SCHOOL OF ENGINEERING
Atlantic Technological Unversity

Obstacle Avoidance Car based on Vision System

Student
Haohan Zhu

Submitted for the Bachelor of Engineering (Honours)
in Electronic Engineering

Supervisor
Fabian Connolly B.E. MEng Sc.

Submitted to the Atlantic Technological Unversity, May 2022

ABSTRACT

Obstacle Avoidance Car based on Vision System

by

Haohan Zhu

Vehicles are used by a wide range of people worldwide, with more and more people buying and owning vehicles and more and more traffic accidents occurring every year. When people use vehicles to travel, they often ignore whether there are other objects in front of them, so many accidents occur when the driver starts the vehicle and hits an obstacle, with severe consequences. In addition, when people drive for long periods in a relatively static environment, they tend to become lax and tired to be letting down their vigilance on the road.

Therefore, this paper designs a system that detects the presence of an obstacle before the vehicle is started and enables lane following to assist the driver. The system uses a single webcam to achieve full functionality and low cost.

Declaration

I declare that I am the sole author of this thesis and that all the work presented in it, unless otherwise referenced, is my own. I also declare that this work has not been submitted, in whole or in part, to any other university or college for any degree or qualification.

Name
May 2022

Name (Supervisor)

Acknowledgements.

Foremost, I would like to express my sincere gratitude to my project manager Mr. Fabian Connolly for his very pertinent advice and assistance during my project. I would also like to thank Ms. Saritha Unnikrishnan for her help in this project and for pushing us to learn more. Secondly, all the teachers and staff that I met during my joint training at the Institute of Technology, Sligo, helped me to progress with my studies and integrate into the Irish culture. They also helped me in many different ways and pushed me to study. Finally, I would like to thank my friends and family for their support and encouragement throughout the year.

Abbreviations

ADAS	Advanced Driver Assistance Systems
NDA	Navigation Data Standard Association
SAE	of the Society of Automotive Engineers
LDWS	Lane Departure Warning System
LKS	Lane Keeping System
FCW	Forward Collision Warning
BSD	Blind Spot Detection
OpenCV	Open Source Computer Vision Library
DAS	Driver Assistance System
RGB	Red, Green and Blue
HSI	Hue Saturation Intensity
ROI	region of interest
NLD	No Lane Departure
RLD	Left Lane, Right Lane Departure
LLD	Left Lane Departure
VALM	Vehicle Crossing Mark
MPC	model predictive control
PID	proportional–integral–derivative controller
TTC	Time-to-collision
D	distance between two vehicle
TH	Time Headway
GNN	Global Nearest neighbor
PDA	Probabilistic Data Association
JPDA	Joint Probabilistic Data Association
MHT	Multiple Hypothesis Test
PCA	Principal Component Analysis
HOG	The Histogram of Oriented Gradients
CNN	Convolutional Neural Network
RF	radio frequency
TX	transmission
RX	reception
HATS	Hardware Attached on Top
SD	Secure Digita
GPIO	General-purpose input/output

Table of contents

1 INTRODUCTION **1**

2 LITERATURE REVIEW **2**

2.1 OVERVIEW 2
2.2 SAFE ROAD TRAFFIC 2
2.2.1 Essentials of surveillance and obstacle avoidance systems on automobile *2*
2.2.2 Limitations of Manually driven cars and autonomous vehicles *2*
2.2.3 Automobile design *3*
2.3 ADVANCED DRIVING ASSISTANCE SYSTEM (ADAS) 3
2.3.1 Lane Departure Warning System (LDWS) *4*
2.3.2 Lane Keeping System (LKS) *5*
2.3.3 Forward Collision Warning (FCW) *6*
2.3.4 Blind Spot Detection (BSD) *7*
2.4 MONITORING AND OBSTACLE AVOIDANCE SYSTEMS ON VEHICLES 12
2.4.1 Environment perception *12*
2.4.2 Privacy protection *15*
2.4.3 Data Fusion *15*
2.5 DEPTH PERCEPTION 15
2.5.1 Zhang's Camera Calibration Method *16*
2.5.2 Disparity Map and Depth Map *16*
2.6 SUMMARY 16
2.7 CONCLUSION 17

3 METHODOLOGY **18**

3.1 METHODOLOGY OVERVIEW 18
3.2 HARDWARE 18
3.3 SOFTWARE 22
3.4 LANE-FOLLOWING SYSTEM 23
3.4.1 Canny edge detector for lane detection *23*
3.4.2 Straight lane detection *25*
3.4.3 A single pixel point represents a straight line *27*
3.5 OBSTACLE AVOIDANCE SYSTEM 29
3.5.1 Build a stereo camera *29*
3.5.2 Camera Calibration *31*
3.5.3 Depth perception distance measurement *33*
3.5.4 Obstacle detection *34*
3.6 SYSTEM DECISION 35

4 RESULTS **36**

4.1 RESULTS OVERVIEW 36
4.2 LANE-FOLLOWING SYSTEM RESULTS 36
4.2.1 The vehicle encounters a bend to the left *36*
4.2.2 The vehicle encounters a bend to the right *38*
4.3 OBSTACLE AVOIDANCE SYSTEM RESULTS 40

5 DISCUSSION **42**

6 CONCLUSIONS **44**

7 BIBLIOGRAPHY **45**

7.1 REFERENCES 45

8 APPENDICES 8-1

8.1 MOTION DECISIONS FOR LANE FOLLOWING SYSTEMS 8-1

List of Figures

Figure 1：THE PARTITION OF THE IMAGE DETECTED BY LDWS....4
Figure 2：Control architecture diagram[14]....5
Figure 3：Take a truck as an example of the blind area of vision....7
Figure 4：BSD system architecture[38]....8
Figure 5：Data association techniques general algorithm[38]....9
Figure 6：Basic principles of multi-target tracking....10
Figure 7：Flow chart of blind spot detection using vision system[37]....11
Figure 8：Implementation process of HOG feature extraction[48-50]....13
Figure 9：Principle of stereoscopic cameras....15
Figure 10: Disparity value....16
Figure 11: Depth value....16
Figure 12: The construction of the car....18
Figure 13: Raspberry Pi Model 3B....19
Figure 14: Block diagram of PCF8591....20
Figure 15: Robot HATS on the car....20
Figure 16: PCA9865 PWM Driver....21
Figure 17: Motor Driver Module....21
Figure 18: The personal hotpot ip address....22
Figure 19: Raspberry Pi ip address....22
Figure 20: PuTTY....22
Figure 21: Thonny IDE under the Raspbian Operation System in VNC viewer....23
Figure 22: Normal distribution in two-dimensional images....23
Figure 23: Blurred greyscale image....24
Figure 24: Convolution masks in x direction....24
Figure 25: Convolution masks in y direction....24
Figure 26: Gradient magnitude....24
Figure 27: Gradient direction....25
Figure 28: Canny edge detection result....25
Figure 29: Mask of the empty image....26
Figure 30: Region of Interst (ROI)....26
Figure 31: The number of lines detected....27
Figure 32: Reject abnormal slope....27
Figure 33: Fitted straight line....27
Figure 34: Lane detection....27
Figure 35: Red, Green, Blue channel image....28
Figure 36: Binary image....28
Figure 37: Pixel Point on lane....29
Figure 38: Left image and right image....30
Figure 39 : Checkerboard pattern picture....31
Figure 40: Find the corner position....32
Figure 41: Camera parameters....32
Figure 42: Undistortion image....33
Figure 43: Disparity map....34
Figure 44: Obstacle Detection....35
Figure 45 The project software flowchart....35
Figure 46: The car followed the lane (turn left)....38
Figure 47: The car followed the lane (turn right)....39
Figure 48: 3D image....40
Figure 49: Test results of the distance measuring system....40
Figure 50: Obstacles are not within the safety zone....40
Figure 51: Obstacles are within the safety zone....41

List of Tables

Table 1：SAE (J3016) AUTOMATION LEVELS 3
Table 2：ADAS SYSTEM. 4
Table 3：Controller's parameter range 6
Table 4：Comparison of several data association methods[40] 9
Table 5: Motion decisions 8-1

1 Introduction

From the Chinese National Bureau of Statistics, it is possible to obtain that the number of car accidents has been on a year-on-year rise from 2016 to 2019 and that the proportion of car accidents where the driver is the cause of the accident is also on the rise. Driving a vehicle requires a great deal of concentration to observe the road environment and make accurate judgments in emergency situations, and after a long period of concentration, drivers will inevitably become fatigued. This has led to the creation of advanced driver assistance systems, and autonomous driving has been a popular area of research in recent years. Autonomous driving involves knowledge areas such as computer vision systems, deep learning, machine learning and sensor data fusion, but the equipment is often expensive. OpenCV provides an open-source library for implementing vision applications and incorporates machine learning methods to process visual information efficiently.

The article structure of this paper consists of the following sections.
Chapter 2: Literature Review. The literature review presents the technologies applied in this project and some knowledge in autonomous driving.

Chapter 3: Methodology. The Methodology introduces how the project implementes the technologies.

Chapter 4: Results. This chapter presents results of this project implementation.

Chapter 5: Discussion. This section discusses where the system has shortcomings and discusses ways to improve it.

Chapter 6: Conclusion. The conclusion summarises the current project implementation methodology and insights into what was learnt during the project.

Chapter 7: Bibliography

Chapter 8: Appendices

2 Literature Review

2.1 Overview

Advanced driving systems and automatic navigation vehicles are currently one of the most popular technologies. With the increase in the number of vehicle owners, the probability of traffic accidents also dramatically increases. Therefore, this literature review investigates the background of automatic navigation vehicles. The limitations of automatic navigation vehicles and traditional vehicles, the application technology of advanced driving assistance systems, and the use of vision systems and sensors in automatic obstacle avoidance vehicles are summarized. Finally, the results of the literature review are summarized and conclusions.

2.2 Safe Road Traffic

Expansion of the scale of cities and the development of the economy and technology, the penetration rate of automobiles has become higher and higher. At the same time, the population of cities is also increasing. Therefore, the frequency of automobile accidents in cities is increasing year by year. Once an automobile driver has inattention, it will usually not be able to quickly collect various information on the road and be unable to deal with emergencies so that accidents will occur correctly[1].

2.2.1 Essentials of surveillance and obstacle avoidance systems on automobile

A vehicle equipped with an obstacle avoidance assist system can respond well to various emergencies encountered during driving. For example, drivers usually cannot see obstacles or pedestrians in the area of the automobile's visual domain that the system cannot observe them. If an intelligent assistance system is used, a double-stage detection mechanism can detect blind areas[2]. As an automobile or pedestrian accesses the areas which is not observable by the driver, the driver will be prompted to prevent dangerous situations. In other aspects, the obstacle avoidance system can efficiently monitor the environment around the vehicle[3]. Once the system predicts that a dangerous situation will occur, it will automatically take strategies, such as emergency braking, steering and deceleration. All in all, the load monitoring and obstacle avoidance system can significantly avoid dangerous driving.

2.2.2 Limitations of Manually driven cars and autonomous vehicles

The enormous impact of manual vehicles is the driver and road conditions. The increased probability of traffic accidents is due to the danger of drivers neglecting or neglecting to sign while driving. In addition, the human body needs a specific reaction time for emergencies. The length of time depends on the individual factors, so when the vehicle encounters an emergency, the driver will often be too late to react and cause an accident.

For autonomous vehicles, many factors affect their driving, including the use and unification of high-precision maps[4], the study of car-following behaviour[5], the limitations of Lidar technology (LIDAR) and the prediction of emergencies.

Vehicles with automatic navigation functions often need high-precision maps[6], and companies that can collect high-precision map information are highly qualified. The map standards between companies are not uniform. Once the systems are bound to a company for map navigation, changing the navigation maps of other companies, the cost of data migration and equipment migration is high. For example, suppose the navigation map of a car wants to migrate from the Opendrive standard to the Navigation Data Standard Association (NDA) standard[7, 8]. In that case, its data model needs to be re-developed. In addition, the recognition function may be difficult to operate normally for roads with more complicated road conditions, so it is potentially dangerous.

2.2.3 Automobile design

One of the necessary conditions for the car to realize an automatic obstacle avoidance function is to use the Advanced Assistant Driving System (ADAS). According to Figure 1, Level 1 of the Society of Automotive Engineers (SAE), the auxiliary system still requires the driver to manipulate the vehicle. The ancillary mode can protect the driver who is driving and the automobile and realize automatic braking, deceleration, and steering in an emergency.

SAE Level	Name	Narrative Definition	Operator
0	No Automation	Reminders and transient assistance	Human
1	Driver Assistance	Horizontal or vertical control assistance	Human/System
2	Partial Automation	Horizontal and vertical simultaneous control assistance	System
3	Conditional Automation	The vehicle is operated by the system, and humans respond according to system requirements.	System
4	High Automation	The car is fully automatic driving, and humans only need to operate in the characteristic environment.	System
5	Full Automation	Cars can drive autonomously under any conditions.	System

Table 1: SAE (J3016) AUTOMATION LEVELS

Vehicles using obstacle avoidance technology include many systems, including navigation systems connected to the Internet of Things, precise positioning systems, high-precision electronic maps, low-error map matching, perception of the surrounding environment, laser and radar perception, and vision systems, Vehicle control system and path tracking[9, 10].

2.3 Advanced driving assistance system (ADAS)

Byung-Kook Koo pointed out that vehicle accidents account for most of the traffic accidents[11]. Most of the factors that cause traffic accidents are human factors, such as driver fatigue, driver's driving experience. Therefore, the objective of ADAS is to reduce the negative impressions of artificial factors on automobile driving.

ADAS uses an amount of sensors to establish on the vehicle to receive sensation form surrounding environment during the driving, solicit data from nearly environment wherever inside and outside the car at the first time, and perform inactive and dynamic intentions. Apprehension, tracking, mingled with navigation map data, arrangement computation and subdivision, so that drivers have ability to perceive possible emergency beforehand and ameliorate the security of active safety technology. While progressing the safety, it effectively increases the driving force, contentment and safety of the vehicle. The sensors used in ADAS principally include surveillance systems, radars and ultrasonics, which can distinguish beam or other parameters used to surveillance the state of the automobile. The typical installation locations are forepart and posterior bumpers, side-view specula, and steering pillar or windshield. Early ADAS technologies mainly used passive alarms. When a vehicle detects a potential hazard, an alarm will remind the motorist to concentration on unnatural automobile or path conditions. Furthermore, current ADAS frequently uses proactive intervention.

The ADAS aims to automatization, acclimate, and magnify vehicle technology to achieve safe and better driving experience[12]. ADAS can also remind the driver to concentration on surrounding environment in real-time. When Emergency occurs abruptly, systems can take safety measures to control the automobile to avoid collisions and traffic accidents.

Lane Departure Warning[13]	LDW
Lane Keeping System[14]	LKS
Forward Collision Warning[13]	FCW
Blind Spot Detection[15]	BSD
Automatic Emergency Braking[15]	AEB
Side Blind Zone Alert[13, 15]	SBZA
Pedestrian protection system	
Electric Vehicle Alarm System	

Table 2: ADAS SYSTEM.

2.3.1 Lane Departure Warning System (LDWS)

Every year traffic accidents that occur vehicles deviating from the road during driving account for a large part of the highway, so there are thousands of casualties every year. So the advancement of the Lane Departure Warning in ADAS can solve a considerable part of this type of problem.

There are two types of LDWS[16]. The first type has no control unit, such as LDW system and Collision Warning system. The first type is also called a passive warning system, usually installed in a Driver Assistance System (DAS) instead of ADAS. It will warn operators when an emergency occurs to remind the driver to avoid potential hazards. The other type is called active intervention. When the system detects that the vehicle is unsafe, it can feedback and adjust the vehicle. Its purpose is to affect the vehicle's behaviour to protect the safety of people and vehicles actively.

In daily life, Lane Departure Warning has a significant impact on reducing the occurrence of traffic accidents. When the driver deviates from the original road while driving, the system will remind the driver to pay attention to the road. Drive along the road. The processing of LDW generally adopts two stages[16], namely the pre-treatment and detection degree.

The pre-processing includes colour area transformation, section of excitement extraction, and FIRSA traffic lane mark segmentation. A piece of RGB colour image in the image information input by the camera can be converted into grayscale to improve the system's response time and operating efficiency. This behaviour aims to eliminate outliers in the real world so that the system extracts the region of interest (ROI) from the image and then analyses it.

Many scientific researchers have also proposed many methods for identifying lanes, such as using color dispersal to catalogue the road appearance[17], converting the image to Hue Saturation Intensity (HSI) color range[18], and using a threshold to extract markings. These measures overcome the tinge of colored images under different brightness conditions. Weaknesses of changes, but generally use Laplacian of Gaussian method, Hough conversion and zenith detection, reverse Hough transformation and other methods to achieve lane departure detection[16, 19].

In addition, to accurately detect whether the lane deviates from the road, the system usually divides the detected lane into three parts, the background, the long-distance area, and the short-distance area.

The area above the blue line is the background block and cannot mark the lane. The space within the blue area and the red box is outlying sphere, and the sphere in the red square is the immediate area. Moreover, according to the curve and straight line of the road and the distribution of vanishing points when turning, five road models are listed: straight path, turn left, turn right, turn left sharply, and turn right sharply.

According to the driver's behaviour, four types of lane departure states distinguish the driving state: No Lane Departure (NLD), Left Lane, Right Lane Departure (RLD), Left Lan Departure (LLD), Vehicle Crossing Mark (VALM).

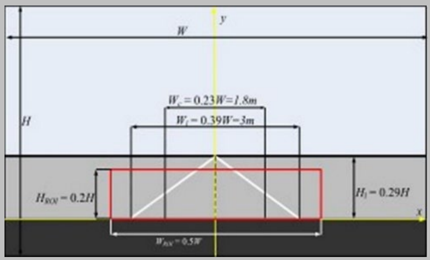


Figure 1: THE PARTITION OF THE IMAGE DETECTED BY LDWS.

To maintain stability of LDWS, processing the images camera inputting when the image can use the piecewise linear stretching function (PLSF)[20]. This technology is better than the previous Gaussian low-pass filter to remove noise and Canny operator generates a single-pixel wide edge. Better performance can improve the contrast of road indications and vehicle signs to improve the accuracy of vehicle road detection under different lighting environmental conditions. In addition, Hough transformation, Kalman filter and Hidden Markov Model (HMM) can all be used in the vision system to improve the Robust of LDWS[21, 22].

2.3.2 Lane Keeping System (LKS)

The basic architecture of Lane Keeping System is Lane Departure Warning system. This technology can ensure that vehicles drive following the lane. There are two general classifications: the first is based on the vehicle's centre of gravity and the foresight spot of other vehicles[14]. To ensure that the vehicle is driving on the prescribed road. The second is based on the development and progress of computer vision systems, which can collect and analyse road information through cameras and further develop various technologies to enhance the stability of the lane maintenance system based on various needs.

Because of the increasing requirements for advanced driver assistance systems, humans have developed many technologies to enhance the control system's performance to guarantee the exactness and Robust of Lane Keeping System. For instance, lateral vehicle motion[23], dynamic feedback methods, model predictive control (MPC) and Kalman filter, these technologies all use control methods based on dynamics and kinematics. Furthermore, it can make the vehicle have better performance when following the lane. However, it is difficult for different vehicles to continue maintaining the automobile’s stability under various complex conditions, including the automobile’s centre of gravity, the automobile’s composition, friction coefficient and smoothness of the road surface, the wind on the side of the vehicle, the degree of tire wear. In order to enable the vehicle to remain in the lane in a more complex, realistic environment, the Lane Keeping System requires robustness to ensure the system's stable operation. The article proposes two methods to solve this problem, namely: robust controller and adaptive control[14, 24, 25].

Robust control methods can effectively deal with uncertain real-life models in driving conditions. Robust control methods can use multi-rate lane keeping control schemes to improve lane-keeping performance and reduce yaw rate fluctuations[8, 26]. Secondly, the state feedback controller applies the lateral offset error to improve the vehicle's driving performance in the curve, and the slow lane detection problem uses the multi-rate Kalman filter algorithm in the vision processing system. This controller can quickly reflect the vehicle's status, issuing instructions and adjustments to the lane-keeping system.

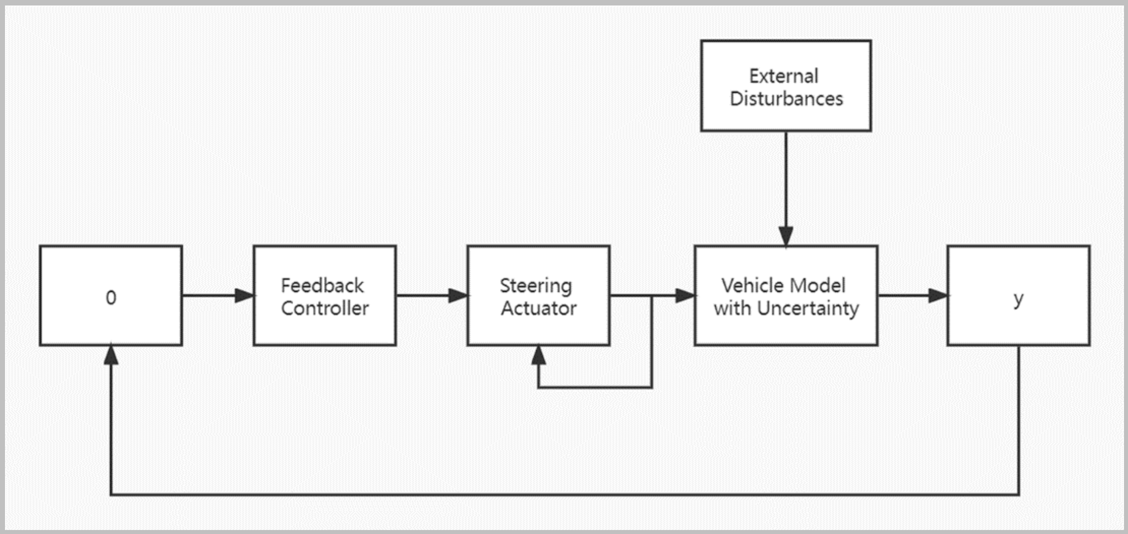


Figure 2: Control architecture diagram[14]

Figure 2 is integrated control structure of Lane Keeping System. This structure aims to design a feedback controller to perform robust control of vehicle objects with parameter uncertainties under the action of curvature, lateral force, and torque disturbances[27]. The sensor measures whether the centreline of the road is at the forward-looking point of the vehicle and the steering angle of the input variable is measured, and it adds an internal to solve the external interference feedback controller[28].

	Shaping Function	Tuning Parameter	Range
	W1(s)	a	[10^-7,1]
H∞		b	[0.1,1]
		c	[1,5]
	W3(s)	d	[0.2,1]
		e	4
		Kp	[0,3]
PID	PID gain	Ki	[0,3]
		Kd	[0,0.6]
	LQR gain	R	1
LDG	Kalman	Q	[10,1000]
	Observer	Qobs	[1,10]

Table 3: Controller's parameter range

There are three standard controllers that can implement LKS[14]. They are the H∞ controller, PID controller[29], and LQG controller. H∞ Controller improves robust performance by gaining frequency and can be widely used to counter diplomatic interference and error models. The PID controller can determine the scan range of the PID controller parameters by adjusting the loop gain to improve the stability of the target object[29]. At the same time, the PID controller is also one of the default choices in the industry. In addition, according to Kibeom's research, H∞ has the best performance and strongest robustness. At the same time, the PID controller chooses a balance between performance and robustness, which is more stable than the other two controllers.

2.3.3 Forward Collision Warning (FCW)

Cars rear-end collision is ordinary traffic accident. The cause is that the velocity divergence between the facade and rear automobile is too significant or the safe distance between two vehicles are too far[30]. A rear-end collision will occur. In response to this situation, the scientists developed the Forward Collision Warning (FCW). When the vehicle moves, the detector will detect the obstacles ahead, determine whether a collision will occur and send a warning.

There are three factors to consider when using Forward Collision Warning, they are time-to-collision, time headway and safety distance.

Time-to-collision (TTC) is a ratio of the distance between two vehicles (D) to the difference between the velocity of following vehicle and the velocity of the preceding car[31].

The calculation formula can conclude that when the value of TTC is smaller, the probability of sending a collision is higher. Assuming the smaller the vehicle distance or the velocity of the following car is much higher than the previous vehicle's speed, the eventuality of rear-end collision will be significantly increased. On the contrary, when the value of TTC is more extensive, the less likely it is for the vehicle to send a collision accident.

Time Headway (TH) is defined as that the time interval between two automobiles passing through the corresponding point one after another[32]. It can be regarded as a conversion of the distance between the two cars. The time interval is used as the one of safety indicators instead of the distance between vehicles.

Safety Distance refers to the distance that must be maintained to avoid collisions between two vehicles during driving. This distance can ensure that the vehicle has enough time to brake until it comes to a complete stop without colliding with the vehicle in front.

The formula for calculating the safety distance is composed of the distance travelled by the driver during the reaction time plus the difference between the distance travelled by the two vehicles, which can represent the actual removing between the automobile in front and the machine behind and considers the impact of different drivers on emergencies. There are different reaction speeds brought about by the driving distance.

According to the Lane Keeping System and Lane Departure Warning System is given above, FCW can estimate and warn the following distance and safe distance from the detected road model and road conditions[33, 34]. Yuan Yuan et al. use aggregating monocular distance measurement to read data from the camera for analysis and multi-scale vehicle detection[35]. Furthermore, the team also use Point-based

calibration to predigest the calculation process and ensure the detection accurateness, and multi-scale detection to improve the detection of long-distance objects reduces the time required to calculate and match the model.
In addition to the above method, Tao Chen et al. also proposed a collision warning arithmetic based on kinematics and road friction, established a braking deceleration model related to the friction coefficient of the road, and simulated the working principle of the ABS vehicle anti-lock device. The minimum distance required for a safe stop[36].
All in all, FCWS can always maintain a safe following distance with the vehicle in front. Furthermore, to detect whether a collision is about to occur to ensure the safety of pedestrians can use a series of information input devices represented by radars, sensors, and cameras.

2.3.4 Blind Spot Detection (BSD)

When a car or pedestrian enters the blind spot of the vehicle's visual field, the driver cannot observe the existence of obstacles from the position of the driver's seat. Currently, dangerous traffic accidents such as collisions and crushing are prone to occur. Therefore, advanced driving assistance systems use Blind Spot detection technology to detect blind spots in the field of vision to avoid accidents such as vehicle collisions and crushing pedestrians caused by blind spots in the field[2, 37].
There are two types of vehicle blindness: static and dynamic. They are the blind spot in the visual domain when the vehicle is stationary and the blind area during driving.
When the car is in a stationary state, there are views of the front of the car, the rear of the car, the sides of the rear door, and the windshield pillar (also called A-pillar)[37], the area covered by the pillar (B-pillar) between the front and rear doors, etc. Blind areas are different due to the height of the driver and the structure of the vehicle.

Figure 3: Take a truck as an example of the blind area of vision

When a vehicle is driving, it often creates a dynamic blind spot of vision due to overtaking, steering and other driving actions. Therefore, detection of blind spots in the visual field should consider the occurrence of this environment.

In order to ensure that the BSD system can work stably under various conditions, BSD generally adopts a multi-sensor fusion system. Shayan Shirahmad Gale Bagi et al. divide the BSD system into the following modules: sensors, software, target detection, sensor fusion and vehicle control[38].

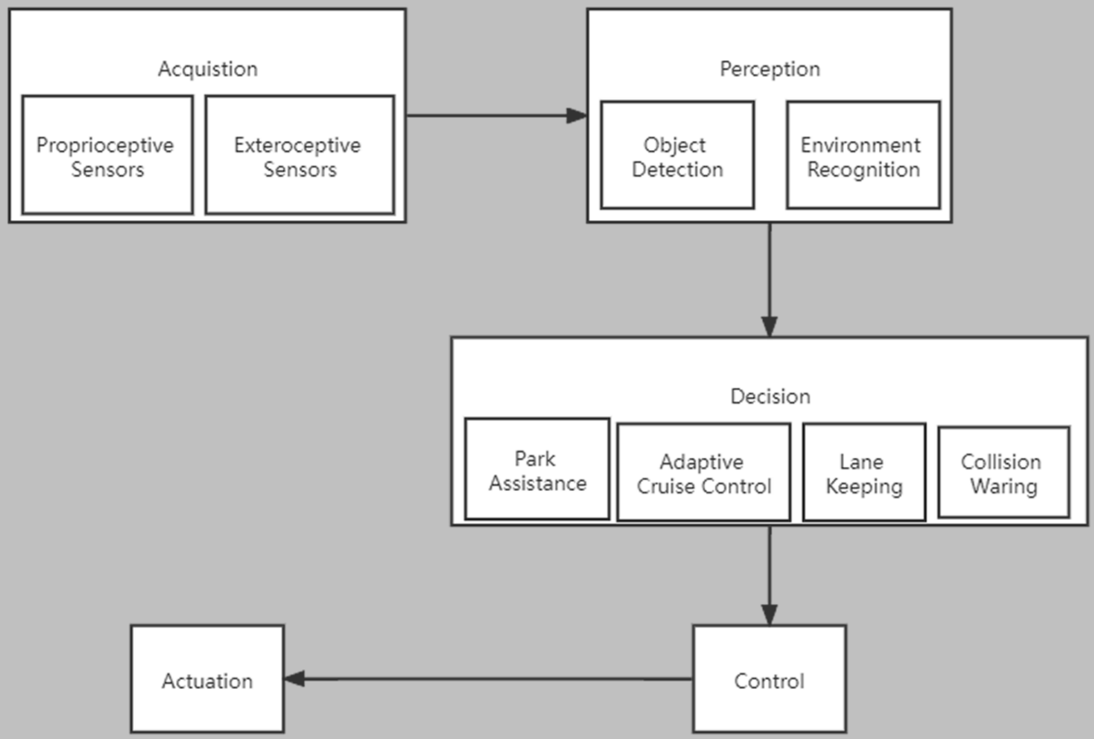


Figure 4: BSD system architecture[38]

2.3.4.1 Data Fusion and Data Association

Each sensor has its own advantages and disadvantages, and data fusion can make up for their shortcomings, thereby improving the accuracy of the system and reducing errors. For example, sensors that use vision are affected by the weather, which affects visibility, while radar sensors cause inaccurate results due to the presence of noise and clutter.

Since the data pattern of each sensor is not the same, it is necessary to synchronize their sampling rate, internal processing time and coverage to ensure the synchronization and correspondence of data in time and space, so data association technology is required.

Global Nearest neighbor (GNN), Probabilistic Data *Association* (PDA), Joint Probabilistic Data Association (JPDA*), Multiple* Hypothesis Test (MHT) and other technologies are commonly used technologies for data association applications on BSD systems[39].

method	**Advantages**	**disadvantages**	**difficulty level**	**scope of application**
NN	Small amount of calculation and simple method	The anti-interference ability is inferior, and the relevancy error occurs when the target density is significant. The operator must add many restrictions using it.	Easy	It is suitable for moments when the signal-to-noise ratio is high, the target density is small, and the scope of application is small.
PDA	Suitable for target tracking in clutter environment	It is necessary to calculate all possible measurement probabilities, and it is	Difficult	It is suitable for target tracking in clutter environment.

		troublesome to meet real-time demands.		
JPDA	It avoids the association errors that may be caused by the uniqueness of the NN method and can better adapt to target tracking in dense environments.	The number of joint events is an exponential function of all candidate echoes, and increases posthaste with the increase of echo density, resulting in a combined explosion in the computational load.	Easy	It is suitable for tracking dense maneuvering targets in a clutter environment.
MHT	It combines the advantages of NN method and JPDA method.	Too much dependence on prior knowledge of the target and clutter.	Difficult	It is suitable for tracking dense maneuvering targets in a clutter environment.

Table 4: Comparison of several data association methods[40]

The purpose of data association is to pair the measured data Zi (i=1, 2, ..., N) from a single or multiple sensors with j known or determined tracks. Simply put, it is to divide all measurement data into j sets and ensure that the measurement data contained in each set come from the same target with a probability close to 1. Data association is a key technology of multi-sensor information fusion, which is applied to track initiation, centralized target tracking and distributed target tracking.

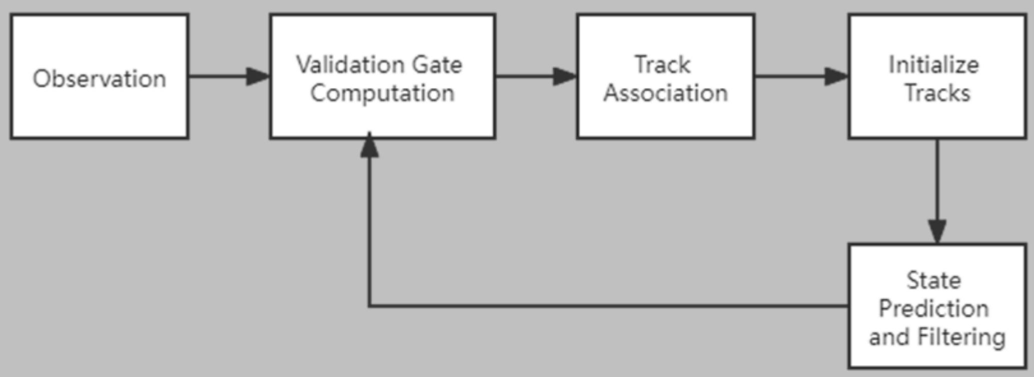


Figure 5: Data association techniques general algorithm[38]

A. The correlation between observation and observation, or observation and point trace: used to start the track or estimate the position of the target.
B. Observation and track association: used to update the target status.
C. Track and track correlation: used for track fusion, and local track forms a global track.
Figure 6 shows the basic schematic diagram of multi-target tracking. Multi-target tracking mainly includes the following essential elements: tracking start and end, the formation of tracking gates, data association, tracking maintenance[40].

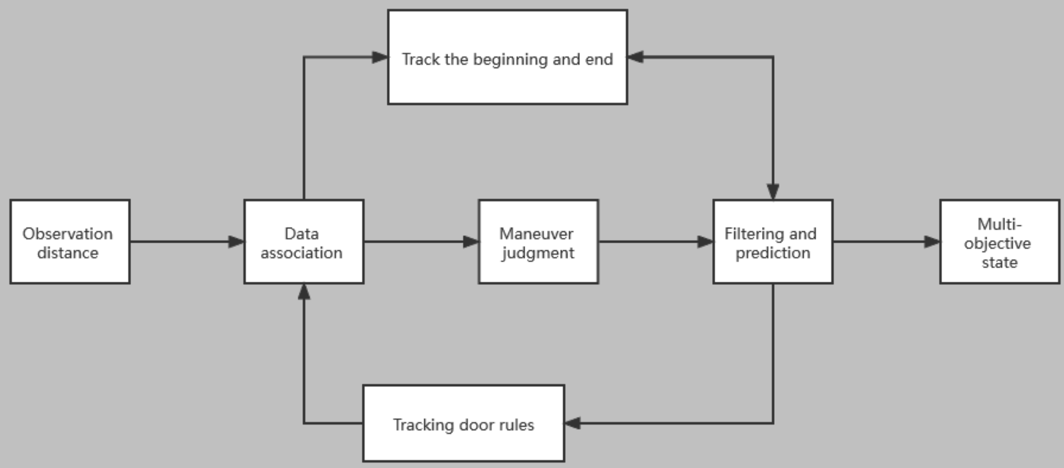


Figure 6: Basic principles of multi-target tracking

2.3.4.1.1 Global Nearest Neighbour (GNN)

The nearest neighbor data association can apply the observation place that falls within the association gate and is "closest" to the predicted position of the tracked target as the observation value associated with the tracking. The minimum value of the target value and the measured value is assigned to the minimum trajectory point, which obtains the trajectory of each item[39].
The global nearest neighbor can minimize the total distance or correlation cost. For the problem of optimal allocation, the correlation result of the global nearest neighbor is to select the one with the smallest total among all pairing results[39]. When the correlation matrix is large, the Munkre algorithm or Burgeois algorithm can solve the problem of the two-dimensional allocation.
Finally, we can use the Euclidean metric, absolute distance or distance statistical function to calculate the nearest neighbour and use the weighted Euclidean distance to judge the nearest neighbour metric.
The advantage of the nearest neighbor data association algorithm is that it has a small number of computation and is liable to execute in hardware. However, it can only be applied to target tracking systems in sparse targets and clutter environments. When the target or clutter density is high, it is prone to mistracing and missing tracking, and the tracking performance of the algorithm is not high[40]. Once the nearest neighbor gets the impression of a cluttered environment, its performance will be unsatisfactory.

2.3.4.1.2 Joint Probabilistic Data Association (JPDA) AND Probabilistic Data Association (PDA)

Joint Probabilistic Data Interconnection (JPDA) is one of the data association algorithms. Its basic principle is that algorithms correspond to the circumstances where the observation data falls into the intersection of the tracking entrance. These observation data come from multiple targets. The purpose of JPDA is to compute the associated feasibility between the observed data and target, and it is believed that all compelling echoes may originate from each concrete target[40]. However, they have different probabilities from different objective. The advantage of the JPDA algorithm is that it does not demand any prior information about the target and clutter, and it is one of the better methods for tracking multiple targets in a cluttered environment. However, when the number of objectives and measurements increases, the computational intricacy of the algorithm will explode, which will result in complex calculations.
Probabilistic Data Association (PDA) is similar to JPDA. The difference is that PDA only tracks a single target in the presence of false-alarms and missed detections, while JPDA can handle multiple targets[39, 40].

2.3.4.2 Detection system based on camera vision system

The expense of monocular cameras is relatively low, so they can be suitable for detecting lane signs, vehicles, pedestrians and determining the distance between vehicles and obstacles. They can be widely used in obstacle

avoidance systems. Yuxiang Guo et al. used an image processing algorithm to detect the domains between obstacles and vehicles using the single two-dimensional image. When monocular cameras aim at an object, the area near the focal point shows clear texture lines, while other areas are blurred images. This operation can simplify the calculation of image analysis. This feature is also called coarse-to-fine analysis[41].
The delicate and coarse resolution layers can be extracted by grading the different resolutions of the image, which is crucial to increase the feature extractor of fuzzy clues and texture clues, and then execute Principal Component Analysis (PCA).

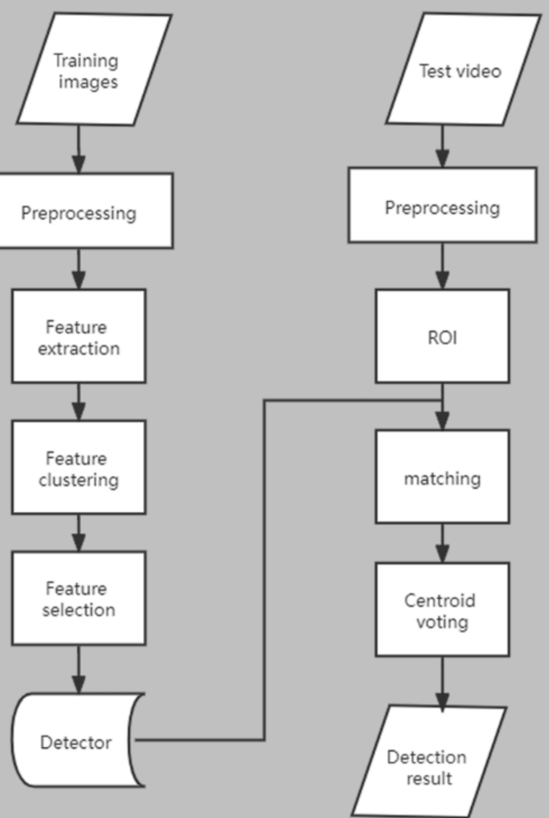


Figure 7: Flow chart of blind spot detection using vision system[37]

Computer vision systems can extract target information through Appearance-Based Features and Edge-Based Features, analyze vehicles based on regions of interest and meaningful feature segments extracted from training images and compare relative centroid information[37]. Then the system adds to the content based on the feature of the component. The final position of the target is determined by majority voting on the entire feature detected in the detection system[42].
To determine the image's border line density and sharpness in the frequency realm, the image needs to be transformed in the dimensional domain. DCT helps to segment the picture into parts of different significance to improve the visual quality[41]. DCT transforms the image from the spatial domain to the frequency *domain and* can be approximated to a straight line using the reforming coefficient.
CNN obtains depth cues through image analysis and feature extraction. Extracting depth cues can reduce the number of weights in the calculation process, and it is not sensitive to changes in the target position in the image[41]. Therefore, depth cues have strong robustness to face various interference behaviours.
The texture cue path and fuzzy cue path respectively represent the preprocessing stage of extracting the texture and fuzzy features[42]. CNN uses distance information for training, estimates depth information, uses coarse and fine analysis to obtain layers of different resolutions, uses principal component analysis and then applies the results to DCT to obtain feature maps, which are calculated and aggregated[43].

2.3.4.3 Radar-based driving blind spot detection system

The BSD module using the radar sensor can convert the intermediate frequency signal read by the radar front end into a digital signal and then use the target detection algorithm to establish a radar coordinate system to locate the target position[44]. It then judges whether the target is in the blind spot area and warns the driver[38].
The linear frequency modulation waveform can measure the relative speed and distance between target vehicles and calculate the distance and speed through the launch frequency and return frequency. Constant false-alarm rate target detection algorithm (CFAR) has a wide range of applications in radar systems[44], and radar signals can be filtered through digital filters to suppress noise and improve system accuracy. The system judges whether the object is located in the blind zone according to the set blind zone coordinate system and whether the object enters the boundary line of the blind zone[45].

2.4 Monitoring and obstacle avoidance systems on vehicles

2.4.1 Environment perception

Environmental perception is one of the crucial prerequisites for vehicles to avoid obstacles. A single perception system is difficult to ensure stable operation in various environments. For example, the visual system and radar system are far weaker in lousy weather than their working conditions in average weather[46].

2.4.1.1 Vision system

The vision system collects images through the camera and converts the colour images into black, white, and grey images, that is image binarization. Then analyze the detection and recognition of the target object and then extract the target feature through image processing. This process requires image division and positioning, dividing meaningful areas, and capturing areas of interest.
Obstacle information obtained by the visual system can be divided into the following processes: pre-processing, target detection, target verification, feature extraction, blind spot area judgment, detection distance, and motion prediction[47].

2.4.1.1.1 Pre-processing

In machine learning, pattern recognition, and image processing, feature extraction begins from an initial set of measurement data. It establishes derived values (features) designed to provide information and non-redundancy, thereby boost consecutive learning and recapitulation steps. When the vehicle is running, the time left for image processing is very short. Therefore, feature extraction needs to accurately extract the features of the target object at a very fast speed.
Features generally include natural features and features that need to be transformed. Traditional features generally include ridges, edges, corners, and regions, while complex features must be transformed and processed, such as principal components, moments, and histograms.
Edge features are pixels that form the boundary or edge between two neighbor image regions. Under normal circumstances, the shape of the edge can be arbitrary, and can also include intersections. Edge-feature is customarily demarcated as a subset of points with large grades in the image. Edges are also regarded as one-dimensional linear structures.
The angle displayed in the image is a point-like feature, which has a two-dimensional structure in part. The traditional angle feature algorithm is to perform edge detection first and then analyze the edge's direction to find the edge's corner. The advanced algorithm can directly calculate the high curvature in the image gradient.
In addition, there is another definition different from the angle, regional characteristics. It should be noted that the area may only consist of one pixel, so multiple area detection can also be used to detect the angle. Area detection can be thought of as reducing the image and performing corner detection on the reduced image.
In addition to areas and angles, ridges are also featuring used in images, and long bars are called ridges. In practical applications, the ridgeline can be regarded as a one-dimensional curve representing the axis of

symmetry. In addition, each ridgeline pixel has a ridgeline width locally. Extracting ridges from grey gradient images is more complicated than extracting edges, corners, and regions. It can be used to analyze long strip images, such as human bodies, roads.
Overall, the extraction of features needs to consider the difficulty of feature extraction, the sensitivity to noise and interference, and the ability to distinguish objects.
The Histogram of Oriented Gradients (HOG) feature is a feature descriptor used for object detection in computer vision and image processing. It combines features by calculating and counting the histogram of the gradient direction of the local area of the image and can use the density distribution of the gradient and the edge direction to describe the appearance and shape of the target[48]. First, the connected area formed by each cell is seen as an integral part of the image. Then collect the gradient or edge direction histogram of each pixel in the cell. Finally, these histograms can be combined to form feature descriptors.
First, calculate the density of each histogram in block[49]. Then normalize each cell in the block according to this density. After the unit is normalized, the superior images can be normalized and organized more quickly and conveniently[48].

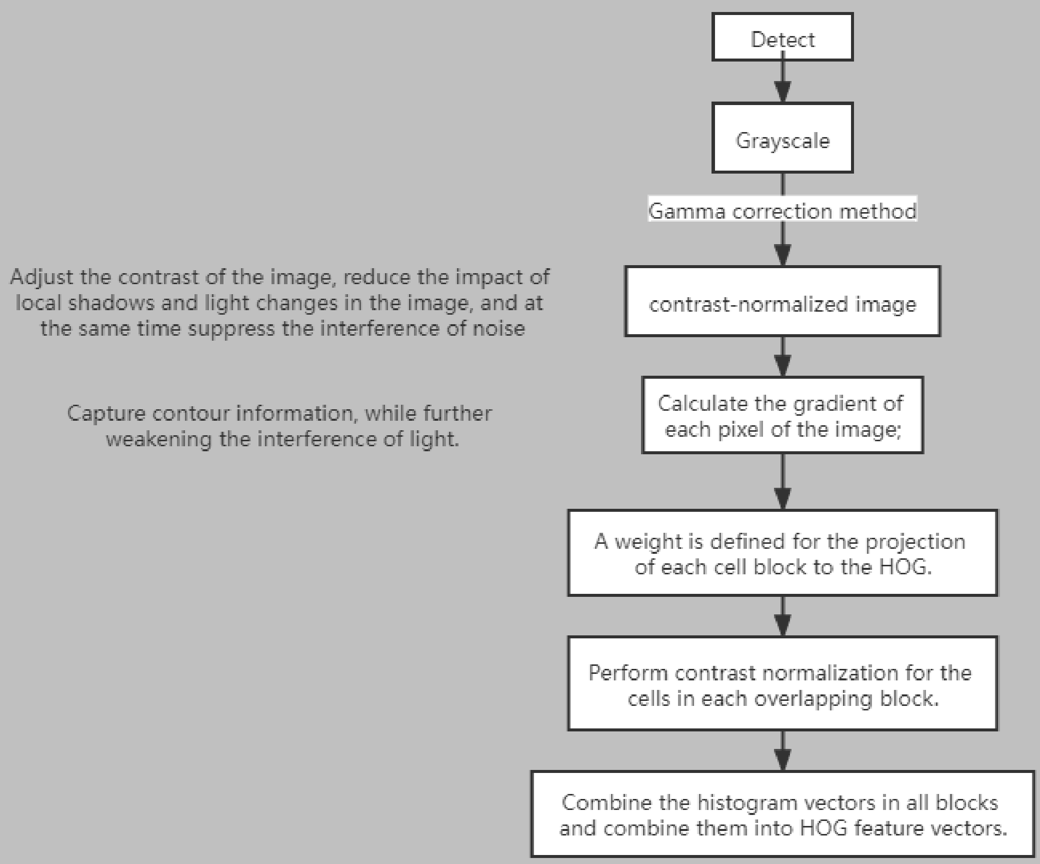


Figure 8: Implementation process of HOG feature extraction[48-50]

In addition, there are Local Binary Pattern and Haar features[51]. LBP is used to describe rotation invariance and grayscale invariance, while Haar reflects the grayscale changes of the image[52]. Therefore, the recognized objects can be classified by comparing templates, machine learning, etc., distinguishing between pedestrians and cars.

2.4.1.1.2 Blind spot area judgment

The main function of blind spot detection is to remind the driver that there are pedestrians or other automobiles in the blind area to avoid mischances due to the blind area of the operator.
The system judges the type of objects in the image by learning object features and comparing templates. For example, vehicles can be identified by features such as vehicle contours and tires, and pedestrians can

be judged by ridge detection and contour recognition. Use data information such as the object's length, width, and height to establish coordinate information to determine whether it is in blind spot area of the car.

2.4.1.1.3 Motion prediction

When the vehicle is running, the camera needs to analyze and predict the movement When the vehicle is running, the camera needs to analyze and predict the movement trajectory of pedestrians and other vehicles, determine whether it will collide with the vehicle, and give an early warning.

In computer vision domain, the campaign of objects in a picture is defined. This campaign is able to cause by camera movement or object movement. Particularly, it refers to the movement of pixels representing the same object in a video image from one frame to the next. This process can be represented by a two-dimensional vector[53]. According to the analysis object and whether the sparse image point is selected for optical flow estimation, the optical flow estimation can be divided into the sparse optical flow and dense optical flow. The use of optical flow estimation requires a basic premise: the lighting conditions remain unchanged.

The use of optical flow calculation to predict the trajectory of an object requires the use of multiple frames of continuous images for analysis. This process can use Convolutional Neural Network (CNN)[53].
Use CNN to extract the depth features of the input image and then integrate these features into the algorithm to calculate the optical flow[54]. CNN can be used to identify and learn the features of the image and can be used to match the identified features in the image. Therefore, the use of CNN can complete the entire process of optical flow calculation, which can significantly improve the efficiency and robustness of the system[54]. CNN is to train subsequent frames and flow fields in a supervised method.

The supervised training method has some shortcomings, and the results are easily affected by data deviations during training. The sensor needs to obtain a large amount of information and data from the outside world, making it simply affected by natural noise and image distortion[55]. The depth and breadth of the acquired image are not as good as that of unsupervised training methods.

Unsupervised training can visualize feature organization and apply it to extended vision tasks, such as depth estimation and scene reconstruction, to reduce the difficulty of obtaining ground truth data sets[55]. For example, the Kalman filter is used to make the estimation of the image smoother[23].

2.4.1.2 Sensors

The environmental perception system of a vehicle can be composed of a vision system and a sensor system. The types of sensors are radar sensors, such as light detection and ranging (LIDAR), ultrasonic sensors, infrared detection sensors, and so on.

2.4.1.2.1 radar sensors

Radar sensors used in automobiles usually include millimetre-wave radar sensors and LIDAR.
Millimeter wave radar is a type of radar that uses short-wave electromagnetic waves. Its emission wavelength is a millimeter wave wavelength, which is also considered a short wavelength, and this is also one of its advantages. The components needed to process the signal are all small, so the work cost is greatly reduced. The radio frequency (RF) components used for transmission (TX) and reception (RX) can be used to reduce power consumption and overall system cost. Another advantage of short wavelength is high accuracy[56].

Lidar is an active measurement method, which is mainly composed of a laser emitting part, a receiving part and a signal processing part. The two main basic functions of LIDAR are ranging and detection. Lidar uses the time difference between transmitting and receiving laser pulse signals to measure the distance of the measured target and establish the coordinates of the target object.

2.4.1.2.2 Ultrasound sensors

When the ultrasonic sensor is working, the transmitting end emits a beam of ultrasonic waves. At the same time as the transmission, timing starts. The emitted ultrasonic waves propagate in the medium. Sound waves have reflective properties. When encountering obstacles, it will reflect. When the ultrasonic receiving end receives the reflected ultrasonic wave, the timing stops. When the medium is air, the speed of sound is 340m/s, from which the distance to the target can be calculated.

2.4.2 Privacy protection

It has become a common fact that the camera reads data. A network attacker can connect the camera to read the data information read by the camera used by the vehicle. In this way, the attacker can obtain the gender, age, location, financial information. From the information leakage to the worst, the personal safety of the driver may be affected.

The camera treats buildings as background information rather than regions of interest. During the process of image binarization, it ignores road feature signs and building information and only reads some necessary feature data, such as ridges and edges. The human body has edge characteristics to represent vehicles[57].

2.4.3 Data Fusion

The purpose of data fusion is to synthesize data from multiple sensors, summarize various data, and produce more reliable estimates and judgments than a single source of information. In the process of multiple types of data running together, various conflicts often occur, such as data model conflicts, data conflicts, and structural conflicts. Therefore, it is necessary to eliminate the conflicts between them. The steps of data fusion are usually divided into two steps, preprocessing and data fusion, to process the signal level, pixel-level and other levels of data[58].

2.5 Depth Perception

Depth perception combines images captured by the camera into an image with depth to identify depth information in 3D space. The image information is stored in a Cartesian coordinate system and cannot be relied upon to read depth information in two dimensions. Stereo cameras capture images from two cameras on the same horizontal plane to create a depth-inclusive image[59].

When an image captures a 3D object from the real world, the camera projects information about the object in 3D space into the projection space of the 2D plane. When there is only one image, the system cannot perceive the object's depth because the distance between the object and the camera is unknown. The system cannot determine the object's position to be measured solely from the camera's orientation and coordinates. Therefore, if the system wants to implement the use of a single camera to establish depth perception to estimate the depth of an object, it must calibrate the camera by measuring the distance between the object and the camera to obtain a part of the parameters, which is the principle of generating a stereo image from a single camera[60].

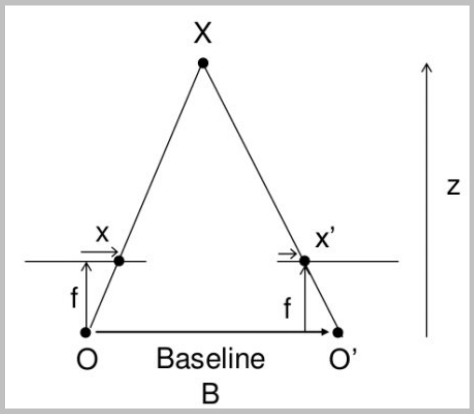


Figure 9: Principle of stereoscopic cameras

The world coordinate system represents the position of the camera and the subject in the real environment. The camera coordinate system is a three-dimensional right-angle coordinate system with the origin at the optical centre of the lens and the z-axis being the lens's optical axis. The world coordinate system is obtained by rotating and translating the camera coordinate system.

2.5.1 Zhang's Camera Calibration Method

Objects are in a three-dimensional world coordinate system. At the same time, the lens sees a three-dimensional camera coordinate system when the camera is shooting, and the three-dimensional camera coordinate system is converted to a two-dimensional image coordinate system when imaging. Different lenses have different conversion matrices when imaging and may introduce distortion, and the calibration serves to approximate the conversion matrix and distortion factor.
Zhang's calibration method uses a chessboard image to set the coordinates of the 3D world and the pixel coordinates of the 2D camera plane, and derives the Homography relationship from the real-world chessboard image plane to the image plane in the camera, and finally mathematically derives the internal and external parameter matrices of the camera

2.5.2 Disparity Map and Depth Map

Disparity map is the deviation in the position of the pixels imaged by two cameras for the same scene, as the stereo camera are usually placed horizontally, so this deviation is generally reflected in the horizontal direction.

$$disparity = x - x' = \frac{Bf}{Z}$$

Figure 10: Disparity value

The depth map is the distance of each point in the scene from the camera. The depth map and disparity map are inversely proportional to the focal length of the camera and the actual distance, so that the depth of the object in 3D space can be mathematically calculated.

$$Z = M\frac{1}{x - x'}$$

Figure 11: Depth value

2.6 Summary

The literature review reviews safe road traffic, analyzes the necessity of applying camera and sensor technology in vehicles, and analyzes current traditional and automatic navigation vehicles' technical limitations and customer needs. In section 1.3, I summarise the application of advanced driving assistance systems in automobiles. The Lane Departure System, Lane Keeping System, Collision Warning System, Blind Spot Detection System are analyzed, and the vision application of the vision system and each sensor in the system is analyzed. And theory, for example, the lane departure system proposes a method of grayscale processing and binarization of the image, the Lane Keeping System proposes the detection and following of the region of interest, and the collision warning system proposes a safe distance and sensor sensing system. The Blind Spot Detection area explains the blind spot area range and area judgment. Subsequently, the concept of data fusion was put forward, which can integrate and process the data read by various sensors to improve the robustness and accuracy of the system.
In section 1.4, I divided the monitoring and obstacle avoidance systems applied to the vehicle into the description of the vision and sensor systems. This part explains various sensors and technologies' application techniques and principles and describes their specific functions and applicability.

2.7 Conclusion

This literature review describes the application of vision systems and sensor systems in vehicles and explains the significance of ADAS in automobiles. The advancement of vision systems is revolutionary for the advancement of smart cars. The obstacle avoidance system judges whether the vehicle is in a dangerous state according to environment in which the vehicle is located, so automobile's environment perception is crucial. The accuracy of the vehicle's perception of the surrounding environment and its response speed can determine whether the system can take measures in a crisis to avoid traffic accidents. The obstacle avoidance system usually consists of many sensor systems. The purpose is to guarantee the accurateness of the data and enhance the robustness of the system. Therefore, the analysis function of the vision system is vital in the obstacle avoidance system. Image binarization can improve the operating efficiency of the system and reduce unnecessary analysis time. The use of CNN can build an accurate and fast framework to ensure the powerful functions of the surveillance system. CNN can be used for various image analyses.

3 Methodology

3.1 Methodology overview

In autonomous driving, automatic cruise control and obstacle avoidance are essential functions. Automatic cruise means that the vehicle allows the driver to drive along the lane without any subsequent car operation, enabling a lane following function. In the process of lane following, the vehicle needs to be able to detect obstacles and avoid them automatically so that the driver does not have to relax and lower his or her guard for long periods and cannot perform the correct actions in the vicinity of an obstacle. Therefore, Lane following systems require obstacle recognition and automatic obstacle avoidance as a safety guarantee for the driver.

The methodology details the use of a single webcam for lane following and obstacle avoidance by a visual obstacle avoidance trolley. The lane following system enables the vehicle to follow the lane automatically by detecting the lane lines and completing the corresponding motion decisions. The obstacle avoidance part uses a single webcam to detect whether an obstacle is within a safe distance and take corresponding obstacle avoidance measures. All the project files are written in Python in the Thonny Python IDE on Raspberry Pi.

3.2 Hardware

This project uses a Raspberry Pi model 3B as the main development board and SunFounder's Smart Video Car Kit 2.0 to build an obstacle avoidance car with a vision system.

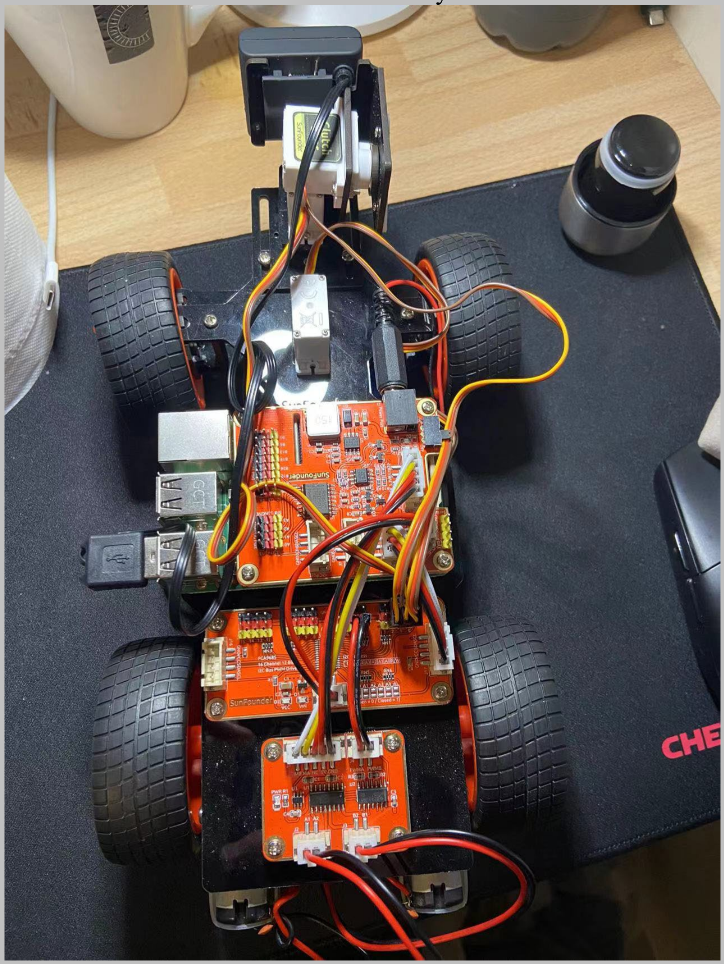


Figure 12: The construction of the car

3.2.1.1 Raspberry Pi model 3B

The Raspberry Pi is a miniature computer based on the Raspberry Pi Foundation, which uses a central processor model ARM Cortex-A53. The Raspberry Pi model 3B is equipped with four USB 2.0 ports to support external webcam access and use and to transfer data via the 40-pin GPIO interface for target functions.

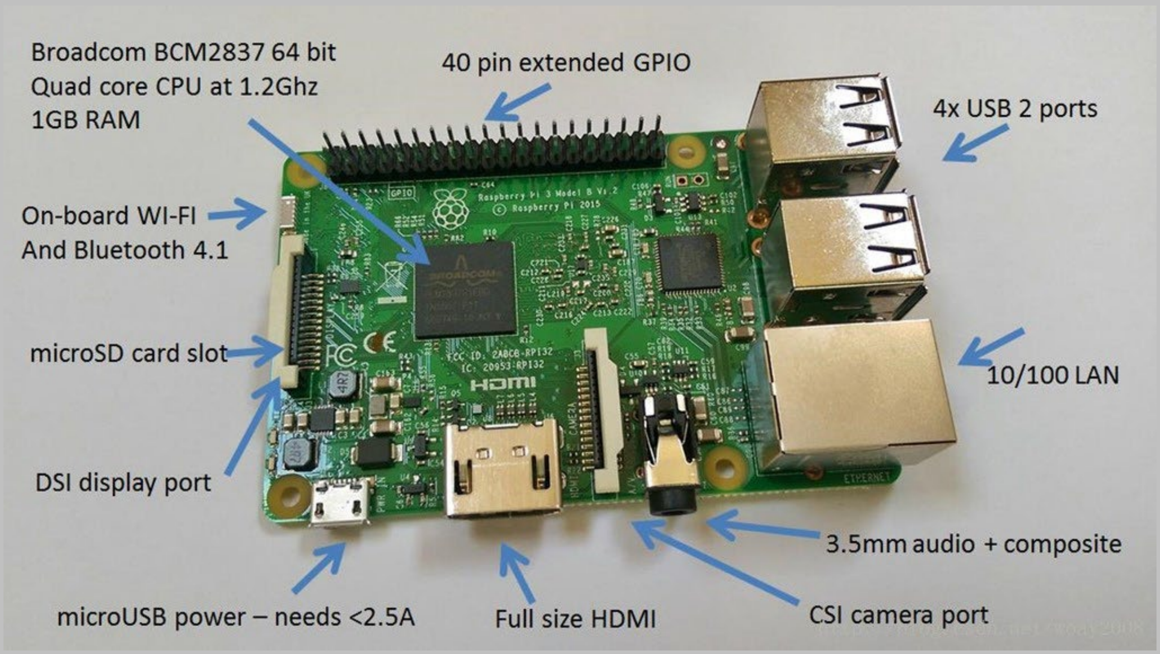


Figure 13: Raspberry Pi Model 3B

Designed for computer programming, the Raspberry Pi is based on Linux and has all the essential functions of a standard computer. It is an ARM-based micro-computer motherboard. Unlike traditional standard computer motherboards that rely on a hard disk to store data, the Raspberry Pi uses an SD card or MicroSD card as the memory drive. Its system uses Python as the primary programming language.

The Raspberry Pi 3B provides a USB port connected to a USB webcam so that the system can capture images for processing and analysis via the camera. The Raspberry Pi 3B model is also equipped with a wireless network card, so there is no need to connect the display via an HDMI cable to show the Raspberry Pi desktop.

3.2.1.2 Robot HATS (Hardware Attached on Top)

Robot HATS is a HATS specifically designed for Raspberry Pi with 40-pin GPIO pins and can be used with various models of Raspberry Pi. Robot HATS connects to the Raspberry Pi through the GPIO port and can power the Raspberry Pi through the USB cable and DC port as the Robot HATS is fitted with an ideal diode designed based on the HATS rules. Protect the Raspberry Pi from damaging the TF card because the battery does not have sufficient power.

The Robot HATS used in this project uses the PCF8591 chip as the microcontroller and consists of a 3.3V 3-wire digital sensor port, a 3.3V 3-wire 4-channel 8-bit ADC sensor port, a 3.3V I2C bus port, a 5V power supply output to a PWM driver, and a 5V VCC on board. SunFounder FTDI Serial to USB 4-wire UART port and a motor control port using the SunFounder motor driver module.

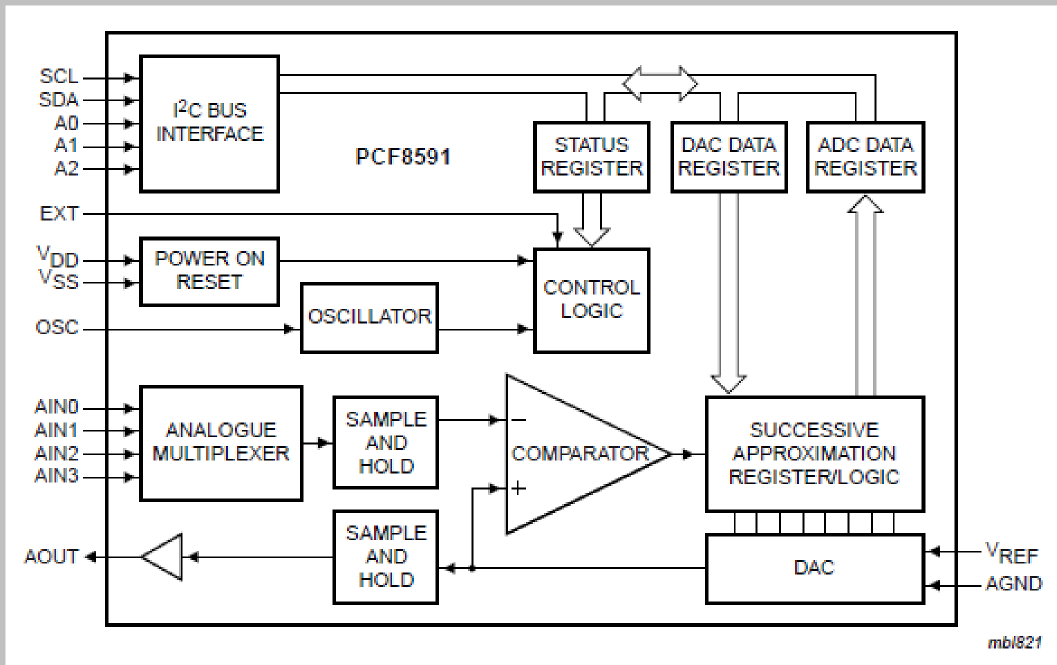


Figure 14: Block diagram of PCF8591

The project uses two 18650 lithium batteries to power the motor module. The Robot HAT uses a simple comparator circuit to check if the power supply is sufficient and indicate the power indicator for feedback. When two lights are on simultaneously, the current supply voltage is greater than 7.9V. If only one light is on, the supply voltage is between 7.9V and 7.4V. If no indicator light means that the current-voltage is less than 7.4V, the motor drive module may not be able to drive the motor properly.

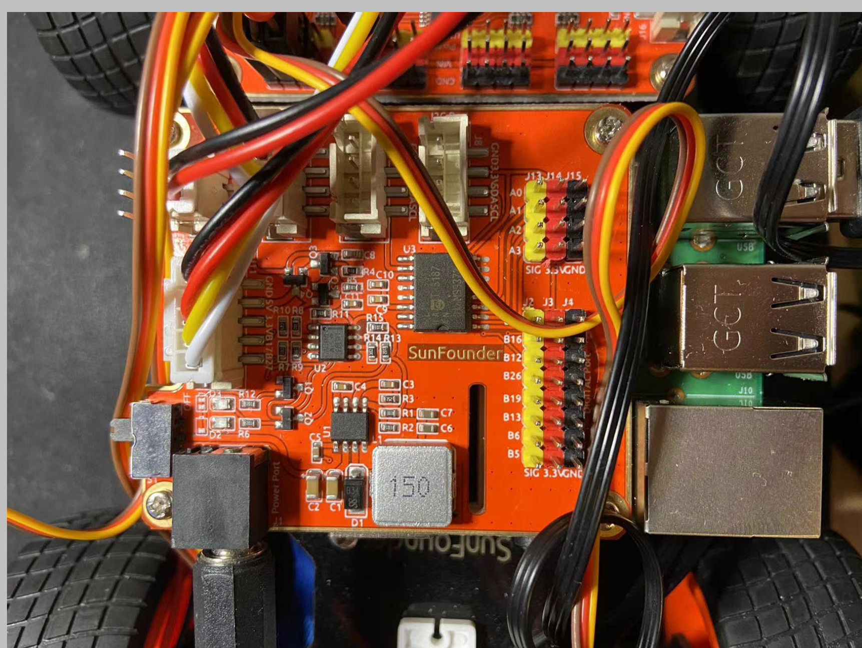


Figure 15: Robot HATS on the car

3.2.1.3 PCA9865 PWM Driver

The PCA9865 PWM Driver (Pulse Width Modulation) is a board connected to Robot HATS by I2C bus and it can control the speed of the DC motor and servo. The PCA9685 is an I2C bus-contolled 16-channel LED controller, each output has it own 12-bit resolution (4096 steps) fixed-frequency independent PWM controller that operates at a programmable frequency from typically 24Hz to 1526Hz with a duty cycle adjustable from 0% to 100% to allow the port to be set to a specific brightness value.

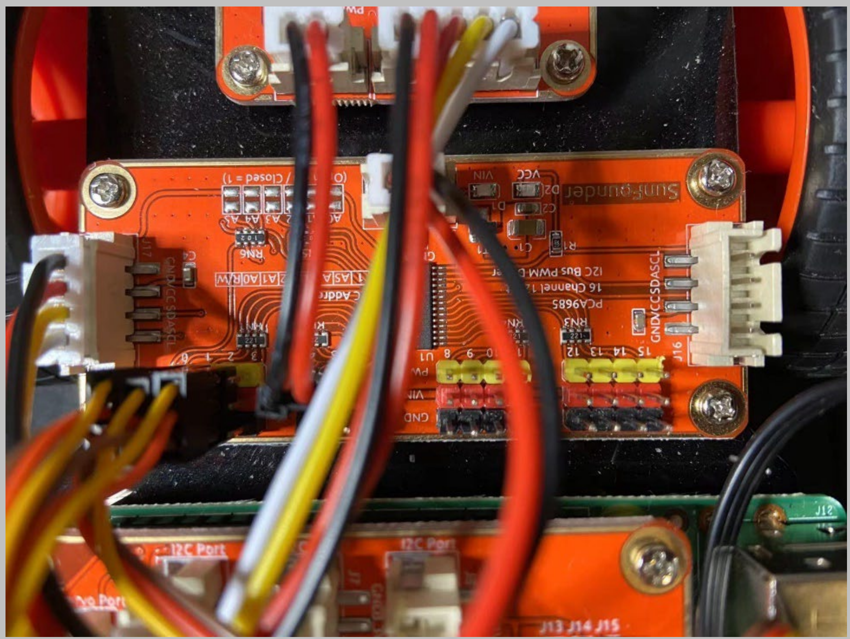


Figure 16: PCA9865 PWM Driver

3.2.1.4 Motor Driver Module

The Motor Driver Module consists of the TB6612FNG and MP1539 chip which can controll the motors' direction and change the PWM signal input for adjusting the speed of the two motors.

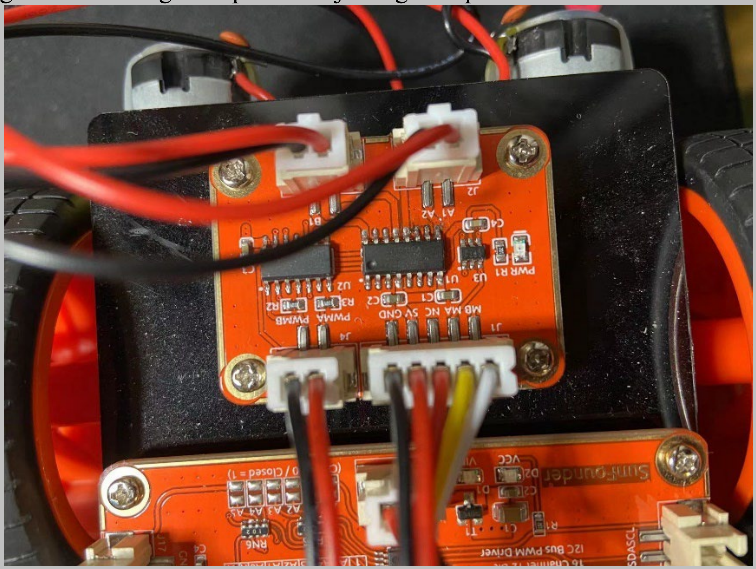


Figure 17: Motor Driver Module

3.3 Software

The Raspberry Pi uses an SD card as the system storage media. Therefore, this project uses the official Raspberry Pi OS as the operating system and burns to an SD card with 64GB of memory. The Raspberry Pi is connected to a laptop via a personal hotspot on the phone to enable remote operation of the Raspberry Pi. The Advanced IP Scanner software and the Command Prompt in Windows can accurately search for devices in the same network environment as the computer. The Raspberry Pi's IP address can be found precisely and establish a connection between the Raspberry Pi and the laptop.

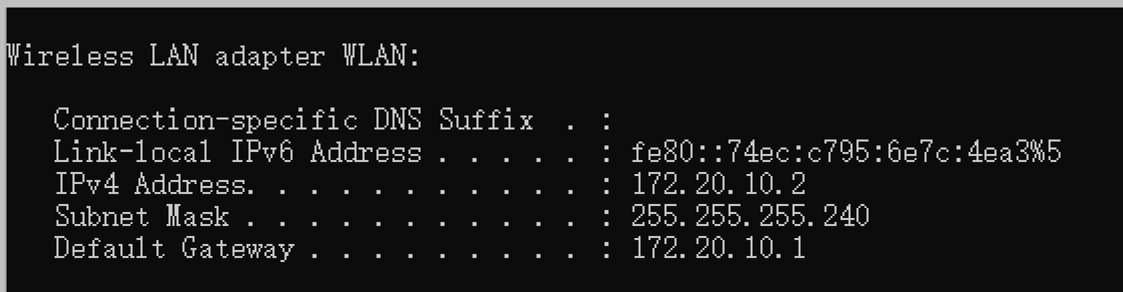


Figure 18: The personal hotpot ip address

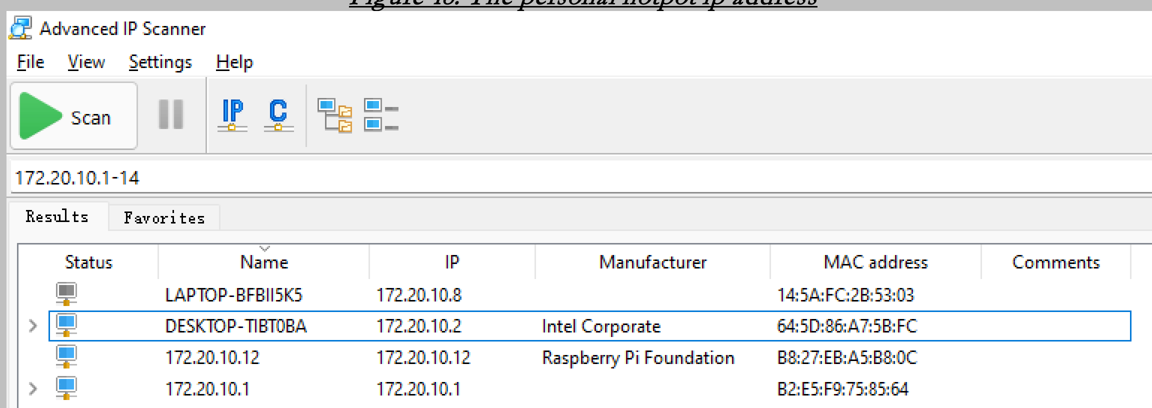


Figure 19: Raspberry Pi ip address

The PC uses the Raspberry Pi using PuTTY and VNC viewer to display the Raspberry Pi's operation system desktop as the programming environment. The VNC viewer uses the Thonny Python IDE, including OpenCV version 4.5.5 and Python version 3.9.2.

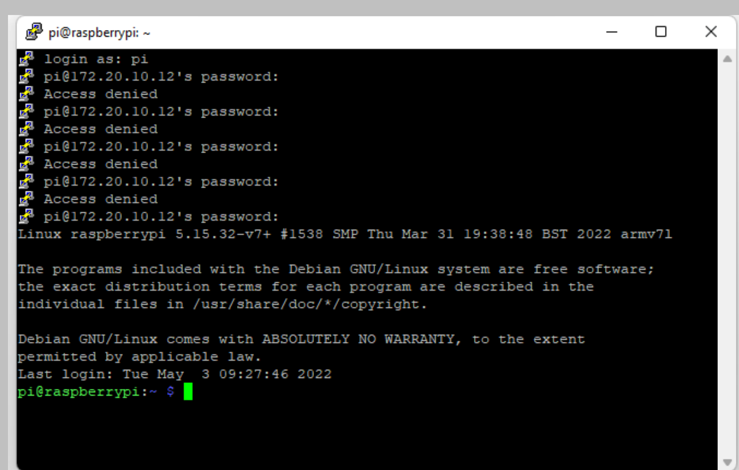


Figure 20: PuTTY

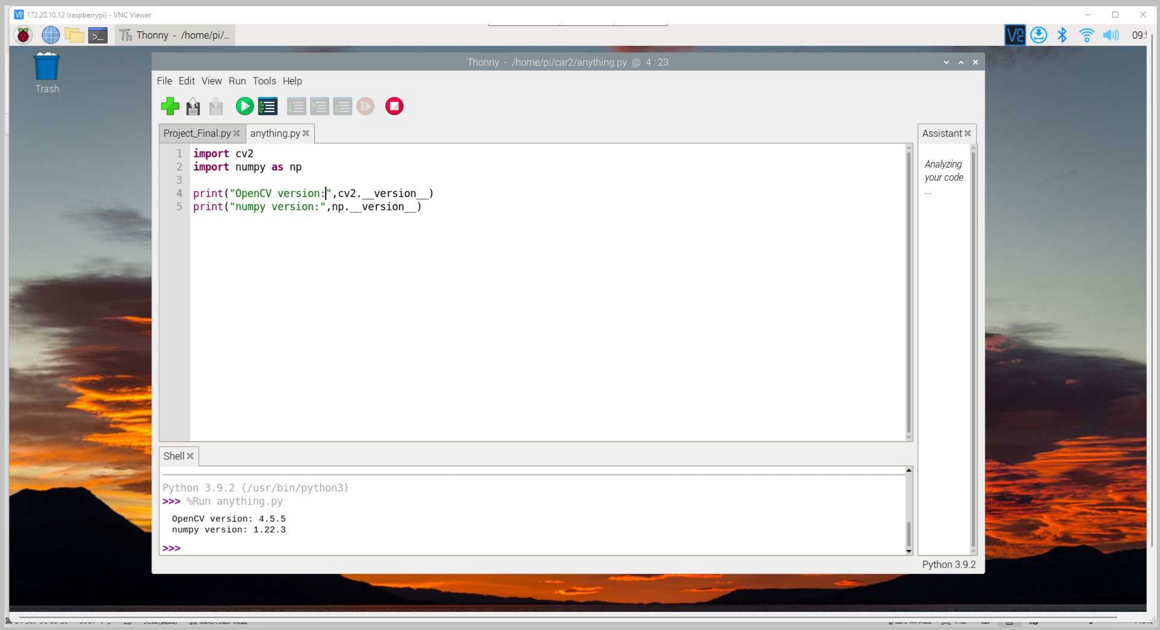


Figure 21: Thonny IDE under the Raspbian Operation System in VNC viewer

3.4 Lane-Following System

The objective of the lane following system is to ensure that the vehicle does not deviate from the set course during travel, and it consists of two components: lane detection and motion decision.

3.4.1 Canny edge detector for lane detection

The Canny edge detector detects lanes in five steps. Firstly the system applies a Gaussian filter to blur the image to smooth it and remove noise. The second is to calculate the gradient in the image to detect edge strength and orientation. The third step is Non-maximum suppression, which makes the blurred image boundaries sharp, followed by a double thresholding method to identify strong edge, non-edge and weak edge. Finally, the Canny detector makes a binary image obtained by processing and defining.

Gaussian blur can reduce image noise and lower levels of detail. Gaussian blur calculates the transformation of each pixel in an image by means of a normal distribution and Gaussian filter kernel, and the pixel values around that pixel point are rederived using a weighted average of that pixel value.

$$G(u, v) = \frac{1}{2\pi\sigma^2} e^{-(u^2+v^2)/(2\sigma^2)},$$

Figure 22: Normal distribution in two-dimensional images.

The image consists of three colour channels, Red, Green and Blue, and the image specifies the pixel value of each channel as (0, 255). For a greyscale image, the three RGB values are the same. So a greyscale image is a single channel image.

Figure 23: Blurred greyscale image

The next step is to find the intensity gradient of the image. The Sobel operator convolves two 3X3 kernels of horizontal variation and vertical variation with the original image to obtain the gradient intensity and orientation of the image.

$$\mathbf{G}_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} * \mathbf{A}$$

Figure 24: Convolution masks in x direction

$$\mathbf{G}_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * \mathbf{A}$$

Figure 25: Convolution masks in y direction

The horizontal and vertical Sobel operators are combined, and the filter finds the gradient magnitude and direction.

$$\mathbf{G} = \sqrt{{\mathbf{G}_x}^2 + {\mathbf{G}_y}^2}$$

Figure 26: Gradient magnitude

$$\mathbf{\Theta} = \operatorname{atan2}(\mathbf{G}_y, \mathbf{G}_x)$$

Figure 27: Gradient direction

The algorithm uses the Sobel operator to obtain a point with a significant edge gradient. It then detects whether the gradient of the surrounding edge points is smaller than that point. If it is smaller than that point, the pixel with a non-maximum gradient is suppressed.
After applying non-extreme value suppression, this project determined a double threshold based on the lane and test environments. If the gradient value of an edge pixel is less than the low threshold, the edge pixel is suppressed. If the gradient value of the edge pixel is higher than the high threshold, the pixel point is a strong edge pixel. If the gradient value of the edge pixel is smaller than the high threshold but higher than the low threshold, then the pixel point is set as a weak edge pixel. For a weak edge pixel, it can only be recognised as a valid edge by the system if it is adjacent to a strong edge pixel.

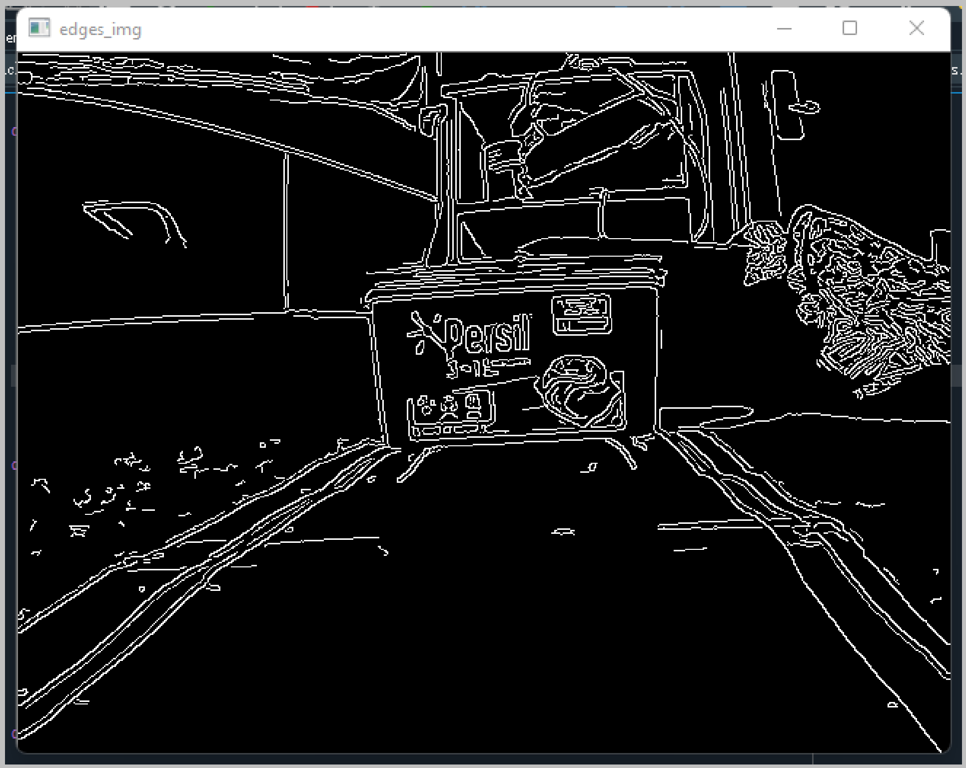


Figure 28: Canny edge detection result

3.4.2 Straight lane detection

When a vehicle is in motion, the environment of the road does not consist of a simple background and lane lines. Generally, the camera detects several objects from far away and extraneous objects on the sides of the road in the near distance. Irrelevant information can interfere with lane line feature extraction, so the system must extract a ROI (region of interest).
ROI determines the lane area in the image by setting a mask. Then the system sets all the pixel values in the area outside the mask to 0. The original image and the mask are then subjected to an AND operation in Boolean to obtain an image containing only the contents of the masked area.
First, the system creates an array of the same size as the original image but with the contents of the matrix empty. The created blank image fills the masked region. The masked image uses a bitwise operation with the original image to obtain a region of interest after edge detection.

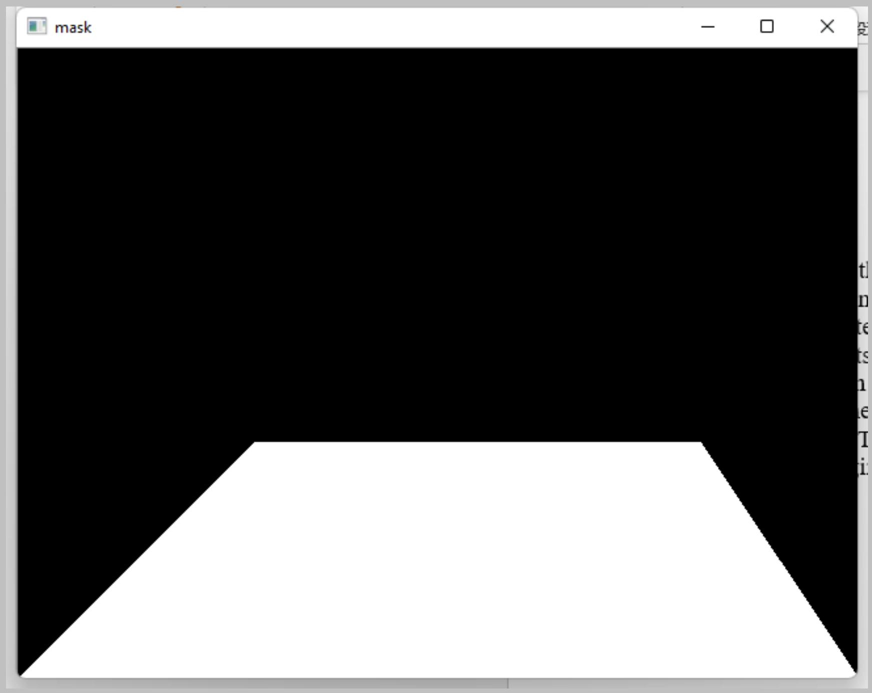


Figure 29: Mask of the empty image

Figure 30: Region of Interst (ROI)

The Hough transform maps a Cartesian coordinate system to a polar coordinate system. A straight line can be determined by a pair of polar diameters and polar angles. Whereas in multiple coordinate points, if they belong together to a straight line, then the line they are on must pass through a common polar point. The system determines that several straight lines belong to the same line if they are within a range of deviation due to the interference and irrational state of the environment if using the Hough transform in a realistic environment. The straight line detection system determines the straight line from two points on the pixel coordinate system and uses Hough's theorem to traverse all detected lines to find the line with the highest number of points matching the polar angle and polar diameter. After straight line detection, the system calculates the slope of the line from the obtained pixel coordinates and determines the direction of the line.

```
In [19]: runfile('C:/Users/Jerem/Desktop/lane_detect/lane_detect.py',
wdir='C:/Users/Jerem/Desktop/lane_detect')
left lines: 7
right lines: 16
```

Figure 31: The number of lines detected

In the process of line detection, the detected lines can contain noise that has not been completely removed from the image, so lines that are not lane lines need to be removed to avoid the detection results being affected by the noise. The system identifies lines that are not lane lines by detecting the average slope of all the lines, subtracting each line from that average, eliminating lines with too significant a difference in slope, and then recalculating the average slope and iterating.

```
left lines before reject: 7
right lines before reject: 16
left lines after reject: 4
right lines after reject: 11
```

Figure 32: Reject abnormal slope

In order to obtain a unique lane line, the system uses a least-squares fitting method. The least-squares fitting method determines a straight line by calculating the maximum and minimum points from the set of x and y coordinates in the line.

```
  return np.array([point_min, point_max]
left line coordinate [[536 358]
 [633 479]]
right line coordinate [[ 71 409]
 [215 288]]
```

Figure 33: Fitted straight line

Finally, the system depicts the straight line on the image through the coordinates of the derived line.

Figure 34: Lane detection

3.4.3 A single pixel point represents a straight line

Traditional Hough's theorem usually produces some errors when the road environment is complex or when there are no clear lane lines. As opposed to traditional lane tracking systems that use Hough's theorem to

read straight lines or curves with a slight curvature, the system chose to use a pixel coordinate system to obtain lane information, given that some lanes may have significant curvature.
First, the system splits the RGB three-channel colour image into three single-channel images of Red, Green and Blue. After comparing the sharpness and distinction of the three images, the programmer can observe that the difference between the Red channel image for the lane and the road is more pronounced in the vehicle test environment and the road environment.

Figure 35: Red, Green, Blue channel image

Consequently, the system selects the red-channel as the source image for image binarisation.
Since lane lines and lanes are distinct in the real world, Image Binarization is sufficient to extract lane information.The advantage is that the information in the image can be made simple.
Image binarization is converting an image to pure black and white by setting a threshold and then setting the greyscale value of the pixels on the image to 0 or 255.

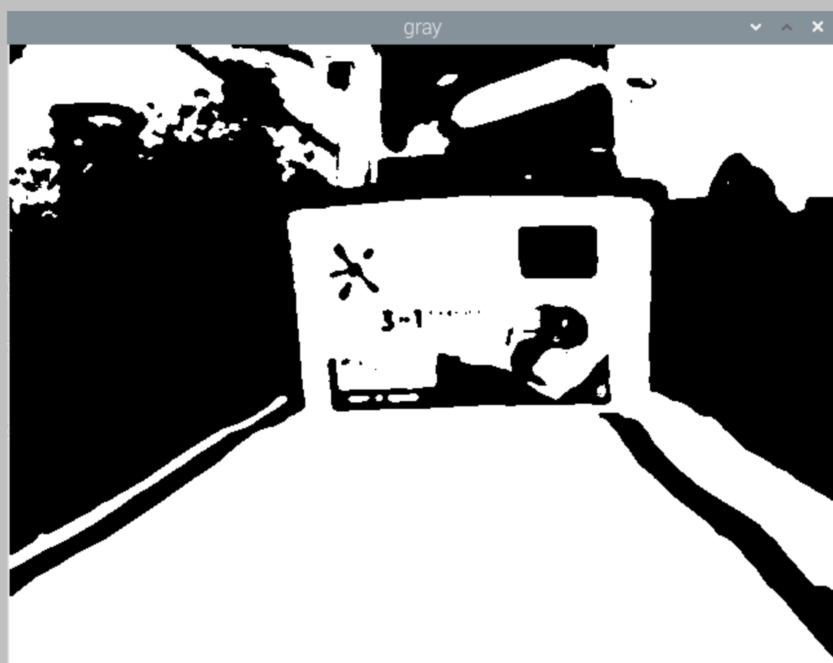


Figure 36: Binary image

The webcam on the Smart video car captures images at a resolution of 640x480 by default. Therefore, the system distinguishes between the left half of the image and the right half by splitting the image's resolution to obtain a resolution of 320x480 separately. The lane detection system defines the area close to the vehicle to avoid failure to identify the lane or misjudge the lane information.

Subsequently, the system extracts the feature point between the white road and black lane lines to determine the left lane and right lane position. The image searches from the middle to the sides in a particular row and determines a pixel point whose value is 0 as lane line points. The points detected on the left half of the image are the left lane line points, and the points detected on the right half are the right lane line points.

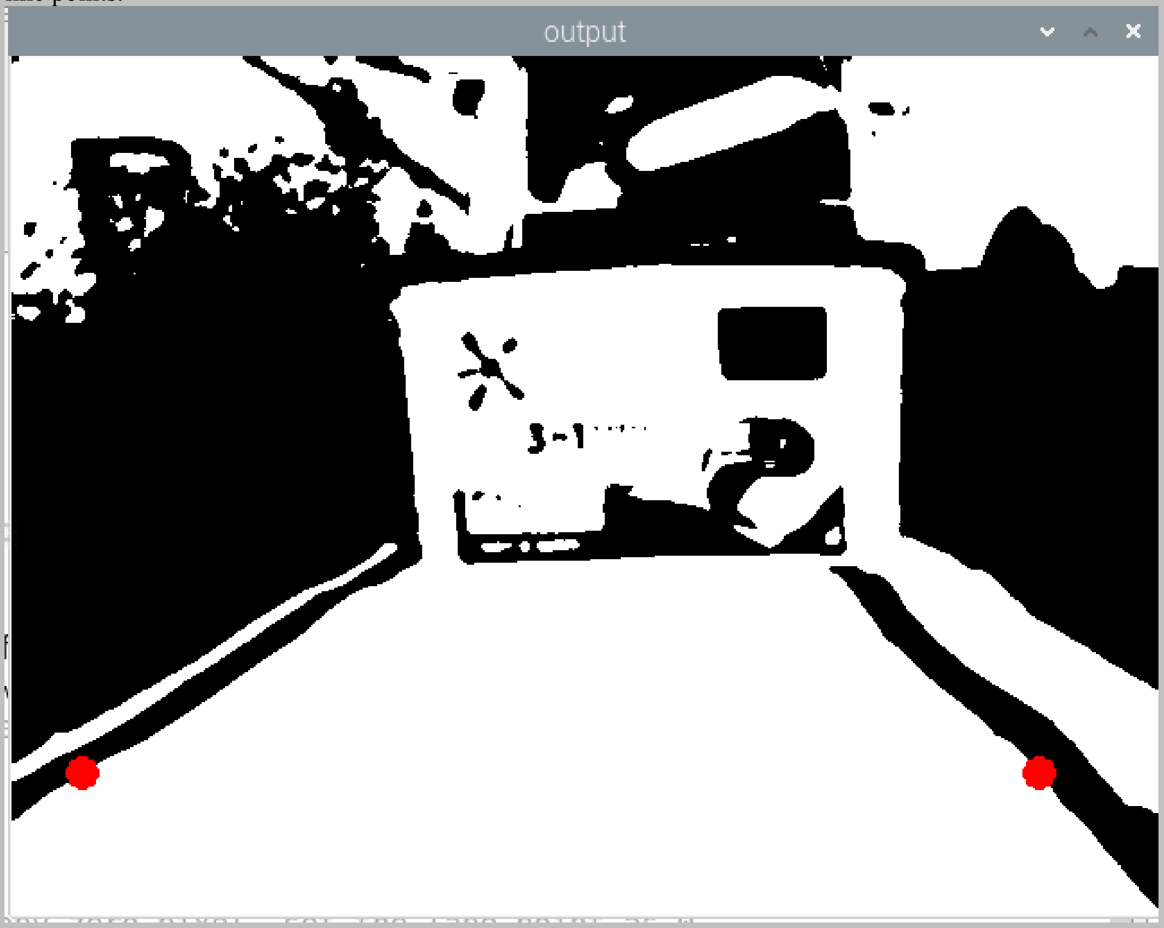


Figure 37: Pixel Point on lane

3.5 Obstacle Avoidance System

This project uses vision sensors to capture the vehicle driving environment. The advantage of vision sensors is that they have a wide detection range and can acquire various information. The project's obstacle avoidance system uses a single camera to create a stereo camera for depth perception of the environment.

3.5.1 Build a stereo camera

A stereoscopic camera is a camera with two or more lenses, each independent. Then stereo camera allows the camera to simulate the human eye and thus perceive the depth of the real world in a two-dimensional image.
As there was only one webcam for this project, the system installed a tilt servo to control the left and right panning of the camera to capture two images at different angles on the same horizontal plane to simulate a stereo camera.

Figure 38: Left image and right image

3.5.2 Camera Calibration

Camera calibration is the process of solving for the internal and external parameters of a camera to find the geometric position in three-dimensional space mapped to its corresponding point in a two-dimensional image to establish a geometric model of camera imaging.
As it is not a standard stereo camera, the system cannot determine whether the images captured twice are on the same level. As a result, when two images are combined to generate a disparity map, the disparity map becomes very noisy and inaccurate. It is impossible to determine the corresponding point between the two images from the Y-axis coordinates in the image. Therefore, the system needs to calibrate the parameters of the camera to remap the image.
OpenCV officially provides a checkerboard image to define real-world coordinates; the checkerboard pattern consists of adjacent black and white grids, with a distinct gradient of colour between each grid. Consequently, the system defines the coordinates in 3D space by finding the right angles formed by the intersection of the checkerboard lines.

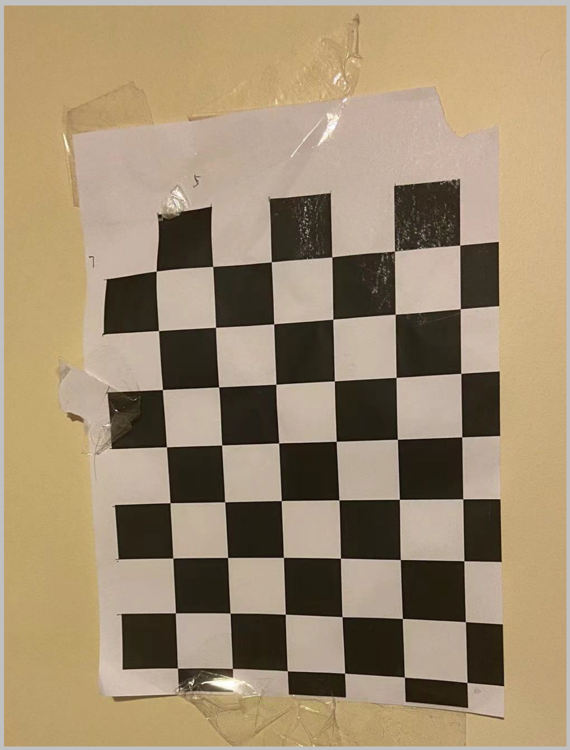


Figure 39 : Checkerboard pattern picture

After the system has read the checkerboard pattern image, OpenCV is used to find the checkerboard corners in the image and return the coordinates of the corners. Next, OpenCV takes the original image and the corners' position information to align the camera better and finds the best corners in the domain of the original position, iterating through the system to get the best result.
The final step in calibration is to pass the 3D coordinates in the world coordinate system and their mapped 2D position in the image to the calibrateCamera function in OpenCV to obtain the corresponding parameters.
The calibration system makes errors in the internal and external parameters of the camera more miniature by reading tessellations taken at different angles.

Figure 40: Find the corner position

```
Camera matrix :

[[1.16880114e+03 0.00000000e+00 3.41389616e+02]
 [0.00000000e+00 1.16999028e+03 2.83051329e+02]
 [0.00000000e+00 0.00000000e+00 1.00000000e+00]]
dist :

[[-1.30948908e+00 -1.91003682e+01  1.82583659e-02  1.99482215e-02
   2.60863489e+02]]
rvecs :

(array([[-0.13278487],
       [-0.22650196],
       [ 3.12459009]]),)
tvecs :

(array([[ 0.612248  ],
       [ 1.43689682],
       [25.14008278]]),)
```

Figure 41: Camera parameters

The camera produces different distortions during the imaging process due to the uneven bending of light. The system defines an ROI region to remove the distortion, extracts the necessary pixels from the image, excludes the unwanted ones, and remaps them into the image using the re-derived camera matrix to obtain an undistortion image.

Figure 42: Undistortion image

3.5.3 Depth perception distance measurement

Disparity map is a disparity in the horizontal coordinates of feature points in the image when the stereo camera captures and combines the left and right images. The closer the object is to the camera, the greater the parallax value.

The ranging system used the BM algorithm to calculate the disparity value. Because the Raspberry Pi used for this project was running an alternative matching algorithm (SGBM algorithm), the SGBM matching algorithm was unable to detect the distance between the object and the camera in real-time due to the image processing performance of the Raspberry Pi.

The BM algorithm divides the frames captured by the two cameras into several fixed-size squares to match. The Sum of Absolute Differences (SAD) between the squares is calculated by scanning the positions of the pixel points of the different squares in the other image and combining the parameters obtained from the camera calibration. Finally, a suitable disparity map is created by adjusting the size of the squares and the range of disparity.

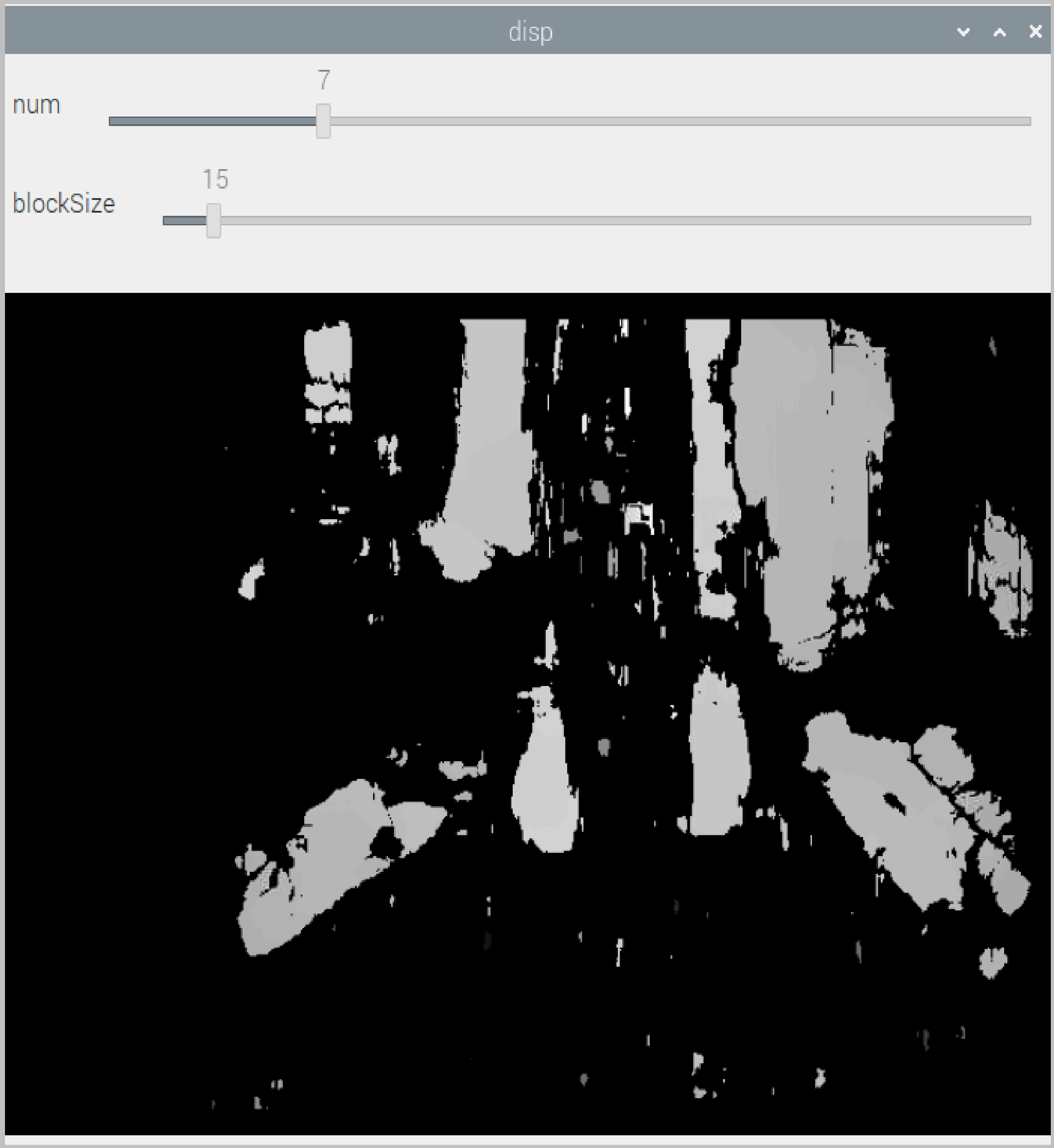


Figure 43: Disparity map

Using the stereo camera's imaging principle, the relationship between the disparity value and the object's depth is inversely proportional. The system can find the depth of the obstacle in the real world.

3.5.4 Obstacle detection

Implementing an obstacle avoidance system requires affirming a safe distance, and a warning is issued when the system detects an obstacle at a depth less than this threshold. Contour detection extracts Obstacle information, and a new mask is created to enable automatic obstacle detection to reduce interference in the depth map captured by the stereo camera. The average of all the depth values in the mask is calculated to obtain a more accurate depth value.

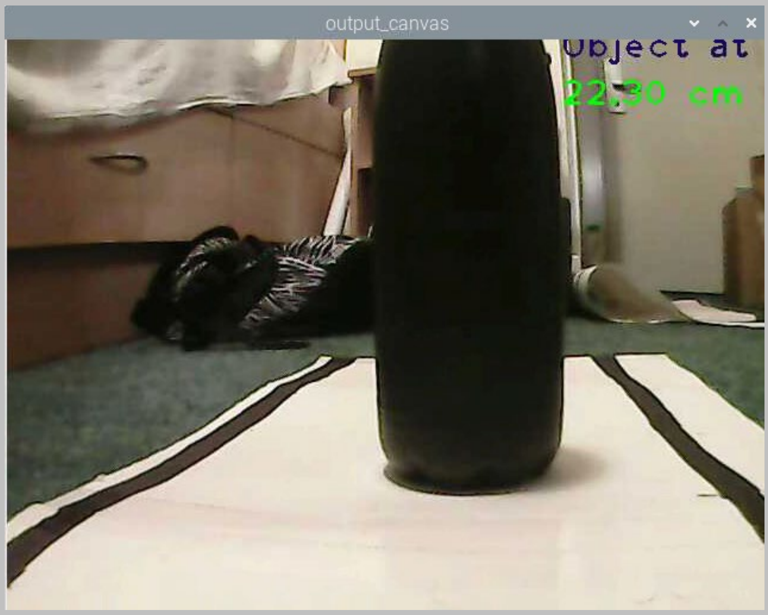


Figure 44: Obstacle Detection

3.6 System decision

This project detects the presence of an obstacle in the safety zone before the vehicle starts. If there is an obstacle in the safety zone, the car stops moving. If the zone is safe, the system executes the Lane-Following system.

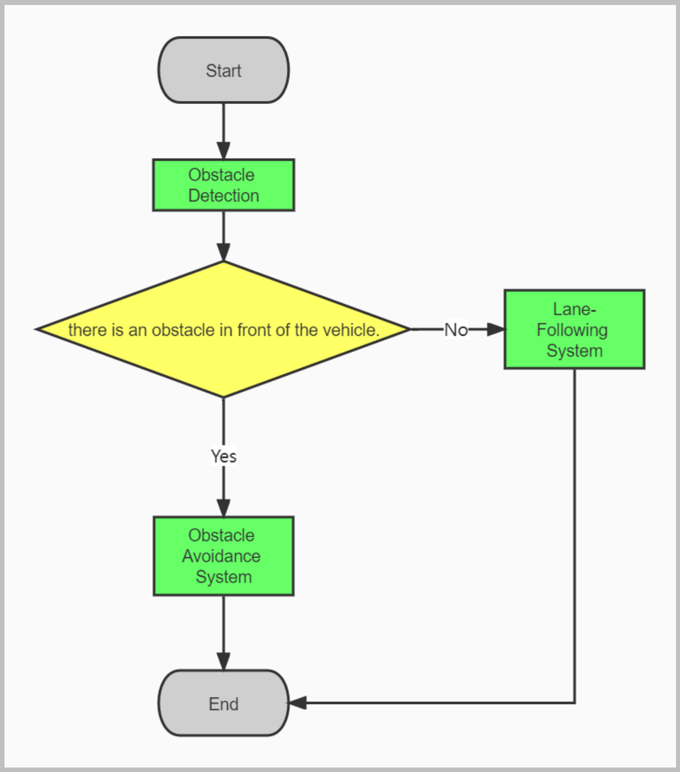


Figure 45 The project software flowchart

4 Results

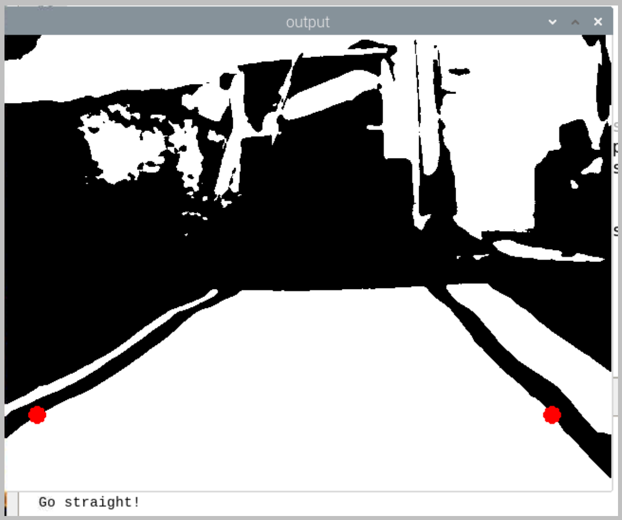
4.1 Results Overview

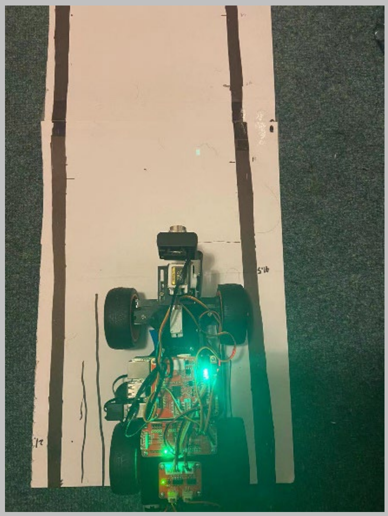
This section presents the results of the lane following and obstacle avoidance systems and the testing of the complete project.

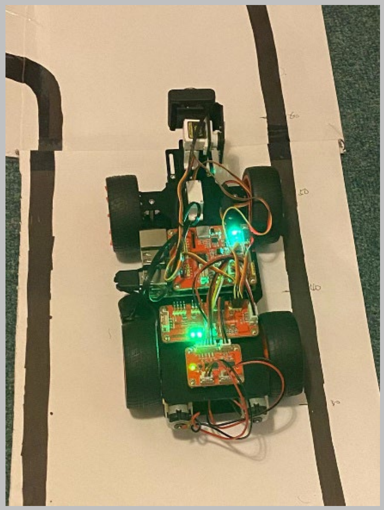
4.2 Lane-Following System Results

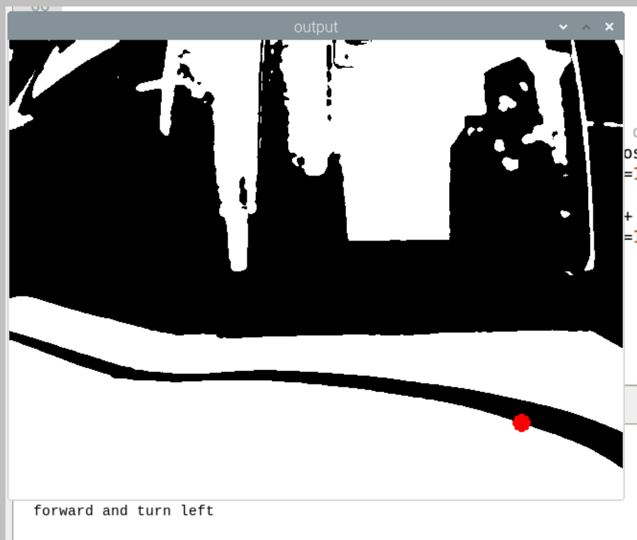
The Lane following system tests various situations under curves and straights to determine whether the vehicle can follow the lane accurately.
The vehicle makes a motion decision based on the currently detected lane lines, and the table in the appendix of the article will show the decision.
In this section, the image on the left shows the lanes detected by the lane following system and the movement decisions made. In contrast, the diagram on the right shows the vehicle's location in a realistic environment.

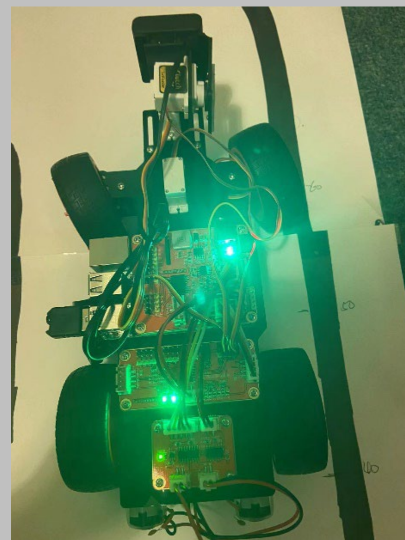
4.2.1 The vehicle encounters a bend to the left

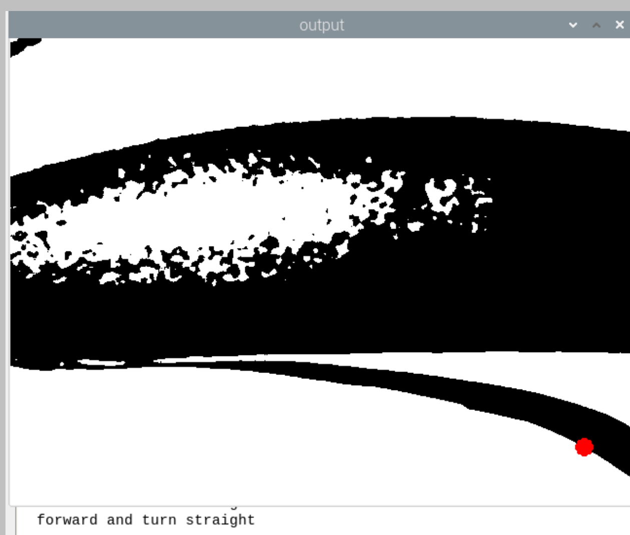




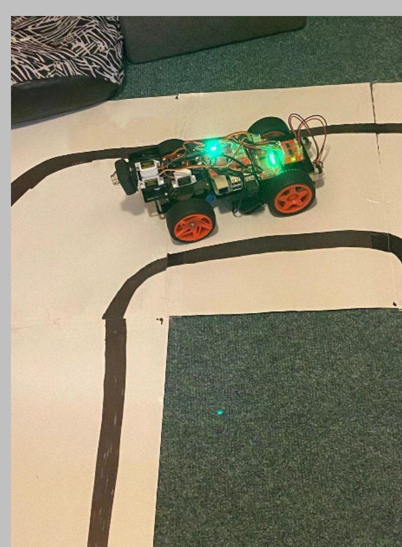



output
forward and turn left




output
forward and turn straight


output



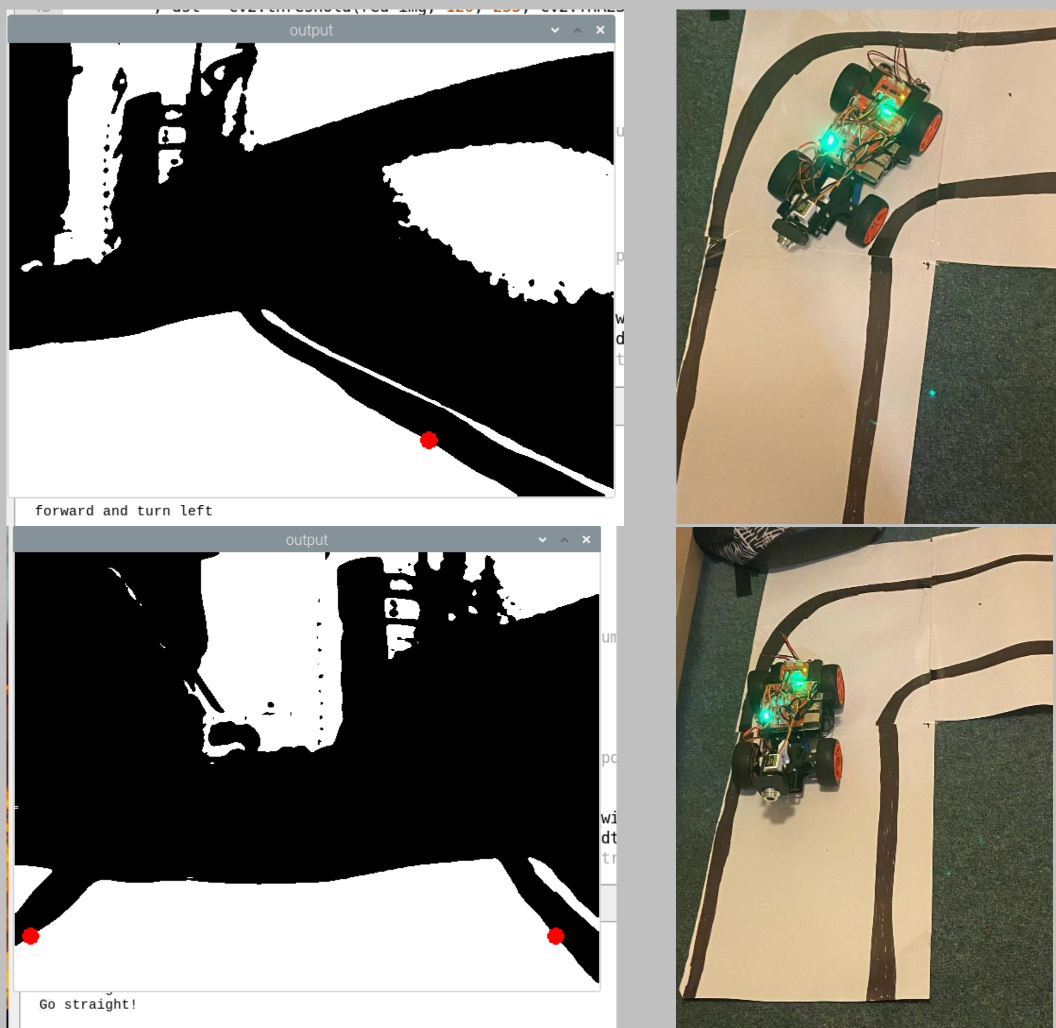
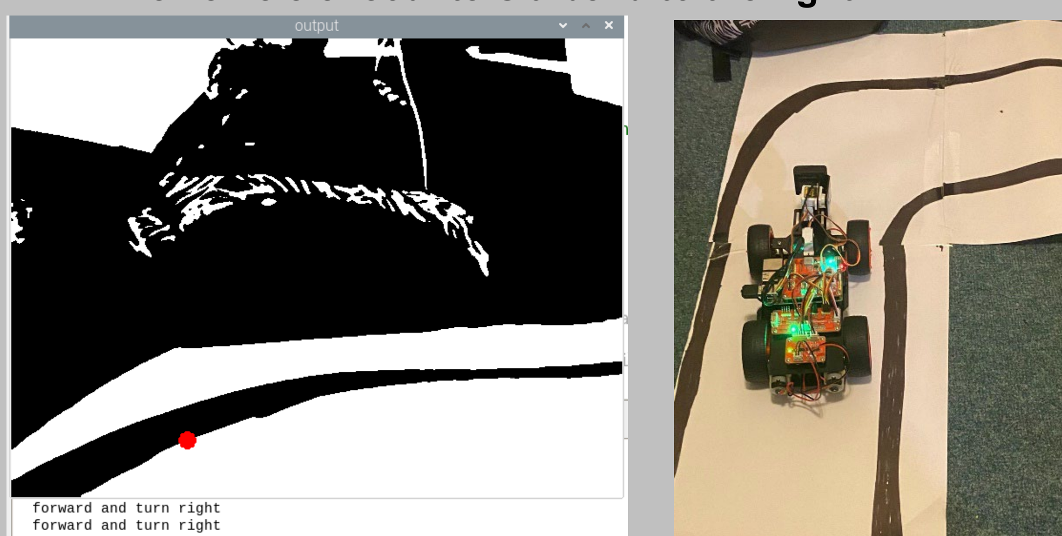


Figure 46: The car followed the lane (turn left)

4.2.2 The vehicle encounters a bend to the right



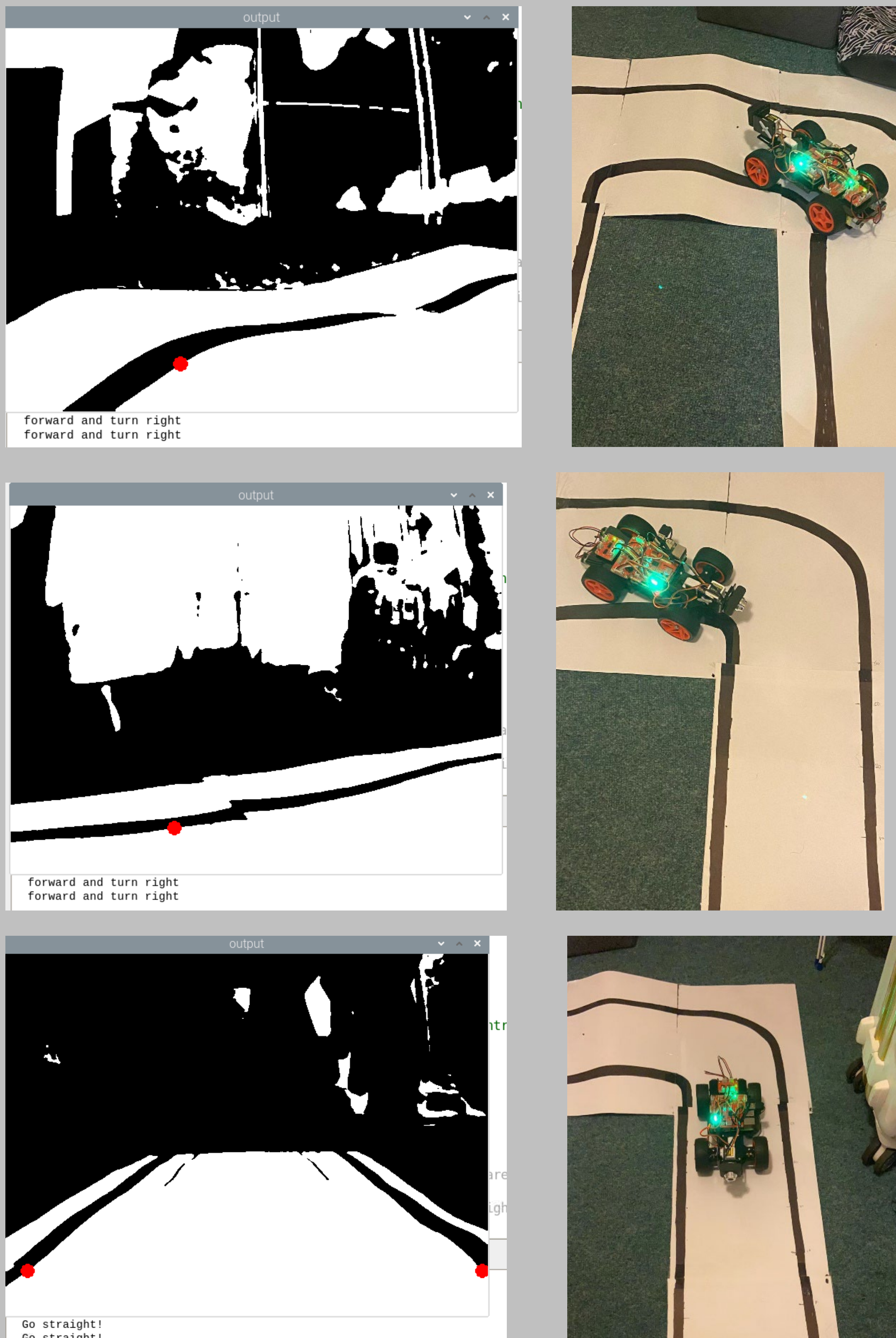


Figure 47: The car followed the lane (turn right)

4.3 Obstacle Avoidance System Results

To test the accuracy of the camera parameters calculated by the system, this project simulated 3D glasses setting the left and right images to separate colour channels and combining them to create a 3D colour map. The 3D image shows the results of the camera calibration as an image. When the 3D image is displayed correctly, the system has calibrated the camera parameters.

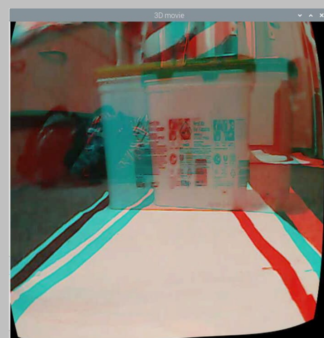


Figure 48: 3D image

The test section sets up a regression function that calculates the disparity value and gets the depth of the obstacle in the real world by clicking on the position of the obstacle in the depth map with the mouse.

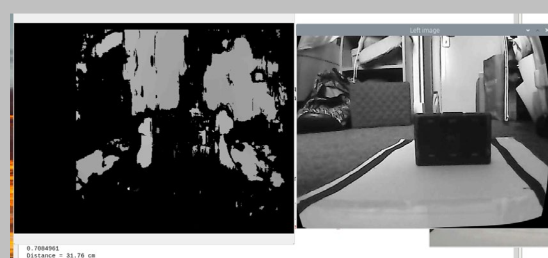


Figure 49: Test results of the distance measuring system

The system defines a safe distance of 30cm in front of the camera. When there are no obstacles within the safety zone, the system shows that the environment is safe. If there are obstacles within the safety zone, the system considers the environment dangerous.

Figure 50: Obstacles are not within the safety zone

Figure 51: Obstacles are within the safety zone

5 Discussion

The project aims to research, design and develop a computer vision-based obstacle detection system that builds a stereo camera from a single webcam and uses it to read information, analyse the data and relay its information to a display. This approach allows the user to detect the presence of obstacles in the visual blind spot before starting the vehicle, and the driver can implement a lane following system to reduce fatigue from prolonged driving. In addition, the system guarantees the safety of drivers who have been relaxing for long periods when the vehicle implements the automatic lane following system and avoids collision accidents or other collisions. A critical factor in ensuring road safety is that the obstacle avoidance system detects the presence of obstacles in real-time while the car is driving automatically.

The project uses a Raspberry Pi as the car's main development board and a car kit from SunFounder to form an intelligent car that simulates a real-world vehicle environment with the smart car and a custom lane. The initial stage of the obstacle avoidance cart uses a camera to detect the presence of obstacles in a safe area. The cart's webcam captures images with a resolution of 640x480 and can cover the entire road area in the immediate vicinity. In order to extend the camera's capabilities and recognition area, the vehicle's camera is equipped with Pan Servo and Tilt Servo to allow the camera to be rotated horizontally and vertically and to create a stereo camera system by capturing images at two different angles in the horizontal direction.

OpenCV (Open source computer vision library) is a library of programming functions primarily for real-time computer vision that runs on a wide range of operating systems, including but not limited to Windows and Linux. OpenCV can be used in technical areas such as computer vision, machine learning and image processing and plays a vital role in vision.

The lane detection section initially uses Hough's theorem to detect straight lines. However, the straight-line fitting section did not work when the lane was curved when implementing the lane following section. The reasons for this are that curved lanes are not straight and to achieve the detection of curved lanes while the detection model can be trained using neural networks. However, due to the performance limitations of the Raspberry Pi, using a large amount of memory and channels to execute the neural network algorithm may result in the system not being able to detect the driving environment in real-time. Therefore, this project uses the detection of the edges of lane lines to detect lanes. Due to the significant difference in colour between the lane lines and the road surface, the pixel point with the most extensive colour gradient can be detected to determine if the current location is a lane.

This method can effectively determine the status of the current lane without failing to recognise the lane coordinates because the lane is curved. However, the disadvantage is that it is susceptible to external interference. System requires the car to be driving on the road free of obstacles in front of the road to operate the lane following the system. In order to eliminate this interference and take into account the importance of obstacle avoidance systems for vehicle driving safety, a system for detecting obstacles has also been implemented in this project. The obstacle avoidance system detects whether there is an obstacle in front of the vehicle and the range of the obstacle avoidance system is larger than the lane range detected by the lane following system, thus avoiding errors in the lane following system.

A vision system built from a single camera implements the obstacle avoidance system in this project. The initial stage of building a depth perception system using a vision system is to build a stereo camera.

However, this project uses Pan Servo to swing the camera to capture images from two different angles to build a depth map. This approach is similar to Panasonic's Lumix FZ70 camera, which creates a 3D image by panning the lens horizontally to select the two best images as the camera performs the capture task. This method creates a depth-aware image, but the two lenses are necessarily close to each other because of hardware limitations, making the resulting depth map less accurate.

The closest distance that the obstacle avoidance system can detect is 20cm, and the furthest is 45cm. When the distance from the location of the obstacle to the camera is not within this range, it may not be possible to give its exact location precisely. When the object's distance is less than 20cm, the system considers it as if the object is at a distance of 20cm from the vehicle, and when the distance of the object is greater than

45cm, the system may not detect the obstacle. The reason is due to the limitations of accuracy and resolution of the webcam, so for practical application in vehicles, a better performing stereo camera needs to be prepared. In addition to that reason, another disadvantage of the obstacle avoidance system in this project is that the vehicle must be kept at a stop while operating. This is because the objects in both images must be kept stationary when the webcam swings left and right to capture the images, and the obstacles in the two images captured while moving cannot establish a coordinate system that is stationary relative to the vehicle.

The end result is therefore an obstacle avoidance system that is executed once to determine whether an obstacle is present in front of the vehicle before it is started. When there is no obstacle in front of the vehicle, the vehicle moves along the road. If there is an obstacle, the vehicle remains stationary until it is restarted.

6 Conclusions

Advanced Driver Assistance helps the driver relax the vehicle's control when the traffic is lighter and prevents fatigue due to long periods of concentration. Furthermore, the obstacle avoidance system ensures that the vehicle is driven in a safer situation. In this project, the width of parallax between different images was tested in different environments to obtain an accurate amount of parallax. In addition, according to the relationship between the depth map and the disparity map, it is necessary to find the coefficient M of the relationship. Calculate the least squares of the distance between the focal length and the lens by iteration, and use the regression algorithm to return to the system's parameters to get an accurate depth value. During testing, the depth values calculated by the system were within 2cm of each other, and the accuracy of the distance detection would be significantly improved if the camera spacing was within an appropriate range. The traditional machine learning approach used in this project is cumbersome and redundant to process while based on the hardware setup of the Raspberry Pi, traditional machine learning is far more efficient than deep learning. The use of machine learning in camera calibration to process multiple Checkerboards taken at different angles and generate camera parameters works well. In the approach of calibrating only by extracting common features of images taken from left and right lenses, the procedure is convenient and straightforward but it requires a high level of consistency and accuracy for images to be filtered and excluded from the considerable number of images that are of poor quality or inconsistent.

7 Bibliography

7.1 References

[1] A. Rasouli and J. K. Tsotsos, "Autonomous Vehicles That Interact With Pedestrians: A Survey of Theory and Practice," *IEEE Transactions on Intelligent Transportation Systems,* vol. 21, no. 3, pp. 900-918, 2020, doi: 10.1109/tits.2019.2901817.

[2] M. A. Sotelo and J. Barriga, "Blind spot detection using vision for automotive applications," *Journal of Zhejiang University-Science A,* vol. 9, no. 10, pp. 1369-1372, Oct 2008, doi: 10.1631/jzus.A0820111.

[3] R. Reyes and R. Murrieta-Cid, "An approach integrating planning and image-based visual servo control for road following and moving obstacles avoidance," *International Journal of Control,* vol. 93, no. 10, pp. 2442-2456, Oct 2020, doi: 10.1080/00207179.2018.1562225.

[4] H. C. Yao *et al.*, "Lane marking detection algorithm based on high-precision map and multisensor fusion," *Concurrency and Computation-Practice & Experience,* vol. 34, no. 8, Apr 2022, doi: 10.1002/cpe.5797.

[5] S. Z. Ding, X. M. Chen, Z. X. Fu, and F. Peng, "An Extended Car-Following Model in Connected and Autonomous Vehicle Environment: Perspective from the Cooperation between Drivers," *Journal of Advanced Transportation,* vol. 2021, Oct 2021, Art no. 2739129, doi: 10.1155/2021/2739129.

[6] J. Jung, M. Park, K. Cho, C. Mun, and J. Ahn, "Intelligent Hybrid Fusion Algorithm with Vision Patterns for Generation of Precise Digital Road Maps in Self-driving Vehicles," *Ksii Transactions on Internet and Information Systems,* vol. 14, no. 10, pp. 3955-3971, Oct 2020, doi: 10.3837/tiis.2020.10.002.

[7] Z. Y. Xiao, D. G. Yang, T. P. Wen, K. Jiang, and R. D. Yan, "Monocular Localization with Vector HD Map (MLVHM): A Low-Cost Method for Commercial IVs," *Sensors,* vol. 20, no. 7, Apr 2020, Art no. 1870, doi: 10.3390/s20071870.

[8] P. Luz, L. Zhang, J. Y. Wang, and V. Schwieger, "Lane-Level Map-Aiding Approach Based on Non-Lane-Level Digital Map Data in Road Transport Security," *Sustainability,* vol. 13, no. 17, Sep 2021, Art no. 9724, doi: 10.3390/su13179724.

[9] N. M. Nakrani and M. M. Joshi, "A human-like decision intelligence for obstacle avoidance in autonomous vehicle parking," *Applied Intelligence,* vol. 52, no. 4, pp. 3728-3747, Mar 2022, doi: 10.1007/s10489-021-02653-3.

[10] J. D. Zhao, B. D. Liang, and Q. X. Chen, "The key technology toward the self-driving car," *International Journal of Intelligent Unmanned Systems,* vol. 6, no. 1, pp. 2-20, 2018, doi: 10.1108/ijius-08-2017-0008.

[11] B. K. Koo, J. W. Baek, and K. Y. Chung, "Weight Feedback-Based Harmonic MDG-Ensemble Model for Prediction of Traffic Accident Severity," *Applied Sciences-Basel,* vol. 11, no. 11, Jun 2021, Art no. 5072, doi: 10.3390/app11115072.

[12] U. Z. A. Hamid *et al.*, "Autonomous emergency braking system with potential field risk assessment for frontal collision mitigation," *2017 IEEE Conference on Systems, Process and Control (ICSPC),* pp. 71-76, 2017.

[13] G. Li, S. E. Li, and B. Cheng, "Field operational test of advanced driver assistance systems in typical Chinese road conditions: The influence of driver gender, age and aggression," *International Journal of Automotive Technology,* vol. 16, no. 5, pp. 739-750, Oct 2015, doi: 10.1007/s12239-015-0075-5.

[14] K. Lee, S. E. Li, and D. Kum, "Synthesis of Robust Lane Keeping Systems: Impact of Controller and Design Parameters on System Performance," *Ieee Transactions on Intelligent Transportation Systems,* vol. 20, no. 8, pp. 3129-3141, Aug 2019, doi: 10.1109/tits.2018.2873101.

[15] H. Tan, F. Q. Zhao, H. Hao, and Z. W. Liu, "Evidence for the Crash Avoidance Effectiveness of Intelligent and Connected Vehicle Technologies," *International Journal of Environmental Research and Public Health,* vol. 18, no. 17, Sep 2021, Art no. 9228, doi: 10.3390/ijerph18179228.

[16] E. P. Ping, J. Hossen, F. Imaduddin, and W. E. Kiong, "Vision-based lane departure warning framework," *Heliyon,* vol. 5, no. 8, Aug 2019, Art no. e02169, doi: 10.1016/j.heliyon.2019.e02169.

[17] Y. H. He, H. Wang, and B. Zhang, "Color-based road detection in urban traffic scenes," *Ieee Transactions on Intelligent Transportation Systems,* vol. 5, no. 4, pp. 309-318, Dec 2004, doi: 10.1109/tits.2004.838221.

[18] A. Taguchi and Y. Hoshi, "Color Image Enhancement in HSI Color Space without Gamut Problem," *Ieice Transactions on Fundamentals of Electronics Communications and Computer Sciences,* vol. E98A, no. 2, pp. 792-795, Feb 2015, doi: 10.1587/transfun.E98.A.792.

[19] C. B. Wu, L. H. Wang, and K. C. Wang, "Ultra-Low Complexity Block-Based Lane Detection and Departure Warning System," *Ieee Transactions on Circuits and Systems for Video Technology,* vol. 29, no. 2, pp. 582-593, Feb 2019, doi: 10.1109/tcsvt.2018.2805704.

[20] V. Gaikwad and S. Lokhande, "Lane Departure Identification for Advanced Driver Assistance," *Ieee Transactions on Intelligent Transportation Systems,* vol. 16, no. 2, pp. 910-918, Apr 2015, doi: 10.1109/tits.2014.2347400.

[21] M. J. Liang, Z. Zhou, and Q. S. Song, "Improved Lane Departure Warning Method Based on Hough Transformation and Kalman Filter," *Informatica-Journal of Computing and Informatics,* vol. 41, no. 3, pp. 283-288, Sep 2017. [Online]. Available: <Go to ISI>://WOS:000417387600003.

[22] J. D. Zhang *et al.*, "Lane departure warning algorithm based on probability statistics of driving habits," *Soft Computing,* vol. 25, no. 22, pp. 13941-13948, Nov 2021, doi: 10.1007/s00500-020-04704-2.

[23] C. M. Kang, S. H. Lee, and C. C. Chung, "Multirate Lane-Keeping System With Kinematic Vehicle Model," *Ieee Transactions on Vehicular Technology,* vol. 67, no. 10, pp. 9211-9222, Oct 2018, doi: 10.1109/tvt.2018.2864329.

[24] J. W. Lei, J. Yang, J. B. Zhao, and H. L. Wu, "Backstepping sliding mode lane keeping control of lateral position error with dynamic of tire steering device," *Optik,* vol. 127, no. 5, pp. 2439-2443, 2016, doi: 10.1016/j.ijleo.2015.11.100.

[25] N. Tavan, M. Tavan, and R. Hosseini, "An optimal integrated longitudinal and lateral dynamic controller development for vehicle path tracking," *Latin American Journal of Solids and Structures,* vol. 12, no. 6, pp. 1006-1023, 2015, doi: 10.1590/1679-78251365.

[26] Y. S. Son, W. Kim, S. H. Lee, and C. Chung, "Robust Multirate Control Scheme With Predictive Virtual Lanes for Lane-Keeping System of Autonomous Highway Driving," *Ieee Transactions on Vehicular Technology,* vol. 64, no. 8, pp. 3378-3391, Aug 2015, doi: 10.1109/tvt.2014.2356204.

[27] Z. R. Chu, C. Wu, and N. Sepehri, "Automated steering controller design for vehicle lane keeping combining linear active disturbance rejection control and quantitative feedback theory," *Proceedings of the Institution of Mechanical Engineers Part I-Journal of Systems and Control Engineering,* vol. 232, no. 7, pp. 937-948, Aug 2018, doi: 10.1177/0959651818770344.

[28] R. Marino, S. Scalzi, and M. Netto, "Integrated Driver and Active Steering Control for Vision-Based Lane Keeping," *European Journal of Control,* vol. 18, no. 5, pp. 473-484, Sep-Oct 2012, doi: 10.3166/ejc.18.473-484.

[29] R. Marino, S. Scalzi, and M. Netto, "Nested PID steering control for lane keeping in autonomous vehicles," *Control Engineering Practice,* vol. 19, no. 12, pp. 1459-1467, Dec 2011, doi: 10.1016/j.conengprac.2011.08.005.

[30] A. H. Jamson, F. C. H. Lai, and O. M. J. Carsten, "Potential benefits of an adaptive forward collision warning system," *Transportation Research Part C-Emerging Technologies,* vol. 16, no. 4, pp. 471-484, Aug 2008, doi: 10.1016/j.trc.2007.09.003.

[31] J. S. Jermakian, "Crash avoidance potential of four passenger vehicle technologies," *Accident Analysis and Prevention,* vol. 43, no. 3, pp. 732-740, May 2011, doi: 10.1016/j.aap.2010.10.020.

[32] M. Taieb-Maimon and D. Shinar, "Minimum and comfortable driving headways: Reality versus perception," *Human Factors,* vol. 43, no. 1, pp. 159-172, Spr 2001, doi: 10.1518/001872001775992543.

[33] J. B. Cicchino, "Effectiveness of forward collision warning and autonomous emergency braking systems in reducing front-to-rear crash rates," *Accident Analysis and Prevention,* vol. 99, pp. 142-152, Feb 2017, doi: 10.1016/j.aap.2016.11.009.

[34] J. Wang, X. Zhang, H. Kang, and L. Y. Deng, "Test Method and Risk Factor Definition of Forward Collision Warning System," *Ieee Access,* vol. 8, pp. 47730-47740, 2020, doi: 10.1109/access.2020.2979520.

[35] Y. Yuan, Y. W. Lu, and Q. Wang, "Adaptive forward vehicle collision warning based on driving behavior," *Neurocomputing,* vol. 408, pp. 64-71, Sep 2020, doi: 10.1016/j.neucom.2019.11.024.

[36] T. Chen, K. Liu, Z. Y. Wang, G. Deng, and B. Chen, "Vehicle forward collision warning algorithm based on road friction," *Transportation Research Part D-Transport and Environment,* vol. 66, pp. 49-57, Jan 2019, doi: 10.1016/j.trd.2018.04.017.

[37] B. F. Lin *et al.*, "Integrating Appearance and Edge Features for Sedan Vehicle Detection in the Blind-Spot Area," *Ieee Transactions on Intelligent Transportation Systems,* vol. 13, no. 2, pp. 737-747, Jun 2012, doi: 10.1109/tits.2011.2182649.

[38] S. S. G. Bagi, B. Moshiri, H. G. Garakani, and M. Khoshnevisan, "Blind Spot Detection System in Vehicles Using Fusion of Radar Detections and Camera Verification," *International Journal of Intelligent Transportation Systems Research,* vol. 19, no. 2, pp. 389-404, Jun 2021, doi: 10.1007/s13177-021-00254-5.

[39] A. Sinha, Z. Ding, T. Kirubarajan, and M. Farooq, "Track Quality Based Multitarget Tracking Approach for Global Nearest-Neighbor Association," *Ieee Transactions on Aerospace and Electronic Systems,* vol. 48, no. 2, pp. 1179-1191, Apr 2012, doi: 10.1109/taes.2012.6178056.

[40] F. Castanedo, "A Review of Data Fusion Techniques," *The Scientific World Journal,* vol. 2013, p. 704504, 2013/10/27 2013, doi: 10.1155/2013/704504.

[41] Y. X. Guo, I. Kumazawa, and C. Kaku, "Blind Spot Obstacle Detection from Monocular Camera Images with Depth Cues Extracted by CNN," *Automotive Innovation,* vol. 1, no. 4, pp. 362-373, Nov 2018, doi: 10.1007/s42154-018-0036-6.

[42] M. Ra, H. G. Jung, J. K. Suhr, and W. Y. Kim, "Part-based vehicle detection in side-rectilinear images for blind-spot detection," *Expert Systems with Applications,* vol. 101, pp. 116-128, Jul 2018, doi: 10.1016/j.eswa.2018.02.005.

[43] Y. M. Zhao, L. Bai, Y. C. Lyu, and X. M. Huang, "Camera-Based Blind Spot Detection with a General Purpose Lightweight Neural Network," *Electronics,* vol. 8, no. 2, Feb 2019, Art no. 233, doi: 10.3390/electronics8020233.

[44] G. R. Liu, M. Z. Zhou, L. L. Wang, H. Wang, and X. S. Guo, "A blind spot detection and warning system based on millimeter wave radar for driver assistance," *Optik,* vol. 135, pp. 353-365, 2017, doi: 10.1016/j.ijleo.2017.01.058.

[45] E. Hyun, Y. S. Jin, and J. H. Lee, "Design and development of automotive blind spot detection radar system based on ROI pre-processing scheme," *International Journal of Automotive Technology,* vol. 18, no. 1, pp. 165-177, Feb 2017, doi: 10.1007/s12239-017-0017-5.

[46] R. Labudzki, S. Legutko, and P. Raos, "THE ESSENCE AND APPLICATIONS OF MACHINE VISION," *Tehnicki Vjesnik-Technical Gazette,* vol. 21, no. 4, pp. 903-909, Aug 2014. [Online]. Available: <Go to ISI>://WOS:000341262900027.

[47] M. Pervaiz, Y. Y. Ghadi, M. Gochoo, A. Jalal, S. Kamal, and D. S. Kim, "A Smart Surveillance System for People Counting and Tracking Using Particle Flow and Modified SOM," *Sustainability,* vol. 13, no. 10, May 2021, Art no. 5367, doi: 10.3390/su13105367.

[48] J. Brookshire, "Person Following Using Histograms of Oriented Gradients," *International Journal of Social Robotics,* vol. 2, no. 2, pp. 137-146, Jun 2010, doi: 10.1007/s12369-010-0046-y.

[49] B. Li and G. Huo, "Face recognition using locality sensitive histograms of oriented gradients," *Optik,* vol. 127, no. 6, pp. 3489-3494, 2016, doi: 10.1016/j.ijleo.2015.12.032.

[50] X. Hu, Y. P. Huang, Q. Q. Duan, W. Y. Ci, J. Dai, and H. M. Yang, "Abnormal event detection in crowded scenes using histogram of oriented contextual gradient descriptor," *Eurasip Journal on Advances in Signal Processing,* Aug 2018, Art no. 54, doi: 10.1186/s13634-018-0574-4.

[51] Y. Zhao, W. Jia, R. X. Hu, and H. Min, "Completed robust local binary pattern for texture classification," *Neurocomputing,* vol. 106, pp. 68-76, Apr 2013, doi: 10.1016/j.neucom.2012.10.017.

[52] K. Y. Park and S. Y. Hwang, "An improved Haar-like feature for efficient object detection," *Pattern Recognition Letters,* vol. 42, pp. 148-153, Jun 2014, doi: 10.1016/j.patrec.2014.02.015.

[53] D. L. Yang, X. Y. Zhong, D. B. Gu, X. F. Peng, G. L. Yang, and C. S. Zou, "Unsupervised learning of depth estimation, camera motion prediction and dynamic object localization from

video," *International Journal of Advanced Robotic Systems,* vol. 17, no. 2, Mar 2020, Art no. 1729881420909653, doi: 10.1177/1729881420909653.

[54] Z. G. Tu *et al.*, "A survey of variational and CNN-based optical flow techniques," *Signal Processing-Image Communication,* vol. 72, pp. 9-24, Mar 2019, doi: 10.1016/j.image.2018.12.002.

[55] J. H. Mun, M. Jeon, and B. G. Lee, "Unsupervised Learning for Depth, Ego-Motion, and Optical Flow Estimation Using Coupled Consistency Conditions," *Sensors,* vol. 19, no. 11, Jun 2019, Art no. 2459, doi: 10.3390/s19112459.

[56] A. Etinger, B. Litvak, and Y. Pinhasi, "Multi Ray Model for Near-Ground Millimeter Wave Radar," *Sensors,* vol. 17, no. 9, Sep 2017, Art no. 1983, doi: 10.3390/s17091983.

[57] Z. B. Xiong, Z. P. Cai, Q. L. Han, A. Alrawais, and W. Li, "ADGAN: Protect Your Location Privacy in Camera Data of Auto-Driving Vehicles," *Ieee Transactions on Industrial Informatics,* vol. 17, no. 9, pp. 6200-6210, Sep 2021, doi: 10.1109/tii.2020.3032352.

[58] G. Nachouki and M. Quafafou, "Multi-data source fusion," *Information Fusion,* vol. 9, no. 4, pp. 523-537, Oct 2008, doi: 10.1016/j.inffus.2007.12.001.

[59] A. Goshtasby and W. A. Gruver, "DESIGN OF A SINGLE-LENS STEREO CAMERA SYSTEM," *Pattern Recognition,* vol. 26, no. 6, pp. 923-937, Jun 1993, doi: 10.1016/0031-3203(93)90058-5.

[60] W. Bin Ng and Y. Zhang, "Stereoscopic imaging and computer vision of impinging fires by a single camera with a stereo adapter," *International Journal of Imaging Systems and Technology,* vol. 15, no. 2, pp. 114-122, 2005, doi: 10.1002/ima.20044.

8 Appendices

8.1 Motion decisions for lane following systems

Left lane point situation	Right lane point situation	Decision resilt
It is detected and is close to the edge of the image.	It is detected and is close to the edge of the image.	Vehicle go straight ahead.
No pixel points were detected.	The pixel point is close to the edge of the image.	Vehicle go straight ahead.
No pixel points were detected.	The pixel point is close to the centre of the image.	Vehicle turn left.
The pixel point is close to the edge of the image.	No pixel points were detected.	Vehicle go straight ahead.
The pixel point is close to the centre of the image.	No pixel points were detected.	Vehicle turn right.
No pixel points were detected.	No pixel points were detected.	Vehicle stop moving.

Table 5: Motion decisions