School of Civil and Mechanical Engineering

MXEN4000-4 Mechatronic Engineering Research Project

Progress Report

Development of CAV Testing Platforms for Cyber Security Research

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Summary
The evolution of Connected Automated Vehicles (CAV) demands unified systems to ensure persistent connections with external entities, enabling communication with other vehicles on the road. However, during these interactions, CAV could be exposed to potential external network threats. This document seeks to summarise the necessary components and configuration for a platform designed to test the resilience of CAV to such external threats. Contemporary autonomous navigation and control mechanisms rely on various integrated systems. The components described outlined within this progression report are industry standard methods, representing the latest in CAV control and communication technology. These tools will be deployed to gauge their robustness against potential hazards on road and cyber related threats and attacks.

The focus of this report is to outline the progression of the model CAV testing platform. During the development of the model the original concept has seen multiple revisions throughout its assembly and configuration. Insights gained from the construction and testing of various components has allowed for these modifications to be deployed and has aided in the overall performance of the design. Initial conceptualisation of the vehicle was tailored to prevalent technology used within the growing CAV sector. The focus of the works was completed to validate the model’s relevance to the topic of cyber security. The model has been aligned with modern standardised technology and techniques used within industry as to provide a standard for testing modern CAV.

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Problem Statement

Connected Automated Vehicles (CAV)

“Recently, the technology behind autonomous vehicles has advanced significantly, and more cars have the capability of being driverless. However, there are a lot of concerns about the security and safety of these cars. This project aims at developing a testbed for Connected and Autonomous Vehicles (CAV) to be able to evaluate the security aspects of these vehicles. The CAV system consists of an On-Board Unit (OBU), Application Unit, Roadside Unit (RSU), and Sensors. An OBU is responsible for displaying warnings, offering services, and managing communication with a vehicle's sensors. The Application Unit is responsible for high-level activities. The roadside unit (RSU) is used to provide connectivity to the internet, extend the messaging domain, layover early warnings and so on. The sensors will send environmental information to the vehicle and include an ultrasonic sensor, a radar, and a lidar.”

Phase 1 - Initial Conceptualisation and Model Development

Decomposing the set of requirements listed within the problem statement shows a multilayered task. Ultimately, the system will need to encompass multiple subsystems and modules which will perform various roles within the structure of the vehicle. Given the nature of the task, the vehicle will need to be able to navigate autonomously, discern on hazards, obstacles, road traffic components and pass on relevant details of the model’s situational awareness to third parties. The design thus far has been split into three major channels each with respective subcomponents. The major modules are broken into a sensor groups, communication, and vehicle drivetrain-power systems.

The sensing framework includes embedded circuits that utilise various sensory data sources. Industry CAV applications predominantly rely on the use of environmental sensors such as LiDAR, stereo camera-based vision systems (CV), and ultrasonic detection. Combining these systems allows CAV to construct a 3D virtual environmental map based on the data from these channels. Having multiple sensory channels is crucial for CAV reliability, as their navigational capabilities hinge on accurate and readily available data. With multiple channels, a CAV can cross-check and refine its perception based on the aggregated data, rather than relying on a single source. This enriches the CAV's environmental awareness and offers multiple data sources for validating its situational understanding.

The communication components are a crucial feature in this testing platform. Communication tools encompass various transceivers like WIFI, 5G, Bluetooth, GPS, and radio modules. CAV come equipped with processing power that allows them to discern their position and autonomously navigate. The positional data is developed using various motion and proximity based sensory modules such as GPS, Inertial Measurement Unit (IMU) and CV. This information is to be utilised for the CAV state of awareness and will be relayed to external entities, who can then utilise, interpret, and potentially modify the vehicle's dynamics. The security of this connection between the CAV and the external party is the main emphasis of our research.

Lastly, the vehicle drivetrain-power systems encompass the vehicle dynamics and distribution of control signals to the steering, motors, and breaking components. The system also required a means of safe power management which can reliably supply all components with their required power during a suitable duration.

Primary Systems

Sensory Group

The sensors deployed within the model have been implemented to strengthen the ability of the CAV to reliably perceive its environment. Each of the sensor varieties has been selected based upon its functional limitations and proficiencies. The ability of the sensors to cover potential weaknesses between modules is vital, as the inability to detect hazards based upon their composition or orientation could cause the CAV to collide with objects while operating *Litman (2020)*. This is evident in situations where the LiDAR might be considered. The module relies on light based optical hardware to perceive distances, certain environmental conditions or object composition could impact its effectiveness in detection. The Ultra-Sonic and radar modules are robust against varying light conditions and can provide the needed detection within this scenario. The adaption of these sensors has been configured to promote the most optimal orientation as to provide the greatest field of view *Litman (2020)*.

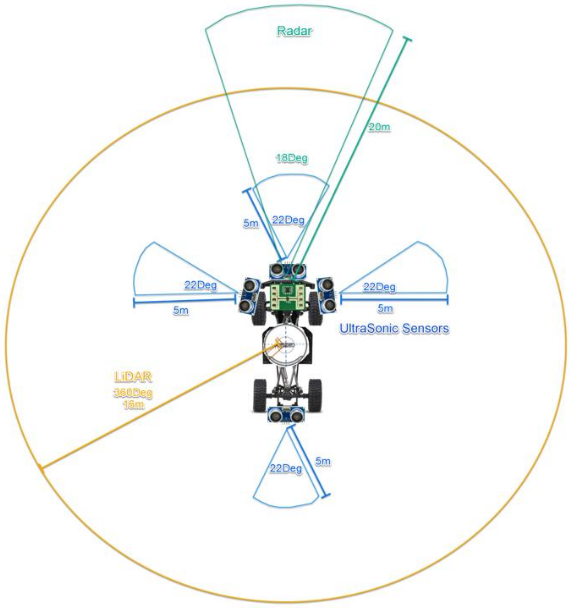

Figure 1 Sensor Arrangement

24GHz Microwave Radar

The microwave radar sensor operates on the principle of transmitting and receiving radio waves to determine distances. When contrasted against the other fitted distance sensors, the module offers several advantages. Notably, long distance sensing, compactness, low weight, muti-target tracking. This sensor provides consistent and reliable performance adverse environmental conditions, demonstrating the capacity to penetrate most atmosphere contaminants, including particulate matter such as dust, smoke, and fog. A noteworthy feature of this sensor is its ability

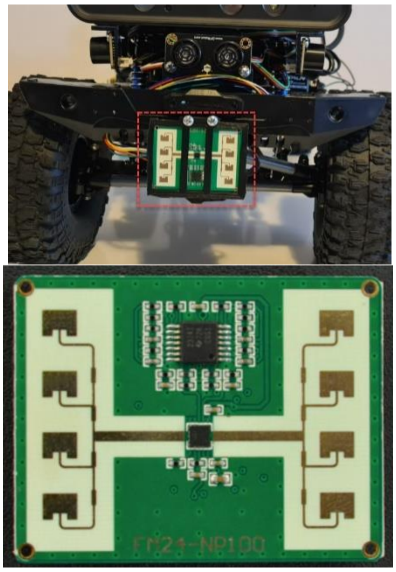
Figure 2 Microwave Radar Module

to ascertain distances from multiple target objects simultaneously *(24GHz Microwave Radar Sensor Wiki - DFRobot, n.d.)*. When utilising the multi-target tracking there was a requirement to filter through the UART communication data in order to sort items by their relative radar cross section. Upon initial testing the radar module would only return objects of the greatest cross section. This proved to be problematic during testing as the module would only return large objects within the field of view and would neglect objects of concern. This created a need to filter through the serial data and return objects respective of their distance and of a significant proportion to the CAV *(24GHz Microwave Radar Sensor Wiki - DFRobot, n.d.)*.

3D Stereo Graphic Computer Vision

The stereovision module has been adapted using an Orbecc Astra 3D camera with stereo graphic cameras. This module has proven to be more problematic during the development of the CAV. These varieties of cameras are more primarily suited for specialised optical 3D model development and depth mapping rather than object detection. The video format type from the 3D cameras opposed to traditional 3-channel RGB camera formats has made the compatibility of the camera with the chosen driving model extremely difficult. This is due to the prior training and optimisation of the driving model to a particular pixel format when utilising its convolutional Neural Network *Gilbert (2022)*. The network architecture selected promotes speed and responsiveness when applying the CV based driving model and has shown limited results due to this incompatibility. A proposed modification to amend this issue will be to supplement a standardised format USB-Webcam to provide the appropriate data format as to allow for the model to begin real world self-driving and testing. With the given 2D camera format, the pixel data will require calibration in order to align with the models perception. Common problems related to camera distortion due to the 2D sensor plane will be addressed using the pinhole camera model. The model utilises the mathematical relationship within light projections to a 2D plane from a 3D object *Gilbert (2022)*.

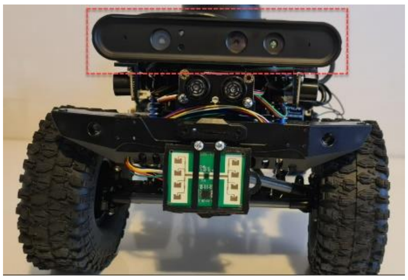

Figure 4 Orbbec 3D Camera

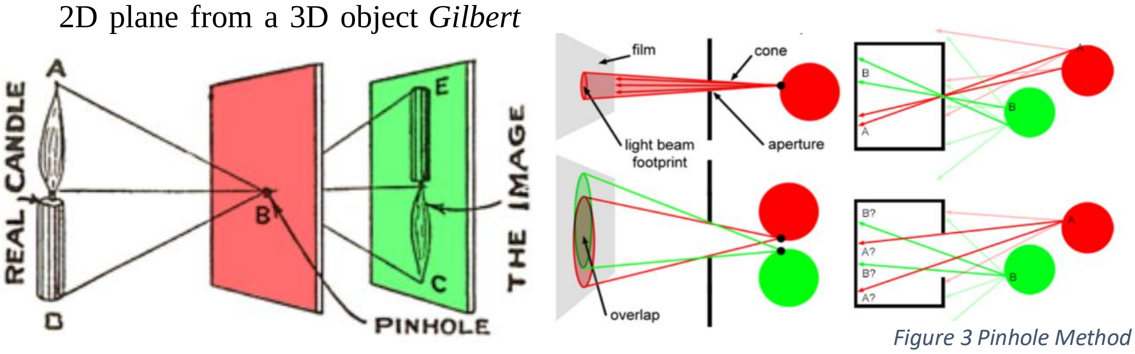

Figure 3 Pinhole Method

The characteristics of this form of projection can cause either positive/negative radial distortion and tangential distortion. The most common type of distortion found within general purpose image processing is Positive radial distortion where images may appear closer than they are *Gambling (2003)*. The form of distortion could present issues to the functionality of the driving model where inaccurate image data can be passed onto the model.

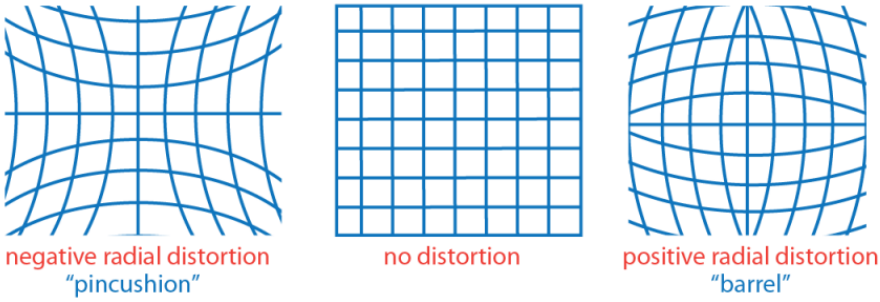

Figure 5 Varieties of Image Distortion

Compensating for this type of radial distortion can be achieved through applying calibration models through OpenCV. The math which governs this relationship can be described using a 3D distortion model as follows *Gambling (2003)*.

Figure 6 Tangential Distortion Model

$$s \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_1 \\ r_{21} & r_{22} & r_{23} & t_2 \\ r_{31} & r_{32} & r_{33} & t_3 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

The 3D point axis for the given image are shown by the coordinates *X, Y, Z. u* and *v* represent the 2D coordinates of the projection points within the pixel data.

The initial matrix containing intrinsic camera parameters c_x, c_y, f_x, and f_y. Represent the central point of the image and the focal lengths respectively *Gambling (2003)*.

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = R \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} + t$$
$$x' = x/z$$
$$y' = y/z$$
$$u = f_x * x' + c_x$$
$$v = f_y * y' + c_y$$

The second matrix including the r_{mn} parameters form the rotation-translation matrix. These parameters are formed from extrinsic variables which are dependent on the cameras motion through an environment. These values will aid the model's ability to discern objects while in motion. The 2D camera format will require the images to be undistorted when attempting to render 3D objects. This can be achieved through using the function. Once the image translational distortion function has been solved, the camera calibration and radial distortion can be initialised. The distortion coefficients found within the radial model can be discerned through the Fitzgibbon division model. *rdistorted=rundistorted(1+krundistorted2)* The function describes the relationship between radial distance from the distortion centre to the radial distance in the undistorted image multiplied by the radial distortion coefficient *k*. The model when applied through 3D translation scenes can be

$$x'' = x' \frac{1 + k_1 r^2 + k_2 r^4 + k_3 r^6}{1 + k_4 r^2 + k_5 r^4 + k_6 r^6} + 2 p_1 x' y' + p_2$$
$$y'' = y' \frac{1 + k_1 r^2 + k_2 r^4 + k_3 r^6}{1 + k_4 r^2 + k_5 r^4 + k_6 r^6} + p_1 (r^2 + 2 y'^2) + 2 p_2 x' y'$$
$$\text{where} \quad r^2 = x'^2 + y'^2$$
$$u = f_x * x'' + c_x$$
$$v = f_y * y'' + c_y$$

adapted into a 6th order polynomial which accounts the for all camera calibration distortion coefficients *Gambling (2003)*.

Figure 7 Fitzgibbon Radial Distortion – Calibration Method

Camera calibration and evaluation of the distortion coefficients can be achieved through the implementation of inbuilt tools with OpenCV and a calibration map. Where photos of the map will be taken at differing angles, allowing for the Fitzgibbon model coefficients to be experimentally determined *Gilbert (2022)*.

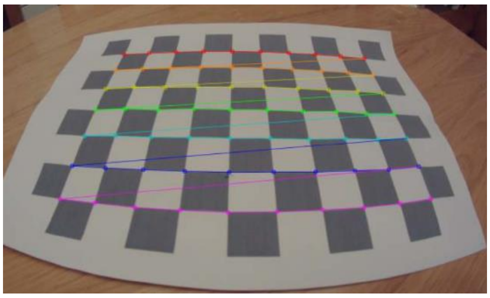

Figure 8 Calibration Map

The effectiveness of the model's object detection has shown reliable performance when passed appropriate on road data. The below figures show case the model's ability to discern traffic-based object within the field of view. The video provided was taken by a POV dashboard camera from a tour bus in Japan. The raw video footage was process by the object detection model and the appropriate boundary boxes were applied to the image features *Gilbert (2022)*.

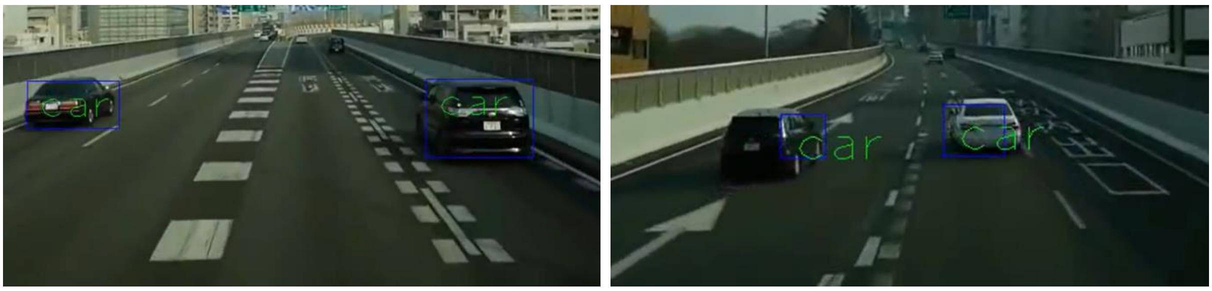

Figure 9 Object Detection OpenCV

LiDAR

Utilising the Slamtec A2M12 LiDAR module has yielded a reliable means of environmental awareness. The module relies on the tracking of laser emission in order to perceive distance. The module has provided a 360˚ field of view with relative accuracy at 16m. Integrating the LiDAR within the model has allowed for

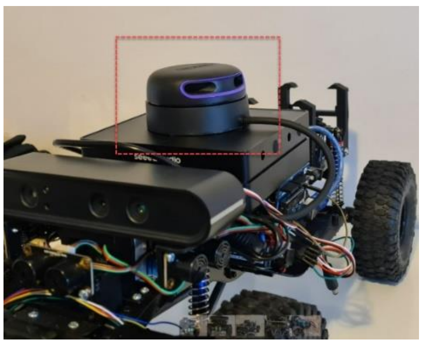

Figure 11 LiDAR Module

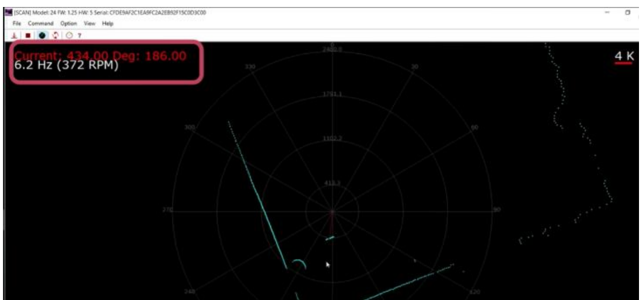

Figure 10 SLAM Mapping and Localisation

the development of two situational awareness protocols involving Simultaneous Localisation and Mapping (SLAM) and hazard detection. The use of the slam system generates a 2D dot map to be formed around the module where detected objects are rendered allowing for additional localisation to be achieved within the environment *Malik (2023)*. The system has aided in the models ability to perceive proximity related to the environment along with the perception of objects conflicting with its trajectory. The module has been mounted to the top of the CAV in order to provide an unobstructed field of view during operation. The configuration of the LiDAR can be done through two different methods, the initial method was achieved through the use of the Slamtec SDK through RoboStudio. This allowed for the 2D dot map generation which has been used for during system localisation. The second feature if through direct data acquisition of the module angle and distance measurements from the measured angle *Malik (2023)*. The data is passed on to the driving model where the distances are factored into the control of the CAV during its operation.

Ultra-Sonic Sensors

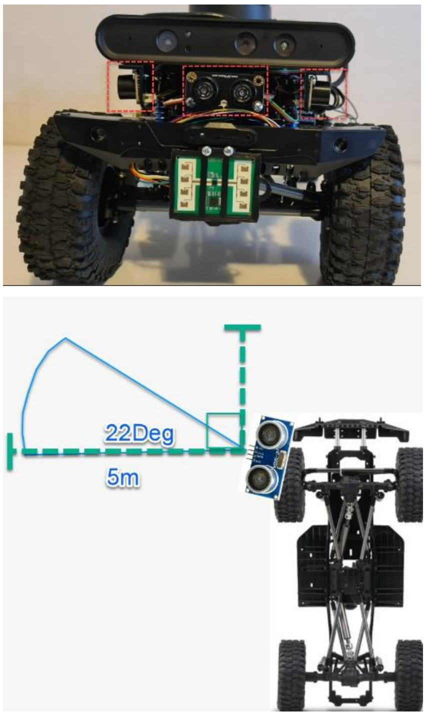

Figure 12 Ultra-Sonic Sensor Modules

The URM09 Ultra-Sonic Sensors provide the most robust and reliable means for distance measurements within the model. The use of these components has been added to provide accurate short distance measurements where the Lidar and Radar performance tends to diminish. The effective distance of the unit is 20mm-5000mm which an accuracy rating of ~1%. Within the build there are 4 modules which have been fitted to the front, back, left, and right. For the left and right sensors, the orientation of the module has been slightly biased to the front of the vehicle. This has been done as to improve the desired field of view, where on road obstacles are more likely to reside. These sensors provide a necessary high accuracy low distance defence to obstacles within the environment where the other modules tend to poorly perform *Smoot (2021)*. During testing the modules tended to interfere with one other during their operation, this was likely due to the timing of the sonic pulses while operating, a solution to this issue was to stagger the use of the sensors where each of the sensors were allowed a window for their operation rather than being run simultaneously. Once amended, the sensors provided the desired short range object detection.

Vehicle Drivetrain-Power System Subcomponents

Power Supply

While designing a CAV testing platform particular consideration need to be made about the dynamics and power management of the model. Due to the array of sensors, computer modules and the electric drive train a suitable power delivery system needed to be developed. Considering its application during testing, priority has been given to the storage potential within the CAV battery pack. The pack provided consists of 2 11.1V 5000mAH 3cell LiPO batteries. The configuration of the cells feature a series connection providing a combined storage capacity of 5000mAH at 22.2V. The storage capacity of the given pack produces 111wH which can nominally run all hardware on the model for 1.03Hrs. The high-capacity battery pack was deemed necessary as down time during testing could potentially impact progression of the project. The main connection between the battery pack and DC-DC converter has been fitted with an inline fuse as to preventative measure to potential damage to the model's hardware.

Component	Power Consuption Nominal (w)
WIFI-BT	0.4
GPS	1.65
LTE	0.64
DC Motor	91.44
Servo	15.8
IMU	0.036
LiDAR	0.6
Ultra Sonic	0.624
Stereo Camera	0.48
Radar	0.08
CPU - GPU	1.25
MCU	0.22
DC-DC converter Coef	0.95
Total Power Consuption (w)	107.559
Battery Capacity (wH)	111
Projected Run Time (H)	1.032

Figure 14 Module Power Consumption Estimate

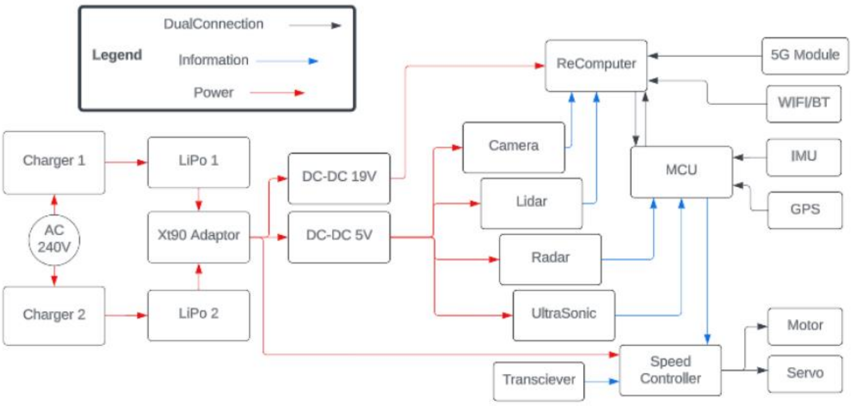

Figure 13 Model Interconnections and Wire Map

Steering and Drivetrain

The drive train of the CAV is composed of a 12V Brushed DC motor, Electronic Speed Controller (ESC), Servo Steering motor, and gearbox. During the construction of the model some issues related to the steering dynamics were noted. Primarily the limited steering angle achievable by the steering servo. The issue was multifaceted where the tyres experienced a high degree of friction when undergoing turning. This was due to the high traction low durometer tyres, locked front differential and added mass to the CAV chassis. The solution to these issues was to relocate the battery pack to the rear of the model. The original design had

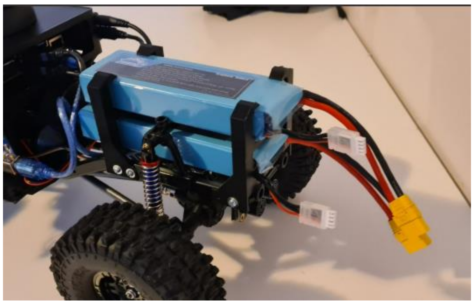

Figure 15 Battery Pack

positioned the battery pack on the central flanks of the vehicle, this was originally done as to lower the models centre of gravity as to improve corning performance but had shifted more weight over the front axle. A 3D printed bracket was created to allow for the positioning the pack on the rear axle. This had pushed the centre of gravity up but more importantly back towards the rear reducing the normal force experienced by the front two wheels.

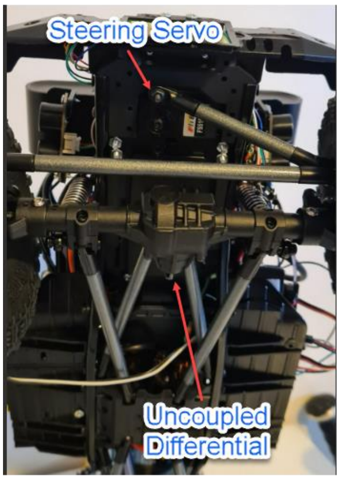

Figure 16 Steering Linkage and Differential

The second modification was to uncouple the front axels drive shaft from the front differential of the model. Due to the locked differentials present on the model, the wheels were unable to turn independently of one another. This made a particularly large impact on the model's manoeuvrability at low speeds. The chassis design from the factory was intended to be deployed as an off road 1/10 scale RC offroad vehicle which would benefit from the locked differentials and all wheel drive. However, considering the application for an on-road vehicle these benefits would likely cause handling and cornering issues while also decreasing driving range and efficiency. As to minimise these losses and to improve the steering performance and steering angle the front drive shaft was removed, transitioning the platform from all wheel drive to rear wheel drive.

Driving Model

The driving model selected to manage the cars dynamics was an opensource driving software supplied by donkey car. The Python based software presented an extremely adaptable platform for customisation of the CAV driving and vision models. The software acts as a handling service for multiple autonomous driving related features such as computer vision, LiDAR, trainable ML driving models and customisable parts which are implemented using APIs. The software can be extended with a gym feature which acts as a model training simulator, the ability to simulate on road driving conditions with customisable sandbox style maps allows for complete control of the models training process. When considering model training, the ability to simulate provides many advantages compared to real world training. Ultimately the Donkey Car software acts as an interface between the applied driving model and the cars dynamic hardware such as the steering acceleration and breaking.

Figure 17 Model Training Simulator

The features within the control model software include:

- Conversion of the model's acceleration/breaking/steering outputs into control signals for the model's drivetrain
- Collecting real time data from training and testing of the driving model
- Defining the driving models and computer vision architecture
- Training the driving model via the customisable simulator
- Pre-processing the visual pixel data
- Auxiliary access to the car's hardware, status and on road data via a remote web service.
- Ability to add customisable parts in the form of APIs

The applied controller for the cars dynamic hardware was achieved through serial communication to an auxiliary Arduino Uno. The MCU acts as a PWM signal generator which relies on the models control signal values as inputs which are then converted into usable PWM control signals for the throttle, steering and breaking.

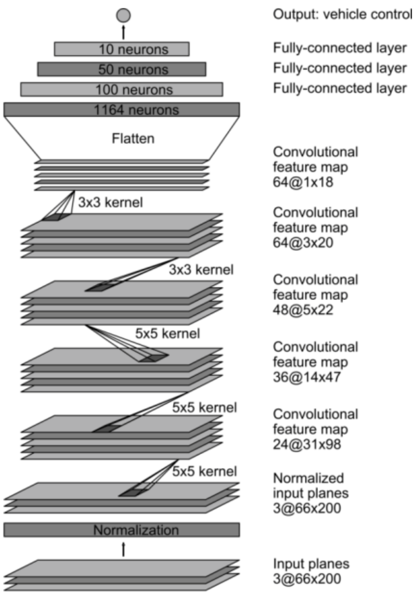

Figure 19 CNN Model Architecture

The driving model was adapted from NVIDIAs driving model architecture which contained 3 fully connected layers, 5 convolutional layers, 1 normalisation layer, and an input/output layer *Barla (2023)*. Implementing the NVIDIA driving model relies on the customised training of the Fully-connected layers. Within the Nueral Network (NN) the paramters (weights and biass') are set based up on the training provided to the model. The models training which was completed through the simultor application utilises the convolutional layers to distringuish features within the environment. The abaility for the model to be able to determine lane markings and other road features such as signs, traffic lights and hazzards. For localised navitagtion the driving model I soully responsible for the vehicles localised pathway planning, lane keeping and steering within the model, the sensor array has equal

$$convolution(i,j) = (I * K)(i,j) = \sum_{m} \sum_{n} I(m,n)K(i-m, j-n)$$

Figure 18 Convolutional Operation Within CNN

ability to regulate the breaking and acceleration of the vehicle. This is done to ensure robost object detection while in opporation. The Convolutional Neural Network utilises convolutional opporations to extract the feature map and boundary regions of objects present in the field of view and can be described by the function *Barla (2023)*.

Within the dense NN layers the models generalisation process will attrempt to distinguish objects within the scene. The objects of interest to the model will be generalised through the use of activation functions which compose the Neurons within the system. These nodes rely on the use of the Rectified Linear Unit (ReLU) and Leaky ReLU activation functions. These functions enable the model to better generalize and closely match the desired function *Barla (2023).*

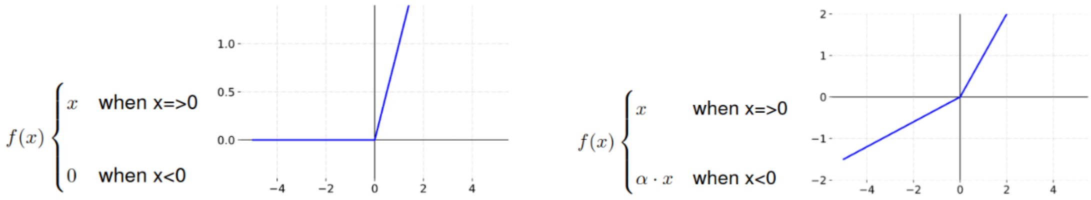

Figure 20 Models NN Activation Functions

The model is constructed with regularisation layers and dropout regularisation. These methods are used to develop more robust models which are more resistant to overfitting during training, improving the model's flexibility and reliability. The application of these techniques attempts to prevent the model from over fitting the training data, neurons within the model can be adjusted to 'drop out' during training. This forces the model to reduce dependency on overused neural pathways within the network during training, this is done to improve model performance during testing where input data may be more variable than the training data provided. The regularisation within the neural network is completed by the function below *Barla (2023)*. The ability of the model will be dependent on its capability to approximate functions of a complex nature. Without the addition of regularising functions, the model will be less capable of generalising, which will likely become more biased and less versatile.

$$\mathcal{J}(w^{[1]}, b^{[1]}, \ldots, w^{[l]}, b^{[l]}) = \frac{1}{n}\sum_{i=1}^{n}\mathcal{L}(\hat{y}^{(i)}, y^{(i)}) + \frac{\lambda}{2n}\sum_{l=1}^{l}||w^{[l]}||^2$$

Figure 21 Regularisation Model Within CNN

Phase 2 - CAV Network Project

With the advances in autonomous vehicles, transportation has shifted towards more interconnected Autonomous Vehicles (CAV). This defines a necessity for advanced, robust, and secure networks. CAV are sophisticated mobile computational platforms that rely on continuous streams of data for navigation, decision-making, and communication. These large data-driven systems require reliable communication between vehicles, infrastructure, networks, and stakeholders. The demands of these interactions require networks that are fast, reliable, and capable of handling vast amounts of data with minimal latency. Moreover, given the safety-critical nature of transportation, these networks must be fortified with high standards of cyber-security to prevent potential threats as to ensure the safety of all road users. The development of specialized networks to the requirements of CAV is essential as these networks will be the primary resource that supports the next generation of smart transportation systems. These advances have a great potential to making our roads more efficient, safer, and adaptive to the needs of all road users.

Hardware Requirements

1. **On-Board Unit (OBU):** Equip each CAV capable hardware which can manage multiple communication mediums including WIFI, Bluetooth, GPS, and 5G-4G LTE.
2. **Remote Connectivity (RSU):** Ensure high-speed, low-latency cellular connectivity for the CAV, prioritizing 5G-4G LTE.
3. **GPS Modules:** For accurate localization and tracking.
4. **Vehicle Communication:** Support Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), Vehicle-to-Network (V2N), and Vehicle-to-Pedestrian (V2P) communications.
5. **Data Storage:** Solutions to handle large data generated by the CAV.
6. **Central Servers:** For data processing, storage, and real-time analytics.

Software Requirements

1. **Stack and Communication Protocol:** Development of a stack that supports WIFI, Bluetooth, GPS, and 5G-4G LTE to facilitate intercommunication.
2. **Authentication Mechanisms:** To verify and identify modules communicating on the CAV network for unit observation and prevention of unauthorised connections.
3. **Data Processing and Aggregation:** Software to process the raw data from individual vehicles to be extrapolated and utilised.
4. **Traffic Management System:** To provide oversight, optimisation, and coordination between vehicles.
5. **System redundancy:** In case one communication medium fails, there should be an automatic switch to a backup communication medium.
6. **Potential Updates:** Capability to remotely update the software of CAV for enhancements and security patches.

Cybersecurity Requirements

1. **Intrusion Detection Systems:** Monitor the network for malicious activities and unauthorised access.
2. **Vulnerability Checks:** Periodically check the system for vulnerabilities.
3. Firewall and Network: Separate the CAV network from other networks and control incoming and outgoing network traffic.

Testing and Validation

1. **Simulation Environments:** Before deploying in real-world scenarios, simulate the network in a controlled environment to test its efficiency and reliability.
2. **Field Testing:** Test the CAV in real-world conditions to validate network reliability and data accuracy.

This list represents a generalized set of essential components for the development of a networking platform tailored to connected automated vehicle management systems. It is non-exclusive, and additional features may be required based on specific needs or expanded functionality *Rahman and Abdel-Aty (2020)*.

Conclusion of Phase 1 – Fabrication of Initial CAV Model

After completing the initial concept model for CAV, several improvements have been identified for future iterations. This arises mainly from the challenges encountered when designing from scratch. Potential areas for optimising future model development could be seen from implementing the following methods:

Standardise Components: Adopt a more standardized list of components. Prioritize the use of compatible and tested hardware over creating new systems from the ground up. This approach is expected to reduce costs, save time, and enhance data sharing between vehicles and servers.

Focus on a Primary Test Vehicle: The model from this project phase should be the primary vehicle for testing. Harnessing its advanced sensory technology and computational power for multiple vehicles would not be cost-effective. Its capabilities should be the benchmark for gathering performance data.

Utilise Auxiliary Test Vehicles: Additional vehicles should serve as secondary test units, designed to mimic other road users. They don't need the complexity and cost of the primary model. There are cost-effective platforms available with sufficient sensory and autonomous driving capabilities that can complement the primary model, without the need for multiple high-end systems.

Data Sharing and Analysis: The primary model should efficiently record and share data regarding its actions and the relative position to auxiliary CAV, and vice versa. Even though the auxiliary vehicles share their data with the primary, the focus should be on analysing the responses of the primary vehicle.

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