Collision and Avoidance Modelling of Autonomous Vehicles using Genetic Algorithm and Neural Network

COLLISION AND AVOIDANCE MODELLING OF AUTONOMOUS VEHICLES USING GENETICAL ALGORITHM AND NEURAL NETWORK

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Abstract

This thesis is to study the optimisation problems in autonomous vehicles, especially the modelling and optimisation of collision avoidance, and to develop some optimisation algorithms based on genetic algorithms and neural networks to operate autonomous vehicles without any collision. Autonomous vehicles, also called self-driving vehicles or driverless vehicles are completely robotised driving frameworks to allow the vehicle to react to outside conditions within a bunch of calculations to play out the undertakings. This thesis summarised artificial intelligence and optimisation techniques for autonomous driving systems in the literature.

The optimisation problems related to autonomous vehicles are categorised into four groups: lane change, motion planner, collision avoidance, and artificial intelligence. A chart had been developed to summarise those research and related optimisation methods to help future researchers in the selection of optimisation methods

Collision Avoidance is one of streamlining issues in autonomous vehicles. Several sensors had been used to identify position and dangers and collision avoidance algorithms had been developed to analyse the dangers and to use vehicles to avoid a collision. In this thesis, the current research on collision avoidance has been reviewed and some challenges and future works were presented to select the research direction of this thesis, the aim of this research will be the development of optimisation methods to avoid collisions in a predefined environment.

The contributions of this thesis are that (1) a simulation model had been developed using Matlab for collision avoidance and serval scenarios were proposed and experimented with. The sensors are used as the inputs to determine collision in the learning preparation of the algorithm; (2) a neural network was used for collision avoidance of autonomous vehicles; (3) a new method was proposed with the combination of genetic algorithm and neural network. In the proposed frame, the neural network is used for decision making and a genetic algorithm is used for the training of the neural network. The results and experimentation show that the proposed strategies are well in the designed environment.

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Publications

Yogesh Gadinaik, Jian-Ping Li, Fun Hu, “A Brief Review of Optimisation Problems and Methods for Autonomous Driving,” AIERC conference April 23rd, 2021

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I wish to give my special thanks to my parents for their love, support and encouragement, without whom I would never have enjoyed my study and without them, I would not be here.

1 Introduction

Autonomous vehicles are progressively picking up consideration around the world. The potential of this innovation is obvious, and it is expected to drastically alter transportation, as we know it today (Joshua Joy, 2017). Autonomous vehicles help receive help diminish defilement in urban regions by improving driving and fuel effectiveness to help control the activity stream and to stop issues. In addition, autonomous vehicles will speed up individual and cargo transportation, as well as increase security by decreasing human error. Within the last years, the limits of autonomous vehicles have been pushed due to the reality that industry, governments, and investigation teachers are contributing tremendous sums of both human time and cash (Metz, 2018). Fully autonomous vehicles must be a reality, as was the case by November 2020, Google's self-driving cars had driven more than ten million miles 90 a long time of human driving experience. Technology exchange has moreover been created, and inquiries about propels are being steadily presented in current commercial vehicles within the way of the Advanced Driver Assistance System. Moreover, a few companies: Nissan, Mercedes, Volvo, and Tesla. They have reported their eagerness to have 2022 distinctive models of a commercially reasonable autonomous vehicle.

1.1 Background

As we grow and the number of cars increases, this impacts the public transportation infrastructure and safety issues. There are more than one billion vehicles on the streets, and although the world and many individuals have been murdered in the car, chances of the failure to take over a street or remain on a street (Bagloee *et al*., 2016). As a result, collision avoidance frameworks and indeed autonomous vehicles have been researched for many a long time to help drivers to drive securely and comfortably. The primary prerequisite of such a framework is to detect road and objects, deterrents, and street surfaces. Numerous earlier driver assistance frameworks are slowly showing up in unused vehicles. then, extravagance cars have been prepared with front and raise confronting radars for finding objects in front of and behind the vehicle. The modern vehicles have Dazzle Spot Detectors which use cameras situated on both sides to raise sees mirrors. In the past few decades, governments in most countries have taken serious measures for road safety by introducing both static and dynamic techniques, such as Closed-Circuit Television (CCTV) cameras and road sensors (Hussain and Zeadally, 2019). However, despite these efforts, according to the UK government report, about 1460 reported road deaths and 23529 killed or seriously injured casualties in 2020 in the UK. To minimise driving errors and reduce hazardous situations on the road, alternative techniques such as communication among cars and self-driving vehicles are popular during the past decade, and several working models have been developed by different OEMs. An autonomous vehicle, or a driverless vehicle, can run itself and perform all the necessary functions without any human intervention, through the ability to sense its surroundings (Hulse *et al.*, 2018). Normally, a fully automated driving system is used as an autonomous vehicle to allow the vehicle to sense the surrounding environments, make quick and prompt decisions, navigate on the road, and perform all kinds of manoeuvres. There are tons of expenses for conventional human-driven vehicles, for models, the expense of petroleum, and vehicle support. In general, autonomous vehicles and technology are perceived to have the potential to remove many of these existing negative externalities. Autonomous vehicles are designed to dramatically reduce traffic accidents. This assumes that autonomous vehicles can drop the impact of a human factor on the occurrence of a traffic accident. Even if the number of accidents is lower than a human driver, there are still some traffic accidents in the testing phase. Due to the limitation of techniques and some specific environments, collisions are one of these accidents.

A "Collision Avoidance" framework has the goal of fostering well-being highlights in authors so that there is avoidance of crashes with vehicles or an obstacle in the manner. In terrible climate conditions, these frameworks are particularly helpful. While driving the principal goal of these frameworks is to forestall crashes of the vehicle due to their recklessness or vulnerable side (Kuang Huanga, 2019b). These days vehicular correspondence is becoming well known. The essential benefits of Collision Avoidance are to diminish or preferably kill, switching impacts of specific significance to take out the risk of turning around the walkers. Altogether diminishing the number of scratches and minor crashes, although of low setback hazard, are costly and tedious to fix, and which corrupt the visual appearance of the armada to help activity inbound areas – for example, busways, and tight roads. (Hamid, 2016) To help drivers to keep away from significant impacts, shunts and drivers should be satisfactorily prepared in their use, drivers need to keep a feeling of carefulness and stay away from over-dependence on emotionally supportive networks and admonitions. These days, improvement in car ground vehicles leads to major activity and congestion, where street security is more concerned. In later patterns, collision avoidance is an important calculation to be considered as one of the car security applications. These automotive security applications are more concerned with all human security and security systems. Agreeing to the Association for Safe International Road Travel (ASIRT) (Prabhakaran and Sudhakar, 2018), owing to vehicle crashes, 3,287 people are dying each day. To dodge such inescapable collisions, the calculation is displayed for car ground vehicles. (Md, 2015) Collision avoidance expects the situation, educates the driver, and picks up programmed control of the framework quickly in circumstances of distraction or driver's carelessness. The collision avoidance models proposed in many of the research articles discuss constraint or predefined motion in diverse road scenarios. Recently, an intelligent system is preferred for autonomous vehicles. Nevertheless, such constant motion does not apply to real roads. This motivates to set up adaptive lane switching as a part of this novel research on the detection of obstruction. Adaptive methods are the futuristic research preferred in current trends. In many applications, including automotive, intelligent systems are more preferred to obtain constraint-free where the response of the system is more suitable for real-time applications. In automotive industries, the key role of the researcher is to develop an adaptive collision avoidance algorithm to sidestep imminent collisions. The background of this research is all about the impact of constraint motion on the surrounding vehicles, especially adjoining vehicles. The study of constraint motion is the depth of the chapter on the literature survey. The drawback of proposed methods with constraint motion leads to the motivation of this research and the development of a collision-free environment during overtaking and making the system more adaptive to existing methods. The mathematical model of the proposed method incorporates the position of adjoining vehicles as the key role in the development of adaptive lane switching. Collision avoidance is one of the key components in the functioning of the vehicle to prevent accidents. To supply the best solution, the algorithm should be able to perform more quickly. When it comes to on-road driving, the vehicle should be able to detect objects and perform collision avoidance. Collision Avoidance depends on several components like cameras, lasers, sensors, and radar to screen things that are going on and around a vehicle. With security sense and see other vehicles, activity signals, street signs, as well as cruisers, bikers, and people on foot. The input data is not computer systems that prompt a few sorts of activity from the car or the driver. To induce the driver's consideration, the computer can issue alarms or notice consideration, the computer may issue alarms or notices such as blazing dashboard light, an arrangement of beeps, a pull on the driver's seat belt, or vibration within the controlling wheel. In terms of forwarding, collision signs, such as sounds showing closeness or getting ahead of them. (Pendleton *et al*., 2017) The Autonomous vehicle is a full streamlining and more efficient, more secure vehicle, and more helpful. Over the most recent five years concerning writing, there have been many new assembling organizations, new ventures, and joint efforts, with the main point of improving and fostering a completely programmed autonomous vehicle. Vehicle versatility is quickly expanding and developing with promising elements. In day-to-day life, deep learning, and specifically, neural networks are getting more popular. The neural network has been considered an important breakthrough, and its results are beating ultramodern solutions on problems such as object detection and classification or semantic segmentation and understanding (even surpassing human capabilities. Either being used as a new way for extracting robust features, replacing hand-crafted ones, or end-to-end trainable systems, CNNs (Convolutional Neural Networks) are of special interest nowadays. This context motivates us to take part in the research and development of new and robust Convolutional Neural Network-based algorithms that will perform a key role in the perception systems of autonomous vehicles, substituting standard computer vision approaches.

1.2 Research Aim and Objectives

In the real world, a human can effortlessly drive between the paths by overtaking every one of the obstacles. With regards to moving the vehicle from one point to the destination, there are three issues characterised by collision avoidance, i.e., object identification, direction arranging, path model, and vehicle model. Where is the path model construction? The vehicle model characterises the qualities and dynamic conduct of autonomous vehicles. Also, the direction forecast to conquer the identified deterrent. The main goal of this thesis is to exploit neural network capabilities to efficiently perform collision avoidance in the autonomous driving context. I aim to achieve this high-level goal by tackling and combining genetic algorithms with neural networks to create an efficient framework to distinguish objects or obstacles and stay away from a crash in the most limited time. Item identification is a perplexing cycle dependent on the huge raw information received by the sensors to search for and limit, with the information to be used. In this thesis, neural networks and genetic algorithms are combined to keep the vehicle between the paths and avoid obstructions.

The details of the goals are shown in the following,

1) To view the different streamlining issues in autonomous vehicles and strategies in the literature, especially optimisation problems and collision avoidance in autonomous vehicles.
2) To foster a functional and improved algorithm for collision avoidance used in the created system
3) To study how neural networks and evolutionary computation (i.e, genetic algorithms) can be implemented for collision avoidance.
4) Planning a few situations to evaluate the structure and calculations.
5) Publishing academic papers on collision avoidance of autonomous vehicles.

1.3 Goals & Structure of the thesis

This thesis presents six chapters describing methods developed and applied contributions to improving autonomous vehicle collision avoidance.

Initially, Chapter 1 outlines how autonomous vehicles are demanded in day-to-day life and are being acknowledged in everyday life. The development in the technology to meet demands. Followed by the aim & goal of the thesis. To show how the focus point of the propositions is leaned towards collision avoidance and the strategy for research work.

Secondly, Chapter 2 shows how autonomous vehicles were developed since the 1920s till date. Including summarizing all the functioning components of autonomous vehicles. Self-driving is everything about how a vehicle sees, how it understands the environment, how it finds its location, how it decides the best route, and how it controls itself while in pursuit.

Autonomous vehicle functioning is categorised into two major categories i.e., (hardware-based and software-based). By highlighting major components of the vehicle which define a vehicle as an autonomous vehicle. Along with the possible approaches of the sensors equipped and their range. The following questions will be answered.

1) Where how the vehicle has its subsystem to perform the predefined function according to finding, positioning, trajectory, collision avoidance, and execution.
2) What are the challenges to making fully functioning operational autonomous vehicles?
3) What are the pros & cons of autonomous vehicles?
4) What are the various applications of autonomous driving vehicles?

and finally, the conclusion of the chapter.

Chapter 3: Autonomous driving is done with all components' integration. Autonomous vehicles have problems such as Car following, lane changing, path planning or trajectory planning, and collision avoidance with artificial intelligence and deep learning for decision making. The chapter will show the possible methods of perfecting the problems. How the vehicle is pursuing the environment and finding itself to reach the destination. Highlighting the pros and cons and research gaps of autonomous vehicles.

Chapter 4: Collision avoidance has become one of the major safety concerns in daily life. The manufacturers are developing technology to keep up with the safety norms of the government. This Chapter emphasises more on the importance of collision avoidance and justifies, why this thesis is important in terms of collision avoidance? To achieve such control on the vehicle dynamics the vehicle is defined along with current research in the market.

Chapter 5 says the problem statement and steps taken to perfect autonomous vehicles. The major focus is on elaborating neural network and genetic algorithms including the parameters with step-by-step solving of the problem and validating the parameters and experimentation to check the working of the framework. Explaining how the genetic algorithm and neural network are linked to each other to perform the collision avoidance task. discussion on outputs such as the impact of the increase in population with help of various runs of simulations gained from MATLAB. Finally, chapter 6 discusses the result and concludes the thesis.

Chapter 6 will brief about the importance and the combination of neural networks and genetic algorithms that can be helpful to tackle the collision in autonomous vehicles and will be presented conclusions and directions towards where future works can be worked on.

Chapter 7 elaborates the future work upon the successful implementation of the proposed combination of neural network and genetic algorithm. What further developments and modifications are to be considered to develop the framework.

1.4 Work Plan

The tasks will be presented according to the aims of this thesis, as well as an intended Gantt chat for their execution as shown below in Table 1-1.

Task 1: *Work plan & Literature Review:* This task aims to supply full information on how the research work will be conducted. Based on the obtain a review of autonomous vehicles and the application of optimisation theory and algorithms in autonomous vehicles' operations, such as collision avoidance, lane changing, motion, and trajectory planning.

Task 2: *Finding research gap and paper publication.*

The task aims to focus on finding the research gap and enlisting the methods where the evolutionary method can be applied. A chart will be used to list all the autonomous vehicles' operation or optimisation problems and to search all the existing optimisation methods that have been used to solve the found problems. The chart will help to find the research gap and future work. Collision avoidance will be selected for my research direction and paper publication based on research gaps.

Task 3: Transfer report & Modelling Learning design and developing new algorithms. Based on the first work on the research gaps, some ideas will be found to support the development of optimisation algorithms and model the problem to reach the optimal solution and proceed to write the problem and solution proposed.

Task 4: Developing algorithms and applying them to solve collision avoidance problems. some optimisation algorithms will be applied or developed (if needed) to improve the operation performance of autonomous vehicles

Task 5: Drafting thesis and research papers.

Table 1-1: Gantt-chart for over three years of research

	Task Name	2019			2020												2021												2022											
		10	11	12	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8	9	10	11	12
Task one	Work Plan						★																																	
	The literature review in General																																			★			
Task two	paper in AIERC																			★																				
	Paper 1																																							
Task three	Transfer Report																							★																
	Initial Model																																							
	Track Modelling																		★																					
Task four	Programming Modelling																						★							★										
	Algorithm Implement																															★								
Task five	Writing up																																			☆			
	Milestone	Date	Ta																																					

			s k
	Research	Mar/ 2022	The literature review will be in progress till giving my thesis.
	Publication	April/ 2021	Submitted the first conference paper AIERC (**A Brief Review of Optimisation Problems & Methods for Autonomous Vehicles.**

2 Autonomous Vehicles

2.1 Introduction

There is huge demand (Nascimento, 2019) for new autonomous vehicles which are battery-powered with lightweight and improved technology that has made autonomous vehicles popular with reduced cash, pollution, less energy consumption, and increased transport accessibility. Evolution of the autonomous vehicle took place Since the 1970s, in recent years, there have been huge investments in autonomous vehicles. Waymo by google has more experience on actual driven miles on road. (Campbell *et al.*, 2010) The autonomous vehicle senses the environment and runs without human intervention. An autonomous vehicle could be driven anywhere only when it proves to have a secured collision system for safe rides. The vehicle must have collision avoidance as a critical function and various developments are Suggestions Available in this field. Significant growth of transportation in a few years has created demands for the improvement and development of diverse autonomous driving vehicles in terms of transportation, especially since most of the mobility is engaged on roadways.

The intense usage of vehicles on the road has caused huge concern for safety on the road. Increased usage of vehicles caused heavy uncontrollable traffic and accidents on roads. This leads to creating an intelligent transportation system to perform communication, and information control like CCTV- closed-circuit television and processing to reduce traffic & accidents on road and use efficiently. (Anderson *et al.*, 2014). Due to high competition, there is more focus on rapid developments and the demand for autonomous vehicles is increasing exponentially. Which makes manufacturers keep up and fulfil the demands. (Fagnant and Kockelman, 2015) Figures 2-4 show which countries are well equipped for autonomous vehicles. In (Feigenbaum, 2018) forecast states autonomous driving vehicles are expected to cover about 50% of the market, and 40% of all vehicles travel by 2040. As the vehicle will depend on the components to get the information and process the required information out of huge data, which leads to data management systems. The aim is to capture the opportunities and challenges which occur after the introduction of Autonomous vehicles (M. Campbell, 2010). To show the impact of autonomous vehicles over the last five years publications are used to supply a comprehensive and updated narrative. Safety Concerns for Autonomous Vehicles

First, there were many debates concerning autonomous vehicles coming onto the road. To keep the standard of safety, international guidelines to allow vehicles on the roads have been established. (Hussain and Zeadally, 2019) The ISO26262 standard was formed to ensure all the systems are considered safe and no defects are present in the system to avoid. It is a challenging task to find the threshold of safety and set the limits for allowable risk. Where there is a focus researched to find a solution for every situation, which is still an ongoing process.

Concerning the survey, the public has safety concerns about autonomous vehicles dated July 17-21, 2020. About 1003 responses were sampled using a blind panel with an overall margin of error for the research was ± 3.02% with a 95% confidence (Elaine, 2020). Where 62% say safety is lowered by the prospects of multi-tasking during the ride by 15% and helping the driving impaired.

Most of the human errors that cause accidents are recognition, decision, and performance such errors cause a cascade effect. The autonomous vehicle is a program to avoid such categories of errors from happening.

Features of autonomous vehicles which are based on safety concerns are as follows:

- Emergency braking (Xu *et al.*, 2019). It is a feature where an autonomous vehicle uses sensors and cameras to measure the distance between itself and the surrounding traffic to apply the brakes to slow down, and to alert the driver for upcoming emergency collisions.
- Lane control (Yang *et al.*, 2018). Regarding the lane marking on the road, the cameras are used to check whether the vehicle is at the centreline of the lane and alert if the vehicle is drifting off the lane.
- Stiff structure. Every manufacturer conducts destructive testing to ensure they qualify for the safety code, but the windshields are also designed to be durable and have better insulations.
- Cross-car communication (Peng *et al.*, 2017). Autonomous vehicles communicate with each other to update the situations and the scenarios which they experience and update their system and gain experience.

2.2 History of Autonomous

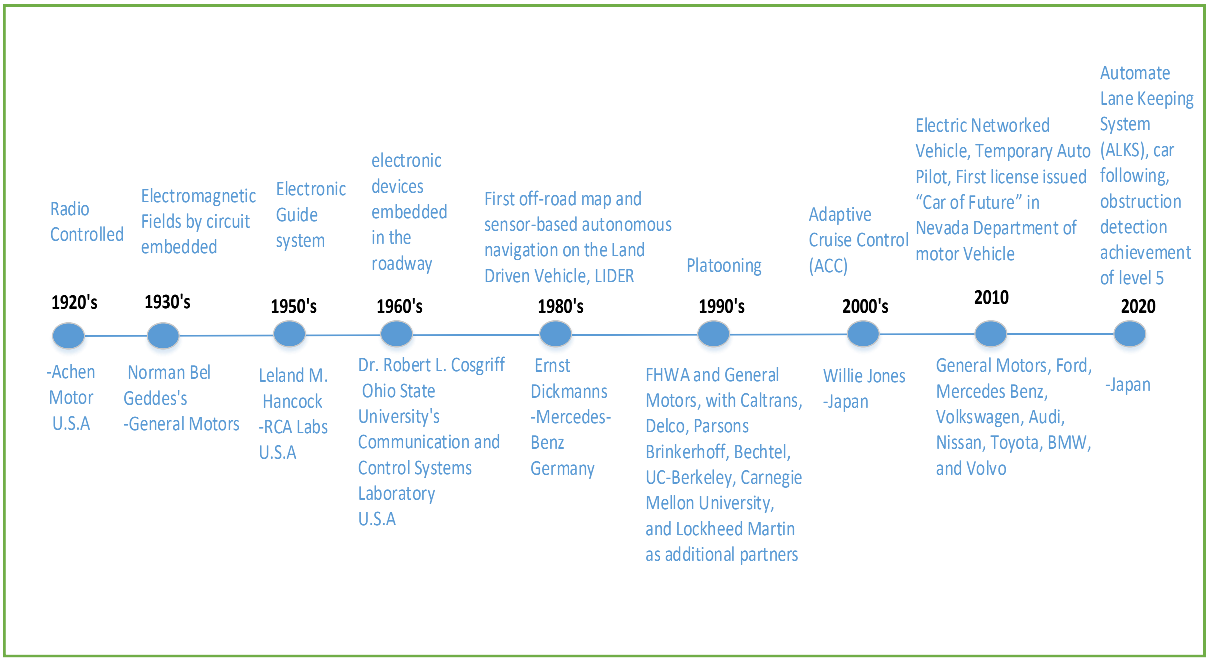


Figure 2-1: Shows the timeline of automotive developments.

As illustrated in Figure 2-1 the development of autonomous vehicles. The first attempts in the 1920s to form autonomous vehicles used a Radio-controlled vehicle called "chandler" which followed a car by radio impulses caught by a transition antenna by Aachen Motor (Wei *et al.*, 2017, Yuan Chen 2019). In the 1930's Norman Bel Geddes by General Motors achieved mobility by radio-controlled propelled via electromagnetic fields by circuit embedded (Claudine Baduea, 2019). In 1953, RCA labs are created with wire-laid controls on the floor by Leland M Hancock and followed by U.S. Route 75 in Cass County, Nebraska, which had been used as an experimental traffic counter with the collaboration of General motor by special radio receivers with radio receivers and visual warning devices with ability of automatic steering, acceleration, and brake control. In the 1980s the most revolutionary and innovative technology like a vision-guided vehicle by Mercedes Benz robotic van designed by Ernst Dickman, HRL laboratories, universities like Maryland, Carnegie Mellon, The DARPA (Defence Advanced Research Projects Agency)- funded autonomous land-driven vehicles used LIDER, Computer vision, successful autonomous robotic control. Carnegie Mellon University was successful in using a neural network to steer and control autonomous vehicles (Claudine Baduea, 2019).

The world’s first driverless 2005 vehicle was the Park shuttle used in Netherlands Schiphol airport by artificial reference points and made by magnets embedded in the road surface for cross-referencing location (Li *et al.*, 2019). In 2010 major automobile manufacturers including General Motors, Ford, Mercedes Benz, Volkswagen, Audi, Nissan, Toyota, BMW & Volvo introduced a driverless car system. The institute of control engineering of the technical university Braunschweig demo proved the first licensed autonomous driving vehicle on German highways.

2.3 Functions of Autonomous Vehicles

Figures 2-2 is to show how vehicles perform autonomously and perform complex functions with the components.

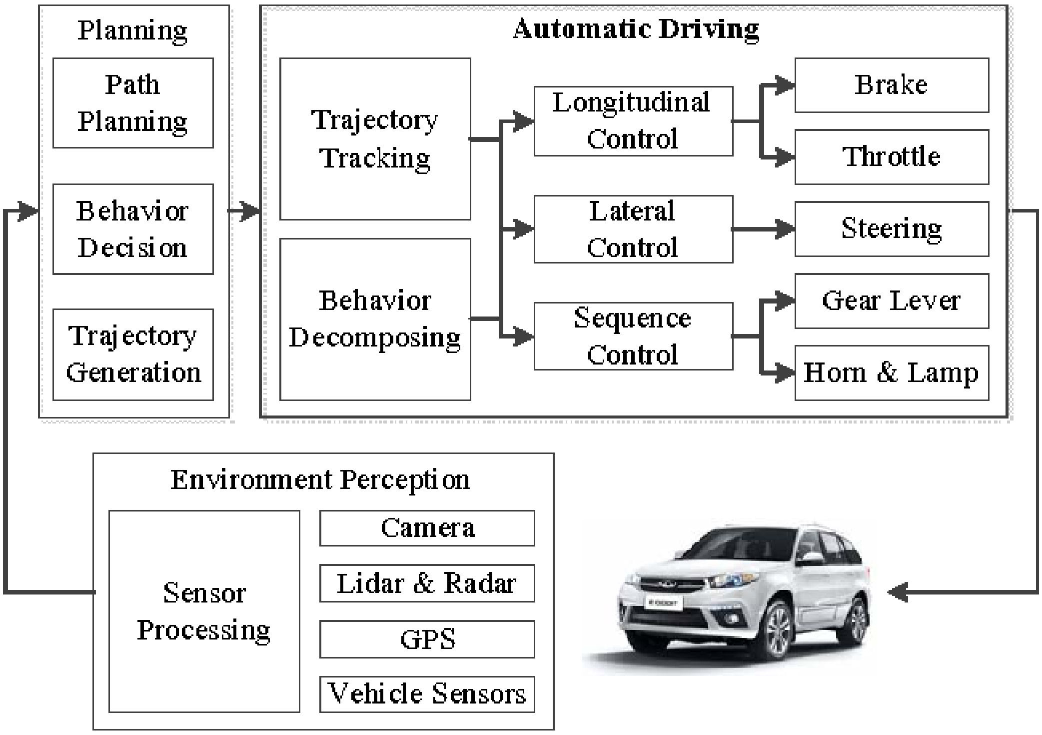


Figure 2-2: Functioning of autonomous vehicles (Joel Jana, 2019)

a) Vision (Joel Jana, 2019). Humans can see the road condition with their eyes. an autonomous vehicle should have a function of vision as humans. Computerised vision can design beyond human capabilities (Xu, 2017). version aims to detect things near the car with the support of LIDAR (Gonzalez *et al.*, 2017), laser, and camera. The process of images from a camera is used to identify obstruction find conditions and LIDAR is used to measure the distances.

b) Integration of sensors (Jo *et al.*, 2012). For instance, if a vehicle is surrounded by vehicles and has slow movement, humans can understand the scenario of traffic by seeing the environment and listening to the sounds. When it comes to the autonomous vehicle the information collected from the sensors and images to recognise the environment and derive the condition and act accordingly (Jo *et al.*, 2012). Different sensors are used in designing and developing autonomous vehicles.
c) Locate (Tu *et al.*, 2018). It is important to get the coordinates to know the exact location of the vehicle (Ye and Yamamoto, 2018). Normally GPS (Global Positioning System) is to find the exact position of a vehicle.
d) Path planning (Li *et al.*, 2019). It involves an important system to reach the vehicle from one point to another using seeing, understanding the environment and knowing the exact location (Mersky and Samaras, 2016). Path planning is important for autonomous vehicles to decide where to go. Optimisation algorithms have been used to plan paths from one place to another place. Path planning is used to avoid any obstructions and keep moving till the destination.
e) Overall control (Kuang Huanga, 2019b). Once the destination is completed and the path is defined as all the controls are supposed to work like steering, braking accelerating.

The autonomous vehicle has an autonomous system that is computer-guided and controlled, where human intervention is no more needed to control the vehicle. Every newly manufactured autonomous vehicle is equipped with the most advanced feature and crash avoidance technology (Pagnon, 2013). Features like blind-spot monitoring, lane monitoring, and forward-collision warnings will be the key components of fully self-driving vehicles. Most car accidents caused due to human error while switching to driverless will drastically reduce the number of accidents. Advanced evolutionary calculation algorithms called evolutionary strategies are executed to perform automatic Optimisation.

The following are features that are based on Optimisation.

- Parking Assistance (Seo and Shin, 2019). Parking Assistance moves the vehicle into a parking spot performing angle parking, perpendicular, or parallel parking (Francesco Esposto, 2020). The parking helps with coordinated control of steer angle and vehicle slow movement which performs collision-free in available constrained areas of space.

- Cruise speed control (Kuang Huanga, 2019b). Cruise speed control is equipped with lane-keeping aid which keeps the vehicle at study speed and alarms the driver on the deviation from the lane (Mersky and Samaras, 2016). The sensors are designed to identify the white/yellow lines on the road and control the steering to stick to the current lane and alert deviation from its warning buzzer or a small counterforce to the wheel.
- Speed adjustment according to path condition (Zhang *et al.*, 2018). When a vehicle is on the road there are different collisions or interferences, there will be spontaneous requirements of acceleration and deaccelerate. As it is strongly dependent upon path speed adjustments on the crossing and sharp turns.
- Braking management or Autonomous Emergency Braking AEB (Xu *et al.*, 2019). It is a system that checks and watches out for further road conditions signs and traffic to prepare the vehicle for emergency braking.
- Proximity alerts with other vehicles and driving adaptations (Jo *et al.*, 2012). Proximity sensors are used for verifying how close the vehicle is to the other objects in the environment. Mainly used in the parking aid which plans the available space and executes the parking process based on the exact area available.
- Monitoring of the operating condition (Xiong *et al.*, 2019a). The vehicle checking system is correlating the planned and executed functions of the vehicle for example path of the vehicle whether the vehicle is on an exact path as derived and speed, and a trajectory as per the plan to remove the errors and run flawlessly.
- Obstruction detection system and road users (Gonzalez *et al.*, 2017). An obstruction detection system was made to overcome accidents. For collision justification use sensors as an input to detect an imminent crash (Althoff and Mergel, 2011). Sensors like the Global positioning system can detect fixed dangers such as predefined stops. Sometimes the vehicle crossovers the limitations without any response from the driver, hence immediate brakes are applied.

2.4 Structure and Levels in Autonomous Vehicles

2.4.1 General structure

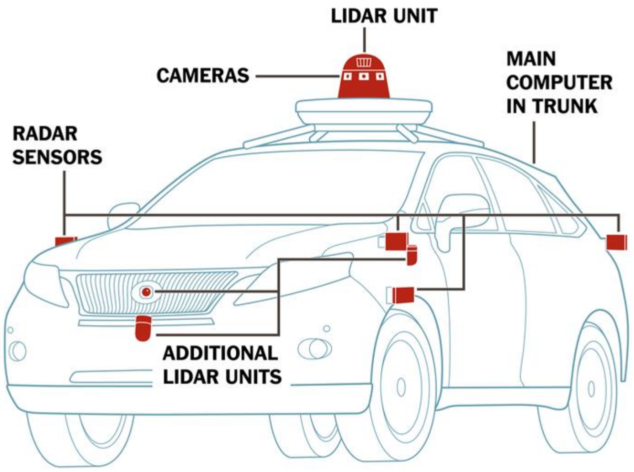


Figure 2-3: The general structure of autonomous vehicles (Davies, 2015)

Every part has gone through extensive research, with the integration of disciplines such as electrical, transportation, software, hardware, IT, electronics, engineering, law, ethics, and philosophy Bagloee *et al.* (2016).

Usually, the autonomous vehicle execution is conducted by hardware, where hardware can be further classified as sensors, processors, and actuators (Davies, 2015). while all the visualization is done by the physical elements as illustrated in Figure 2-3. Autonomous vehicles continuously interact with objects things in the environment like pedestrians, bicyclists, and other vehicles, this communication is controlled by programs. Sometimes the program seeks information from the control room for instant reflection (Anderson *et al.*, 2014). This information will be stored and had whenever further needed such an ability to decide at the right time will improve functionality.

- How does the car know where they are? (Metz, 2018). Companies like Waymo & Uber have begun by building a 3D map of the place. The hardware collects environmental information to create a map. Based on the generated map the autonomous vehicle uses algorithms to execute self-driving (Gonzalez *et al.*, 2017). By continuous creation of a map, the vehicle keeps updating and building the map and overcoming hurdles like other cars, pedestrians, and cyclists.

- How does the Autonomous vehicle use the information? One of the tedious tasks is the vehicle needs to extract the required data for the huge raw data. Based on the rules and algorithms the vehicle responds to the selective data.

2.4.2 Software

Consistent improvement in technology whether it comes to hardware or software. Fully autonomous vehicles are the future and will defiantly replace drivers. This will increase safety on roads and concern the fundamental functions of autonomous vehicles and all the applications are as follows perfected to use most of it (Ren *et al.*, 2019). Vision, sense generalization, planning & control are the major functions of autonomous vehicles.

Optimisation in an autonomous vehicle is based on collision avoidance, lane changing, velocity control and breaking. There are various methods to optimism about the problem. The software can call the brain of the autonomous vehicle; it is a key to controlling various aspects. Below are tasks in understanding software.

a) *Sensor processing* provides information like position & motion with environment and obstacles mapped to the system.
b) *Localization* to find cars' current location with the map of that position.
c) *Obstacle tracking* for the identification of moving and static objects.
d) *Path planning* for path determination
e) *Behavioural module* to overcome unpredictive environments
f) *Control to function* to check the performance and state of all parts such as throttle, brake, gear shift, and steering.

2.4.3 Hardware

Figure 2-4 has been used in developing autonomous vehicles. It has seen remarkable developments in the physical and different vehicle parts. The vehicle nowadays can manage more weight and is lightweight at the same time due to the ability of engineering and research (Bagloee *et al.*, 2016). Along with precise machining and manufacturing of the vehicle structure and parts, parts like chassis frames are made up of thin aluminium walls and usage of carbon fibre composite panels with reduced weight and more strength (Pendleton *et al.*, 2017). Hardware does not have to go through updates, it will require maintenance as specified by the manufacturer for relubrication in between product life span.

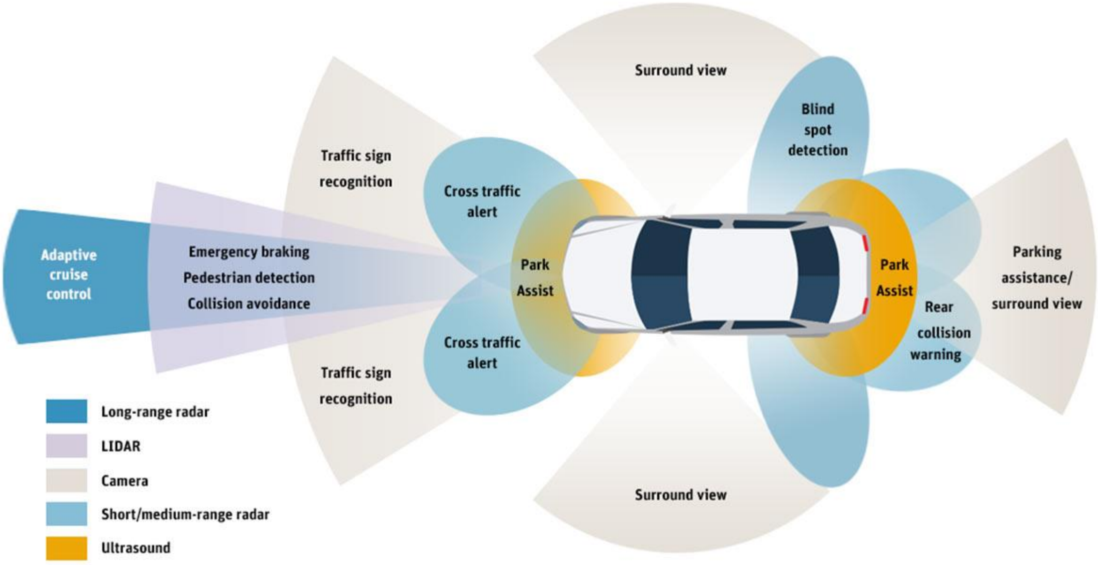


Figure 2-4: Various functions of sensors (Garcia-Garcia et al., 2018)

Run an autonomous vehicle makes use of a route framework to decide the path to follow with several types of sensors to process the driving task. Usually, the central processing unit is the key to processing multi-tasks and executing the defined programs (Mohamed, 2018) with the help of gathered data by the sensors and executing the same by a set of algorithms. The following are the most important components involved in the operation of autonomous vehicles which consist of sensors.

i. Cameras:

It supplies a vision for autonomous vehicles. The range is highlighted in Figure 2-4. Cameras are the only part that can differentiate environmental conditions, objects in conditions like day and night vision possibility to function properly (Garcia-Garcia *et al.*, 2018). The visibility is affected by a change in condition, and it is difficult to detect non-illuminating objects in low light conditions. This may create an error inability to detect the distance to the nearer objects and cause cascade effects. Cameras are the eyes of the car which see and interpret objects into information. But just like birds can see a 360-degree view of their external environment. Where programs work on finding cars, road marks, road conditions, pedestrians, traffic signs & cyclists (Youngtae Jo, 2015).

ii. Radars:

Sir Robert Alexander Watson-watt’s invention Radio Detecting and Ranging. Since 1935 they have been created and have been massively used in many areas. The radar sensor is dynamic and emits electromagnetic radiation to clarify the targets. The emanating and acceptance of the flag are carried by a single receiving wire since the sensor is always exchanging in sending and getting mode. Where the sent radiation has waveform and defined bandwidth. By observation of the eco from the environment is picturised through reflected strength of frequency to decide their range, angle, and velocity (Xu *et al.*, 2019). As compared with the camera the Radar precision is unaffected by natural conditions like haze, rain, and light. the ability to distinguish a question depends on the object's reflection quality. Reflection is affected by different variables like an estimate, removal, and the transmission control of the protest. Radio Detection & Ranging are immensely powerful equipment to gauge the distance and speed of the vehicle in real-time (Jo *et al.*, 2012). Where it works by sending and receiving radio waves and detects objects in fog and rain. The shape and size of the pedestrians, cyclists and motorbikes are small and complex. but there will be no metallic parts to reflect radar signals. Sometimes reproduced radar images may be out of proportion to their actual size. Such scenarios may cause you to make inaccurate decisions by the system. Nowadays radar is most common for illustration planes, rockets following, discussing activity control, and maritime applications.

Advantages:

- Bad climate execution: frequencies at 30-300ghz are the line of finding and meeting contraction due to assimilation in barometrical gases i.e. (0.3-0.5 dB/km) the sensor does, in any case, can distinguish objects in obscurity, cloudiness, rain, and snow for brief separations needed for car applications
- Run and extend rate: Car radars give exact extend estimation in differentiate to detached sensors.

Disadvantages:

- Clutter and false reflections: the number of objects the environment reflects transmitted radar signals; undesirable reflections called clutters for the event road surface.

- Resolution: The spatial determination of the radar is destitute. Subsequently, the ability to Watch objects is restricted.
- Elevation: since car radars have no assurance in stature and a wide column. It can be troublesome to recognise hindrances from moo overhead objects for event road signs, bridges, and burrows.
- LiDAR:

Light Detecting and Ranging the working principle of LiDAR (Light Detection and Ranging) (Gonzalez *et al.*, 2017) stays the same as Radars but rather than radio waves. LiDAR (Light Detection and Ranging) employs laser beats. Concurring Waymo's lidar reality sheet LiDAR (Light Detection and Ranging) bounces a laser off a question at an amazingly tall rate- i.e., millions of beats each moment and degree how long the lases take to reflect off the surface. (Kim and Park, 2020). Whereas Lidar tends to create a 3d image of a detected object and creates a real-time map. Lidar can be used to create a 360-degree map. (Jang *et al.*, 2016, Adarsh S, 2019). Regarding their high-channel Lidar can find long-distance objects as illustrated in figure 3 for cruise control (Kim and Park, 2020). This information is used to generate precise, 3D images of the objects and create a virtual environment around the vehicle along with gestures, motion towards which direction, and actual shape and size. But LiDAR (Light Detection and Ranging) (Gonzalez *et al.*, 2017) is one of the most expensive sensors with a shorter range and is more vulnerable to part failure than radar (Kim and Park, 2020).

Advantages:

- Resolution: the beam of lidar is often very contract. Few lidars degree at a few hundred points and a few points of rising in one clear. Which supplies the pixel map and hence gives more information and minute details of the environment.
- Clutter: Being a contract pillar systems discovery, LiDAR (Light Detection and Ranging) (Gonzalez *et al.*, 2017) does not meet clutter to the same degree as radar.
- Grayscale: The photodetector can effectively find reflected concentrated, in this way giving a grayscale picture. Which is majorly used to screen path markings.
- Light condition: LiDAR (Light Detection and Ranging) (Gonzalez *et al.*, 2017) is insensitive to light conditions.

Disadvantages:

- Terrible climate: In difficult rain, mist, or snow, there's execution corruption.

Soil stores: LiDAR (Light Detection and Ranging) (Gonzalez *et al.*, 2017) is touchy to earth stores on the focal point. Soil stores on the following vehicle may cause changed intelligence and hence issues in discovery

2.4.4 Automation Levels in Autonomous Vehicles

Concerning the mechanization level, it is categorised into six levels. Level 0: No automation. The driver performs all viewpoints of the driving assignment; no framework mediates as it were cautions and caution. The driver must continually screen the drive (Feigenbaum, 2018).

- Level 1 (Driver Help) This framework can take the directing or acceleration slowing slow. The driver must persistently carry the other. The driver must always screen the drive. The driver must be prepared to continue full control instantly.
- Level 2 (Halfway automation): This framework takes over both controlling and acceleration/slowing in a characterised case. The driver must continually screen the drive. He must be prepared to continue control promptly.
- Level 3 Conditional Automation: This framework takes over both directing and increasing speed in a characterised use case. It can recognise its limits and inform the driver (Fagnant and Kockelman, 2015). The driver does not have to screen the drive but be prepared to continue control inside a given time outline in case the framework so demands. The driver does not need to check the drive but is ready to resume control within a given period if the system so requests.
- Level 4 (High Automation): driving tasks can rave over to the system in a defined use case. No intervention of driver to check or act or as a backup.
- Level 5 (Full Automation): The vehicle is in full control and can take over the entire dynamic driving task in all use cases. It is fully system controlled.
- Level 6 in the autonomous car is not that far from where well-known manufacturers like Waymo, Google, Tesla, Audi, and Mercedes Benz have proven tested vehicles on road (Claudine Baduea, 2019).

A new study is based on Technology and innovation, Infrastructure, Policy & Legislation, and Customer acceptance in autonomous as shown in *Figure 2-5* (Jones, 2019) vehicle market regions including the U.S., Canada, Germany, France, U.K. Italy, Russia, China, Japan, South Korea, Taiwan, Southeast Asia, Mexico, Brazil, etc. Netherlands and Singapore are the countries to support driverless cars, followed by the United States based on infrastructure, legislation, and customer acceptance. The figure below suggests categorizing the requirements and ranking of different countries for the seamless operation of autonomous vehicles (Bresson *et al.*, 2017). For instance, infrastructure, technology and innovations, policies, and legislation, with the requirements to accept autonomous vehicles in their rating. Which says which country is doing well in implementation and using autonomous vehicles on road.

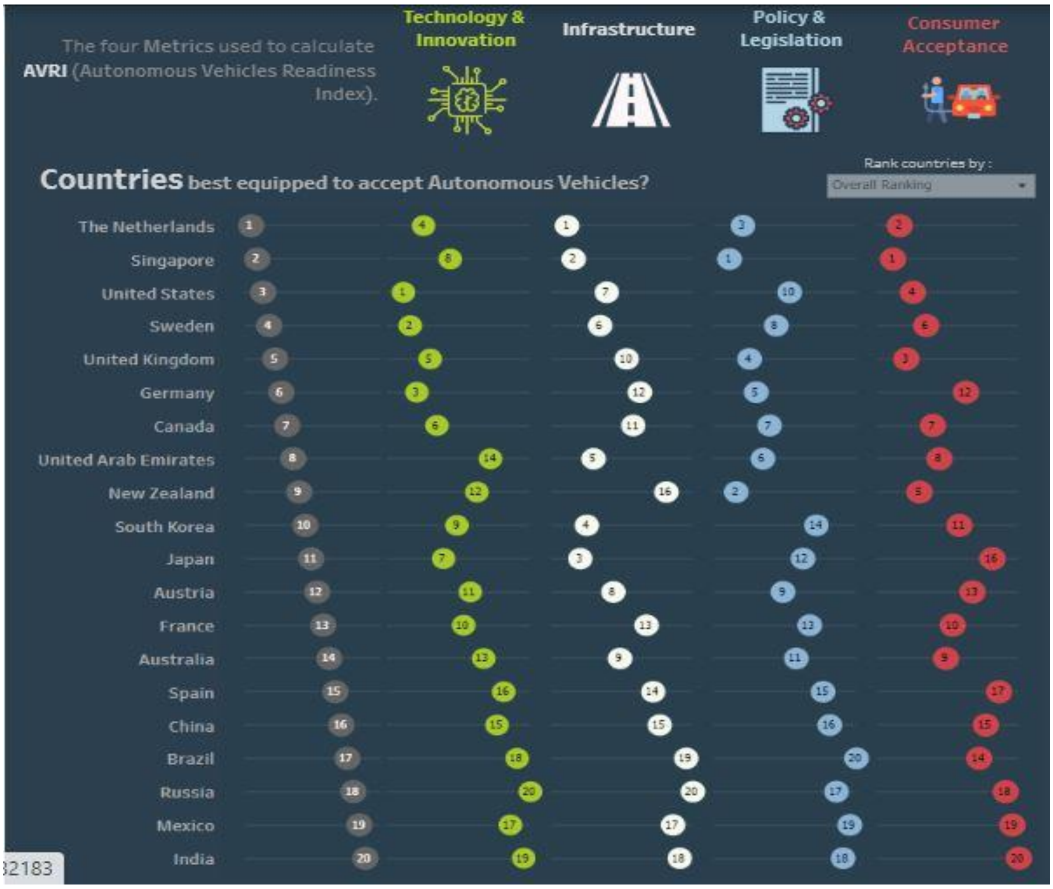


Figure 2-5*: Autonomous Vehicle Readiness Index (Bresson et al., 2017)*

2.5 How do Autonomous vehicles Work?

Autonomous cars depend upon all the functioning (software) components (like processors to execute software, machine learning systems, and various algorithms), and hardware (like actuators and sensors) illustrated in

Figure 2-5 (Md, 2015). With the help of sensors, autonomous vehicles create a map of the surrounding. For live feeds to check what all objects are around are being checked by sensors, radars and to detect the various signals and road identification cameras and sensors like LIDAR (Light Detection and Ranging) (Gonzalez *et al.*, 2017) which detect the surrounding based on the bounding pulse of light with this information various algorithms are used to filter and rectify the information. This information from all the sensors input to the software and processed data is output to control actuators, which control acceleration, brakes, and steering (Shuiying W, 2012). Finally, the execution on the road based on the type of road, various signals, random objects, and movement recognition algorithms help the software to drive and navigate.

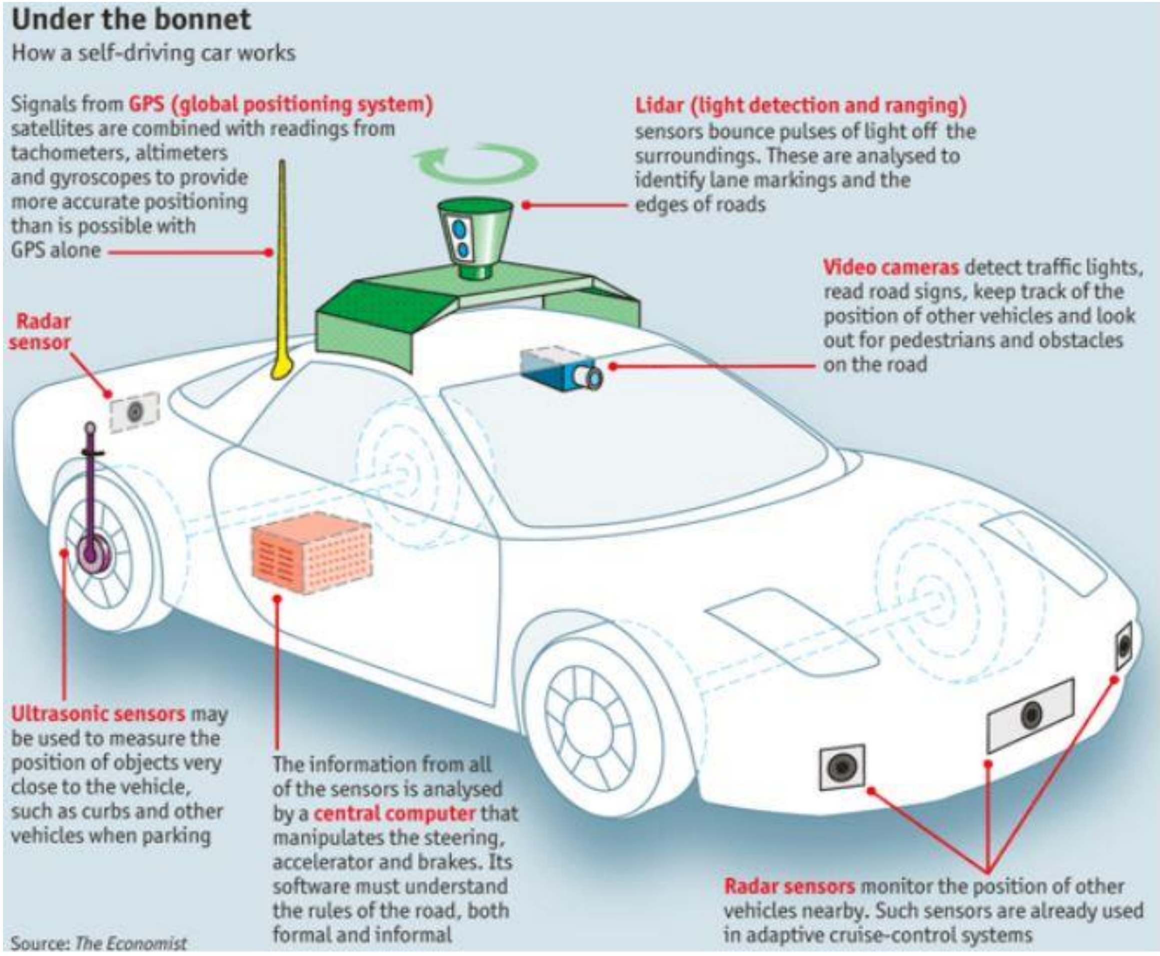


Figure 2-6: How a self-Autonomous vehicle works (Shuiying W, 2012)

According to IEEE 802.11p information like location, position and speed acceleration, and other control information to the neighbouring. In this manner, sensors are brought into use to sense the surroundings as shown in

Figure 2-6 of a vehicle became an intensive study for autonomous research. Whereas several models were made but due to safety concerns, only a few were successful, commercialised, and mass-produced. Major manufacturers like Tesla, BMW, Mercedes, Audi, Toyota, Honda, Ford, Kia, Volkswagen, and Hyundai started supplying inbuilt features like parking sensors, and cruise control. where safety points and customer points of view there was a tremendous increase in the competition.

Especially, such research has been consistent growth in development. Collision detection and avoidance systems are designed to reduce collisions in the automobile sector (Kenney, 2011). Usually, crashes occur due to the destruction of the driver or sudden brake down or uncertainty in the mechanism. Hence there is also a focus on vehicle cooperative driving i.e., vehicles will communicate with each other, study the pattern of traffic, and perfect the traffic to avoid cascade effects.

A general view of how the vehicle processes objects and sees the world to process the desired driving functions.

Figure 2-7: How Autonomous vehicles see the road (Md, 2015)

Sebastian Thrum, a well-known computer scientist, educator, and robotics developer from Germany have categorised the tasks by the software's follows:

1) Environment making as shown in Figure 2-7 (Md, 2015) to estimate the information on motion, position & environmental obstacles.
2) Position reference to communicate between cars and find their position.
3) Tracking obstacles to define static and dynamic objects.
4) A behaviour module to reflect constraints to process an unpredictable environment.
5) Vehicle actuators control the brake, throttle, and steering wheel.

As mentioned, the above tasks are iterative between the start and endpoint of the vehicle. After obtaining basic information, the vehicle must define the relevant data to consider for decision making as shown in Figure 2-7.

The basic aim of an autonomous vehicle is to reach from one point to the destination by processing the above tasks. The vehicle must perceive the environmental information, plan the trip, navigate throughout the path, and control movements on the road. The major key factors for a vehicle to drive itself are vision and object detection. These two features play a significant role when a vehicle is in motion, things like instantly stopping in traffic, and uncertain pedestrians to stop running over them. Concerning the detection of an object, the algorithms used specifically cover feeling, object detection, motion planning, tracking, improvising the process, and techniques. In the huge data, it requires more time at the same time to process the complex environment and various scenarios to overcome unpredictably situations. (Nascimento, 2019) Here Artificial intelligence plays a significant role in understanding and reflection. When it comes to autonomous vehicle vision, it is a vast and time-consumed task, such as. to process image recognition and categorise the captured data. But object detection is a complex task in types of environments with the different data provided by sensors which include shadows, and identical systems in light conditions. The algorithms should with data after processing all the drawbacks and rectifications.

Considering Asimov's (John, 2019) laws to protect humans are as follows:

1. The autonomous vehicle should avoid collisions with a pedestrian on the road.
2. The autonomous vehicle should not collide with another vehicle.

3. The autonomous vehicle should not collide with any other objects in the path.

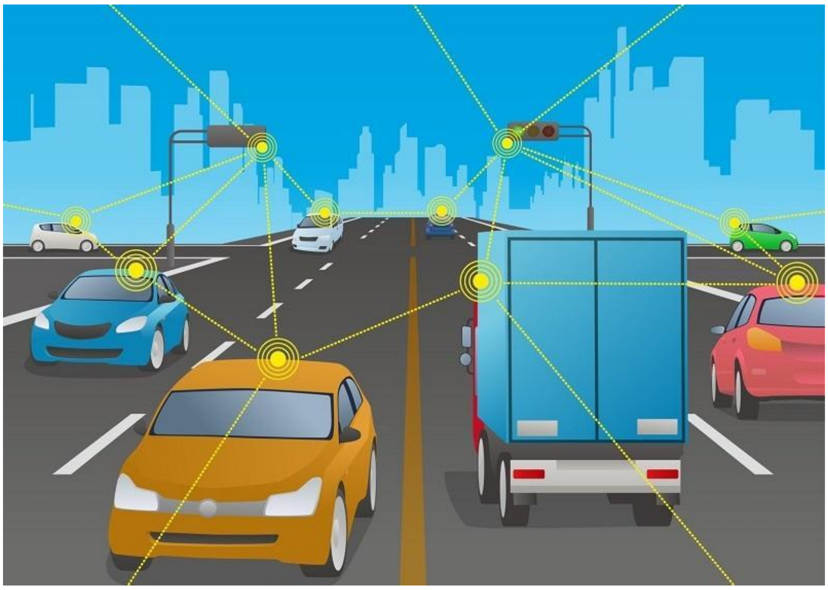


Figure 2-8: Autonomous vehicles connectivity (Li et al., 2019)

2.5.1 Collision, environment, and scenario analysis system

As real-time data is needed to identify the positions of objects moving in a vehicle, various sensors and visual sensors are combined to obtain that information (Li *et al.*, 2019). Those sensors include radars, Ultrasonic sensors laser rangefinder, LIDER Light detection and range, SLAM Simultaneous localization, and mapping lasers to define the actual location of the vehicle (Jang *et al.*, 2016).

2.5.2 Locating coordinates and positioning

Regarding location identification, pieces of research have been done for different techniques for actual coordinates identification, such as DSRC Dedicated Short-range Communication, V2V Vehicle to Vehicle, GPS Global Positioning System & INS International Navigation System (Balas, 2019, Martinez and Jimenez, 2019, John *et al.*, 2019). Data from a single sensor cannot meet these requirements alone and therefore it is necessary to combine sensors to get the exact location. In this process to have correct information it is necessary to correct sources of errors. The most popular is every handheld device equipped with GPS. However, it does not supply correction when it comes to off-road like forests and indoor locations (Jinyin C, 2019). Most autonomous vehicles will use the IoT (Juan antonio Guerrero ibáñez, 2015) Internet of things, where each vehicle will share its location and the exchange of information will help to correlate the actual location and speed every moment (Solmaz, 2019).

The following are the advantages of exact locating and positioning of the system (Gibson, 2019):

A. Delivers Integrity

It is a matter of safety of life if there is a huge deviation in location accuracy. It will be difficult to rely on and trust the data that the positioning system provides. To have confidence in the position and velocity output by the system, the system should have predefined acceptable limitations to process reliable data.

B. Supplies Absoluteness

The physical reference can be created on the earth's fixed datum. With this common frame of reference, accuracy can achieve to create a map.

C. Enhances localization

Location is defined as a reference to latitude longitude and altitude. When it comes to self-driving vehicles, a correct position makes localization more correct. This will increase the vehicle's capability and safety on the road.

D. Evolves for automotive

Despite having satellite signals, still so many unavoidable factors like the impact of the atmosphere on the deviation of the standard signal. The error correction will meet and ensure correct localization.

E. Quickens Convergence Times

(Gibson, 2019) The time it takes a vehicle from the first observation of the satellite signal until reporting the position is referred to as “convergence time. comparison to the vehicle sensor's location data and the satellite data will generate a final position, velocity, and time. Sometimes the vehicles pass under the bridge. hence there will be a disturbance in the satellite signal. Where the vehicle is on its own with the internal sensors to find itself.

F. Improved cost equation for autonomy

Satellite positioning comes at a cost that is high and not affordable to all vehicles. The joint cost of the correction and positioning matters a lot to get the affordable advanced sensor in an autonomous vehicle.

2.5.3 Position change, the planning system

An autonomous vehicle will tend to reduce road fatalities. In this section to understand the abilities of the vehicle the following questions:

i. How does an autonomous vehicle decide how to go next?
ii. How Is the information from the sensor processed to decide?
iii. Is there any interaction to clarify the input data?
iv. Is there any communication between autonomous vehicles moving in traffic?

Waymo has a link to communicate and get clarification on the input information. Such has a construction site and unpredicted condition.

The very first task is to discretise collision checking with road alignments. To simplify and use the roads effectively, especially on highways. Majorly to obtain human-like driving ability, autonomous vehicles will be subjected to a logical set of rules like what would a human do in some unpredictable situations. The rules supply and impose restrictions on the planning system which should always be satisfied (Broggi, 2015). Whereas the traffic rules defined concerning cost function to find low-cost planning. (Martinez and Jimenez, 2019) depicted that a strategy to synthesise the movement that damages as it were the least needed rules for the briefest sum of time. Even though the method includes challenges of programmed control blend still incorporates their application to non-deterministic frameworks and erratic natural conditions. When it comes to genuine activity scenarios incorporate complex intuition among the different street clients and vehicles that ought to have the capacity to define and decide the right course of movement concerning the eases and keeps going in its path and its pre-set course decided by route (He *et al.*, 2019). This function of the vehicle requires a lot of experiments and testing to be perfected to define the accuracy of the vehicle. As a vehicle is in pursuit of the lane to make sure the alignment of the vehicle is in the exact centre of the lane (Kim and Park, 2020). The navigation system is used to stay constantly in the position, where nowadays cameras and sensors are used to trace the road marking the centre line and two borderlines are used to define the centricity of a vehicle to the lane at the same time the cameras are detecting obstruction on the road to update every movement of the nearer object (Zhang *et al.*, 2019, Bello-Salau *et al.*, 2019).

2.5.4 Trajectory planning system

Considerable progress has been made in both the safety of the driver and the safety of life in the environment. The safety features such as airbags and crumple zones are intended to prevent injuries. This will function only when the trajectory of the vehicle is accurately planned. To make sure the vehicles must communicate near around for references. This will also potentially help to improve the flow of traffic as there will be well coordination amongst the vehicles and proper use of road space availability. The vehicle's ability to preserve driving soundness within the occasions of changes in course and speed arranged by movement arranging. The vehicle co-relates with planned and concerning the movement of the vehicle travel in a line, while covering curve lines the speed should be kept by braking and acceleration to keep stability (Zhang *et al.*, 2019, Pérez-Carabaza *et al.*, 2019). The trajectory is nothing but the movement of a vehicle by steering it may continue in a straight line or curve to avoid a collision, overtake another vehicle, or change the lane by automatically adjusting accelerating, braking, or directing to return to solidness. Direction control oversees the execution of changes in speed and headings. (Lin *et al.*, 2019, Hu and Sun, 2019).

2.6 Current Research

The autonomous vehicle is a developing innovation that gives a secure and proficient transportation experience. As part of the intelligent frameworks, includes an exceptionally wide application prospect. autonomous vehicles refer to a course of vehicles that can conduct detecting and decision-making, track planning, and following. Due to the application of advanced sensing technology and the development of vehicle state estimation calculation, the state data of the vehicle gets to be more observable and more precise. The demand and the growth of autonomous vehicles in terms of technology are rapidly increasing, and the research in all the areas such as vision, sensors data execution and controlling the vehicle has evolved.

2.6.1 Vision

Recent advances in computer vision have revolutionised areas of research including robotics, automation, and self-driving vehicles. The self-driving car industry has grown markedly in recent years, in no small part enabled using ultramodern computer vision techniques (Mohamed, 2018). However, there are challenges in the field. One of the most difficult problems in autonomous driving is feeling. Once autonomous vehicles have a correct feeling of the world around them, planning and control become easier. The focuses are on sensing with computer vision and the capabilities of computer vision and neural networks for use in fully autonomous self-driving vehicles.

Autonomous driving is an exceptionally complicated issue. Specialists and the car business have been chipping away at creating autonomous vehicles for quite a long time. One such organization is General Motors which, in 1958, delivered a self-driving vehicle directed by a radio-controlled electromagnetic field. Various vehicle organizations refined this thought (Joel Jana, 2019). Notwithstanding, the test of carrying full autonomy remained. The excursion arrived at a fascinating point about 2005 when a couple of groups of researchers had the choice to finish the DARPA (Defence Advanced Research Projects Agency) test (subtleties in the video underneath). This test includes a 240-kilometre desert course. Persistent endeavours from researchers have made it conceivable to preliminary autonomous vehicles on open streets.

Following the Defence advanced research projects agency (Campbell *et al.*, 2010) challenge in 2005, scientists featured the criticality of view of the world around the vehicle. From that point forward, a ton of organizations started to foster autonomous vehicles zeroing in principally on insight using vision. autonomous vehicle organizations have changing procedures for carrying insight around an autonomous vehicle. (Mohamed, 2018) Most organizations use a mix of RADAR, LIDAR and SONAR, and cameras. Tesla is a huge organization alone that does not use LIDAR in its autonomous vehicles, principally zeroing in on RADAR and cameras, and using SONAR to find close to handling objects. Regardless of the variety between organizations, every one of them places PC vision innovations at the front.

Notwithstanding ongoing advancement, (Xiaozhi Chen, 2017) autonomous driving faces extraordinary difficulties in addressing the 3D world around a vehicle using PC vision as it were. It is hard to carry precise portrayal since cameras produce 2D pictures and do not straightforwardly give profundity data of items. While papers have been distributed on 3D recreation from various 2D pictures from cameras in various areas, 3D reproduction is computationally costly. Hence, few organizations are using RADAR and LIDAR.

Vision can supply a lot of raw information to the system. Processing such huge data is a task. Such data is needed for better ways to detect objects and perform collision avoidance functions. It is the same method as a human seeing the environment and taking a decision, on what next is to do. Based on the vision the computer decides as per the program and logic of the algorithm to function as per instruction.

2.6.2 Integration of Sensors

Advances in hardware and sensor innovations have prompted the improvement of various progressed vehicle frameworks intended to help drivers in controlling their vehicles under ordinary conditions and keep away from moderate effects during crisis circumstances (Gonzalez *et al.*, 2016). The electronic driver help is not inside and out new; frameworks, for example, Anti-Lock Braking or Electronic Stability Control have been used to control discrete vehicle frameworks for quite a few years. What makes late advancements distinctive is the ability of these frameworks to intercommunicate and control a more noteworthy extent of vehicle activity, making it progressively normal for the vehicle to enhance driver input.

As vehicles outfitted with Advanced Driver Assistance Systems and Crash Avoidance Systems (CAS) (Sabzevari, 2009) become progressively universal, and as we see the development of monetarily accessible semi-autonomous vehicles, we will normally see more instances of these vehicles associated with genuine, the time lethal, crash episodes.

2.6.3 Locate

Confinement is a stage carried in most robots and vehicles to situate with a minuscule safety buffer. Assuming we need to settle on choices like overwhelming a vehicle or characterizing a course, we need to know what sensor combination is around and where we are restricted. Just with this data, we can characterise a direction.

Worldwide Positioning System (GPS) (Jo *et al.*, 2012) or NAVSTAR are the US framework for situating. In Europe, we talk about Galileo; in Russia, GLONASS. The term Global Navigation Satellite System (GNSS) is an extremely normal satellite situating framework today that can use a considerable number of these subsystems to expand exactness.

2.6.4 Overall Control

In day-to-day life more research and resources are allotted to software development. The software works on sophisticated telematic to complex collision avoidance systems. Usually, the updates are released in patches and good patch management is non-negotiable. Up-gradation is a consistent process and should be done efficiently (Pendleton *et al.*, 2017). For instance, in collision avoidance, the system relies on the feedback and information provided by the sensors and cameras. Hence there should be regular calibration and flawless up-gradation of software.

Based on the literature review of the last five years. Significant innovations have been made in autonomous driving vehicles. Autonomous vehicle routing is especially for processing various data and deriving the desired output (Nascimento, 2019). There are also certain limitations of the sensor. The role of the research is to integrate data and knowledge, from the sources of the sensor. Developing a correct model for an autonomous vehicle is challenging. This leads to the system identification approach to solving the problem. Due to the involvement of various sensors, the risk of hardware and software faults in terms of sensor failure, actuators malfunctions, and processing failure (Jing Ren, 2019). To overcome such issues and ensure reliable performance outcomes. The flow chat shows the various problems in autonomous vehicles and the methods used to solve the problem. As the chat links problems to a method, it shows the evolutionary algorithms are more successful and majorly used to solve the problem.

Regarding major problems, very few manufacturers like tesla already integrated a certain level of automation. In difficult to develop an AI-enabled automated car that runs without human intervention with 100% safety. The problems are classified as car following, lane changing, motion planning, trajectory planning, path planning, and collision avoidance.

2.7 Challenges and Future Research

Currently, A well-known autonomous vehicle, Waymo, has driven over ten million miles. has achieved about level 4, but only on certain pre-defined suitable routes, with specific daytime and weather. Where systems are available only on pre-mapped highways (Claudine Baduea, 2019). Now comes the actual challenge, how designers design the vehicle system. Which eventually acts as humans and performs as if humans are acting in all conditions (Nascimento, 2019, Kuang Huanga, 2019b). Software is the key to utilizing using, actuators, various algorithms, and a powerful processor to execute. Still, there is a parcel of challenges in planning a completely autonomous framework for the driverless car. Stated below shows an overview of the cost, maps, software, simulation, and solutions as shown in Table 2-1: Implementation challenges (Hussain and Zeadally, 2019)

Table 2-1: Implementation challenges

Aspect	Challenge	Implications	Possible Solution
Cost	• Hardware cost • Software cost • Management cost	• Reduction in car ownership Adverse effect on business and auto industry	• Mass production will relax this issue
Maps	• Real-time generation takes enormous computing resources • Storage overhead • Extreme weather conditions Changing environment and road structures • Real-time collision avoidance	• The poor mapping may jeopardise the functionality and autonomous cars • Need more resources	• Big data solutions cooperative mapping through Neighbours
Software complexity	• Test and validation Requirements are not complete • Environmental complexity causes software instability Software cost	• Delay in the commercialization of consumer thrust is an issue Investment risk to investors	• Driving profiles and fail-safeness • Focus more on AI and deep learning-based solution

	• Software security right-of-way provision through software is difficult • Object detection and time to respond		
Simulation	• No universal simulator Different simulators for different modules proprietary tools • Difficult to evaluate all the requirements	• Incomplete testing and validation • An economic alternative for autonomous car testing Validation of simulation results is hard	• Focus on open tools. Make the data available for testing. A comprehensive approach is essential

Taking after is a few of the major challenges:

A. Environmental Challenges like road, weather, and traffic conditions:

Certain highly unpredictable conditions like dense fog & severe precipitation, uncertain conditions with a change in time and location, Sometimes the road condition is not up to the mark such as potholes (Youngtae Jo, 2015, Jung *et al.*, 2020), no marking of the lane, mountain roads, tunnels, unclear signboards. While considering all such scenarios and no scope of downtime and failure vehicles must perform in any weather condition (Martinez and Jimenez, 2019). However, the same conditions are causing problems for humans. But at the same time, the technology of radar and vision will be more efficient than a human. The algorithms will supply the best suitable solution and are safer than humans.

B. Training the AI model with machine learning:

Concerning sense, perceive, decision, and act the software algorithm must overcome a large amount of information in the shortest processing time. Real-time response of systems that are defined with certain time restrictions so that they can meet real-time expectations. computational complexity when it comes to AI and deep learning regarding the data and amount of complexity of computation GPU Graphics Processing Unit (D. Yershov, 2016) Graphics processing Unit or (TPU) Tensor processing unit can be highly optimised for fast computation, accuracy minor change in date for classification and prediction algorithm may lead to change in behaviour dramatically and cause catastrophic results, reliability some time the image recognises the picture is not appropriate which make the neural network stop classifying, safety and security point of view possibilities of confusing AI algorithm due to change in the sensor data stream (Nascimento, 2019). Law and government challenge every state and country to have their own rules and regulations. It becomes difficult to keep all regulations and standards for the manufacturer (Kim, 2018). The open road with unlimited objects leads to delay in rectification and identification consumes time and leads to extraordinarily complex and more processing time (Jung *et al.*, 2020). As semi-autonomous vehicles are not mature where ethical values are sometimes tedious to formalise social acceptability or public feeling (Nascimento, 2019). Use & availability of data for sensors real-time Data collection from the environment. Other challenges like Legal and ethical issues, extracting relevant and correct data, and Computing Framework, based on data on how the vehicle must go ahead.

C. Accidental Liability (Parkinson *et al.*, 2017):

Who will manage accidents caused by autonomous vehicles? The manufacturer, the passenger in the latest developments, the car does not have any steering. Where there will be no choice for humans to require control of the vehicle in a crisis.

2.8 Pros & Cons

2.8.1 Pros

Implementation of the autonomous vehicle into transportation will help humans and reduce fatigue and the ways listed below.

i) Machines do not get tired (Campbell *et al.*, 2010)

Unlike Humans, machines never get tired. As per statistics, there are accidents seen due to drivers falling asleep. Whereas in the autonomous vehicle the commuting time can use to do other things like sleep, read & communicate.

ii) No more human errors

As human nature, multiple thoughts are going into the mind. Therefore, less focus on driving. As autonomous vehicles are executing the programs hence there will not be any distraction. (Wang *et al.*, 2019b)

iii) Risk-free

Driving frustration may lead to accidents, drinking, and driving where people ignore the regulations and drive. Where the autonomous vehicle will run throughout by itself once the destination is provided. (Geng *et al.*, 2019) (Wang *et al.*, 2019b)

iv) No rules violation

Concerning the program, will be no violation of rules, as compared to autonomous people who are moody in terms of driving. (Jabri *et al.*, 2019).

v) Support for the mobility of old people

The physically challenged people face problems with commuting as most of the time they must rely on others. (Martinez and Jimenez, 2019) The same goes for retired old people who cannot drive due to low physical conditions and must be dependent.

vi) Multi-tasking

Commuting time can be used for many other works.

vii) Support to environment

Most autonomous vehicles are electric and do not emit any pollutants to the environment. With low fuel consumption and improved ecological for print.

viii) Reduced organised traffic

Since vehicles will communicate with each other there will be more clarity and well-organised traffic because of optimal flow in traffic. (Digani *et al.*, 2018).

2.8.2 Cons

i) Loss of driving jobs (Fagnant and Kockelman, 2015)

The transportation industry has a significant role in employment. Where the drivers needed for long coordination to transport goods will lose their daily income. At the same time, most people use cabs/Taxis for daily commuting which will be diverted to autonomous vehicles.

ii) High first investments, maintenance costs & technical errors

As it is new in the industry and every manufacturer has invested plenty of capital in research to make the vehicle safer on the road. Hence, in the beginning, autonomous cars will be quite expensive. At the same time, technology is new in the market and developments are going on. Which may have certain bugs and issues in the software which will need to fix. At the time of breakdown, it will be difficult to find the right person to fix the issue. Thus, the maintenance of autonomous vehicle bay is quite different and high in terms of cost.

iii) Privacy concerns & hacking issues (Fagnant and Kockelman, 2015)

Day-to-day life data is misused, where anyone can gather the data and commercialise it. Maintaining trust in personal data is highly unreliable. Where numbers of hackers are gone up as the vehicles connected to the cloud and where There is a substantial risk of a breach. Where manufacturers are trying to make sure data, and systems are highly protected to fight against hacking. Such attacks may cause interruption of vehicle functioning and cause accidents.

iv) Laws and regulation restrictions

Every country has its law and getting approval permission to be allowed on their road is quite a tedious procedure and strict regulations as any mistake may cause loss of lives. The manufacturers are stuck in getting approved and satisfactory safety concerns.

v) Losses in actual fun of driving

People have made their career in driving and would prefer manual driving; some enjoy driving as their hobby. Where autonomous lags in that art of fun.

vi) Sensor's limitation

Poor weather conditions such as fog, rain & snow prevent clarity on road. Which may lead to accidents. Sometimes the images are not clear enough for the computer to make decisions which creates confusion.

2.9 Applications

2.9.1 Metropolitan applications

In metropolitan conditions, autonomous vehicles will alter city plans and vehicle 4%, 1% possession models. Today, individual vehicles are just users of the time, as 95% are spent in rush hour gridlock and left. (Broggi, 2000) Self-driving vehicles, together with 75% with vehicle sharing administrations, are relied upon to further develop vehicle usage rates up to 90% and to diminish the number of vehicles up to 2015. This would lead to more limited and less expensive excursions, fewer mishaps and fatalities, and cleaner and more decent urban areas. Likewise, public transportation in metropolitan urban areas is progressively significant to address traffic and versatility challenges. In any case, the overview performed by the 16% European Commission (2013) shows that just of European residents use public transportation as their principal method of transport. The principal explanations behind the low use of public vehicles are costly tickets and unpredictable travel times. (Juan antonio Guerrero ibáñez, 2015) Because of an autonomous transport armada, the costs identified with the driver staff would disappear, and running occasions would be more unsurprising. autonomous vehicles are likewise expected to conduct better fuel use, prompting decreased costs. These elements would significantly decrease the last expenses, unveiling transportation as a more alluring choice, and diminishing the number of vehicles. (Pérez-Carabaza *et al.*, 2019, Liniger *et al.*, 2015)

2.9.2 Industrial applications

Autonomous driving advances can be extremely useful for on-street driving applications, yet in addition for rough terrain applications, for example, rock pits, mining regions, building locales, and stacking terminals. It's assessed that up to 69% of the mishaps including pull trucks in mines brought about by administrator exhaustion (Balas, 2019). In a mining site, autonomous trucks can achieve complex assignments, like the stacking and dumping of rubbish. Distantly, in an order focal, human administrators are answerable for administering every one of the activities and mediating if fundamental. regulatory expenses because of expanded guidelines over natural consistency (Bai *et al.*, 2019). autonomous vehicles empowering foundation development and law adaptation are significantly less difficult than in a metropolitan climate. Likewise, The difficult issues that should be tended to in metropolitan conditions are missing in exceptional, encased regions. In mining conditions, it is expected that autonomous vehicles can 20%, by 15%, expand usefulness while diminishing fuel use by up to 8% 40% upkeep costs, and tire life improvement MIT (Massachusetts Institute of Technology) Technology Review, 2016. For example, studies show that, when looking at 16% of manual-driven trucks, autonomous trucks travel less distance and sit inactive if 3 hours less. By wiping out the human-on top of its factor, the number of human fatalities is likewise expected to diminish. By lessening fuel use, ozone harmful substance discharges, and working expenses, autonomous take trucks add to a more harmless to the ecosystem mining industry (Wang *et al.*, 2019b).

2.10 Chapter Conclusions

Autonomous vehicles are a separate field of research. From university research to industrial mass production technology has consistently developed. However, reliable driving is still causing several challenges. Errors in the feeling of the environment and up-to-the-mark sensors. (Nascimento, 2019) Most of the focus will come to AI systems by integrating all the algorithms and performing the desired execution just the way Alexa and Google Homework do. The major focus is on Collision avoidance to perform safer rides on the road. As when it comes to collision the time needed to respond is noticeably short and should be safe enough. Further chapters will focus on attempts to improve collision avoidance systems. The complete system has subsystems that are dependent on each other for processing and decision-making based on the same data for functioning. Every vehicle will be interacting with each other for real-time data and solving complex issues like question location, course arranging, and real-time choice making. Further research is needed to understand user acceptance and ensure system security and integrity.

3 Optimisation Problems of Autonomous Vehicles

3.1 Introduction of Optimisation

3.1.1 Representation of Optimisation Problems

The optimisation is to find the best practical solution to a problem with the satisfaction of design constraints. The aim, called objective, could be anything to reach a maximum or minimum (Yan, 2018). An optimisation algorithm is a process to find the best solution with a repeat iteration by comparing or evaluating the objective function until the solution has been found.

The below example for the standard method of representing the objective function

Mathematically, an optimisation problem defined as

$$\min_{\vec{x}}/\max \vec{f}(\vec{x}) \tag{3.1}$$

$$st.\ \vec{g}(\vec{x}) \leq 0 \tag{3.2}$$

$$\vec{h}(\vec{x}) = 0 \tag{3.3}$$

were $\vec{x}$ are design variables/parameters. Different $\vec{x}$ presents assorted designs. Normally $\vec{x}$ is a vector. The problem is called one dimension optimisation problem if its dimension is one, or it will call an n-dimensional optimisation problem. (Gasparetto *et al.*, 2015) The parameter may be extremely sensitive, or some may or may not affect the solution hence the assumption and variables should choose wisely. Therefore, it is particularly important to choose wisely and limit variables.

$\vec{f}(\vec{x})$ are the design aims that the design hoped to achieve? If a design hopes to make the objective to be minimum, this optimisation problem called the minimization problem, or it is the maximization problem.

Constraints are the limitations to few useful connections among the plan factors and other plan parameters fulfilling certain physical wonders and certain asset impediments. There are two types of constraints:

1) Inequality constraints: the practical connections among the variable are either more noteworthy than, less than, or break even with, asset esteem.
2) Equality constraints: the design variables must satisfy equations.

The process to find the best solution is called the optimisation algorithm. It is impossible to solve by applying a single formulation procedure. since the aim is a design problem and associated, therefore, (Rowan McAllister, 2017)

3.1.2 Types of Optimisations

According to the property of objective functions, optimisation problems are divided as:

- Minimisation problems. The objective function will be minimised. The less the objective value, the better solution.
- Maximisation problems: The objective function will be maximised. The larger the objective value, the better solution.
- the mixed optimisation problem: Assuming that there are objective functions in an optimisation problem, some objective is hoped to be minimum, and some are hoped to be maximum. In solving this kind of optimisation problem, the maximum objective should change to the minimum objective by using mathematical transforms.

According to the type of objective functions, the optimisation problem can divide:

- Linear programming: The objective function is a linear function of decision variables. The management optimisation problems are linear programming.
- Quadratic optimisation: The objective function is the quadratic function of decision variables.
- Nonlinear optimisation. the objective function is nonlinear. The engineering optimisation problems are nonlinear optimisation.
- Multi-objective optimisation. The goals are more than one.

3.2 Optimisation Problems

Table 3-1 provides the list of problems that occur in autonomous vehicles with the junction of the problem statement and what are the various methods used to solve the problem.

Table 3-1: Overview of Optimisation problems

Sr. No	Problem	Statement	Methods	Ref.
1	car-following and lane-changing scenarios	To keep continuous velocity, for real-time motion planner along with road region and vehicle shape identification along with collision avoidance	*1) Mean-Field Game - MFG* *2)* Newell's simplified linear car follows the model *3)* Lane Changing robust fuzzy control approach	*(Gong et al., 2016, Wei et al., 2017)*
2	Motion planner, Trajectory	To plan space and search best fit trajectory with hierarchical and complex driving tasks to supply automatic steering input	1) Accelerated Particle Swarm Optimisation - APSO (Stefano 2019) 2) Adaptive controller with the fuzzy supervisory system for trajectory tracking control of an autonomous vehicle 3) The model predictive control changed the objective function	(Amer *et al.*, 2018, Wei *et al.*, 2017, Christian Meerpohl, 2019, Lim *et al.*, 2018, Zhang and Wang, 2019, Wang *et al.*, 2019c, Xiong *et al.*, 2019b, Hu and Sun, 2019, Zhang *et al.*, 2019, Lin *et al.*, 2019, Chai *et al.*, 2019, Pérez-Carabaza *et al.*, 2019)
3	Path Tracking	control scheme includes three parts: the non-linear model predictive path tracking controller, the lateral stability controller, and the best torque vectoring controller	1) Fractional Order Extremum Seeking Controller FO-ESC (Fractional Order Extremum Seeking Controller) (Fractional Order Extremum Seeking Controller) (Dadras, 2017)	(Arzamendia *et al.*, 2017, Prabhakaran and Sudhakar, 2018, Wang *et al.*, 2016, Wang and Zhou, 2019, Ren *et al.*, 2019, Chen and Liu, 2019, Guo, 2019, Wang *et al.*,

			2) The model predictive controller	2019b, Juhász *et al.*, 2019, Bai *et al.*, 2019, Dadras, 2017, Yang *et al.*, 2019, Mohammadzadeh and Taghavifar, 2019, Li *et al.*, 2019, Yardimci and Karpuz, 2019)
4	Collision Avoidance	To solve the problem of insufficient searchability of the unmanned surface vehicle- USV (Unmanned Surface Vehicle) (Geng *et al.*, 2019) collision avoidance planning algorithm	1) Improved Ant Colony Optimisation Algorithm 2) Artificial Potential Field Algorithm 3) Rollover model 4) A fuzzy curved regression model 5) State frame & Model predictive control 6) Dynamic Programming	(Wang *et al.*, 2019a, Geng *et al.*, 2019, Pérez-Carabaza *et al.*, 2019)

3.2.1 Problem 1: Lane Changing

3.2.1.1 Description

Lane change is one of the most common behaviours of vehicles. Since autonomous vehicles have become more popular and the future of the automotive industry, lane change has become a hot field of research for scholars all over the world. The generation of lane change path is the precondition of lane change, and the result of path planning decides whether the vehicle is fast, smooth, and safe when changing lanes (Yang *et al.*, 2018). The aim of the path changing is for a vehicle to move to an adjoining path with certain imperatives to move faster or avoid a collision (see Figure 3-1. There is research in the literature that had discussed trajectory planning techniques. The conventional calculations of lane changing are chart look or geometric-based approaches. Dublin curve was a very efficient method to generate a path for vehicles, but it was not practical, because the curvature of the path was a discontinuity. When a car is going to track the path precisely, it should stop at the joint nodes. So, trajectory continuity is particularly important for trajectory generation. A diverse strategy was based on using the B-spline bend (Maekawa); however, this method could cause a complex calculation and a lower speed, at the same time the maximum lateral acceleration generated in the lane change was difficult to control. Lin et al conducted a study on path planning using the method of field. This method is needed to treat a vehicle as a point. Therefore, this method may not be practical for safety because of missing the geometry information of vehicles. (Chen *et al.,* 2013) presented methodology on the Bezier curve for path planning. The curve could solve quickly, and efficiently and satisfy the real-time requirement of autonomous vehicle path planning see (Yang et al., 2018).

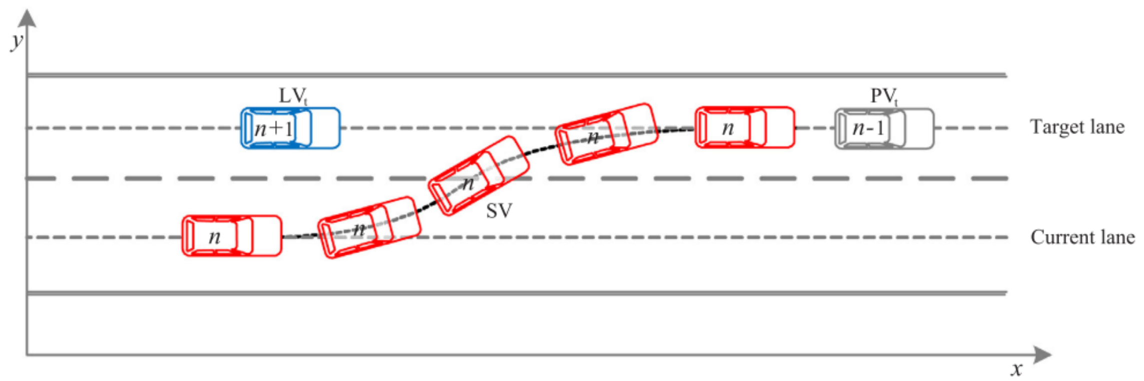


Figure 3-1: Lane changing (Gong et al., 2016)

It must achieve and keep continuous velocity for real-time motion planners along with road conditions with the pre-defined region and the vehicle shape identification with collision avoidance. (Gong *et al.*, 2016) Car-following and lean changing are the features of level 4 autonomous vehicles i.e., the vehicle is capable of monitoring both vehicles and the roadway to decide when and how to change lanes and turn. The path-changing issue may be exceptionally critical because it is initialised as an on-demand action after steering along an indicated sideways way from the current path to the adjoining path. Normally, the vehicle keeps a wanted longitudinal speed and arrangement the vehicle after the path alters such that the lane-keeping assignment can be continued easily.

3.2.1.2 Model for Lane Change

Lane change can be simplified as a model shown in

Figure 3-2 (YONGGANG LIU, 2019). A vehicle will move from one lane to an adjacent lane. In Figure 3-2, Vehicle E is an ego vehicle, and Vehicle TP, TR and P are the vehicles inside the target lane, the rear vehicle into the target lane and the following vehicle into the original lane, respectively. the vehicle will leave the original lane and switch to a target lane. A lane change model will decide the path of the Vehicle.

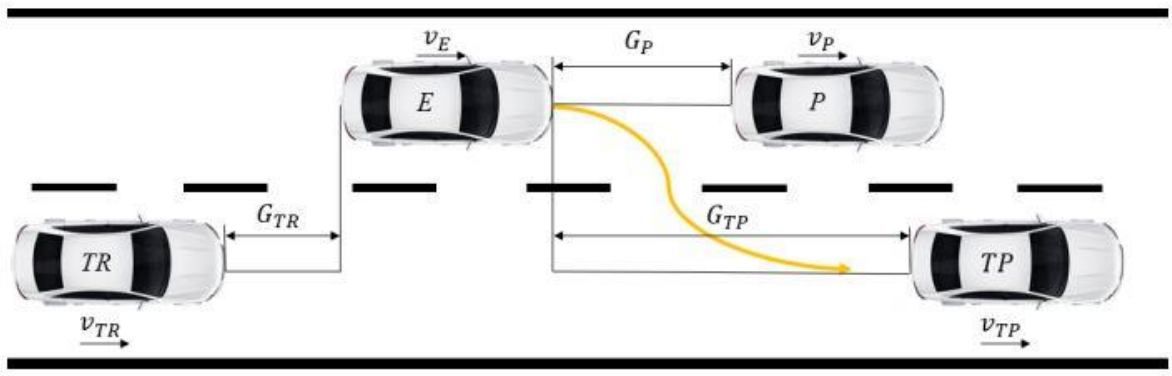


Figure 3-2: Lane changing model (YONGGANG LIU, 2019)

It is easy to understand that Vehicle TP, TR, and P will affect the decision. However, more factors should be considered in the lane change.

- Objective or benefit of lane change

The purpose of lane change is to increase the driving speed, obtain greater space ahead, or leave the road.

The string speed in the future can be converted into the speed of the preceding vehicle. Thus, the speed benefit can express as

$$v_{benefit} = \min\left(v_{set} - v_p, v_{TP} - v_p\right) \tag{3.4}$$

Were, v_{set} means the speed of the vehicle. The open space between the front vehicle and the front of the car is represented by relative distance and can be expressed as $G_{TP} - G_P$.

The driving benefit model can say as follows:

$$f_{benefit} = f(v_{benefit,}\, G_{TP} - G_P) \quad (3.5)$$

- Safety

Safety is most important in lane change. The vehicle should avoid any collision with other vehicles. It is easy to understand that the greater the gap and relative speed between Vehicle E and Vehicle TR the safer the lane change process is. Also, a minimum safe gap is needed for a lane change, The following safety model can be expressed.

$$f_{safety} = \begin{cases} -\infty, & G_{TR} < G_{TRmin} \\ f(G_{TR}, v_E - v_{TR}), & G_{TR} < G_{TRmin} \end{cases} \quad (3.6)$$

$$G_{TRmin} > 0 \; is\ the\ minimum\ safe\ gap\ between\ E\ and\ TR$$

- Tolerance

The autonomous vehicle may choose to use lane alter with over advantage and security work, but the distance between E and P may be large, and the vehicle may keep changing the lane often. Subsequently, it is vital to set up resilience. When E is near P, the autonomous vehicle will take after P in ACC (Advanced Cruise Control) mode, and the anticipated distance is decided by the speed and the time progress. Thus, tolerance shows can be set up as

$$f_{tolerance} = f(G_p - v_E . t_h) \quad (3.7)$$

Were $t_h > 0$ is the time headway.

3.2.1.3 Methods to solve lane changing problem

Lane changing can be converted into three stages as shown in Figure 3-3 (M.L Ho and P.T Chan 2007).

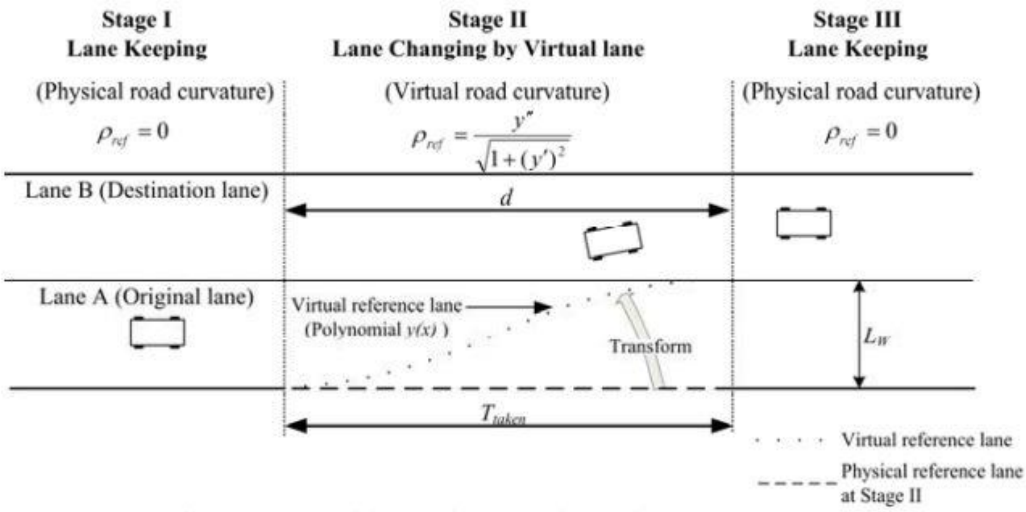


Figure 3-3: Lane changing Stages (Yang et al., 2018)

- Stage I. The first stage is where the vehicle is on the straight lane and the curvature is zero. The lane-keeping controller alters the vehicle position by measuring the horizontal separate from the physical reference path stamping on the street with the help of a sensor.
- Stage II. When a vehicle moves from one point to another point, there will be obstacles coming across the road. To overcome obstructions the virtual reference lane is proved by the polynomial equation as shown in Figure 3-3 which is derived based on longitudinal distance (d), lateral acceleration limit (a_{max}), and lane width (L_w). The actual steering angle and the polynomial equation will be used to calculate the lateral position by the property of the bicycle model.
- Stage III. When the vehicle comes across the curvature the vehicle's lateral position is kept by a lane-keeping controller which is measured by hardware sensors. Whereas all three stages are covered by the same controller (Yang *et al.*, 2018). Hence, no other controller will need, or any looked for switching needed.

Throughout the long term, different lane-changing models have been proposed to aid drivers with playing out the activity without slamming into different vehicles. (Gong *et al.*, 2016) Plans, like the vehicle following model, hole acknowledgement model and game hypothesis model, are a part of the famous method by a specialist to foster a path-evolving model. Below is path change models.

A) Gap Acceptance

The model of Gap acceptance is first intended to show conduct at convergences. During the 1960s, (Feigenbaum, 2018) The hole acknowledgement model depended on the basic length diffusion of the holes. The model is likewise used in the path change measure, where drivers measure the distinctions between front and back vehicles in the objective path. Drivers evaluate the access hole in case of a basic unseen hole before tolerating or dismissing it.

B) Game Theory

This model portrays driver collaborations, as most lane-changing (LC) models. Game theory (GT) has been incorporated with lane changing. The blending and giving-way communication portray the driver association in the entrance segment. While few past investigations have shown the worth of research, (Kuang Huanga, 2019a) accepts that few of them have investigated the inspiration and longing for a forgiving way of conduct. (Kuang Huanga, 2019b) have expressed that (Hironori 2015) The model has no useful assumption, and it might have been executed before blending is conducted. Consequently, this theoretical model of game hypothesis ought to fortify with various harmony arrangements, it gives an illustration of LC moves that can be duplicated. Moreover, the exploration additionally introduced one more entrance combining model dependent on GT part that incorporates practical conduct rules.
Modification of the path's identification strategy by (Campbell *et al.*, 2010) can be characterised into two classifications: framework-free and foundation subordinate. Vision frameworks and Differential Global Positioning Systems (DGPS) are two instances of infrastructure autonomous path identification approaches. (Li, *et al.* 2004) and (Yim, 2003) proposed framework-free path identification calculations using vision frameworks to distinguish the painted path markers on the public streets for vehicle direction. (Tan, *et al.* 2003) and (Farrel, 2001) recommended a coordinated DGPS framework with control state calculation for vehicle control.

C) Mean-Field Game (MFG)

(Kuang Huanga, 2019b) The theory of the Mean-field Game was introduced some years ago by (Jean Michel Lasry, 2007). Mean-field diversion is inferred by constraining differential diversion as most autonomous vehicles tend to be limitless. It could be a forward-backwards halfway differential condition Potential Difference Equation (PDE) framework that models autonomous vehicles' non-cooperative speed choices to a visible scale. In Mean Field Equilibrium (MFE) as shown in Figure 3-4, the best velocity control strategy has represented at the Macroscopic level, and a continuous equation solution supplies fine calculation results. But the non-cooperative individuals' controls are more complex. There must be an assumption that autonomous vehicles are predictive and rational agents. The mean-field diversion hypothesis centred on the presence of Nash equilibria, with person procedures created in recreations including an expansive number of specialists modelled by controlled stochastic energetic frameworks. (Kuang Huanga, 2019b). Usually, conducted by misusing the relationship between limited and comparing restrain populace issues.

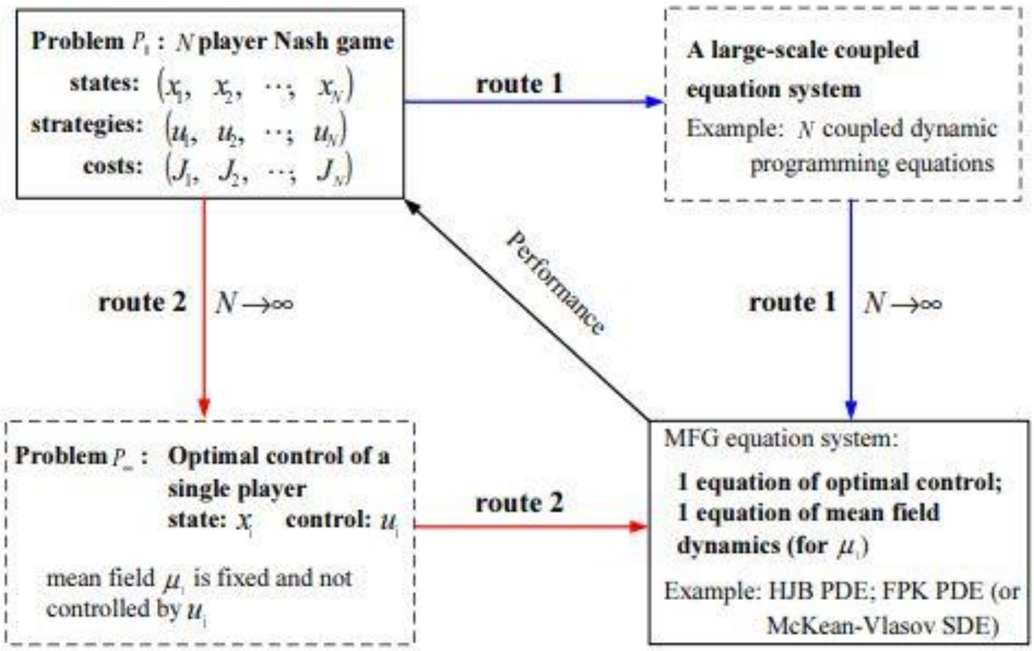


Figure 3-4: Fundamental diagram of MFG theory (Kuang Huang, 2019b)

D) Newell's simplified linear car follows a model

(Kuang Huanga, 2019a) made a demonstration called Newell's hypothesis of limitations. The limitations we confront straightforwardly affect our move through the stages of advancement; these limitations can result in either a quicker or slower progression through the stages. In case you are never challenged to think in a basic way and issue fathom at a youthful age you will never graduate to the final stages of cognitive improvement. A structure and work, an assignment, and the environment can cause limitations.

E) Lane Changing the robust fuzzy control approach

The fuzzy system is the most popular control system used for feature extraction and fault detection systems (Mohammadzadeh and Taghavifar, 2019). To resupply logic of human behaviour characteristics which work on the simple logic of 'n' number of rules as input to resupply output. Figure 3-5 gives an example of the change in the steering angle.

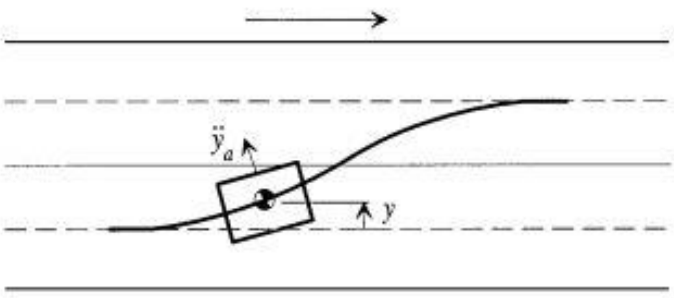


Figure 3-5: Fuzzy logic (Mohammadzadeh and Taghavifar, 2019)

Were, $\ddot{y}_d$ as eight stages, $\ddot{y}_a$ as eight in twenty-four rules as $8 \times 3 = 24$. y as lateral lane displacement. Lateral acceleration error, $\ddot{e}_a := \ddot{y}_d - \ddot{y}_a$

Let $\tilde{Y}$ the linguistic variable of y

$$\tilde{Y} \in \{first, second, third, final\}$$

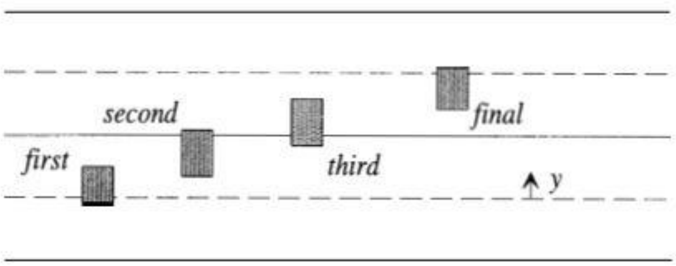


Figure 3-6: Linguistic description of y (Mohammadzadeh and Taghavifar, 2019)

Stage I: Desired to accelerate the vehicle to $\ddot{y}_{max}$

Stage II: first stage region

1) Ramp up until to $\ddot{y}_a$ to reach to $\ddot{y}_{max}$
2) Maintain to $\ddot{y}_{max}$ when to $\ddot{y}_a$ reaches to $\ddot{y}_{max}$
3) Ramp down until to $\ddot{y}_a$ reaches zero
4) Maintain zero acceleration, when $\ddot{y}_a$ reaches zero
5) Ramp down until $\ddot{y}_a$ reaches $-\ddot{y}_{max}$
6) Maintain $-\ddot{y}_{max}$, when $\ddot{y}_a$ reaches $-\ddot{y}_{max}$
7) Ramp up until $\ddot{y}_a$
8) Maintain zero acceleration, when $\ddot{y}_a$ reaches zero.

$\ddot{y}_d$ update during the lane change (shown in Figure 3-7)

$\ddot{y}_{max}$ maximum lateral acceleration

$t = t_0$ The first stage at the time

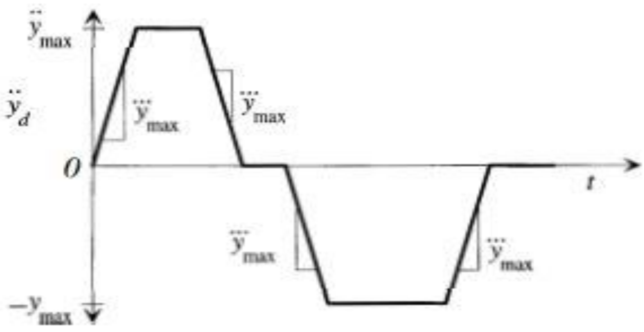


Figure 3-7: Lateral acceleration (Mohammadzadeh and Taghavifar, 2019)

F) A fuzzy curvilinear regression model (Prabhakaran and Sudhakar, 2018)

(Prabhakaran and Sudhakar, 2018) proposed a fuzzy curvilinear regression model for a lane change. The parameters of this model include host vehicle
velocity V_H,
Rear vehicle distance d_r,
Front vehicle velocity $V_{T,r}$,
Front vehicle distance d_f,
Front vehicle velocity $V_{T,f}$,
Maximum long predefined front distance $dlpf$,
Minimum short predefined front distance$dspf$.

Let the product speed of light c, the delay times τ between the successive transmission and reception of a pulse signal, R calculated as.

$$R = \frac{c\tau}{2} \tag{3.8}$$

The target vehicle position, (x, y), is measured using the equation below.

$$x = Rcos\theta \tag{3.9}$$

$$y = Rsin\theta \tag{3.10}$$

The separation between the target and the vehicle was assessed using the Euclidean metric given within the underneath condition.

$$d = \sqrt{(x - x_s)^2 + (y - y_s)^2} \tag{3.11}$$

Were $xs,\ ys$ represent the sensor coordinates of the host's vehicle. Similarly Let the relative velocity VR, Doppler frequency f_D the speed of light c and the carrier frequency f_c , the target vehicle velocity is calculated with the equation below.

$$V_R = \frac{cf_D}{2f_c} \tag{3.12}$$

$$f_D = f_r - f_t \tag{3.13}$$

The Doppler recurrence gauges the distinction between the gotten recurrence f_r and transmitted recurrencef_t. Finally, the target vehicle's speed V_t I assessed based on the vehicle speed V_H and relative speed V_R presents within the underneath condition.

$$V_T = V_H + V_R \tag{3.14}$$

V_T conditionally altered as $V_{T,f}$ to differentiate between the front vehicle velocity and V_T, r for rear vehicle velocity.

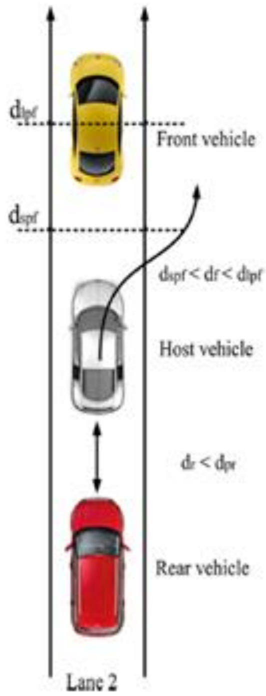


Figure 3-8: Vehicle curvature path (Prabhakaran and Sudhakar, 2018)

$$off = off_F - off_H \tag{3.15}$$

The host vehicle fits a proper curvature path on left side direction LSD as shown in Figure 3-8 on right side direction RSD as illustrated in below figure the parameter $y_{t,\ Left}$ and $y_{t,\ right}$ in below equation signifies the LSD and RSD deviations with regards to the host vehicle coordinate in addition to yaw rate, range represented as w and q, respectively.

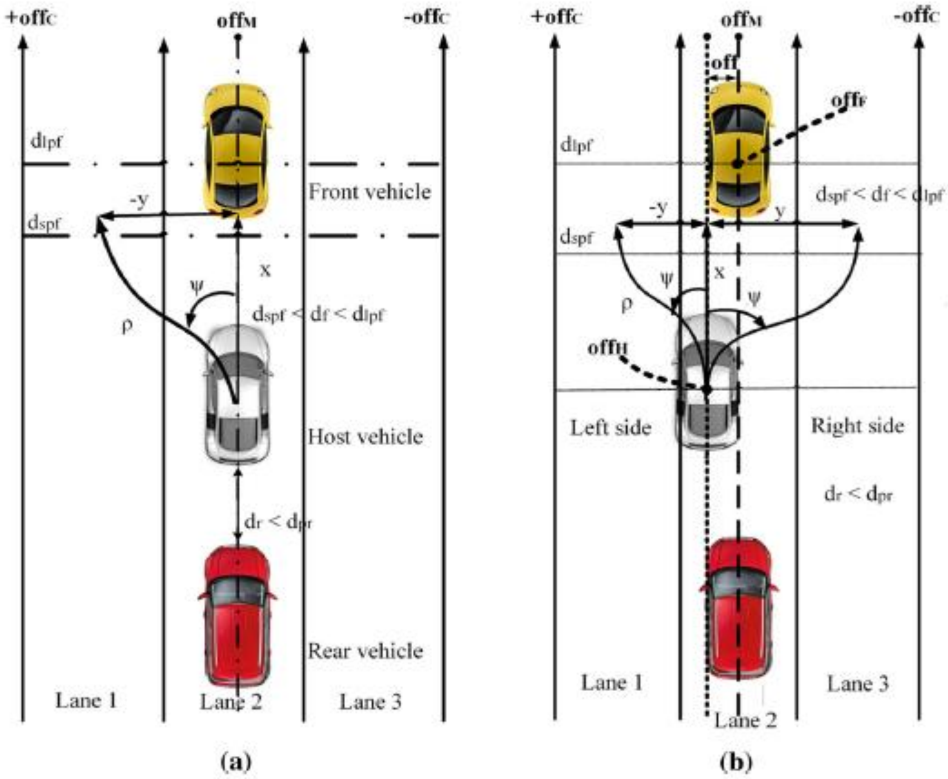


Figure 3-9: a. Constraint curvature motion of the host vehicle. b. Offset curvature motion of the host vehicle (Prabhakaran and Sudhakar, 2018)

The fluffy coefficient $(a_0, a_1, a_2, a_3, a_4)$ of $\tilde{y}_i$ expected to require deviated enrolment work to conduct a versatile curvilinear way. The versatile coefficients of the watched way can be changed by the spread level of the fluffy enrolment work to get the evaluated way. Versatile coefficients moreover help in getting back the authentic way from the watched fluffy way. To invalidate cruel mistakes. Fluffy relapse joined to amend the position blunder at each feeling were $i = 1, \ldots n$. Subsequently making the fluffy relapse using the dubious h-parameter within the watched fluffy way. At each versatile curvilinear way estimation as shown in above Figure 3-9.

3.2.2 Problem 2: Car following

3.2.2.1 Description

Car-following could be a common driving behaviour that features a critical impact on driver security and comfort. Even though a vast number of considers have cantered on car-following models for autonomous vehicles. A car following is one of the foremost critical and common conditions for manual driving, helped driving, or autonomous driving.

With the fast development of the urban activity scale, car following has gotten to be the foremost essential condition experienced by drivers.

3.2.2.2 Model for car Following

The car-following model should be based on a real traffic flow control model. An autonomous vehicle can use sensors to describe the traffic flow motion of the vehicle and can be regulated by the processor based on the best parameters to control the speed. Figure 3-10 (Shuke An, 2020) highlights the area where the vehicle should slow down like a limited zone said collision avoidance space, dynamic following concerning the gap margin.

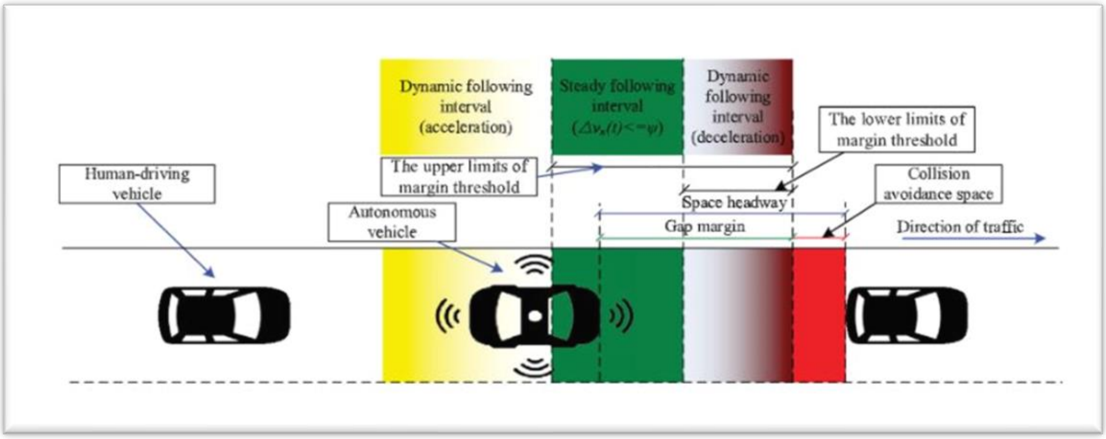


Figure 3-10: Car following terminology (Shuke An, 2020)

Cut-in operation is very normal in driving as said in Session 3.2.1. Due to reasons, some vehicles may change their lane. This will affect the car-following of the cars in the lane. illustrates how the cut-in car will affect the car following.

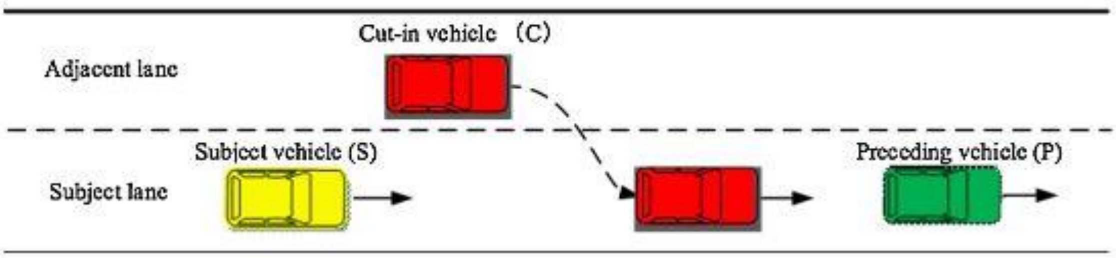


Figure 3-11: Cut-in vehicle (Shuke An, 2020)

3.2.2.3 Method to solve the car following

Car Following is one of the well-known types of research on car-following models and has been cited mostly by researchers. (Gong *et al.*, 2016) constructs a car-following model that highlights three main aims as follows,

- To simulate real traffic behaviour,
- To illustrate driver's characteristics based on the variable of the model,
- To deliberate and compare the model based on the duration

There are car models following in the literature.

- Optimum velocity model

The best velocity model is a traffic flow model proposed by (Bando) the governing equation can express as

$$\frac{dx_i}{dt} = v_i \tag{3.16}$$

$$\frac{dx_i}{dt} = a[v(x_{i+1} - x_i) - v_i] \tag{3.17}$$

were x_i is the position of a car and v_i is the velocity of the car. The parameter "a" is a trigger denoting the speed of the response. This model involves the phase transition from the uniform flow plane to the traffic jam.

The function V(b) denotes the best velocity decided by the intervehicle distance. Here, the following tanh type function taken

$$V(b) = \tanh(b-2) + \tanh(2) \tag{3.18}$$

A car will keep the maximum speed within enough distance to the next car. A car tries to drive at the best velocity decided by the distance to the next car.

A) Wiedemann model

The Wiedemann car-following demonstration was initially defined in 1974 by Rainer Wiedemann. This is known for its extensive use within the microscopic multi-modal activity stream simulation program, The Wiedemann model was developed based on conceptual development and limited available information and needs to calibrate to activity stream information. The foremost thoughts behind the Wiedemann model were used, but the precise shape or formula used within the demonstration is upgraded, utilizing the Naturalistic Driving information that is regarded to be one of the leading accessible sources of "real world" information.

B) Gipps model

The Gipps follow-up model is the foremost commonly utilised method of the collision avoidance class of models. Models of this class point to show a secure taking after separate behind the leader vehicle. Gipps' model is known for being the building piece of the Aim sun microscopic simulator (Casas et al., 2010). It includes two components: speeding up and deceleration sub-models,

Problem 3: Motion Planner, Trajectory, and Path Tracking

3.2.2.4 Description

Motion and trajectory are the pre-defined paths, which execute how the vehicle will move from start to destination (Gonzalez *et al.*, 2016). Trajectory planning also called motion planning to generate a path as a function of time. It is the real-time planning of a vehicle moving from one state to another, by satisfying kinematics limits and constraints by navigation modes. The path will have unpredicted obstructions which will be distinct functions considered by distinct functions, considered as input, and executed. The execution of path tracking is one of the processes, where a vehicle can project the way by studying and following the logic at the instance to create the environment to follow the path. The input of the control framework is given as movement (Yang *et al.*, 2018). As such movement panning cannot work offline, reasonable sensors are prepared to screen the movement and empower the control framework to alter the developments in real-time. The speed point of directing ought to have decided with the correct values to alter the developments in real-time.

The trajectory has a varying reference value for the position and/or velocity fed to the controller. In some cases, strong acceleration and jerk are undesired, which may be prevented by having the trajectory rather than constant speed reference.

(Arzamendia *et al.*, 2017) Way arranging is conducted based on the street arrangement, where the real-time environment is watched, and the foremost fitting movement is shown for the trip. As the movement organiser characterises driving limits to meet the determination. Finally, the criticism control alters in like manner to redress mistakes and overcome obstacles continuously.

Evaluation criteria of control methods are:

i) Path arranging procedures for data passing [e.g., Hierarchical]

ii) Path arranging strategies [calculations used for way planning]

iii) the inside representation of way or direction

iv) Minimization [which limits are considered?]

v) Solution sort [robot, joint space, cartesian space, straight line, using focuses with turns, use of spline.

3.2.2.5 Methods for motion, trajectory, and path planning

A) Accelerated Particle Swarm Optimisation (APSO) Stefano (2019)

By simplifying the standard PSO (He *et al.*, 2019), (Stefano 2019) proposed the APSO algorithm by using only the global best position instead of particle best and global best to update velocity.

Model Predictive Control

Normally ideal control states are assumed to be discrete. Let the state $x(t)$ be completely discernible, the predictive model defined as

$$\min_{u_{t\to t+N|t}} \Phi\left(X_{t+N|t}\right) + \sum_{k=0}^{N-1} L\left(X_{t+k|t,}u_{t+k|t}\right) \tag{3.19}$$

$$X_{t\to k+1|t=f(X_{t+k|t},u_{t+k|t}} \tag{3.20}$$

$$X_{min} < X_{t+k|t} < X_{max}, \qquad k = 0, \dots, N-1 \tag{3.21}$$

$$u_{min} < u_{t+k|t} < u_{max}, \qquad k = 0, \dots, N-1 \tag{3.22}$$

$$X_{t|t} = x(t) \tag{3.23}$$

B) Adaptive controller with the fuzzy supervisory system for trajectory tracking control of an autonomous vehicle (Amer et al., 2018)

Controllers are designed to look ahead distance to guide the vehicles automatically. Considering the yaw rate between the vehicle and the trajectory, Fuzzy supervisory improves the performance in autonomous steering control.

C) Model predictive control with modified aim function (Zhang et al., 2019)

Model predictive control is a method of controlling processes while satisfying a set of constraints mostly used in digital control and process industries. Multiple-model algorithms for tracking are majorly used to predict all the dynamic objects in the surroundings to evaluate multiple movements of series simultaneously for each object and to correlate and update in real-time observations. The optimisation problem formulated as

Minimization $$\sum_{k=1}^{N} J\,(x_{t+k}\,, u_{t+k}) \tag{3.24}$$

Subjected to, $$x_{t+k+1} = f(x_{t+k}, u_{t+k}) \tag{3.25}$$

$$g(x_{t+k}, u_{t+k}) \leq b \tag{3.26}$$

$$l_x \leq\ x_{t+k} \leq\ u_x \tag{3.27}$$

$$l_u \leq\ u_{t+k} \leq\ u_u \tag{3.28}$$

Since the inputs are integrated twice, they may be zero for most of the prediction horizon while still causing a change in system states. The number of prediction steps M for the input then be much fewer than for the output. Thus, reducing the computational cost. The state-space model used is then

i) Fractional Order Extremum Seeking Controller FO-ESC (Fractional Order Extremum Seeking Controller) (Dadras, 2017)

The extremum looking for the controller is a versatile optimisation calculation that decides the method to its ideal point where the characterised fetched work is minimised or maximised.

3.2.3 Problem 4: Collision Avoidance

3.2.3.1 Description

Collision Avoidance technologies are rapidly becoming a major focus for road safety research. Artificial intelligence (AI) techniques (including AI sensors and AI algorithms) have been studied to replace the driver's operation in driving a car, such as looking at heading/consideration, operating vehicle movement, checking traffic conditions, To settle on continuous choices. Research has shown that accidents and crash-related expenses have reduced sharply with the use of AI techniques. Fabricated intelligence wellbeing frameworks do not need a human survey or video access at all and are workable with guaranteeing driver security.

3.2.3.2 Models for collision avoidance

In this section, we consider the simple model that illustrates the consequences of imposing limits on acceleration. The largest slowing comes from the powertrain when the power is reduced rather than from braking. Otherwise, a braking algorithm treating the dynamic of activation must include in the model of collision avoidance.

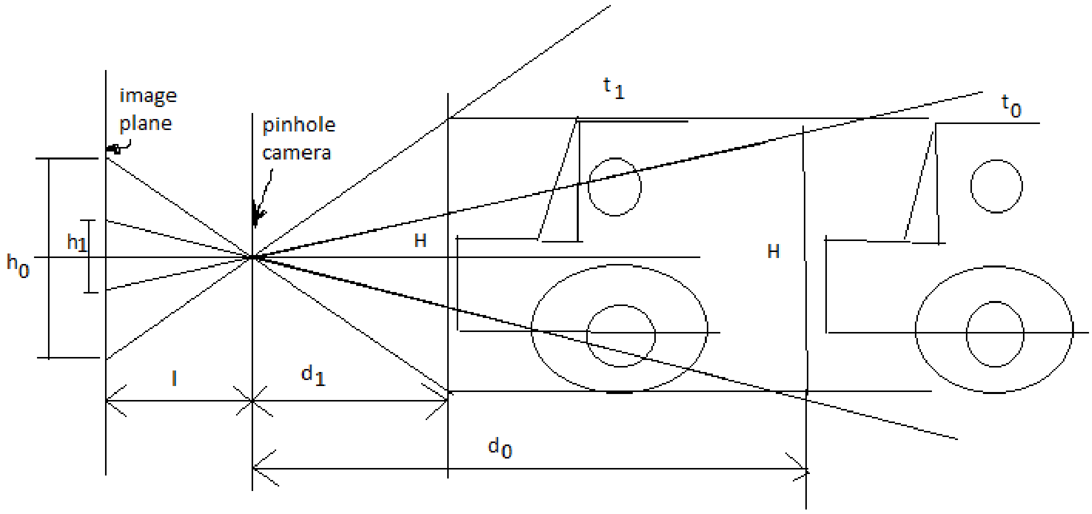


Figure 3-12: Camera Projection

In Figure 3-12, the height H of the preceding vehicle can be mapped onto the image place using perspective projection. The same height H can be mapped to different heights h_0 and h_1 in the image plane, depending on the distance d_0 *and* d_1 of the vehicle. It is obvious that there is a geometric relation between h, H, d, and the focal length f of the pinhole camera and this is what we want to exploit in the following

Project object into the camera

$$h_0 = \frac{l.h}{d_0}\ ;\ h_1 = \frac{l.h}{d_1} \tag{3.29}$$

Relate projection and distance

$$h_0 = \frac{\frac{l.h}{d_n}}{\frac{l.h}{d}} = \frac{d_0}{d_1} \tag{3.30}$$

$$d_0 = d_1.\frac{h_1}{h_0} \tag{3.31}$$

Substitute in the constant velocity model

$$d_1 = d_0 - v_0.\Delta t = d_1\frac{h_1}{h_0} - v_0.\Delta t \tag{3.32}$$

$$d_0 = \frac{-v_0.\Delta t}{l - \frac{h_1}{h_0}} \tag{3.33}$$

Compute time to contact

$$Time\ to\ contact\ = \frac{d_1}{v_1} = \frac{-\Delta t}{l - \frac{h_1}{h_0}} \tag{3.34}$$

3.2.3.3 Methods

There are various methods to conclude the obstacles and process the situation.

A) Improved Ant Colony Optimisation Algorithm (Wang et al., 2019a) (Yang et al., 2019)

Polygonal obstacles are divided into convex and concave polygonal obstacles (see Figure 3-13). Therefore, it is necessary to decide whether the vertex of a polygon is convex or concave. The area of the polygon is shown in the formula.

$$S_{ABCDEFG} = S_{ABba} + S_{BCcd} + S_{DEed} - S_{CDdc} - S_{EFfe} - S_{GFfg} - S_{AGga} \tag{3.35}$$

Where it takes the trapezoid area formula as an example, x_i & y_i are the coordinates of point i each trapezoid area calculated according to the formula

$$S_{ABba} = \frac{1}{2}(y_A + y_B)(x_B - x_A) \tag{3.36}$$

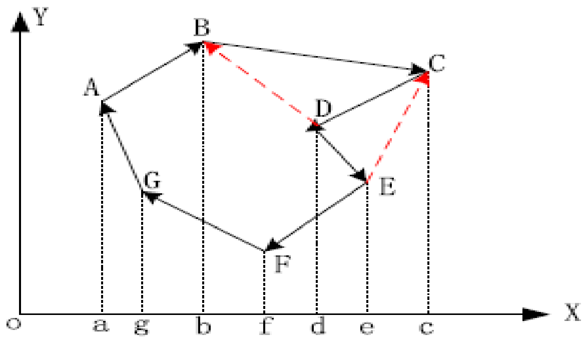


Figure 3-13: Trapezoid area formula (Wang et al., 2019a)

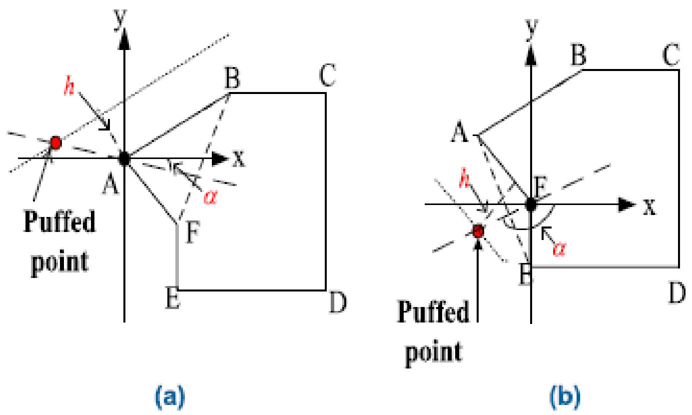


Figure 3-14: Convex and hollow (Wang et al., 2019a)

According to its neighbouring points F & B, the angle between its angle bisector and the positive of the direction of the axis can be obtained, as shown in the below formula

$$\alpha = \angle FAX - \angle\frac{BAF}{2} \tag{3.37}$$

Were h is the manually set safe distance, then the puffed obtained point is the intersection point between the reverse extension line of $\angle BAF$ angle bisector and the parallel line outside the polygon $ABCDE$ with a distance of h from AB (Olivier Orfila, 2019), as shown in formula

$$x = \frac{-h}{\left(\frac{y_B}{x_B} + tan\alpha\right) \cdot \cos\left(arctan\frac{y_B}{x_B}\right)} \tag{3.38}$$

$$y = \frac{tan\alpha \cdot h}{\left(\frac{y_B}{x_B} + tan\alpha\right) \cdot \cos\left(arctan\frac{y_B}{x_B}\right)} \tag{3.39}$$

In 1996, Dorigo *et al*. developed ant colony optimisation which mimics the technique of real-life behaviours to search for food on the shortest path.

B) Artificial Potential Field Algorithm (Wang et al., 2019b) (Chen and Liu, 2019)

Manufactured potential field calculation approaches to treat the robot's arrangement as a point causing potential field with combining consideration to aim and repugnance from impediments. Its fundamental rule is to portray practical scenes by building up a manufactured potential virtual potential field. The way the latter constraints were chosen by shock and fascination created a hurdle and endpoint. Due to the obstacle of the obstacle-to-obstacle evasion way of arranging for autonomous driving vehicles.

Within the handle the obstacle evasion operation, shock created by the object, and attraction created at an endpoint which functions as the inner self car; particularly, at that instance when the sense of self vehicle, obstacle and target point allied well. The attraction produced by the virtual target point seems to lead the self-image vehicle, taking off the neighbourhood least point to fulfil the imperatives of vehicle kinematics elements and streets. In structured streets, it is the most secure to drive within the recentre of arrival if no deterrent is found.

To guarantee the directing point, the speed ought to meet certain conditions for firmness to guarantee controlling execution and controlling stability. (Lin *et al.*, 2019) Taking into thought tire strength, the horizontal speeding up of a vehicle ought not to surpass 0.4g. To expect the sideslip of the vehicle, the horizontal increasing speed of a vehicle ought to not surpass 0.75μg. To fulfil the control of deterrent avoidance, vehicle horizontal speeding up limitation can communicate as

$$mina_y = min\,\{0.4g, 0.75\mu g\} \tag{3.40}$$

Based on the 2-point freedom vehicle model, to derive lateral eacceleration and wheel angle.

$$|\beta_{lim}| = \left|\frac{mina_y(1 + kv_x^2)l}{vx^2}\right| \tag{3.41}$$

Where k is the stable factor of the car, β is the front tire angle, vx is the longitudinal velocity? (Li *et al.*, 2019):

3.3 Solutions for Optimisation Problems

3.3.1 Description

Autonomous vehicles perform based on the data extracted by sensors and AI (Nascimento, 2019) calculations (Nascimento, 2019). Profound learning & Manufactured insights have been universally used with perfect conventional data-driven approaches in different regions of logical inquiry. The headway in ranges like communications, shrewd transportation frameworks, and computational frameworks have opened an unused opportunity for shrewd activity, security, consolation, and productive arrangements. More profound information is needed to perform an optimisation calculation to use optimisation calculations.

AI and deep learning used in autonomous vehicles :

a. Control algorithms
b. Object detection algorithm
c. Decision algorithm

3.3.2 Methods

In the improvement of a design, the objective could be just to limit the expense of creation or to augment the effectiveness of creation (Balas, 2019). An improvement calculation is a system that is executed iteratively by contrasting different arrangements till the best good arrangement is found. With the appearance of PCs, enhancement has turned into a piece of PC-supported plan exercises. There are two unmistakable sorts of improvement calculations utilized today.

A) Deterministic Algorithms. They utilize explicit standards for moving from one answer to the other. These calculations are being used to suit occasionally and have effectively applied for some, design plan issues.

B) Stochastic Algorithms. The stochastic calculations are in nature with probabilistic interpretation rules. These are acquiring prevalence because of specific properties which deterministic calculations do not have.

The following is the list of the methods which are used to perfect.

i) Heuristic techniques

An investigative may be a strategy to unravel the issue quicker than classical strategies or to discover a surmised arrangement when strategies cannot. It is one of the alternate routes often used for optimality, completeness, exactness, or accuracy for speed.

ii) Swarm Intelligence (S.Kalaivani, 2019) (Porras, 2019)

Swarm intelligence is the collective behaviour of a self-organised and decentralised system. The vehicle follows a simple rule without any centralised control system, which is based on the behaviour of animals like flocks' birds, any colonies, animal herding, and a school of fish. (He *et al.*, 2019) Microbial and Bactria growth is based on swarm intelligence (Wang and Zhou, 2019).

Swarm intelligence includes:

a) Partial Swarm Optimisation (POS)

PSO (Particle Swarm optimisation) is regarded as a global optimisation algorithm that can be used to solve a problem whose solution can be described as a point or surface in an n-dimension space (He *et al.*, 2019). Seeded with a starting speed, different potential arrangements are plotted in this arrangement space.

b) Ant Colony Optimisation (Iacobucci *et al.*, 2019)

ACO (Ant Colony optimisation) (Chen and Liu, 2019) was, to begin with, proposed by Dorigo. (Chen and Liu, 2019) find a near-optimal arrangement to the distinctive issues which can be portrayed as chart optimisation issues. Fair as expressed prior, the ants in ACO (Chen and Liu, 2019) attempt to explore the most limited way (Juhász *et al.*, 2019). A celebrated application in remote communication directing is known as Ant Net. In this direction, near-optimal courses are chosen without worldwide data.

c) Swarm-casting

Swarm casting abuses the concept of giving substance downloading to supply high-resolution video, sound, and peer-to-peer P2P information streams (Tong, 2019), which contributes to reducing the required bandwidth.

iii) Expert Systems

The expert framework imitates the human ability to form choices. Expert frameworks fathom complex issues by thinking which extricated from human information. This thinking is represented by the If-Then run the show, rather than procedural coding. The expert framework is categorised into a two-part information base and deduction motor. The information base is composed of rules extricated from human information. For instance, the induction motor applies the extricated run of the show from the information base to known truths. They can incorporate clarification and investigating abilities. There are advanced two modes of induction motors such as forward chaining and reverse chaining.

iv) Logical AI (Nascimento, 2019)

Coherent AI Nascimento (2019) speaks to information from an agent's world. It aims at the current circumstance by sentence in rationale. The operator chooses what to do deducing that a certain activity or course of activity was fitting to reach the aims.

v) Evolutionary Algorithms

Developmental calculations are a subset of developmental calculation in that they as it was including procedures actualizing components motivated by organic advancements such as spread, change, recombination common determination, and survival of fittest. Genetic Algorithms are the most popular evolutionary algorithms.

vi) Fuzzy logic

Fuzzy logic endeavours to fathom issues with an open, loose range of information that creates it conceivable to get a cluster of precise conclusions. (García G, 2019) The fluffy rationale is an approach to variable handling that allows for different values to be managed through the same variable Fluffy rationale is outlined to fathom issues by considering all available information and making the most excellent conceivable choice given the input.

vii) Supervised Learning

It may be a subcategory of machine learning and fake insights it is characterised by its use of labelled information to prepare calculations for ease of classification and exactness. It is usually classified into two classifications and regression (Ankit Laddha, 2016).

Classification: which relates to a specific entity to conclude. Where common classification algorithms are support vectors, design tree, K-nearest neighbour, and random forest.

Regression: which relates to making projections by relating dependent and autonomous variables. By linear regression, logistical regression, and polynomial regression.

As said below are commonly used learning methods

a. Neural networks
b. Linear regression
c. Logistic regression
d. Support vector machine (SVM)
e. K-nearest neighbour
f. Random forest

viii) Unsupervised Learning

Unlike supervisor labels, unsupervised learning uses unlabelled data. Where commonly solved by hierarchical, k-means, and gaussian mixture models. Unsupervised learning used because of the following reason

- Unsupervised machine learning finds all kinds of unknown patterns in data.
- Unsupervised methods help you to find features that can be useful for categorization.
- It takes place in real-time, so all the input data is to be analysed and labelled in the presence of learners.
- It is easier to get unlabelled data from a computer than labelled data, which needs manual intervention.

3.3.3 Conclusions and Research Gaps

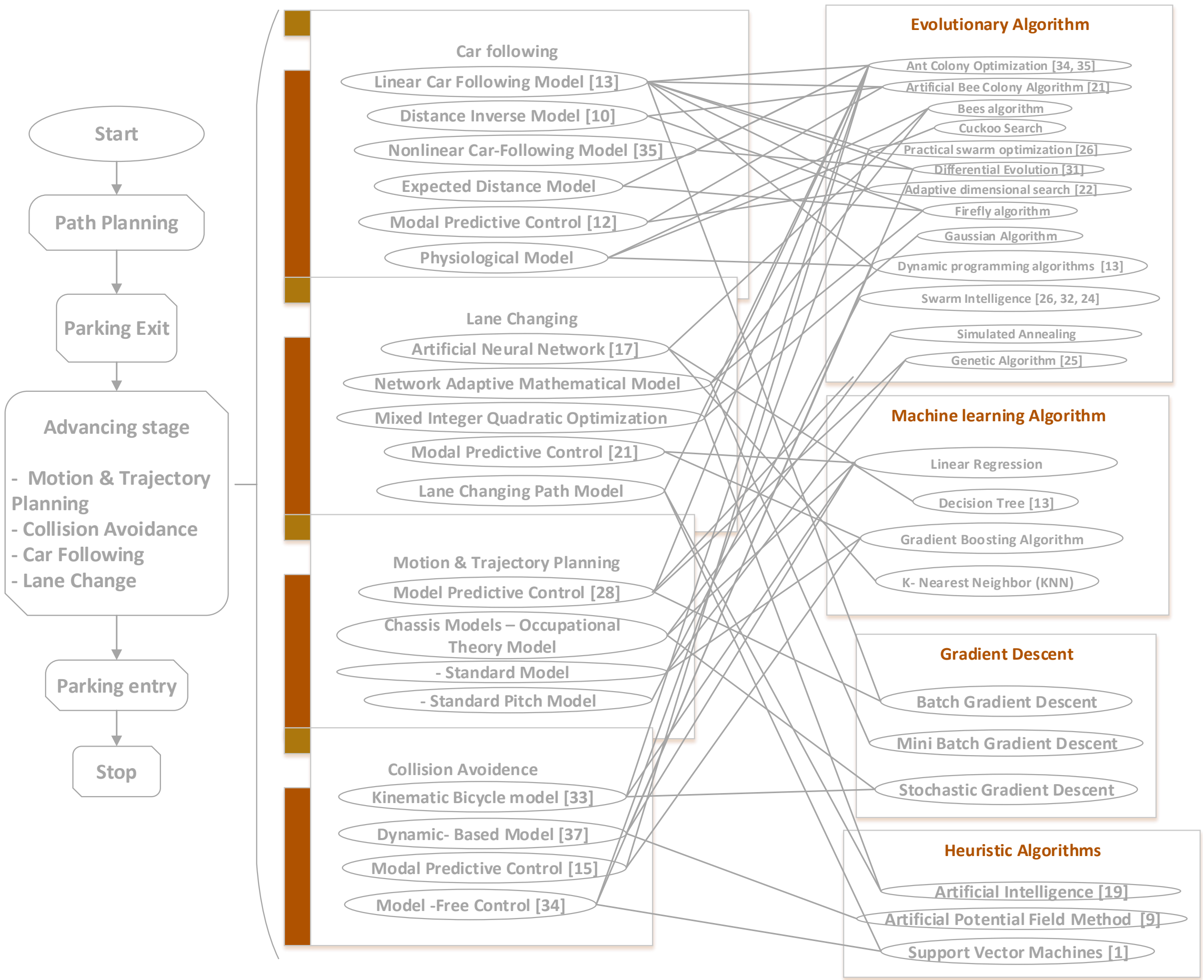


Figure 3-15: Flow chat highlighting different methods used to solve the problem

As illustrated in Figure 3-15, There are various problems in the research and operation of autonomous vehicles, which are categorised as car following, lane changing, motion and trajectory planning, and collision avoidance. The majority of evolutionary techniques are used to solve the problems in autonomous vehicles. When it comes to real-time requirements the time available for computing is very nesting. Hence only genetic algorithms with r brief time the fastest possible computing time can use (Zhang and Li, 2018). Whereas future occurrence and planning can process with evolutionary methods. It is seen that from empirical research, the time taken to generate the desired result is time-consuming. Hence the ranges and limitations are defined for acceptance of certain functions and only those algorithms are implemented. The listed methods have successfully obtained the results, with the integration of sensors by correlating the real-time data.

4 Collision Avoidance of Autonomous Vehicles

4.1 Introduction

Even though advancement has reached in Collision Avoidance where it is categorised in Advanced Driver Assistance Systems (ADAS) (Dahl *et al.*, 2019), there are yet many imperfections that request further upgrades and improvements. The adequacy of Collision Avoidance executions for reality. As street crashes may occur in different situations, an effective Collision Avoidance system can direct the evasion route of the host vehicle in multi-situation risks. For instance, changes at crossing points, high-speed expressway crashes, and Collision Avoidance in packed metropolitan regions are just as impact relief of deduced obscure impediments (Figueiredo, 2009). The National Transportation Safety Board of the United States of America in their 2016 report on transportation security enhancements has recorded the advancement of Collision Avoidance innovation to forestall mishaps (Hamid, 2016). This is important for the most recent proof which legitimises the meanings of late Collision Avoidance contemplates.

Over the most recent couple of years, there has been a fast development in the versatility area across the world. The first important challenge an autonomous vehicle needs to defeat is to keep away from the crash with any static or dynamic snag along its way of movement. The autonomous vehicle can perform crisis moves if it distinguishes any interference. To stay away from any static or dynamic interference in the way of autonomous vehicles it needs to either decelerate to a stand-still on a similar path or move to the adjoining path dependent on the traffic stream of that path (Lakatos, 2019). This task is expected to plan and mimic a vehicle version model for an autonomous vehicle not exclusively to stay away from impact and keep up with the strength of the vehicle yet, in addition, to keep up with collision avoidance on random occurrences.

4.2 Importance of Collision Avoidance:

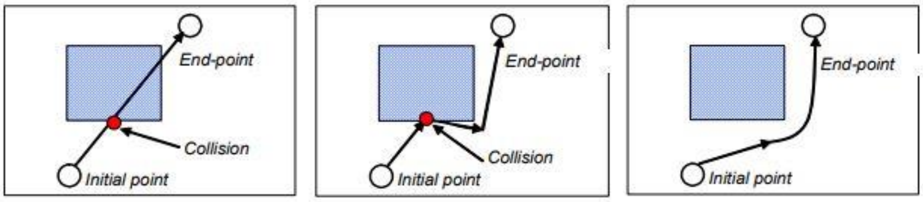
Safe and impact-free travel is fundamental today. It is likewise a chief issue in numerous modern cycles. In aviation and maritime applications, radar-based emotionally supportive networks to stay away from impacts have been utilized for quite a long time. At present, impact version frameworks are beginning to show up in auto applications (Xiaojing Zhang, 2017). The test in planning a crash evasion framework is in adjusting the viability of keeping away from impacts versus the gamble of deceptions. Car applications specific everyday difficulties: thick traffic causes complex situations with many moving items; minimal expense sensors and computational units should be utilized. Besides, the unique capacities of a vehicle might change quickly, e.g., tire-to-street contact might change altogether starting with one second and then onto the next. This thesis discusses the general theory for collision avoidance decision-making and its application in automotive systems. The attention is on managing vulnerabilities in the dynamic interaction and how to oversee complex various hindrance situations. A structure for managing vulnerability is presented. In this postulation, stochastic mathematical coordination is used to assess the certainty of every choice. Moreover, calculations for decision production in different obstruction situations are arranged. The proposed calculations utilize various systems to look through the arrangement of evasion moves, to track down a break way. Novel impact version choice capacities are additionally presented. These capacities address various issues, for example, stopping mechanism qualities, observing the best evasion move for a consistent speed increase movement model and changing impediment elements when the obstruction grinds to a stop. But when it comes to finding the escape point. (Pérez-Carabaza *et al.*, 2019) Sometimes it is difficult to find one where there is furthermore research needed to process in a fraction of a second.

Vehicles on road have caused accidents, and congestion and measures are applied to improve such conditions. It has become a severe problem in various accidents causing cascade effects on the road. Therefore, alternatives such as various systems introduced to perform communication, information control, and processing inherently reduce accidents and increase the efficiency of the transport system. Collision detection and avoidance system are automotive safety systems intended to reduce an imminent collision in the automotive sector the crash is a collision instant owing to the destruction of drive or uncertainty in the automotive. The collision avoidance system will use sensor systems like cameras, RADAR, and LIDAR (Light Detection and Ranging) (Mohamed, 2018). to estimate pre-crash information. Once the imminent collision is detected using a predictive algorithm, the collision detection and avoidance system supply action to take the necessary steps for imminent collisions. Moritz

Klischat (2019) increased demand in the automotive sector led to an increase in traffic congestion. In current trends, collision avoidance is a key factor to be considered as one of the automotive safety applications. The main automotive safety applications are more concerned with human safety security systems. According to (Prabhakaran and Sudhakar, 2018) the Association for Safe International Road Travel (ASIRT), owing to more than 3287 humans are dying every day. To avoid such an imminent collision, the algorithm was modelled for automotive ground vehicles.

4.3 Type of Collision Avoidance

Now and then a 3D picture can substitute with a 2D picture as illustrated in Figure 4-1the vehicles are increasing sharply around the world, and this leads to major traffic congestion, where safety is more concerned.



No collision avoidance   **Local** collision avoidance   **Global** collision avoidance

Figure 4-1: Collision avoidance (Dahl et al., 2019)

The movement of deterrents can cause noteworthy issues. This may be within the frame of interpretation as flow.

When it comes to real-time on the road it is always random and unpredictable which makes it complex to solve the collision avoidance problem and the data provided by the sensor to overcome the random obstacles. (Dahl *et al.*, 2019) created bulk information that must be filtered and rectified correctly and developed a model to predict collision. For modelling impediments, the boundaries of the impediments are characterised by a fanciful field. For a portrayal of these potential areas, the two-dimensional Laplacian of gaussian [2D Laplacian of gaussian] can be used. Sensor-based way arranging plays a major part within the autonomous vehicle, where sensor-based arranging is an irreplaceable work as shown below when situations alter with time are obscure, or there are mistakes within the gear.

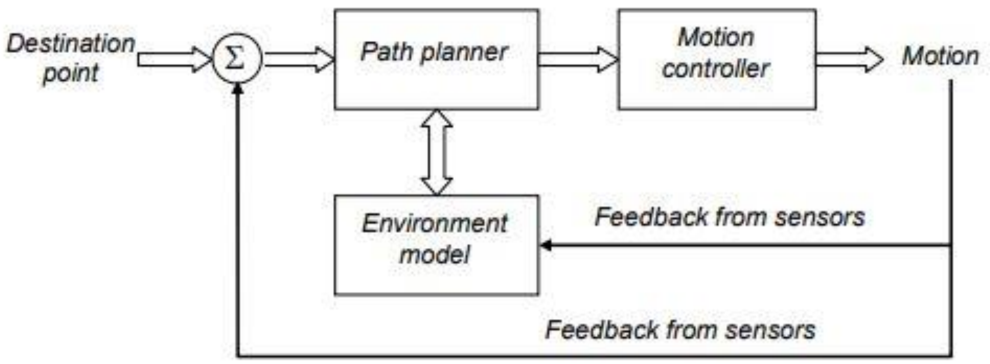


Figure 4-2: Working model of the planner (Simon Hecker, 2018)

According to Association for Safe International Road Travel (ASIRT), more than three thousand are dead per day due to the collision (Simon Hecker, 2018). The collision can be categorised into four phases as given below.

a) Pre-sense: the system senses the danger of collision. The hazard warning will light up when danger is found. The seat belt gets tightened, windows and roof will close all the safety factors are covered.
b) Light slowdown: The vehicle starts slowing down by slow braking.
c) Partial braking & Vehicle stop. The vehicle will break stronger and keep reducing the speed and stop before the collision.

The collision avoidance system has various names for instance: pre-crash system, forward-collision warning system, collision justification system, and collision warning system. The main goal of a collision-avoidance framework is to prevent the collision and divert to a new route towards the destination. Collision or conflict detection is the process of detecting conflicts among two or more moving or stationary objects and to avoid or overcome such conflicts is collision avoidance (Xiaojing Zhang, 2017).

The deterrents within the environment can be categorised as compatible with movement.

a) Static Collision avoidance [stationary object]

A vehicle is moving in a static environment, where the objects are stationary for an instant as shown in Figure 4-3. The collision will happen when the moving car hits a station vehicle or others (such as pedestrians, and buildings). The vehicle is moving in a parking area where it will be navigating itself for parking (Umar, 2018).

Figure 4-3: Static condition (Umar, 2018)

b) Dynamic Environment or Deterministic [has predictable occurrence and position]

It is the condition where a moving vehicle has a collision with other moving objects, as shown in Figure 4-4. (Umar, 2018).

Figure 4-4: Dynamic Condition (Umar, 2018)

c) Uncertain Environment or Random

The uncertain condition as shown in Figure 4-5 is an unpredicted occurrence with freely moving with no pattern and multiple objects in the path where it will require high computing capabilities to categorise and head the planned path.

Figure 4-5: Uncertain Condition (Folsom, 2020)

To understand the types of collision we will first talk about types of automotive crashes. There are types of crashes, namely front-end crashes, rear-end crashes, T-bone angle, or side impacts, Lane switching crashes, parking crashes, head-on, run-off-road collision, intersection collision, and vehicle rollover. There are reasons for the cause of accidents in real road scenarios. (Folsom, 2020) Front-end crashes are the most common accidents in urban or rural areas. These accidents occur due to the sudden brake of the front vehicle, which ends up smashing the front end of the adjoining vehicle. Rear-end crashes are also common accidents on traffic roads. This collision is due to a lack of distance maintenance between two vehicles when travelling in the same lane at a different speed. The fixed distance between adjoining vehicles should be kept to avoid the most common front-end and rear-end crashes. T-bone crashes are due to side impacts caused by a lack of braking to reduce the vehicle speed or lack of driver abstraction.

The head-on collision is mostly happening in traffic where the front ends of two vehicles crash in opposite directions. Besides, such head-on collisions appear in rural areas crash in opposite directions (Li *et al.*, 2021). Besides, such head-on collision appears in rural areas where a lane is not separated by a lane separator. Hence, front-end and rear-end crashes are the most common and vital scenarios in the automotive domain. Therefore, front-end crashes are the most common and vital scenarios in the automotive domain and front-end and rear-end crashers are mostly due to both unclarity in-vehicle mechanisms and the distraction of adjoining vehicle drivers.

There are collision detections and avoidance techniques in the market. The cruise control of collision detection and avoidance is applicable for longitudinal motion control of the vehicle. In the current trends, such a system is applicable in most recent cars. The collision detection and avoidance system in recent cars use a pre-sense plus module which works in four phases (Md, 2015).

- First Phase (Pre-Sense plus): the system executes collision detection, tightens front seat belts, closes windows, closes the sunroof, and activates hazard warning lights.
- Second Phase: Initiate light breaking to make the driver's attention.
- Third Phase: Commands partial breaking.
- Fourth Phase: Possible breaking to avoid the complete collision.

Some features added to the vehicles such as Avoidance Assistance and driving assistants plus are based on the use of advanced methods by combining the front-facing camera, lane-departure warning, and radar sensors to detect adjoining vehicle speed for collision detection and emerging braking system, which pushes acceleration pedal up and applies partial braking to aid the driver for collision justification. Advancement in such techniques is the futuristic research in the development of automotive technology.

4.4 Vehicle Dynamics Model for Optimisation

To solve collision avoidance problems, the vehicle's mathematical model is required to develop some optimisation algorithms for collision avoidance. To derive the effect of motion concerning the geometric relationship the kinematic model is necessary. To describe the behaviours of a dynamic model is introduced (Ferrara *et al.*, 2019), in which a fixed global coordinate system is used to analyse the vehicle dynamics and some internal and external forces on the vehicle are considered, for instance, the driving force and traction force. The tires also play a key role in transferring force using the point of contact with the road (Ni and Hu, 2017).

The bicycle model was developed and used in literature to reduce complexity by being the four wheels to two wheels which are a pair of front and rear wheels. The kinematic model is limited to low speed. To create a dynamic model the natural laws must consider (Hajiloo *et al.*, 2021)

Figure 4-6 shows a bicycle mode, where x, y are axis, ψ is the yaw angle rotation about the vertical axis, v is the vehicle velocity, β is the side slip angle between velocity and a longitudinal axis, δ_f & δ_r are front and rare steering wheel angle, respectively, l_f & l_r are distances from the centerline to the front and rear.

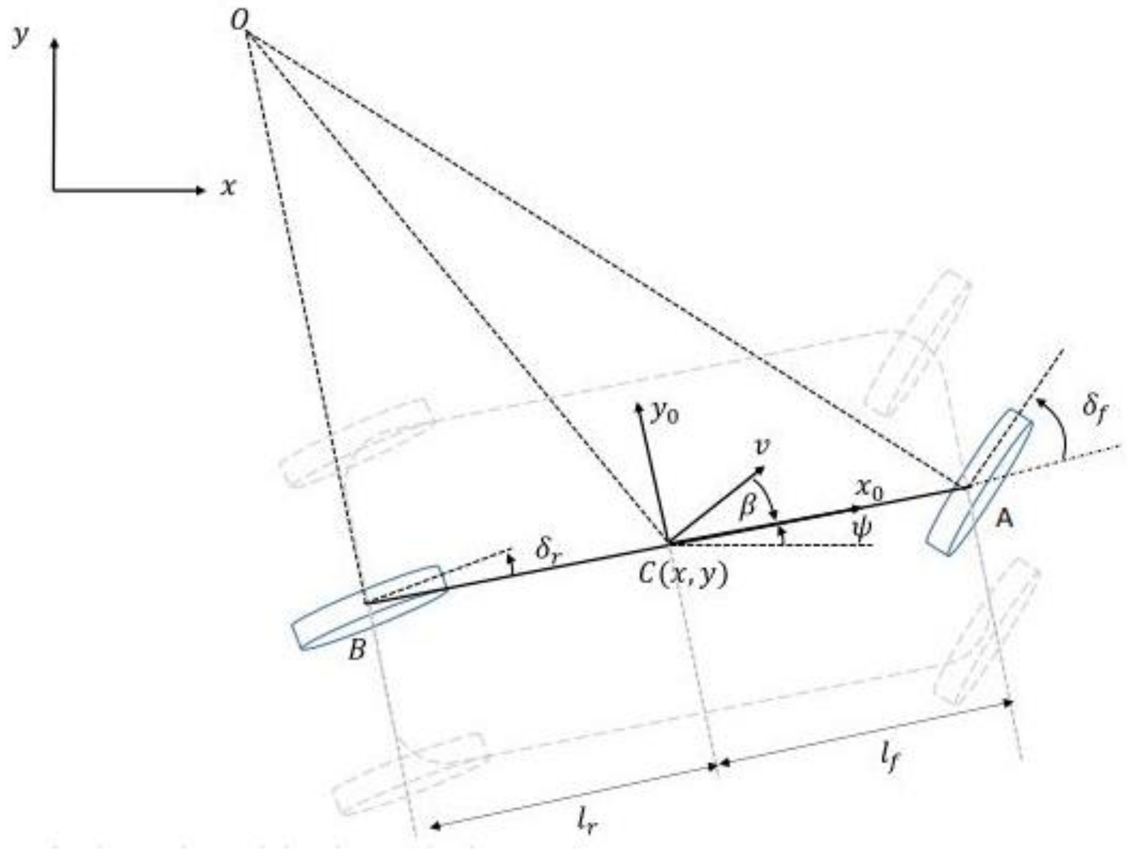


Figure 4-6: Bicycle model (Velocity) (Hajiloo et al., 2021)

If both front and rear wheels can steer and the slip angle on each wheel is zero, the following formula can be obtained. Noticing that the assumptions are only valid at low speed. When it comes to high speed the smallest steer shows a bigger impact on steering the vehicle.

$$\dot{x} = v.\cos{(\psi - \beta)} \tag{4.0}$$

$$\dot{y} = v.sin\ (\psi - \beta) \tag{4.1}$$

$$\dot{\psi} = \frac{v.\cos(\beta).\tan(\delta_f)}{l_f + l_r} \tag{4.2}$$

Whereas β is

$$\beta = \arctan\left(\frac{l_r.\,tan\delta_f}{l_f + l_r}\right) \tag{4.4}$$

Figure 4-6 illustrates the forces in the bicycle model.

F_D Driving Force

F_L Resistance / Load force

F_{Lx} Longitudinal force

F_{Ly} lateral direction

β_f Slip angle in front

β_r Slip angle in the rear

v_f wheel velocity at the front

v_f wheel velocity at the rear

Firstly, the second Newtons' law along the tangential axis which is the direction of course angle to derive longitudinal motion.

$$ma_x = \sum F_r \tag{4.5}$$

To define lateral motion Newton's second law for motion along the normal axis perpendicular to the tangential line.

$$ma_y = \sum F_N \tag{4.6}$$

Whereas $\sum F_N\, the$ sum of forces in the normal axis and a_y is the centripetal acceleration, the angular velocity for road radius?

$$a_y = \omega^2 r \tag{4.7}$$

Therefore, angular velocity can write as

$$\omega = \frac{\mathrm{v}}{\mathrm{r}} \tag{4.8}$$

Precise speed can be composed as the subordinate of heading point or course point K,

$$\mathrm{k} = \psi - \beta \tag{4.9}$$

$$\omega = \frac{\mathrm{dk}}{\mathrm{dt}} = \frac{\mathrm{d}(\psi - \beta)}{\mathrm{dt}} \tag{4.10}$$

$$\mathrm{a_y} = \mathrm{v}.(\dot{\psi} - \dot{\beta}) \tag{4.11}$$

Therefore,

$$\dot{\beta} = \dot{\psi} - \frac{1}{\mathrm{m.v}}.\sum F_N \tag{4.12}$$

Applying newtons law for rotation about the z-axis described the yaw motion

$$J_z.\ddot{\psi} = \sum T \tag{4.13}$$

$\sum T$ the sum of torque,

J_z is the moment of inertia

The sun of forces in a tangential and normal direction and rotary about the z-axis are:

$$\sum F_T = (F_{Dr} - F_{lr}).\cos(\delta_r + \beta_r) - F_{yr}.\sin(\delta_r + \beta_r) - F_{lr}.\sin\beta + (F_{Df} - F_{lf}).cos(\delta_f + \beta_f) - F_{yf}.\sin(\delta_f + \beta_f) \tag{4.14}$$

$$\sum F_N = (F_{Dr} - F_{lr}).\sin(\delta_r + \beta_r) - F_{yr}.\cos(\delta_r + \beta_r) + F_{ly}.\cos\beta + (F_{Df} - F_{lf}).sin(\delta_f + \beta_f) + F_{yf}.\cos(\delta_f + \beta_f) \tag{4.3}$$

$$\sum T = F_{yf}.\cos(\delta_f).l_f - F_{yr}.\cos(\delta_r).l_r \tag{4.16}$$

The differential equation of the vehicle dynamics can describe as,

$$\dot{\beta} = \dot{\psi} - \frac{1}{\mathrm{m.v}}.\sum(F_{Dr} - F_{lr}).\cos(\delta_r + \beta_r) - F_{yr}.\sin(\delta_r + \beta_r) - F_{lr}.\sin\beta + (F_{Df} - F_{lf}).cos(\delta_f + \beta_f) - F_{yf}.\sin(\delta_f + \beta_f) \tag{4.17}$$

$$\dot{\psi} = \omega \tag{4.18}$$

$$\dot{\omega} = \frac{1}{J_z}.(F_{yf}.\cos(\delta_f).l_f - F_{yr}.\cos(\delta_r).l_r \tag{4.19}$$

$$\dot{\mathrm{v}} = \frac{1}{\mathrm{m}}.\Big((F_{Dr} - F_{lr}).\cos(\delta_r + \beta_r) - F_{yr}.\sin(\delta_r + \beta_r)$$
$$- F_{lr}.\sin\beta + (F_{Df} - F_{lf}).cos\big(\delta_f + \beta_f\big) - F_{yf}.\sin\big(\delta_f + \beta_f\big)\Big) \tag{4.20}$$

$$\dot{x} = v.cos\ (\psi - \beta) \tag{4.21}$$

$$\dot{y} = v.sin\ (\psi - \beta) \tag{4.22}$$

Driving influenced by F_D and steering angle δ imposed by the driver. The lateral force generated on the tire depends on tire characteristics and tire slip angle α.

Force can calculate using linear formulation.

To find the slip angle α_f & α_r, the velocity part perpendicular to the centerline extended where Index f & r means front and rear, respectively.

$$v_f.sin\beta_f = l_f.\dot{\psi} - v.sin\beta \tag{4.23}$$

$$v_r.sin\beta_r = l_f.\dot{\psi} - v.sin\beta \tag{4.24}$$

The velocity part in the direction of the longitudinal centreline of the vehicle must be equal, for consideration of the body does not shrink or expand.

$$v_r.cos\beta_r = v_f.cos\beta_f = v.cos\beta \tag{4.25}$$

For velocity terms

$$tan\beta_f = \frac{l_f.\dot{\psi} - \mathrm{v.sin\beta}}{\mathrm{v.cos\beta}} \tag{4.26}$$

$$= \frac{l_f.\dot{\psi}}{\mathrm{v.cos\beta}} - \mathrm{tan\beta} \tag{4.27}$$

$$tan\beta_r = \frac{l_f.\dot{\psi} - \mathrm{v.sin\beta}}{\mathrm{v.cos\beta}} \tag{4.28}$$

$$= \frac{l_r.\dot{\psi}}{\mathrm{v.cos\beta}} + \mathrm{tan\beta} \tag{4.29}$$

For tire slip angle

$$\alpha_\mathrm{f} = \delta_\mathrm{f} - \beta_\mathrm{f} = \delta_\mathrm{f} - \arctan\left(\frac{\mathrm{l_f}.\dot{\psi} + \mathrm{v.sin\beta}}{\mathrm{v.cos\beta}}\right) \tag{4.30}$$

$$\alpha_\mathrm{r} = \delta_\mathrm{r} - \beta_\mathrm{r} = \delta_\mathrm{r} - \arctan\left(\frac{\mathrm{l_r}.\dot{\psi} + \mathrm{v.sin\beta}}{\mathrm{v.cos\beta}}\right) \tag{4.31}$$

Linearization

In the actual case, the vehicle can store only the front wheel. Therefore, $\delta_r = 0$. The load force is only in a longitudinal direction. Hence $F_{ly} = 0$ and driving force implemented o rear wheel, therefore $F_{Df} = 0$. Based on these assumptions the equation will be as.

$$\dot{\beta} = \dot{\psi} - \frac{1}{m.v}.(F_{Dr} - F_{lr}).\beta_r + F_{yr}. + F_{yf} \tag{4.32}$$

$$\dot{\psi} = \omega \tag{4.33}$$

$$\dot{\omega} = \frac{1}{J_z}.(F_{yf}.l_f - F_{yr}.l_r) \tag{4.34}$$

$$\dot{v} = \frac{1}{m}.\left((F_{Dr} - F_{lr}). - F_{yr}.\beta_r - F_{yf}.(\delta_f + \beta_f)\right) \tag{4.35}$$

$$\dot{x} = v.\cos(\psi - \beta) \tag{4.36}$$

$$\dot{y} = v.sin(\psi - \beta) \tag{4.37}$$

Hence the slip angle can write as,

$$\beta_f = \frac{l_r.\dot{\psi}}{v} + \beta \tag{4.38}$$

$$\beta_r = \frac{l_r.\dot{\psi}}{v} + \beta \tag{4.39}$$

The tire slip angle is:

$$\alpha_f = \delta_f - \beta + \frac{l_f.\dot{\psi}}{v} \tag{4.40}$$

$$\alpha_r = \beta + \frac{l_r.\dot{\psi}}{v} \tag{4.41}$$

4.5 Current Research

The automobile business has zeroed in serious endeavours on vehicle wellbeing frameworks to show any future collisions and a versioning framework to save vehicle tenants' and walkers' lives by disposing of or diminishing the all-out number of vehicle crashes. There are two classes of vehicle security frameworks: Passive and Active (Huang *et al.*, 2017). The inactive security approach has grown first. It can save travellers' lives, but unfortunate results limited the impact of the accident when it occurs, so further research on vehicle plans has developed and added to security frameworks, for example, airbags, head insurance frameworks, and seat straps. These have helped to save lives. On the other hand, dynamic well-being frameworks are new and contrast with inactive security frameworks. (Shin KATO, 1996). The fundamental task of dynamic frameworks is to help a driver with keeping away from impacts and to relieve the danger of an accident it is going to happen; this is known as crash forecast. Today, there are instances of these frameworks, for example, Antilock Brakes, Dynamic Stability Control, Improved Visibility Systems, and Electronic Damper Control that have been now introduced and accessible underway vehicles. Besides, late patterns and advances in auto innovation have pushed for more spotlight on dynamic security applications and on the turn of events and presentations of further developed dynamic wellbeing frameworks, for example, forward impact aversion, path keep help, and programmed control.

4.5.1 Sensor-based frameworks developments

These frameworks comprise onboard sensors and processors which gather data progressively to give extra data and alerts to the driver (Hironori 2015). A part of these sensor-based frameworks is computerised to control the driving errand. Likewise, below are some sensors that can manage the traffic conduct by gathering data about the close and from the side of the road signs.

1) Optical Sensors: These sensors, like inactive infrared, laser radar, and camera, are delicate to outer ecological condition particles, like downpour, haze, and snow, which thusly influence the dependability of the information gathered by such sensors (Jo *et al.*, 2012). For instance, the warmth from environmental elements affects the exhibition of the infrared sensors; so, the information will in general be not extremely exact when temperature transcends certain levels. A significant hindrance of optical sensors overall is their absence of ability for direct aim.
2) Electromagnetic Sensors: Differ from optical strategies, these sorts of sensors function admirably under troublesome natural conditions. Even though electromagnetic sensors are more costly than optical sensors, they enjoy the benefit of having the option to give direct reach estimations at short, medium, and long distances (Sabzevari, 2009). Electromagnetic methods are the best part to use when long-range distance estimation is needed. Additionally, one of the critical benefits of Electromagnetic Sensors is their capacity to work and be packaged behind the vehicle belt and, along these lines, are simple to introduce and do not influence vehicle styling.

3) Acoustic Sensors (ultrasonic): These sensors function admirably just for finding objects inside a short reach and can give a minimal expense elective when contrasted and other procedures. Such sensors enjoy the benefits of extremely low cost, little size, a wide field of view, top-notch shaft attributes, and low force use. On the other hand, they have burdens and, thus, are the least utilised in dynamic security applications (Shuiying W, 2012). A part of these hindrances incorporates sluggish reaction, short reach, and affectability to outside climate conditions like downpours and snow. Additionally, a primary hindrance is the Acoustic Sensor's way on the vehicle exterior. Such sensor typically shows up as openings in the guard of vehicles, and such openings are typically not preferred according to a styling perspective.

4.5.2 Software-based frameworks

These frameworks rely upon the remote correspondence between vehicles, or among vehicles and the framework. There are two sorts of correspondence designs: either one way, where the vehicle just gets data from the framework; or two-way, where the vehicle gets and sends data to another vehicle or the framework-based framework. The US Department of Transportation is resolving to investigate distinctive remote innovations for safety, mobility, and natural applications (Anderson *et al.*, 2014). Also, the Department focused on the use of the body for advancements for both car-to-car and car-to-foundation correspondence for applications for dynamic security.

There are sensor-based dynamic wellbeing frameworks as of now accessible available; some parts of these frameworks are presented as standard in vehicles, yet others are just discretionary, for example, leaving help sensors and radar-based versatile journey control (Alexopoulos, 2013). Today, ultrasonic sensors are universally used sensors for leaving help vehicle wellbeing frameworks. These sensors act in a way in which they send ultrasonic waves that reflect from any articles that are in the wave's way. The reflected waves are then gotten and investigated with sensors (Jang *et al.*, 2016). Then, at that point, the measurement between the two can be decided by estimating the time contrast between sending and getting these ultrasonic waves. For instance, the general arrangement has four ultrasonic sensors mounted on the back guard of a vehicle, and a LED shows the distance in cm between the front of the vehicle and the obstacle. At the point when a sensor finds an object, a perceptible admonition started, and as the vehicle or object comes nearer, the recurrence of the "signal" increments. Others have four ultrasonic sensors, a camera, and a presentation screen. These frameworks use ultrasonic sensors that can identify objects, regardless of whether those articles are tiny, in the middle and out to the sides of the vehicle for complete inclusion of the back vulnerable side.

This load of security frameworks includes two significant angles location and understanding of vehicle environmental elements and choices for taking remedial measures. The primary angle should fit for preparing data and choosing whether the recognised snag is genuine or obstructing along the vehicle way or not. There are various advancements embraced in autonomous vehicles like laser scanners, radar, and PC vision for the identification of vehicle environmental elements in the long reach. Every sensor enjoys its benefits and limits. In this manner in later autonomous vehicles combination of various sensors is used for upgrading the potential outcomes to understand and address the vehicle's environmental factors. To conduct sensor combinations various cluttered calculations are grown so far by analysts (Jo *et al.*, 2012).

In the identification and following of hindrances, there are broad examination projects done throughout the planet to foster calculations to use sensor supplied data and joining in the control framework. Scientists have introduced an impact evasion framework dependent on the stereovision framework. This framework is used to distinguish walkers through calculations used for recognizing and following a person on foot. Considering the development of the past research calculation equipped for expecting whether the person on foot will come in the way of the vehicle or not. If there should be an occurrence of any crash with the walker right moves made by the framework either go astray or stop the vehicle. In GPS-based autonomous vehicles, this sensor combination-based impact evasion framework is now conducted by scientists (Jo *et al.*, 2012). In recreation climate, there have been various complex regulators alongside vehicle dynamic models executed. In any case, these frameworks are incredibly non-direct and confused to execute continuously on autonomous vehicles. Even more as of late use of computerised maps for the route of autonomous vehicles is part of ubiquity. In these guides, obstructions can be situated in various areas and these data can straightforwardly be imparted to the GPS route (Jo *et al.*, 2012).

The following basic perspective in any impact evasion framework is to take vital choices or measures to keep away from the crash with the identified obstruction. In autonomous vehicles, the most well-known practice in this viewpoint is to address the controlling point and apply required slowing down to stay away from crashes either by redirecting or dialling back or halting the vehicle. From this angle execution of increasingly more fabricated consciousness (AI) is in progress in autonomous vehicles. Computer-based intelligence is used to computerised the board of actuators and regulators for empowering the impact evasion framework and driver help framework (Bagloee *et al.*, 2016)

Specialists have introduced the pre-impact gathering of frameworks for crash evasion dependent on recognizable proof of obstacle. These are executed for staying away from the crash with walkers and surpassing vehicles moving gradually before the autonomous vehicle. It is to guarantee that to execute soothing measures for advancing or decreasing potential outcomes of crash adequate data are accessible through the nearby sensors set on the autonomous vehicles (Campbell *et al.*, 2010). autonomous vehicles likewise need to gather traffic stream data dependent on the correspondence with different vehicles just as data gathered from a cloud. From the vehicle environmental elements, Advanced Driver Assistance Systems (ADAS) (Hamid, 2016).

At present, there are in every day two expansive classes of security frameworks helpful frameworks and autonomous frameworks. Intra-vehicle interchanges structure the reason for helpful frameworks through nearby sensors structure the reason for autonomous frameworks.

4.5.3 Optimisation of collision Avoidance

Evolutionary algorithms are based on biological processes such as reproduction, mutation, recombination, and selection. Optimisation techniques are critical for estimating correct or best solutions from a set of alternatives (Arzamendia *et al.*, 2017). When a group of people is involved, each person will produce his or her own best answer, and the global best will be the best of the local best. With the help of the fitness function (Porras, 2019), the evolutionary algorithm has won challenging issues with solving challenges. The fitness function is the foundation of evolutionary computation (Miao *et al.*, 2019).

The rapidly expanding popularity of autonomous vehicles has prompted academics to develop better algorithms that can make confident decisions in a real-world traffic scenario, ensuring a safe and collision-free transportation system. The subject of this research study is to ensure that the autonomous vehicle's judgement is correct to avoid collision (Ji *et al.*, 2017). The Genetic Algorithm (GA) has been proposed to tackle collision avoidance firework as the best way to avoid conflict. There are different algorithm methods which are that use GA to use four genes of chromosomal structure: speed, break, inner tyre angle, and time to avoidance (Ferrara *et al.*, 2019). To avert an accident, a field analysis with help of sensor data is used as input from various algorithms.

There are some algorithms used in collision avoidance techniques based on swarm intelligence, such as bat algorithm, Gray wolf optimisation by following the leadership and hunting style of dray wolf, artificial bee colony optimisation, (Lagunes *et al.*, 2018) firefly optimisation with their flickering behaviour, elephant herding optimisation by its herding behaviour, bumblebees mating optimisation mating behaviour that the swarm of the bumblebees performance, lion optimisation algorithm for their level of social behaviour and appearance, water wave optimisation including the chemical reaction optimisation, plant optimisation, the raven roosting algorithm ant colony optimisation mimics the food searching style of ants (Manogaran *et al.*, 2019), runner-root algorithm, bee optimisation based on behaviour of micro-bats, (García G, 2019) cuckoo search inspired by the cuckoo birds concept of using others nest for laying eggs, particle swarm optimisation from fish and birds in group (Porras, 2019).

There are also metaheuristic population-based algorithms in the literature, such as Hunting search, Adaptive dimensional search, Firefly algorithm (Lagunes *et al.*, 2018), harmony search, gaussian adaption, and memetic algorithm.

4.6 Future work and Conclusions

The industries are focusing more on safety, so collision avoidance for autonomous vehicles has become a concern area. As the complexity of the road in the real world is rapidly increasing, collision avoidance problems are becoming more important that need to focus on. Most carmakers are collaborating with researchers and trying to get the best possible technology on road. To reduce the road casualties with few road facilities, there are major research areas that are studied, such as validation and testing, safety and reliability, software quality, computational resources, security and hacking threats, accuracy, and efficiency of object detection in an autonomous vehicle, sensor management in autonomous vehicles. To plan precisely manufacturers should consider sharing the information with other manufacturers to plan and avoid collisions by detecting surrounding vehicles for more accuracy.

The test of the autonomous vehicle is that it needs to beat unsteadiness and keep away from the crash with any static or dynamic obstruction along its way of movement. Autonomous vehicles should have the ability to perform crisis moves to avoid any obstruction and proceed through a new path. To stay away from any static or dynamic object in the way of autonomous vehicles, it needs to either decelerate to a stand-still on a similar path or move to the adjoining path dependent on the traffic stream of that path (Hussain *et al.*, 2015). This undertaking zeroed on the planning and re-enacting collision detection for an autonomous vehicle, not exclusively to stay away from impact and keep up with the firmness of the vehicle yet, in addition, to keep up with the traffic stream.

It is challenged to incorporate all the vehicle frameworks to conduct the ideal control. Further investigation and examination will do in the ensuing activities to incorporate the module for overwhelming and getting once again to the path and for easing back if there is no way of surpassing the interruption (Ji *et al.*, 2017).

5 Modelling of Collision Avoidance in MATLAB

5.1 Introduction

MATLAB is used to simulate various scenarios to examine Collision avoidance as it is one of the fundamental functions of advanced driver assistance (Umar, 2018). A vehicle with obstruction avoidance has sensors to detect the object or explore in the predefined environment, with help of sensors to measure the distance in front of the vehicle in the lane boundaries. The strategy of collision avoidance is to move to the other side by detecting the predefined boundary conditions and move back to the safe position in the lane. The developed model will manage to detect the lane and position the vehicle into the safe centre position of the lane and move at a specific velocity towards destination collision and overcoming by steering right-left.

This research aims to combine two techniques i.e., genetic algorithm and neural network to evolve the vehicle and direct in the predefined environment will foster a powerful model for the autonomous vehicle and plan a direction to trailed by the vehicle. This will do in the MATLAB code for the direction to be followed.

5.2 Statement of Problems

5.2.1 Optimisation Problem

In predefined environment conditions, the vehicle will have to overcome sharp bends on the left and right to reach the destination.

The main problem is described as the following.

- A vehicle moving in the lane should detect the road boundaries and operate towards the destination
- The vehicle should direct itself and turn right or left to avoid a collision.
- A vehicle should evolve and perform better on the next turns.

P is the centre point of the vehicle, p_{new} is the new position of the centre point of the vehicle. θ change in angle to vehicle direction. θ_{new} is the new change in angle to vehicle direction.

The moving car will be modelled as an optimisation problem. An autonomous vehicle will move from the initial position to the destination step by step. The moving car decision from a current position to a new position will be modelled as an optimisation problem. The objective of the optimisation problem is to maximise the moving distance in the current step without collision.

The optimisation problem is defined mathematically as:

$$\max_{\theta,\Delta t} d(\vec{p},\theta,\Delta t) \tag{5.0}$$

Subject to,

$$0 < \theta < \pi \tag{5.1}$$

$$d(\vec{p},\theta,\Delta t) \leq 25 \tag{5.2}$$

$$\Delta t = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{5.3}$$

$$d(\vec{p},\theta,\Delta t) \leq 25 \tag{5.4}$$

$\vec{p}_1(x_1, y_1)$ The starting point of the car (5.5)

$\vec{p}_2(x_2, y_2)$ A new position in the car (5.6)

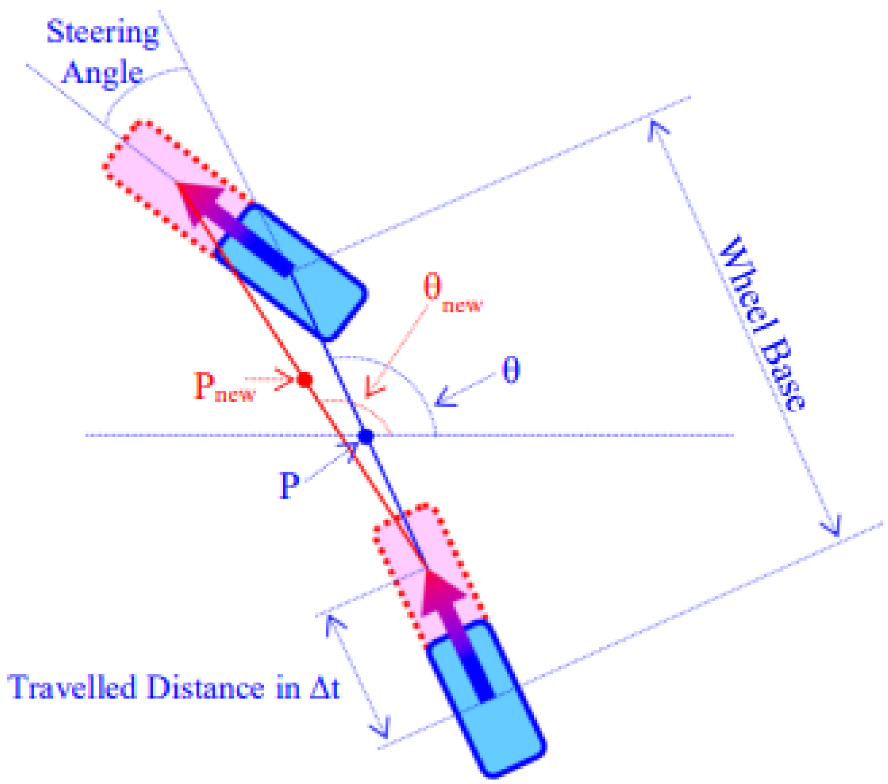


Figure 5-1: Nomenclature of control parameters (Yahui Liu, 2019)

Where the travelled distance is $d(\vec{p}, \theta, \Delta t)$ from one point to another point. There are factors which will affect the calculation of the travel distance. The first parameter is the current position of the vehicle. The other parameters are the travel direction (θ) and the moving step (Δt), which is the distance from the current position to the new position. Normally, the range of sensors is limited. In this thesis, the range of sensors is set as twenty-five meters. Most importantly, the road condition and environment will affect the moving step.

5.2.2 Decision variables

The decision variables of the optimisation problem are the moving direction (θ) and the moving step (Δt). In the developed optimisation algorithm, nineteen rays of sensors were used to present the moving direction.

A neural network will be used to calculate the objective and determine the decision to turn left utilizing a sensor with nineteen rays to sense the distance from the predefined environment as a nodal input for a neural network.

To explore the environment a sensor is used where nineteen lines are coming from the current position. As illustrated below in Figure 5-2, the lines will interact with the road lines and find the intersection point. This intersection can be further used as a weight for a neural network to calculate the moving direction (θ).

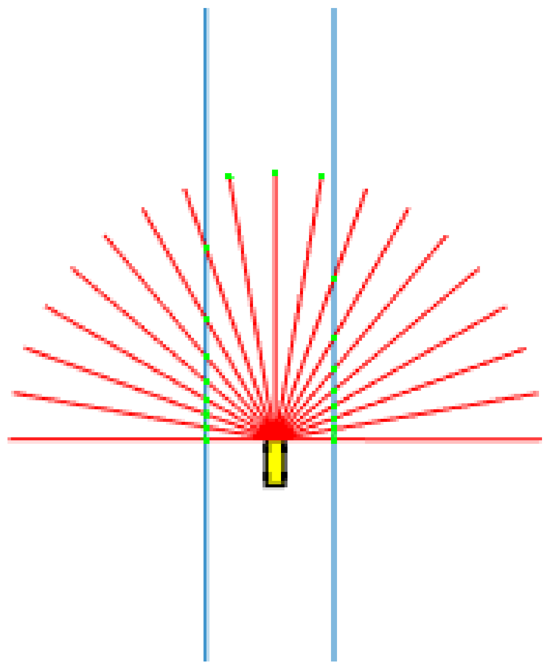


Figure 5-2:Collision Detection

5.2.3 Collision detection

The moving step will be affected by the car's position on the road. A car can only move the boundary of the road. The method of line segment intersects intersection method is applied to find Intersections of line segments and determine the moving step in each direction of the sensor line (Figure 5-3).

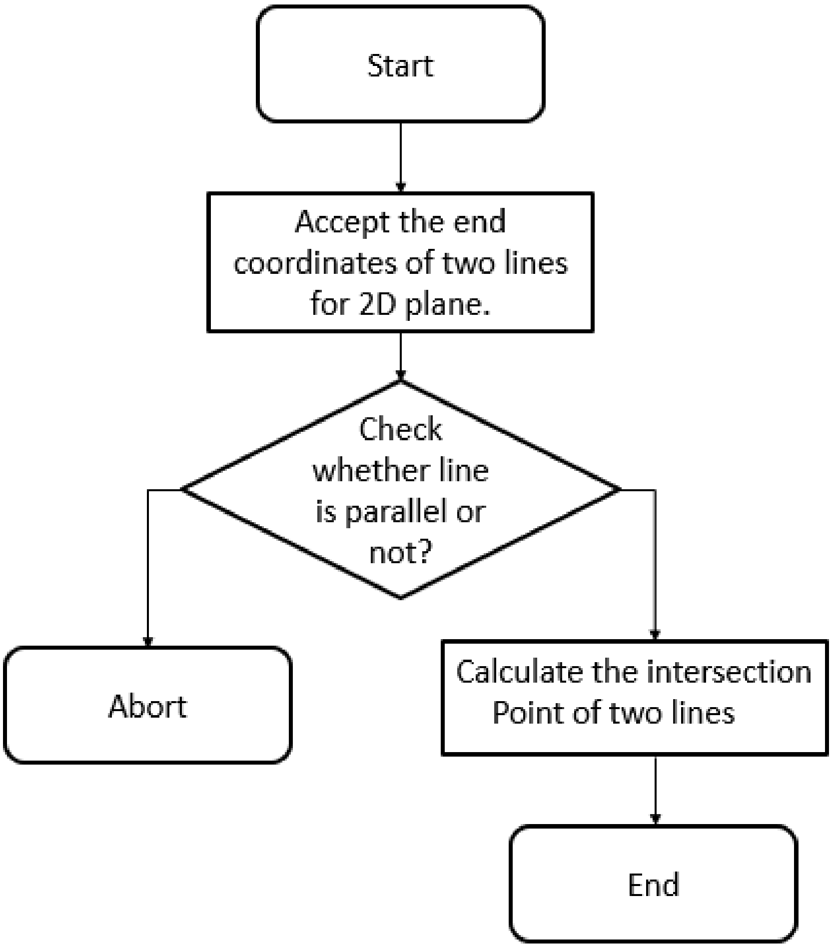


Figure 5-3: line segment intersects intersection

Pseudocode of Collision detection : (Appendix pg. 121)

Step 1: Input four coordinates of two lines.

Step 2: Compute both the equations in form of ax + by + c = d.

Step 3: Before finding the intersection point coordinate, check whether the lines are parallel or not from the values of the slope of each line.

Step 4: To find the values of the intersection point, x-coordinate, and y-coordinate, eliminate the x-coefficient by making it equal in units in both the equations, which would lead to getting the value of y coordinate of the intersection point.

Step 5: Similarly, to compute the x-coordinate eliminate the y-coefficient from both the equations by making their coefficients equal in units which again leads to obtaining the x-coordinate of the intersection point

5.3 Flowchart of Operating Autonomous Vehicle

illustrates the flowchart of operating an autonomous vehicle.

Figure 5-4 (a) shows the main process of this operation. The initialisation of the simulation process includes:

- The setting of the parameters of the genetic algorithm. Based on the research result, the parameters of GA are set as population size (300), Mutation Probability (0.05), Crossover Probability (0.5)

- Setting parameters and training a neural network. A neural network is configured with two outputs and three layers. Whereas the first layer contains nineteen inputs (sensor beams) processing individual distances from collision and middle hidden layer to process, and segregate left and right-side distances and final layer to provide decision for which direction to be preferred with value. A genetic algorithm is used to produce some data to train the neural network.

- Setting sensor data. The sensor range diameter of 50mtrs considering only the front of the vehicle for collision detection with a 25mtrs range.

- Setting car information are Car wheel Base: 2.6m, Car width: 1.7m, car length: 4.3m, car wheel Length: 0.45m, car wheel Width = 0.22m.

After the initialisation, the car is moved from the start position to the destination by using the “Move next step” subroutine, which is shown in

Figure 5-4(b). The following actions in the moving car are included:

- Show the car's current position, including sensor beams. Figure 5-1 illustrates the position of the vehicle with the front and rear wheels in the bicycle model. Where
- Figure *5-9* and Figure 5-10 show the red line as sensor beams for collision detection.
- Run a neural network to determine how to move the car.
- Check and confirm the car move step, On every individual step, the vehicle position is updated. sensor weights on that position are fed to the neural network for real-time steering decisions.
- Move the car, once the environment and components are set to deliver the output the vehicle is set to move in the predefined environment.

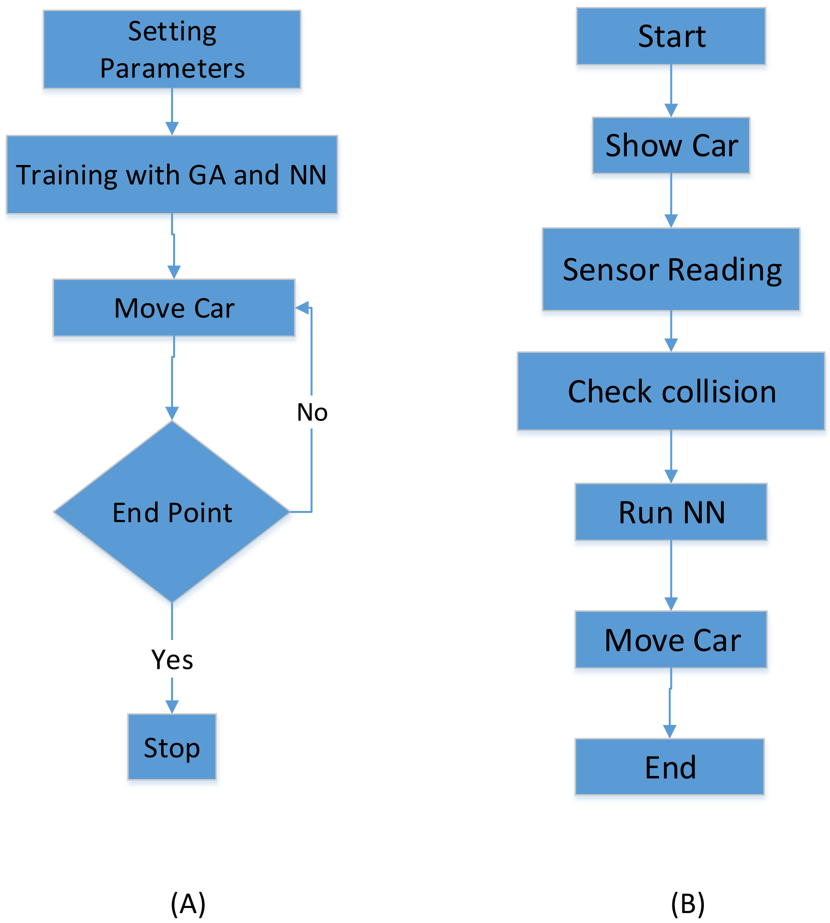


Figure 5-4: Working process

5.4 Neural Network

5.4.1 Introduction

Neural networks are a subset of machine learning and a valuable tool for deep learning algorithms and have been used in many areas like examination and versatile control, discourse and design acknowledgement and classification. These systems are based on statistical estimation and control hypotheses. This field has been used within the collision avoidance issue together with other heuristics plans like hereditary calculations, but it is not conceivable to decide exactly if the ultimate arrangement is ideal, regularly being this one a great approximation. (Krizhevsky *et al.*, 2017) had built a neural organiser with unsupervised learning to compute unused directions that are close to the ideal direction in clashes with two vehicles or any objects.

The reason that neural networks are applied is that

(1) the operation of vehicles is very complicated and many factors affect the operation, such as real road conditions and some obstacles on the road. Neural Network is a possible tool for a vehicle to learn the current road conditions.

(2) Some researchers applied a neural network to autonomous vehicles, but no report has been found on the application of neural networks in collision avoidance in the literature. This thesis was trying to do some innovative work to explore the possibility of neural networks in collision avoidance.

There are many sensors in the autonomous vehicle. The data provided by sensors are huge to streamline the data provided by the sensor the neural network comes into the picture to use only the required data to decide. The sensor used in our experiment is to detect line intersection as a collision. The single sensor with 19 outputs is used to provide distance from the car front to the boundary conditions. 19 lines will provide 19 distances which are fed as $x_1, x_2, x_3, x_4, x_5 \ldots\ldots x_{19}$ as input to the neural network as shown in *Figure 5-5*.

5.4.2 Neural Network Model

Figure 5-5 shows the neural network with 3 layers. The inputs are the distance measured by the sensor and the outputs are the operation of the vehicle.

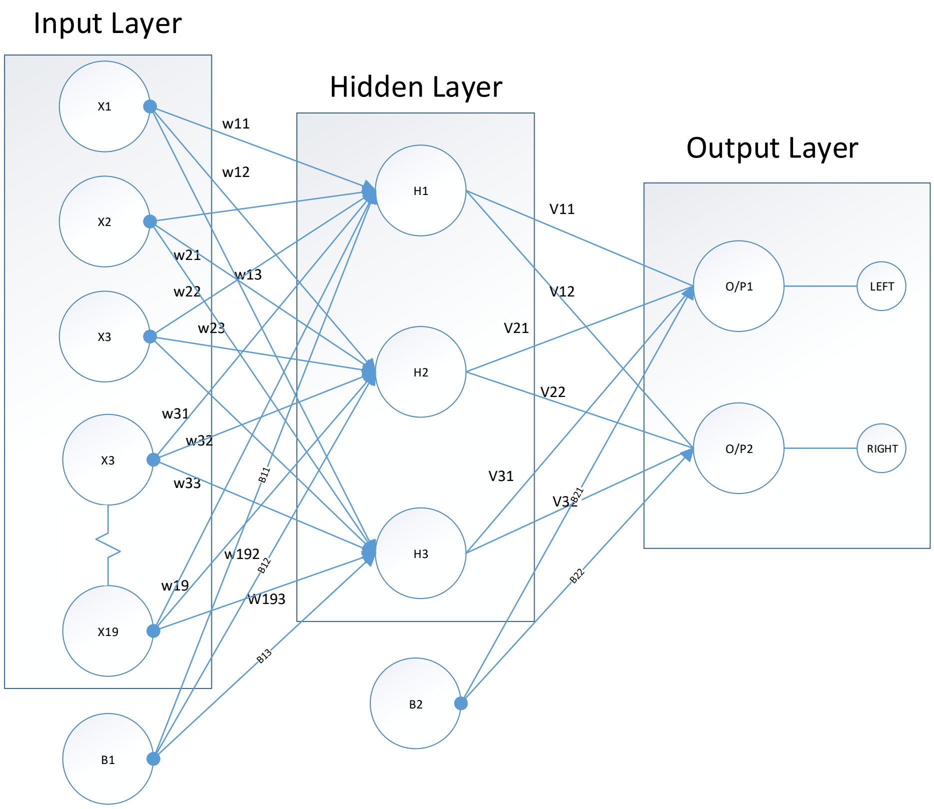


Figure 5-5: Neural network configuration

Starting feed at that point flow through a neural organiser and later, to a yield layer of two neurons: cleared out and right directing choice (Krizhevsky *et al.*, 2017). These yields are used to direct the car by controlling the point.

The feed-forward neural organiser could be a layered arrangement so that the 19 outputs from the sensor are fed to the Neural network as an input. Where neurons are in one layer as it met neurons within the following layer. A Feedforward neural organiser has one input layer and one yield layer and between these, there may be one or few covered-up layers called the hidden layer. To calculate the yield of the feed-forward neural arrange one covered-up layer would begin with making a covered-up unit shown below in *Figure 5-5*$N_1, N_2, \ldots, B_1$.

$$a_j = \sum_{i=1}^{D} x_i \omega_{ji}^2 + \omega_{j0}^2 \tag{5.7}$$

Were, ω_{jI}^2 are the weight and ω_{j0}^2 weights related to the inclination neurons which are generated through an evolutionary genetic algorithm. The superscript (Contreras-

Castillo, 2016) proved that the parameters have a place in the primary layer of the organization. The exercises changed by applying a non-linear enactment work h.

$$z_j = h(a_j) \tag{5.8}$$

Similarly, the output unit activities calculated as

$$a_k = \sum_{i=1}^{D} \omega_{kj}^2 z_j + \omega_{k0}^2 \tag{5.9}$$

Finally, the output activities a_k transformed using an activation function to obtain output the output y_k to decide where to turn

$$y_k = h(a_k) \tag{5.10}$$

Actuations calculated for the layer, and these are the passes through an enactment work. The coming yield is the input to the following layer. This handle is supplanted until the ultimate yield layer. In this way, the data forward is engendered through the organization. Two layers are called completely connected if all hubs within the first layer are associated with all hubs within the other layer. finally, these two output provides the turning values to the vehicle from -90 to + 90. To navigate through the predefined environment based on equation no. 5.11

5.4.3 Activation Functions

The probability needs to occur between 0 and 1. Hence below-shown sigmoid turns out to be the best option. The Neural Network structure is simplified as possible. With only three layers the objective of collision avoidance is achieved. Whereas the Popular method of non-linear activation is the sigmoid function, which is used in the current work

$$h(x) = \sigma(x) = \frac{1}{1 + e^{-x}} \tag{5.11}$$

The first layer takes 19 inputs and 1 bias. The second i.e., the hidden layer has 3 inputs and one bias.

5.4.4 Weight Initialisation

(Xavier, 2010) have proposed a strategy for initializing weight in a Manufactured Neural Organise. The equation accepts the non-linearities between layers, which is an invalid suspicion. Nevertheless, Initialisation works well in applications. The strategy to incorporate corrected straight unit enactment capacities and recommended that weights drawn from ordinary dissemination with zero cruel and standard deviation

$\sigma = \sqrt{\frac{2}{n_l}}$ were n_l is the number of nodes on each layer. This process is to implement weights in the system. The biases were triggered zero.

Integrating GA with NN:

The generated chromosomes for distance are further used as weights on the Neural network. By making the output satisfy the ideal conditions such as weights should not be too small and zero and the weights should have some good variance.

5.5 Genetic Algorithm

5.5.1 Process of a Genetic Algorithm

Figure 5-6 illustrated the main steps of a Genetic algorithm (GA) used in this thesis: The first population of the points in the state of space was randomly generated. Then the fitness of individuals in the population will be evaluated. Then selection process reproduces or selects individuals to formulate a new generation according to their fitness. Afterwards, individuals of the population were picked at random by pairs according to the cross probability and the two parents were replaced by two new-generated children. In the last step, the remaining individuals were picked at random again, and a mutation operator was applied, to slightly change their structure. At those genetic operations, a new population has been created, and those processes will repeat. The different steps are detailed in the below session.

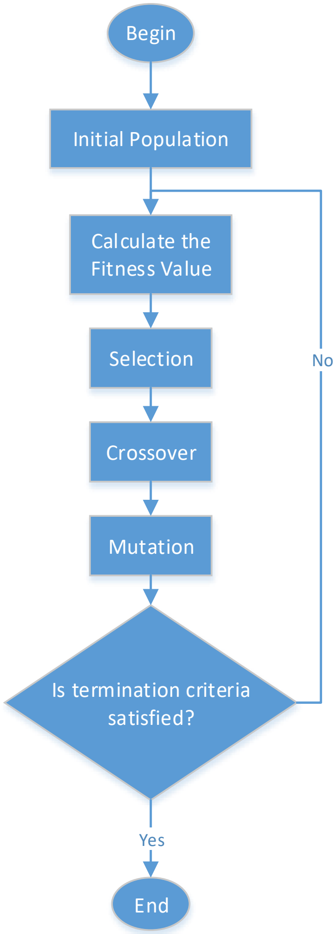


Figure 5-6: Genetic algorithm

A Hereditary Calculation is used to perfect the Manufactured neural organise approach. Within the Hereditary Calculation, a population of N entities, each with the weights in a counterfeit neural arrangement is initialised and encoded into a string of digits called Chromosomes (Jamwal *et al.*, 2019). The digits building up the chromosomes added to as qualities. A wellness degree must be characterised to choose which individuals are wellness degrees and should be characterised to choose. A Hereditary Calculation shapes an individual in two ways: One was called “change” where the weights of the organization in a chromosome are altered with a certain likelihood; the other way chromosomes frame two modern chromosomes, which in turn speak to two modern systems.

There are few critical contrasts between how the Counterfeit Neural Organise was overhauled with a GA. (Jinyin C, 2019) proposed a profound Q-learning. A Hereditary

Calculation assesses the execution of set-off preparing information by characterizing a wellness work. These wellness measures are thought to not mislead with the rewarding work used in the profound Q-learning. Within the profound Q-learning calculation the weight was overhauled at each step with backpropagation. Within the Hereditary Calculation, unused individuals are shaped based on the execution over the complete preparing set. A hereditary Calculation does not include any angle data for upgrading and can be proficient at dodging neighbourhood optima.

5.5.2 Fitness

The travelled distance is $d(\vec{p}, \theta, \Delta t)$ is the fitness of the developed genetic algorithm. Its calculation method is shown in Section 5.2.

5.5.3 Selection

Within the handle of chromosome assessment, the selection mechanism handles selecting two fitter chromosomes for a generation. The hybrid operator is dependable for presenting unused chromosomes (offspring) to the following era, and the transformation administrator manages to create a new set of data within the offspring. An estimate of two is chosen in our model since it regularly yields a more diverse population which might lead to more profound misuse of the chromosome to anticipate untimely convergence of homogenous chromosomes.

To guarantee that the quality of the chromosomes will not be distorted within the assessment handle, we apply an elitism scheme, in which one chromosome is allowed to replace by a sibling. Typically, the wider exploitation of the look space is given when the population has nearly merged. Moreover, it decreases the disruption which may cause by the change. The method of choosing chromosomes used to create a modern person is called determination.

5.5.4 Crossover

The Crossover operator we used was the barycentric crossover: 2 parents are recombined by choosing randomly $\alpha \in [-0.5, 1.5]$ and creating child 1 (resp child 2) as the varying centre of some randomly chosen weight of $(parent_1, \alpha)\big(resp\ (parent_1, 1-\alpha)\big)$ and $(parent_2, 1-\alpha)\ (resp(parent_2, \alpha))$.

5.5.5 Mutation

The mutation operator used adds noise to one of the weights of the neural network. The mutation probability here is 10%.

5.6 Training Neural Network with a Genetic Algorithm

This session is designed to explain how a combination of a neural network and the evolutionary algorithm is used to train the neural network for making a decision.

A. The connection between Genetic algorithms and Neural networks with chromosomes

A chromosome is a string in a genetic algorithm and is used to represent the decision variables of an optimisation problem. In a neural network, weight factors are important parameters to determine the quality of the model. In this thesis, a neural network is used to operate autonomous vehicles and an optimisation process is developed to optimise the weight factors of a neural network model. Therefore, a chromosome in this thesis represents the weight factors of a neural network.

B. Generating chromosomes in a Genetic algorithm

Figure 5-7 shows the process of generating string/chromosomes in a genetic algorithm. Genetic operators, such as selection, crossover and mutation, are used to generate new chromosomes in a generation.

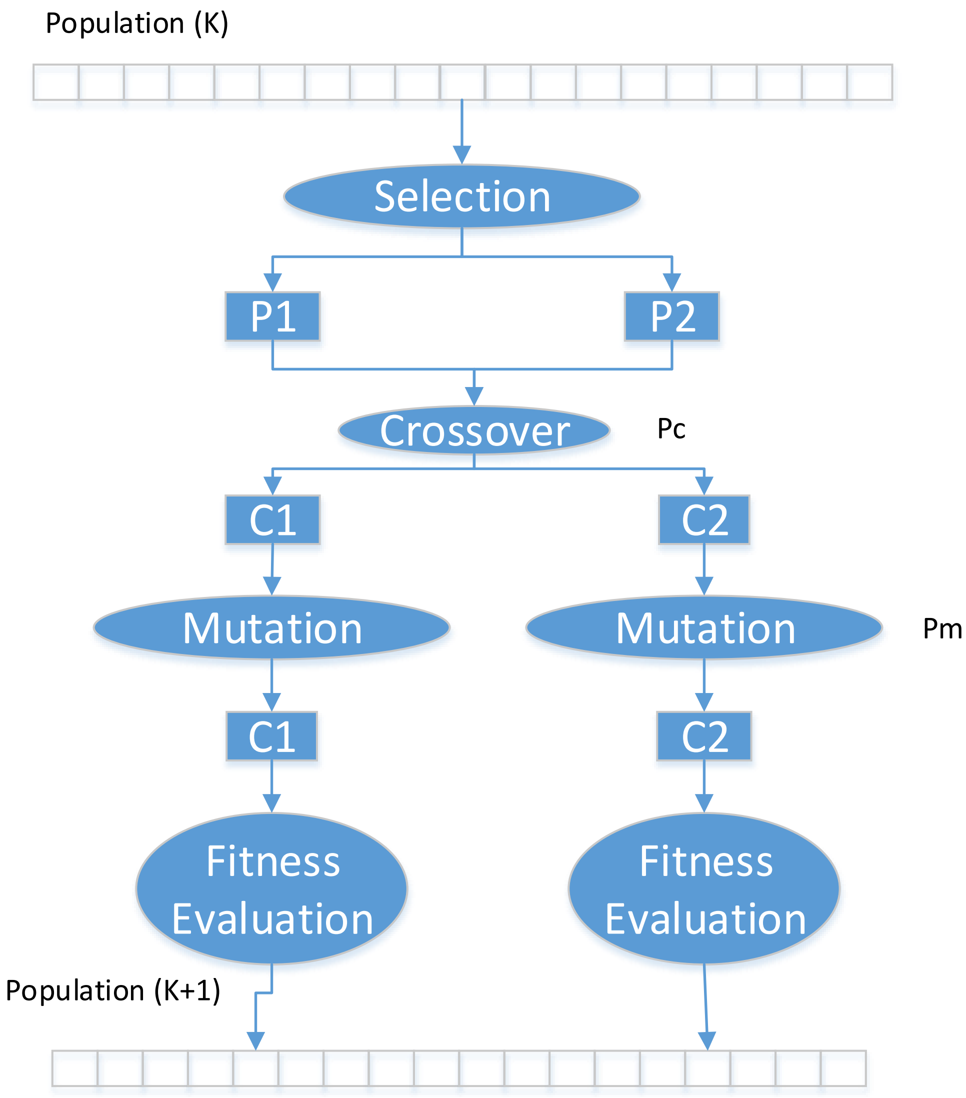


Figure 5-7:Flow chat of Genetic algorithm chromosomes

C. Evaluate fitness by using Neural Network

The generated chromosomes are used as weights in a neural network shown in Figure 5-8. A chromosome (string) will be split into sub-strings and each substring will represent a corresponding weight factor. For given weight factors, a neural network will calculate its fitness (maximum moving distance) without any collision.

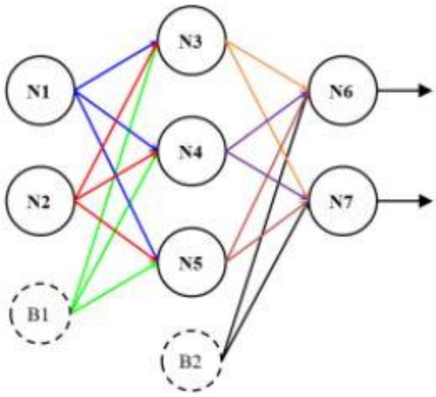


Figure 5-8:Feedforward neural network for Chromosome

Chromosome

For N1 = $w_{13}w_{14}w_{15}$

For N2 = $w_{23}w_{24}w_{25}$

For bias 1 = w_{B1_3} w_{B1_4} w_{B2_5}

For N3 = $w_{36}w_{37}$

For N4 = $w_{46}w_{47}$

For N5 = $w_{56}w_{57}$

For bias 2 = $w_{B2\_6}w_{B2\_7}$

D. The optimisation process of the genetic algorithm will improve the weight factors

The process will be repeated for some generations so that better weight factors can be obtained.

5.7 Results and Discussion

5.7.1 Vehicle Steering

Impact of the neural network: to simplify and conclude the decision-making variable the Neural network is decided based on the provided weight.

With combined effect, the following points observed

- Impact of combination of algorithms
- quicker decision
- Improved learning

The ability of steering in the predefined environment conditions improved in terms of an increase in the population size. Without a sensor, the vehicle cannot have the real-time data to process on road. The integration of learning with the support of sensors makes provision to react to the realistic environment.

A neutral network generates a steering angle to decide which direction to steer, as illustrated below figure the lines are closer at the right end and the process in the neural network has turned the vehicle towards the left.

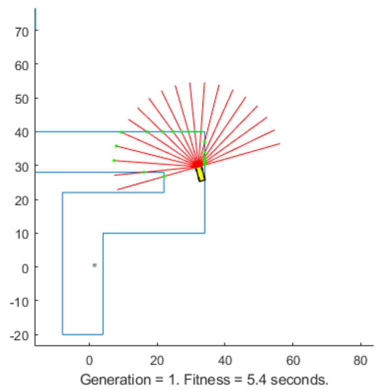


Figure 5-9: Turn Left

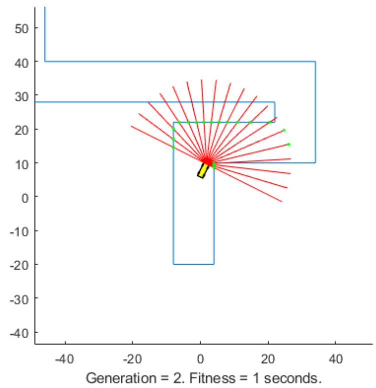


Figure 5-10: Turn Right

As shown above, the vehicle turns right as the intersection points are closer shown in the figure where the vehicle will turn in the opposite direction.

5.7.2 Impact of beams numbers consideration

The sensor is used to detect the object. The number of sensor beams affects the performance (fitness)., showing the effects of the number of sensor beams on fitness.

It is easy to see that the more the beam number, the higher the fitness, this means that the system will have a higher probability to identify the boundaries or collisions.

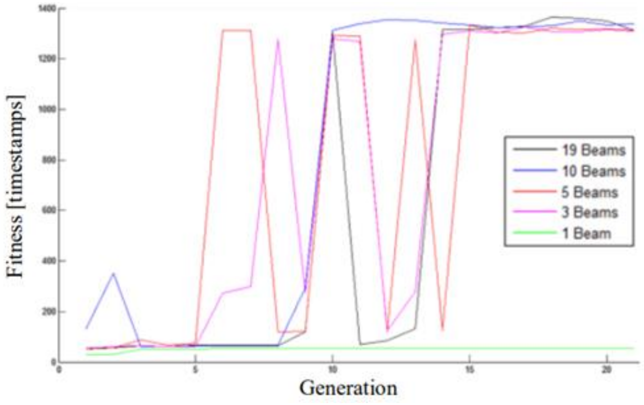


Figure 5-11: Collision detection by different Numbers of beams

5.7.3 Vehicles run on the predefined road condition

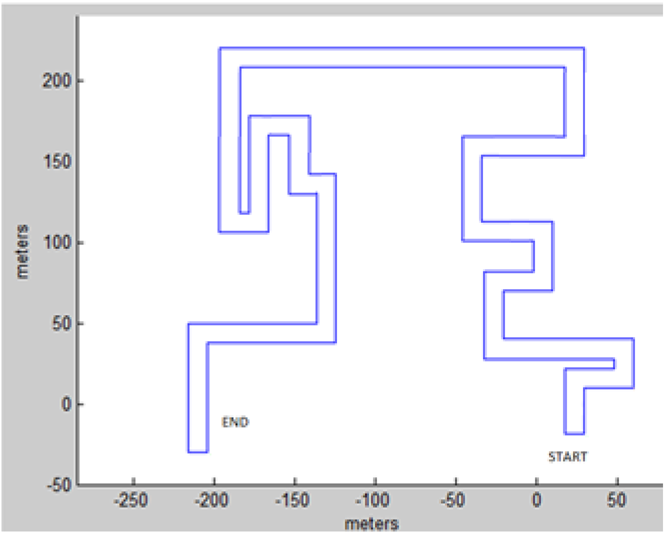


Figure 5-12: Road map

In this case, vehicles will run on a road map shown in Figure 5-12. The general track is formed with left and right twists, where the vehicle must cover all the distance from start to end. Vehicles will detect the boundary of the road and decide their path. The trial aims to look at the capacity of the car to memorise the assignment of self-drive through an inactive environment that does not incorporate any energetic objects. The assignment is to guarantee the vehicle's learning ability to continue with collision avoidance with energetic objects.

The three-layer Artificial Neural network is used in this case study. Sigmoid activities for all neurons were chosen to use for all our trials. The trials show that the output does not change if the layers changed, but sometimes, the same result is obtained with a faster calculation. More hidden layers best the results but increased complexity.

5.7.4 The trial runs on the population

Population size indicated chromosomes in one generation, in which the performance will be maximised.

Figure *5-13* to Figure *5-17* shows the ability of a vehicle to learn and direct itself in a predefined environment. The results indicate illustrated are based on a trial run by considering the same parameters and changing the population size.

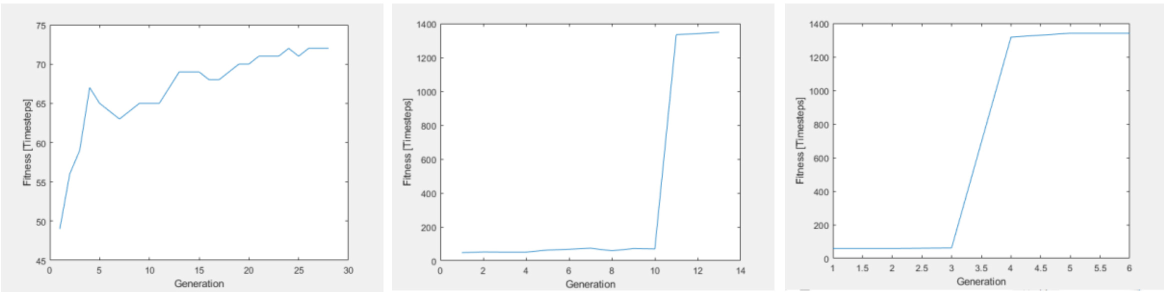


Figure 5-13: Simulation run with one hundred population

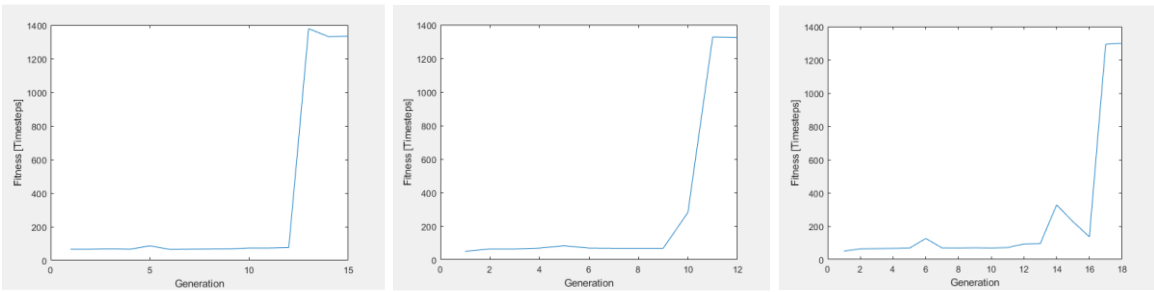


Figure 5-14: Simulation run with three hundred population

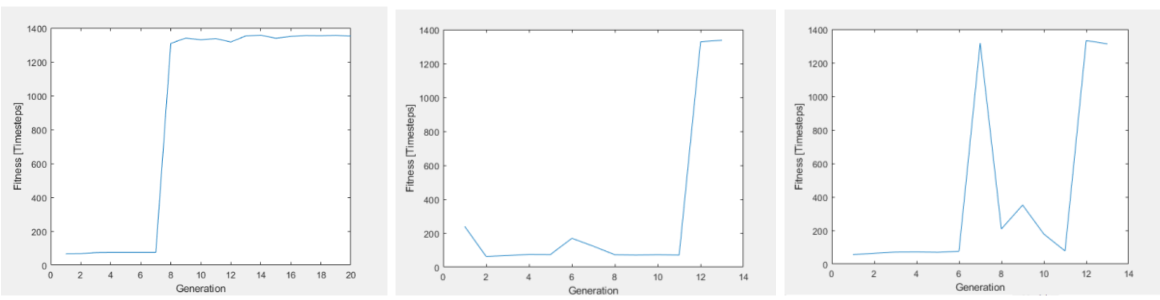


Figure 5-15: Simulation run with five hundred population

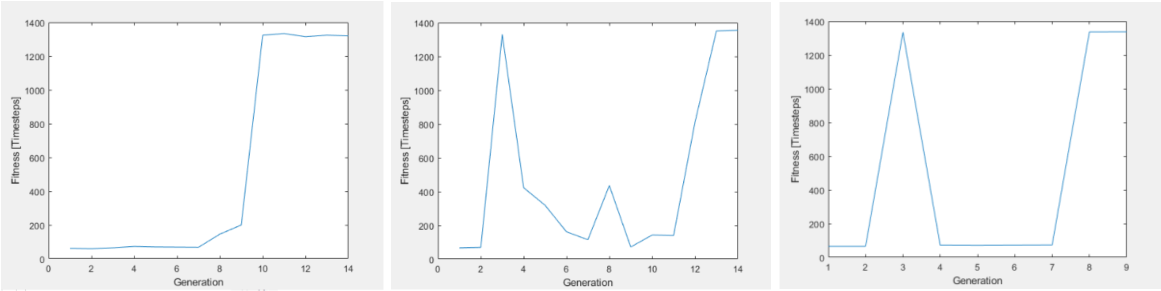


Figure 5-16: Simulation run with six hundred population

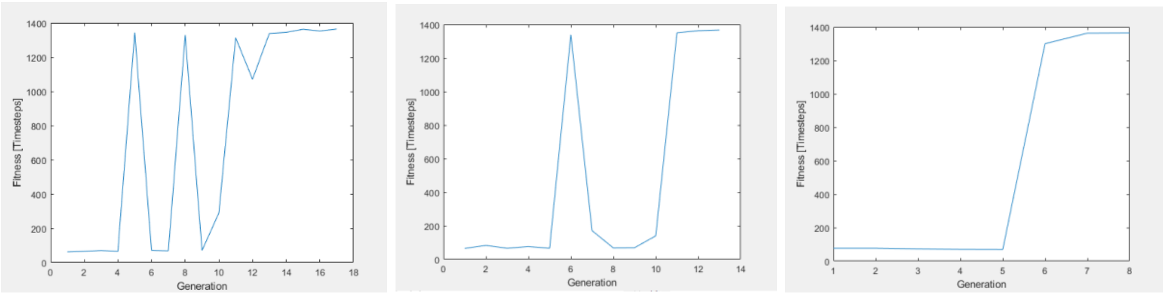


Figure 5-17: Simulation run with eight hundred population

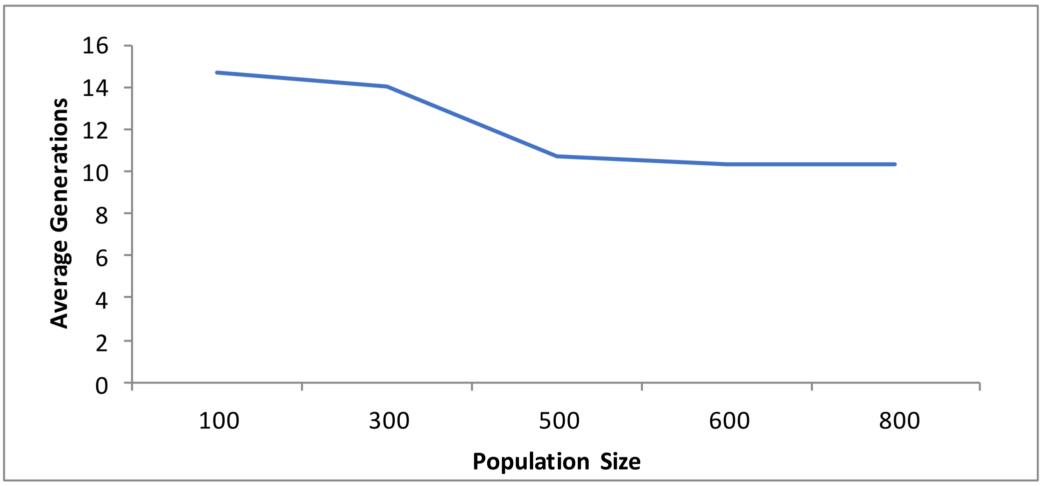
The trial run aims to confirm the ability of self-learning. To memorise to move from start to next point avoiding collision with the inactive predefined road. For time being there is no involvement of dynamic objects. The simplified track with vertical and horizontal edges generated for testing as shown in *Figure 5-13* to

Figure *5-17*. The experiment results as illustrated in Table 5-1 and Figure 5-18 The learning process has taken less than 20 generations. The fact that vehicle learns on average takes only 10-12 iterations to achieve the destination by overcoming the critical left and right turns. Table 5-1, and Figure 5-18 show that the average generations for the algorithm to achieve the training results decreases.

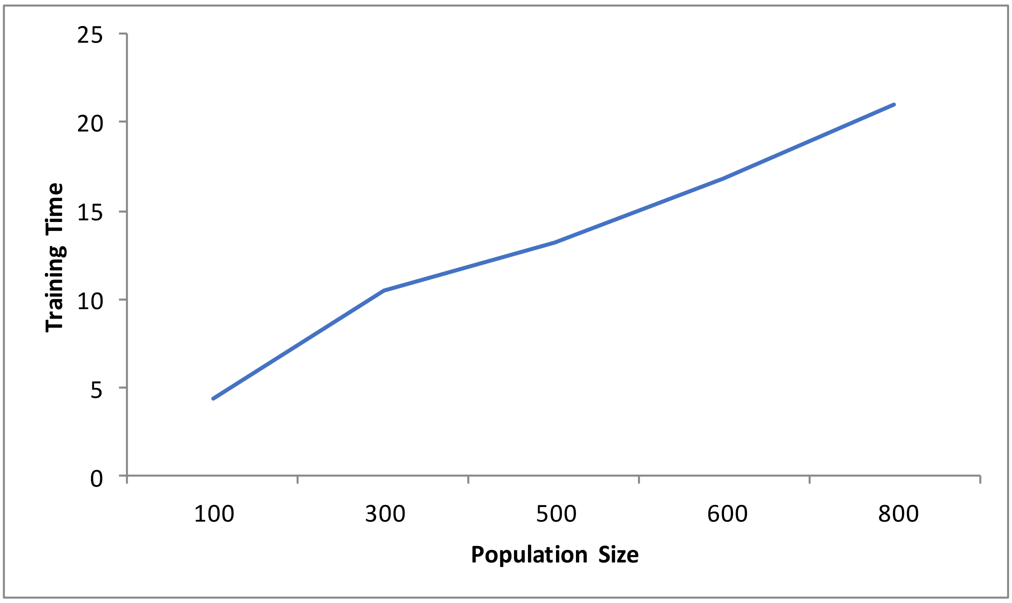
Table 5-1: Summary of trial runs

No.	Population Size	Average Generation	Training Time for NN (sec)
1	100	14.67	4.30
3	300	14.00	10.48
5	500	10.67	13.24

6	600	10.33	16.87
8	800	10.33	21.03



(a) Average Generation vs Population Size



(b) Training Time vs Population Size

Figure 5-18: The effects of population size on training performance

6 Conclusion

Using the simple decision-making neural network to solve the collision between a vehicle and the predefined road or boundary condition has given a very good result. It has shown the genetic algorithm can be used to train Neural networks without knowing the optimal solution. The trial runs are summarised in section 5.7.4 The trial runs on the population, *Figure 5-18: The effects of population size on training performance* have demonstrated that an increase in the population size has caused a reduction in the number of generations. At the same time, the training time of the neural network will increase with the increase in the population size.

6.1 Contributions

- Understanding autonomous vehicles. More than three hundred papers and publications have been collected to review the history and current state of autonomous vehicles. Autonomous vehicles can drive themselves with advanced sensors and complicated algorithms and can solve many problems issued by human drivers such as tired driving, accidents, and drift controller, but also introduce many challenges in research, development, and legalisation. The success of autonomous vehicles in the real world will depend on techniques, such as sensors, algorithms, and connections of cars. Collision avoidance was selected as my research topic because it is an important task for autonomous vehicles, and more research is needed to improve the prediction of risk and the efficiency of algorithms.
- Studying optimisation problems in autonomous vehicles. optimisation takes a vital role in developing autonomous vehicles, especially in collision avoidance. There are optimisation problems in designing and developing autonomous vehicles. They are categorised as car-following, lane changes, motion planner and trajectory, and collision avoidance. There are algorithms in the literature that have been developed and applied to solve those problems. A chart has been developed to show the existing relationships among problems and algorithms. This will help us to find the research gap and develop our methods.
- Coding in MATLAB for collision avoidance. configured in MATLAB project that implements and provides a simulation for vehicle self-learning of collision

avoidance with a distance finding sensor using an evolutionary artificial neural network. The neural network navigates the vehicle on the predefined road and uses evolved vehicles to proceed.

Two cases had been developed:

Case 1 is T To evaluate vehicles for self-learning and remembering boundaries to avoid hitting the boundaries of the field.

Case 2: vehicles run on a designed predefined road without collision with the road boundaries. The vehicle utilizes a sensor that computes N crossing point profundities with the predefined road and afterwards takes care of these N values as contributions to the network. The sources of info then, at that point, went through a network lastly to a result layer of two neurons: left and right turning angle. These angles are used to turn the vehicle by concluding the vehicle's directing point.

Each vehicle is a different chromosome in a generation (or a unique set weight for the neural net) which is evaluated and potentially carried through to the next generation by a fitness score. The fitness score has a different definition in each of my experiments for collision avoidance self-learning.

Programming Configurations are;

- The vehicles measurements and its wheels (base and measurements)
- To find real-time distance sensors reach and number of beams intersection points
- Neural network design
- Number of vehicles and their substitution system

6.2 Research Gap

Based on the literature review, the following research gaps have been found.

1) Object detection

Object detection is the eye of autonomous vehicles. Accuracy and efficiency are key requirements of object-identification algorithms. Optimisation is also a particularly important method for object detection. Normally, collision avoidance problems can be described as control and optimisation problems and then be solved by using numerical optimisation techniques. To deal with such object detection constrained optimisation in intelligence by a collaboration of genetic methods with a neural network to achieve output with specific problems and configuration at hand. Even though existing techniques can be used for object detection, there are still many challenges in hardware and software to supply accuracy in finding objects and damages.

2) Safety

There are presently no "Cutting edge" or "Creation Level able" independent driving frameworks, inferable from the steadily expanding complexity and trouble of continually refreshing information bases and reproducing a great many various situations, which need a lot of processing power. Moreover, the actuators and handling framework expected for full vehicle independence acknowledge the part of the room. It is difficult to integrate them into existing vehicles or current vehicle plans that most clients used. To dynamic run-time safety assurance system is needed to dynamically analyse the inputs received by vehicles. If the specified condition is not met, the system cannot be used on road switches from safe mode to warning mode. If it is unable to produce a safe, minimal risk manoeuvre, it returns control to the driver.

3) Collision avoidance

Collision avoidance is especially important for autonomous vehicles and is an active research area to improve the safety of vehicles. Even though data in the literature how that existing autonomous vehicles are much safer than human-driving cars, many factors will affect vehicle collisions, such as the accuracy of data including a map, the efficiency of the algorithms for deciding and the error of operating systems.

6.3 Innovations and Contributions

The main objective of the framework is to propose methods for autonomous vehicles to avoid collisions by detecting boundaries and obstacles around them. To implicitly detect the objects and keep the vehicle away from obstacles, the framework will be evaluated in different scenarios.

The contributions of this research include:

- Modelling complex collision avoidance problems for autonomous vehicles. A framework will develop for the simulation of collision avoidance of autonomous vehicles. Several simulation scenarios with random obstacles will be proposed to evaluate the proposed framework.
- Applying machine learning techniques in developing algorithms for collision avoidance.
- Combining evolutionary algorithms and neural networks in this research.

An evolutionary algorithm with a neural network will be applied for collision avoidance. Instead of using the best chromosome directly to vehicles, the population is used to each vehicle to learn again. The first simulation results show that our results can find solutions in a brief time.

To improve the efficiency and accuracy of the prediction of obstacles and the operation of the vehicle, an evolutionary Neural Network should have the capability to learn in different scenarios with random obstacles. A simulation tool, called Carmaker, will be used to simultaneously learn collision avoidance.

The autonomous vehicle will identify obstacles with shape and size and at once plan of action. The concept is based on a modification of existing methods to improve the process and shorten the processing time. The is vehicle-controlled with sensors so that the autonomous vehicle can safely navigate. Scenarios will be created by introducing small and medium-sized obstacles on the intentionally left-hand side or right-hand side of the road lane. The aim is to detect the object accurately and overcome the obstruction in the lane and navigate the vehicle throughout.

7 Future Research

7.1 Modelling of Collision Avoidance of Complex Scenarios

Scenario 1: The main function of vehicles is to keep in the lane as shown in Figure 6-1. The research will be on minimising the time of travel of an autonomous vehicle where the vehicle can travel without interaction with the lines. When it comes to detecting obstacles and avoiding collisions will make it complex, as shown in Figure 6-1 centreline of the track with curvature, where some random obstacles will be placed on the track and the vehicle functioning will be evaluated on the new track. Thus, the result will be evaluated and discussed.

To plot the different strategies in different random first neural network weights.

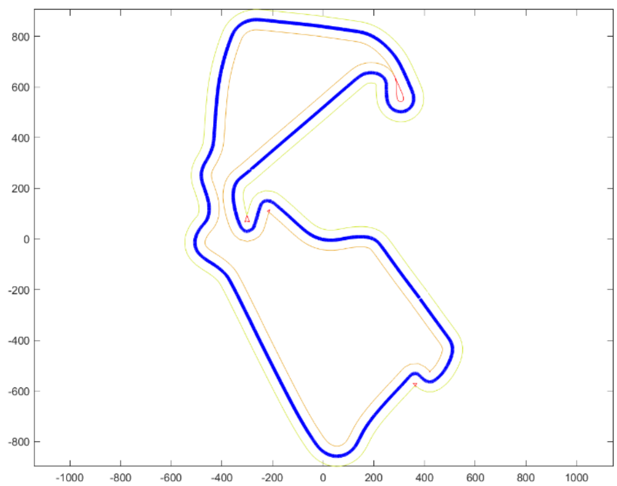


Figure 7-1: New Road Pattern

As illustrated in the above Figure 7-1, the track is based on a centreline with complex curvatures and will have random obstacles on the path.

Scenario 2:

Obstacles will randomly place on the road. An autonomous vehicle will avoid those obstacles.

7.2 Studying machine learning in collision avoidance

Machine learning can give autonomous vehicles the capability of finding obstacles and other dangers during running. A proper machine learning framework should be important in designing and developing autonomous vehicles.

In this research, the existing machine learning (artificial intelligence) methodologies will be used to build a machine learning framework that is suitable for autonomous vehicles.

7.3 Developing Algorithms

Algorithms are one of the key components of autonomous vehicles and take a significant role in avoiding a collision. In developing a collision avoidance simulation demonstration system, the following algorithms will develop:

(a) Decision algorithms:

(b) Neural network:

(c) Optimisation Algorithms:

Developing multiple neural interference systems for non-linear trajectory suiting short-range to slow speed and avoid the collision with the objects coming in the way.

7.4 Publishing Academic Papers

The topic for the papers based on the research will be as follows:

1) "Evolutionary algorithm with neural network for collision avoidances of autonomous vehicles,"
2) "Autonomous vehicle obstacles Identification with shape and size and immediate plans of action."

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Appendix 1: MATLAB Codes

```
%% Clear factors, close current figures and make results index
clc;
clear all;
close all;
mkdir('Results//'); %Directory for Storing Results

% Fake Neural organization and Genetic Algorithm Configurations
ndrOfNeuronsHiddenLayer = [3];
ndrOfOutNodes = 2;
unipolarBipolarSelector = 0; % where, 0 is unipolar, - 1 is for bipolar
draw_each_ndrOfGenerations = 1;

GA. ndrOfGenerations_max = 100;
GA. good fitness = 2000;

GA. population size = 200; % to set the Population Size
GA.corssoverProblem_mean_percent = 95;          % To create the hybrid site dependent on ordinary conveyance with a mean
GA.corssoverProbem_stdDev_percent = 5;          % where, standard deviation of 95% and 5% of the chromosome length individually.
GA.mutationProblem = 0.10;                      % Mutation Rate Probability on a normal
GA.selection_criteria = 0;                      % 0: Tournament, 1: Truncation
GA.tournament_size = 10;                         % Tournament Size if selection_option = 1
GA.truncation_percentage = 40;                  % Percentage of Truncation if selection_option = 1
GA.replacement_option = 0;                      % 0: All kids supplant guardians except if best ceil(PercentBestParentsToKeep),
                                                % 1: Use great guardians dependent on competitions and add different kids
                                                % 2: Use great guardians
                                    % (From all vehicles) considering competitions and adding different kids
GA.PercentBestParentsToKeep = 10;
GA.keptParentsAreGolobal_option = 1;            % 1: Kept guardians are from all best vehicles
GA.weightrange = 1;                             %weight rage is regarding the ordinary conveyance
                                                % Vehicle and sensor Configurations (for individual Chromosome)
car.wheelBase = 2.6 Mtr;                        % axles to axles. Genuine Car is 2.6.
car.width = 1.7 Mtr;
car.length = 4.3 Mtr;
car.wavelength = 0.45 Mtr;
car.wheel width = 0.22 Mtr;

sensor.angle = [0 10 20… 180] * pi/180;         % just to investigate front region
sensor.range = 25 Mtr;
sensor_radius_ratio = 0.05;                     % sensor_circle_radius = proportion * car.width;

dt = 0.1 Sec;                                   % Time Step for continuing
break = 5 Sec;                                  % during break the change is set to be minimum 5 for x and y
smallXYVariance = (8)^2;                        % more modest than or equivalent smallXYVariance [meters^2], wellness assessment stops (break).
carpeted = 10 m/s;

%% Climate Configurations
% env.nbrOfCars = 2;
% env.dx_dy = [150 1-400 150 400 - 150 - 200 - 150 400 200 - 150 - 400 - 150 200 - 300 150 300 150 - 400 - 400 - 400 width]
% env.initial_point = [-7 - 19];
% env.start_points = [0 0]; 0 160]; % starting situation of vehicle [x y; x y; ...]
% env.start_headings = [90 - 90] * pi/180; % beginning to wards hostile to clockwise in Degrees

car.width = 2.6;
num = 100;
num2 = 10;
env.ndrOfCars = 8;
env.dx_dy = [num - num - num];
env.intial_point = [0 0];

% env.start_points = ((num-1-num2)*rand(env.nbrOfCars,2)+1+num2/2); % Car Starting Positions [x y; x y; ...]
env.start_points = [20 30; 40 30; 60 30; 80 30; 20 60; 40 60; 60 60; 80 60];
env.start_headings = (180*rand(1,env.nbrOfCars)- 90) * pi/180;          % Car Starting Heading Counter Clock Wise [Degrees]

env.start_steerAngles = zeros(1,env.ndrOfCars) * pi/180;                % [Degrees] Counter Clock Wise (For all Cars)
env.destination_dot_radius_ratio = 1;                                   % sensor_circle_radius = proportion * car.width;

%% Ascertain Number of Input and Output NodesActivations
nbrOfInputNodes = length(sensor.angles);                                 %=Dimention of Any Input Samples
Network_Arch = [nbrOfInputNodes nbrOfNeuronsInEachHiddenLayer nbrOfOutNodes];

%% Ascertain chromosome Size
GA.chromosomeLength = 0;
previousNbrOfNeurons = Network_Arch(1);
for i=2:length(Network_Arch)
   GA.chromosomeLength = GA.chromosomeLength + (previousNbrOfNeurons + 1) * Network_Arch(i);
   previousNbrOfNeurons = Network_Arch(i);
end

%% Instatement
Chromosomes = cell(1,env.nbrOfCars);
for car_id=1:env.ndrOfCars
   Chromosomes{car_id} = zeros(GA.populationSize,GA.chromosomeLength);
   Chromosomes_Fitness{car_id} = zeros(GA.populationSize,1);
   BestFitness_perGeneration(car_id,:) = - 1 * ones(1,GA.nbrOfGenerations_max);
   AvgFitness_perGeneration(car_id,:) = - 1 * ones(1,GA.nbrOfGenerations_max);
end

nbrOfTimeStepsToTimeout = break/dt;

%% Irregular Chromosomes the Go Ahead!
for car_id = 1:env.ndrOfCars
   for pop = 1:GA.populationSize
      Chromosomes{car_id}(pop,:) = GA.weightsRange*(2*rand(1, GA.chromosomeLength)- 1);
   end
end
MoveCars;
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%ApplyGA%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%
work [Chromosomes_Childs] = ApplyGA(GA, Chromosomes, Chromosomes_Fitness)

    % Since the number of chromosomes is not necessarily GA.populationSize
    smaller population size = length(Chromosomes_Fitness);                    % Should be considerably number !

    % Choice
    if (GA.selection_option == 0) % Tournament
        T = round(rand(smallerPopulationSize,GA.tournament_size)*(smallerPopulationSize-1)+1); % Tournaments (Random from 1 to smallerPopulationSize)
        [temp idx] = max(Chromosomes_Fitness(T),[],2); % Index to decide the champs
        WinnersIdx = T(sub2ind(size(T),(1:smallerPopulationSize)',idx));       % Winners Indeces
    elseif (GA.selection_option == 1)                                          % Truncation
        [temp V] = sort(Chromosomes_Fitness, 'drop');                          % Sort wellness in climbing request
        nbrOfSelections = round(smallerPopulationSize*GA.truncation_percentage/100);   % Number of chosen chromosomes
        V = V(1:nbrOfSelections); % Winners Pool
        WinnersIdx = V(round(rand(smaller population size,1)*(nbrOfSelections-1)+1));   % Winners Indices
    end

    % Hybrid
    all_parents = Chromosomes(WinnersIdx,:);
    first_parents = all_parents(round(rand(smallerPopulationSize/2,1)*(smallerPopulationSize-1)+1),:);     % Random smallerPopulationSize/2 Parents
    second_parents = all_parents(round(rand(smallerPopulationSize/2,1)*(smallerPopulationSize-1)+1),:);    % Random smallerPopulationSize/2 Parents
    references_matrix = ones(smallerPopulationSize/2,1)*(1:GA.chromosomeLength); % The Reference Matrix
    randNums = (GA.corssoverProb_stdDev_percent * GA.chromosomeLength/100) * randn(smallerPopulationSize/2,1) + GA.corssoverProb_mean_percent * 
GA.chromosomeLength/100;
    randNums = min(round(randNums), GA.chromosomeLength);     % Truncation
    randNums = max(randNums, 1);                          % Truncation: Vector of smallerPopulationSize/2 length of irregular numbers in scope of 
1:GA.chromosomeLength
    idx = (randNums*ones(1,GA.chromosomeLength)) > references_matrix;     % Binary lattice of chose qualities for each guardians couple
    Chromosomes_Childs1 = zeros(size(first_parents));
    Chromosomes_Childs2 = zeros(size(first_parents));
    % Do genuine corssover
    Chromosomes_Childs1(idx) = first_parents(idx);
    Chromosomes_Childs1(~idx) = second_parents(~idx);
    Chromosomes_Childs2(idx) = second_parents(idx);
    Chromosomes_Childs2(~idx) = first_parents(~idx);
    Chromosomes_Childs = [Chromosomes_Childs1; Chromosomes_Childs2];

    % Transformation
    idx = rand(GA.chromosomeLength, smallerPopulationSize);
    idx = (idx' <= GA.mutationProb);                                   % Indeces for transformations
    mutedValues = GA.weightsRange*(2*rand([1,sum(sum(idx))]) - 1);     % Random transformation esteems from - 1 to 1
    Chromosomes_Childs(idx) = mutedValues;                             % Do genuine change

end
%%%%%%%%%%%%%%%%%%%%%%% LINESEGMENTINTERSECT%%%%%%%%%%%%%%%%%%%%%%%%%%%%


capability out = lineSegmentIntersect(XY1,XY2)
%LINESEGMENTINTERSECT Intersections of line portions.

    validateattributes(XY1,{'numeric'},{'2d','finite'});
    validateattributes(XY2,{'numeric'},{'2d','finite'});

    [n_rows_1,n_cols_1] = size(XY1);
    [n_rows_2,n_cols_2] = size(XY2);

    if n_cols_1 ~= 4 || n_cols_2 ~= 4
        error('Arguments should be a Nx4 matrices.');
    end

    %%% Plan frameworks for vectorized calculation of line convergence focus.
    %-------------------------------------------------------------------------------
    X1 = repmat(XY1(:,1),1,n_rows_2);
    X2 = repmat(XY1(:,3),1,n_rows_2);
    Y1 = repmat(XY1(:,2),1,n_rows_2);
    Y2 = repmat(XY1(:,4),1,n_rows_2);

    XY2 = XY2';

    X3 = repmat(XY2(1,:),n_rows_1,1);
    X4 = repmat(XY2(3,:),n_rows_1,1);
    Y3 = repmat(XY2(2,:),n_rows_1,1);
    Y4 = repmat(XY2(4,:),n_rows_1,1);

    X4_X3 = (X4-X3);
    Y1_Y3 = (Y1-Y3);
    Y4_Y3 = (Y4-Y3);
    X1_X3 = (X1-X3);
    X2_X1 = (X2-X1);
    Y2_Y1 = (Y2-Y1);

    numerator_a = X4_X3 .* Y1_Y3 - Y4_Y3 .* X1_X3;
    numerator_b = X2_X1 .* Y1_Y3 - Y2_Y1 .* X1_X3;
    denominator = Y4_Y3 .* X2_X1 - X4_X3 .* Y2_Y1;

    u_a = numerator_a ./denominator;
    u_b = numerator_b ./denominator;

    % Find the contiguousness network of converging lines.
    INT_X = X1+X2_X1.*u_a;
    INT_Y = Y1+Y2_Y1.*u_a;
    INT_B = (u_a >= 0) and (u_a <= 1) and (u_b >= 0) and (u_b <= 1);
    PAR_B = denominator == 0;
    COINC_B = (numerator_a == 0 and numerator_b == 0 and PAR_B);

    % Organize yield.
    out.intAdjacencyMatrix = INT_B;
    out.intMatrixX = INT_X .* INT_B;
```

```
    out.intMatrixY = INT_Y .* INT_B;
    out.intNormalizedDistance1To2 = u_a;
    out.intNormalizedDistance2To1 = u_b;
    out.parAdjacencyMatrix = PAR_B;
    out.coincAdjacencyMatrix= COINC_B;

end

capability B = repmat(A,M,N)
    m = length(A(:,1));
    if (m == 1 && N == 1)
        B = A(ones(M, 1), :);
    else
        B = A(:, ones(N, 1));
    end
end


%%%%%Feedforward%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
work yields = Feedforward(Sample, Chromosome, Network_Arch, unipolarBipolarSelector)

    % Feed Forward
    enactments = [Sample 1];                                    %Adding Bias Node
    startId = 0;
    for Layer = 2:length(Network_Arch)
        d1 = length(activations);
        d2 = Network_Arch(Layer);
        loads = Chromosome(startId+1 : startId+d1*d2);
        weigths = reshape(weights, d1, d2);
        enactments = activations*weigths;

        if (unipolarBipolarSelector == 0)
            enactments = 1./(1 + exp(- actuations));
        else
            enactments = - 1 + 2./(1 + exp(- actuations));
        end

        if (Layer ~= length(Network_Arch))                      %Adding Bias
            enactments = [activations 1];
        end
        startId = d1*d2;
    end

    yields = enactments;

end
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%GetEnvlines%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

work [Lines] = GetEnvLines(env)

Lines = zeros(length(env.dx_dy),4);

intial_point = env.intial_point;
for i=1:length(env.dx_dy)
    new_point = intial_point;
    if (mod(i,2) == 1)
        new_point(1) = new_point(1)+env.dx_dy(i);
    else
        new_point(2) = new_point(2)+env.dx_dy(i);
    end

    Lines(i,:) = [intial_point(1) intial_point(2) new_point(1) new_point(2)];
    intial_point = new_point;
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%LineSegment%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
    validateattributes(XY1,{'numeric'},{'2d','finite'});

%          string = [string 'Vehicle' num2str(car_id) ' Gen#/Chrom#=' num2str(Generation_ids(car_id)) '/' num2str(Chromosome_ids(car_id)) ...
%               ' BestChrom#:F=' num2str(BestFitnessChromoID(car_id)) ':' num2str(Chromosomes_Fitness{car_id}(BestFitnessChromoID(car_id))) ' - '];
        string = [string num2str(Generation_ids(car_id)) '/' num2str(Chromosome_ids(car_id)) ...
            '(' num2str(BestFitnessChromoID(car_id)) ':' num2str(Chromosomes_Fitness{car_id}(BestFitnessChromoID(car_id))) ') - '];
    end
    disp(string);

    if (save_option)
        saveas(gcf, sprintf('Results//fig%i_%i.png', Generation, timesteps),'png');
    end

    % Increment lifetimes by one
    LifeTimes = LifeTimes + 1;

    % Emphasize Cars in that timestep
    for car_id = 1: length(collision_bools)
        % Update Fitness
        % Wellness = - sqrt((carLocation (1)- env.destination(1))^2+(carLocation(2)- env.destination(2))^2);
        % Wellness = sqrt((carLocation(1)- carLocation_initial(1))^2+(carLocation(2)- carLocation_initial(2))^2);
        Wellness = LifeTimes(car_id);

        % Assuming vehicle is in same spot after nbrOfTimeStepsToTimeout has passed, set rotating_around_my_self_bool
        rotating_around_my_self_bool = 0;
        if (LifeTimes(car_id) >= nbrOfTimeStepsToTimeout)
            Old_Locations{car_id} = [Old_Locations{car_id}(2:end,:); carLocations(car_id,:)];

            mean_x = mean(Old_Locations{car_id}(:,1));
            mean_y = mean(Old_Locations{car_id}(:,2));
            var_x = mean((Old_Locations{car_id}(:,1)- mean_x).^2);
            var_y = mean((Old_Locations{car_id}(:,2)- mean_y).^2);

            if ( var_x <= smallXYVariance && var_y <= smallXYVariance )
                rotating_around_my_self_bool = 1;
```

```
        end
    else
        Old_Locations{car_id}(LifeTimes(car_id),:) = carLocations(car_id,:);
    end
    if (collision_bools(car_id))
        if (Fitness > max(Chromosomes_Fitness{car_id}))
            BestFitnessChromoID(car_id) = Chromosome_ids(car_id); % Save Best Fitness
        end
        Chromosomes_Fitness{car_id}(Chromosome_ids(car_id)) = Fitness;
        if (Fitness >= GA.goodFitness)
            Car_Finished_Pool(car_id) = 1;
            BestFitnessChromoID(car_id) = Chromosome_ids(car_id);
        end
        ResetCarAndLifeTime;
        on the off chance that (~Car_Finished_Pool(car_id))
            Chromosome_ids(car_id) = Chromosome_ids(car_id) + 1;
        end
    elseif (rotating_around_my_self_bool)
        Chromosomes_Fitness{car_id}(Chromosome_ids(car_id)) = 0; %TODO Is this great ?
        ResetCarAndLifeTime;
        on the off chance that (~Car_Finished_Pool(car_id))
            Chromosome_ids(car_id) = Chromosome_ids(car_id) + 1;
        end
        rotating_around_my_self_bool = 0;
    end

    % Leap to vehicle future if fundamental
    if (Chromosome_ids(car_id) > GA.populationSize && ~Car_Finished_Pool(car_id))
        if (Generation_ids(car_id) >= GA.nbrOfGenerations_max)
            Car_Finished_Pool(car_id) = 1;
            Chromosome_ids(car_id) = BestFitnessChromoID(car_id);
        else
            % Substitution TODO: I supplant all with childs
%               if (GA.replacement_option == 0)

%                   if (GA.keptParentsAreGolobal_option) %(TODO) Commented for quicker run for the present
                    for i=1:env.nbrOfCars
                        All_Chromosomes((i-1)*GA.populationSize+1:i*GA.populationSize,:) = Chromosomes{i};
                        All_Chromosomes_Fitness((i-1)*GA.populationSize+1:i*GA.populationSize) = Chromosomes_Fitness{i};
                    end
                    [tmp idx] = sort(All_Chromosomes_Fitness, 'slip');
                    idx2 = idx(1:nbrOfParentsToKeep);
                    ParentsToKeep = All_Chromosomes(idx2,:);

                    [tmp idx] = sort(Chromosomes_Fitness{car_id}, 'slip');
                    idx2 = idx(1:end-nbrOfParentsToKeep);
                    Current_Chromosomes = Chromosomes{car_id}(idx2,:);
                    Current_Fitness = Chromosomes_Fitness{car_id}(idx2);
%                   else %TODO
%                   end
                Chromosomes_Childs = ApplyGA(GA, Current_Chromosomes, Current_Fitness);
                Chromosomes{car_id} = [ParentsToKeep; Chromosomes_Childs];
%               elseif (GA.replacement_option == 2)
%                   Chromosomes_Childs = ApplyGA(GA, Chromosomes{car_id}, Chromosomes_Fitness{car_id});
%                   T = round(rand(GA.populationSize,GA.tournament_size)*(GA.populationSize-1)+1); % Tournaments (Random from 1 to GA.populationSize)
%                   [temp idx] = max(Chromosomes_Fitness(T),[],2); % Index to decide the champions
%                   WinnersIdx = T(sub2ind(size(T),(1:GA.populationSize)',idx)); % Winners Indeces
%                   console
%
% %                     Chromosomes_Fitness Chromosomes_Childs
% %                     Chromosomes{car_id}
%               end

            Chromosome_ids(car_id) = 1;
            Generation_ids(car_id) = Generation_ids(car_id) + 1;
            Chromosomes_Fitness{car_id} = 0 * Chromosomes_Fitness{car_id};
            BestFitnessChromoID(car_id) = 1;
        end
    end
    current_chromosome = Chromosomes{car_id}(Chromosome_ids(car_id),:);

    % Apply sensor perusing to ANN to compute steerAngle
    yields = Feedforward(sensor.readings(car_id,:), current_chromosome, Network_Arch, unipolarBipolarSelector);
    steerAngles(car_id) = pi/2 * (outputs(2)- outputs(1)); %From - 90 to 90 degrees
%     sensor.readings
%     [yields steerAngles(car_id)*180/pi]
%     console

    % 2D vehicle directing material science (Calculate carLocation and carHeading)
    frontWheel = carLocations(car_id,:) + car.wheelBase/2 * [cos(carHeadings(car_id)) sin(carHeadings(car_id))];
    backWheel = carLocations(car_id,:) - car.wheelBase/2 * [cos(carHeadings(car_id)) sin(carHeadings(car_id))];
    backWheel = backWheel + carSpeed * dt * [cos(carHeadings(car_id)) sin(carHeadings(car_id))];
    frontWheel = frontWheel + carSpeed * dt * [cos(carHeadings(car_id)+steerAngles(car_id)) sin(carHeadings(car_id)+steerAngles(car_id))];
    carLocations(car_id,:) = (frontWheel + backWheel)/2;
    carHeadings(car_id) = atan2( frontWheel(2) - backWheel(2) , frontWheel(1) - backWheel(1) );
  end
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%Movecaretimestep%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Move Car and Draw Environment - Get Sensor Readings and Collision State
work [newCenters sensor_readings carLines collision_bools] = MoveCarsTimestep(carbocations, carHeadings, prev_carLines, ...
                                        steerAngles, vehicle, sensor, env, display_option)

% Intializations
sensor_readings = zeros(length(carHeadings), length(sensor.angles)); % line for every vehicle
sensor_lines = cell(1,length(carHeadings));
carLines = cell(1,length(carHeadings));

sensor.angles = sensor.angles - pi/2;

collision_bools = zeros(1,length(carHeadings));
```

```
%% Colors Configurations
car_outer_color = [0 0 0];
car_inner_color = [1 1 0];
car_wheels_color = [0 0 0];
sensor_beam_color = [1 0 0];

% Draw Environment
if (display_option == 1 || display_option == 2)
    for i=1:length(env.lines(:,1))
        line([env.lines(i,1) env.lines(i,3)], [env.lines(i,2) env.lines(i,4)]);
    end
end

% Draw Destinations
% if (display_option == 1 || display_option == 2)
%     plot(env.destination(1), env.destination(2), 'r.- ', 'markersize', 10*env.destination_dot_radius_ratio*car.width);
% end

for car_id = 1:length(carHeadings)
    % Draw vehicle
    carCentre(1) = carLocations(car_id,1) - (car.length/2)*cos(carHeadings(car_id));
    carCentre(2) = carLocations(car_id,2) - (car.length/2)*sin(carHeadings(car_id)); theta = carHeadings(car_id);
    carLines{car_id} = draw_rectangle(carCentre, theta, car.length, car.width, car_inner_color, car_outer_color, display_option);

    % Compose Car Number
    if (display_option == 1 || display_option == 2)
        text(carCentre(1), carCentre(2), num2str(car_id));
    end

    %Draw Four Wheels
    if (display_option == 1)
        newCenters = rotate(car.wheelBase/2, car.width/2, carHeadings(car_id));
        newCenters = newCenters + carCentre;
        theta = carHeadings(car_id) + steerAngles(car_id);
        draw_rectangle(newCenters, theta, car.wheelLength, car.wheelWidth, car_wheels_color, car_wheels_color, display_option);

        newCenters = rotate(car.wheelBase/2, - car.width/2, carHeadings(car_id));
        newCenters = newCenters + carCentre;
        theta = carHeadings(car_id) + steerAngles(car_id);
        draw_rectangle(newCenters, theta, car.wheelLength, car.wheelWidth, car_wheels_color, car_wheels_color, display_option);

        newCenters = turn(- car.wheelBase/2, car.width/2, carHeadings(car_id));
        newCenters = newCenters + carCentre;
        draw_rectangle(newCenters, carHeadings(car_id), car.wheelLength, car.wheelWidth, car_wheels_color, car_wheels_color, display_option);

        newCenters = turn(- car.wheelBase/2, - car.width/2, carHeadings(car_id));
        newCenters = newCenters + carCentre;
        draw_rectangle(newCenters, carHeadings(car_id), car.wheelLength, car.wheelWidth, car_wheels_color, car_wheels_color, display_option);
    else
        newCenters = [0 0]; %TODO: Should be a significant worth
    end

    % Draw Sensor Beams
    sensor_readings(car_id,:) = zero
```