory system for trajectory tracking of an autonomous armoured vehicle. (2018).

[5] Jodi Joseph Asiag. *How Ultrasonic Sensor Data is Powering Automotive IoT*. Last accessed 16 September 2017. 2021.

[6] Autonomous vehicles: challenges, opportunities, and future implications for transportation policies. *Journal of Modern Transportation* 24(4) (2016).

[7] J. Betroni L. Guanetti. An adaptive cruise control for connected energy-saving electric vehicles. (2017).

[8] BOSCH, Corner Radar Sensor (2021).

[9] BOSCH, Front Radar Sensor (2021).

[10] BOSCH, Mid-Range Sensor (2021).

[11] Transportation Association of Canada. Geometric Design Manual Part 2 (2001).

[12] National Robotics Engineering Center. *Autonomous Platform Demonstrator*. Last accessed 16 September 2017. 2021.

[13] Jessica Shea Choksey. What is LiDAR, and How Does it Work? (2021).

[14] Paul Deutsch. Design of Horizontal Curves ().

[15] Yan Ding. Three methods of vehicle lateral control : Pure Pursuit, Stanley and MPC (2020).

[16] DJ Fagnant and K Kockelman. Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. Transp Res Part A 77 (2015), 167–181.

[17] J. Firoozi R. Guanetti. Safe Adaptive Cruise Control with Road Grade Preview and V2V Communication (2018).

[18] Donald B. Gennery. A stereo vision system for an autonomous vehicle (1977).

[19] Kristin Gillespie. *Ultrasonic Sensors: Advantages and Limitations*. Last accessed 16 September 2017. 2019.

[20] GPS.gov. What is the government's commitment to GPS accuracy? (2021).

[21] Gabriel M Hoffman. Autonomous automobile trajectory tracking for off-road driving: Controller design, experimental validation and racing (2007).

[22] Jaeyoung Moon I Bae. Toward a Comfortable Driving Experience for a Self-Driving Shuttle Bus (2019).

[23] Nidhi Kalra James M. Anderson. Autonomous Vehicle Technology (2016).

[24] Erkan Adali Kadir Haspalamutgil. Adaptive Switching Method for Adaptive Cruise Control (2017).

[25] Hojun Kim. Localization of a car based on multi-sensor fusion (2018).

[26] Scott Kovesdy. An open, transparent, industry driven approach to safety (2018).

[27] KPMG. Connected and Autonomous Vehicles - the UK Economic Opportunity (2015).

[28] D. Lin X. Gorges. Simplified Energy-Efficient Adaptive Cruise Control based on Model Predictive Control (2017).

[29] Long Range Radar Specifications. *Continental* (2021).

[30] C. Lu and A. Aakre. A new adaptive cruise control strategy and its stabilization effect on traffic flow. (2018).

[31] M McDonald and J Piao. *Advanced driver assistance systems from autonomous to cooperative approach. Transp Rev 28:659–684*. 2008.

[32] Daniel V McGehee et al. Review of Automated Vehicle Technology: Policy and Implementation Implications (2016), 41.

[33] Maggetto Mierlo M. Driving style and traffic measures influence on vehicle emissions and fuel consumption (2004).

[34] NHTSA. *The Road to Full Automation.*

[35] Tamas Becsi Oliver Toro. Design of lane keeping algorithm of autonomous vehicle (2015).

[36] Sharon L. Poczter and Luka M. Jankovic. The Google Car: Driving Toward A Better Future? *Journal of Business Case Studies (JBCS)* 10(1) (Dec. 31, 2013), 7. ISSN: 2157-8826, 1555-3353. DOI: 10.19030/jbcs.v10i1.8324.

[37] Rajesh Rajamani. *Introduction to Longitudinal Control*. Springer, 2011.

[38] Pontus Riis. Simulation of a distributed implementation of an adaptive cruise controller (2007).

[39] Li Wang Rui Fan. Computer Stereo Vision for Autonomous Driving (2020).

[40] R Isermann S Dermann. Non-linear distance and cruise control for passenger cars (1995).

[41] *SAE International Releases Updated Visual Chart for Its "Levels of Driving Automation" Standard for Self-Driving Vehicles*. 2018.

[42] Smartrak. Why Mobility as a Service is the future of transportation (2021).

[43] Jarrod M. Snider. Automatic steering methods for autonomous automatic path tracking (2009).

[44] *SUPER CRUISE™ Convenience & Personalization Guide*. 2021.

[45] THALES. 7 Benefits of autonomous cars (2017).

[46] Anthony Townsend. The 100-Year History of Self-Driving Cars. *OneZero* (Aug. 2020).

[47] United States Department of Transportation. Automated Vehicles for Safety (2021).

[48] Helbing D Treiber M Hennecke A. Congested traffic states in empirical observations and microscopic simulations (2000).

[49] Silvas Van Nunen Verhaegh. Robust Model Predictive Cooperative Adaptive Cruise Control Subject to V2V Impairments (2017).

[50] Milankumar Ambalal Vivek K. a Comparative study on Stanley, LQR and MPC controllers for path tracking applications (ADAS/ AD) (2019).

[51] Junmin Wang and Rajesh Rajamani. Should Adaptive Cruise-Control Systems be Designed to Maintain a Constant Time Gap Between Vehicles? (2004).

[52] Meng Q Wang w. Camera bassed decision making at roundabouts for autonomous vehicles (2018).

[53] Leah A. Wasser. The Basics of LiDAR - Light Detection and Ranging - Remote Sensing (2020).

[54] Wikipedia. Automobile drag coefficient (2021).

[55] Wikipedia. *Futurama (New York World's Fair)*. Mar. 2021.

[56] Wikipedia. Global Positioning Sensors (2021).

[57] Wikipedia. History of self-driving cars (2020).

[58] Wikipedia. Mobility as a service (2021).

[59] Wikipedia. Ultrasonic transducer (2021).

[60] Designed to Innovate YellowScan. LiDAR vs. Radar (2020).

[61] P Fancher Z Bareket. Evaluating headway control using ranger versus range-rate relationships (1994).

[62] P Fancher Z Bareket. Headway Control systems and the heacy commertial vehicle : A case study. (1995).

[63] Chen J Zhao P. Design of a control system for an autonomous vehicle based on adaptive PID (2012).