INTELLIGENT ROAD RECOGNITION SYSTEM FOR AUTONOMOUS VEHICLE

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ABSTRACT

An autonomous vehicle is a self-driving vehicle, that requires no operator to be involve in performing the set tasks. It is developed to assist humans in everyday tasks with the advantages of eliminating errors and reducing the need for human observation. For an autonomous vehicle to move with flexibility or to adapt to a new road environment, it needs to have human-like perception and intelligence. This project proposes an intelligent visual perception system for an autonomous vehicle. It consists of a camera vision system that captures the road image. The image features are extracted using simple image processing algorithms and are trained using artificial neural network (ANN). The trained system is able to recognize some predetermined road patterns. Further experimental tests are designed to justify the performance of the system settings. An optimized set of image quality and the ANN network structures are chosen.

ABSTRAK

Kenderaan autonomi merupakan kenderaan yang memandukan sendiri, tanpa melibatkan pengendali dalam pelaksanaan tugas-tugas yang ditetapkan untuk kenderaan. Ia direkakan untuk membantu manusia dalam tugas-tugas harian, mengurangkan kesilapan dan keperluan pemerhatian dari manusia. Untuk kenderaan autonomi untuk bergerak dengan fleksibiliti atau untuk menyesuaikan diri dengan persekitaran jalan raya baru, ia perlu mempunyai persepsi dan kepintaran seperti manusia. Projek ini mencadangkan sistem persepsi pintar visual untuk kenderaan autonomi. Ia terdiri daripada sistem penglihatan kamera yang menangkap imej jalan. Ciri-ciri imej akan diekstrak dengan menggunakan algoritma pemprosesan imej yang mudah dan dilatih dengan menggunakan rangkaian neural tiruan (ANN). Sistem terlatih dapat mengenali beberapa corak jalan yang telah ditetapkan. Ujian eksperimen direka untuk mewajarkan prestasi tetapan sistem. Satu set kualiti imej dan struktur rangkaian ANN yang optimum telah dipilih.

TABLE OF CONTENTS

	ACKNOWLEDGEMENT	**i**
	ABSTRACT	**ii**
	ABSTRAK	**iii**
	TABLE OF CONTENTS	**iv**
	LIST OF TABLES	**vii**
	LIST OF FIGURES	**viii**
	LIST OF SYMBOLS AND ABBREVIATIONS	**x**
	LIST OF APPENDICES	**xii**
CHAPTER 1	**INTRODUCTION**	**1**
	1.1 Problem statement	2
	1.2 Aim	2
	1.3 Objectives	2
	1.4 Scopes	2
	1.5 Outline of the thesis	3
CHAPTER 2	**LITERATURE REVIEW**	**4**
	2.1 Introduction	4
	2.2 Autonomous driving vehicle	5
	2.3 Types of sensors	5
	2.3.1 Radar	6
	2.3.2 Laser Detection and Ranging (LADAR)	6

	2.3.3 Camera	7
	2.3.4 Stereo camera	8
	2.3.5 Comparison of types of sensors	8
	2.4 Data processing	9
	2.4.1 Image feature extraction	10
	2.5 Types of algorithms for road recognition	12
	2.5.1 Image processing algorithm	12
	2.5.2 Kalman filter	12
	2.5.3 Particle filter	14
	2.5.4 Artificial neural network	16
	2.6 Comparison of the types of algorithms for road recognition	21
	2.7 Theory of ANN	24
	2.7.1 Developing procedure of ANN	25
	2.7.2 ANN structure	26
	2.8 Summary	26
CHAPTER 3	**METHODOLOGY**	**28**
	3.1 Introduction	28
	3.2 Project flow	28
	3.3 Procedures	29
	3.3.1 Hardware setup	30
	3.3.2 Image acquisition	32
	3.3.3 Image processing & feature extraction	33
	3.3.4 Artificial neural network	36
	3.4 Experiments & data analysis	37

	3.4.1 Experiment 1: Image processing and image feature extraction test	38
	3.4.2 Experiment 2: ANN performance	39
	3.4.3 Experiment 3: Overall system	40
	3.5 Summary	40
CHAPTER 4	**RESULTS AND ANALYSIS**	**42**
	4.1 Introduction	42
	4.2 Image processing test	43
	4.3 Artificial neural network test	44
	4.3.1 Number of hidden neuron	45
	4.3.2 Number of output neuron	48
	4.4 System combination	52
	4.5 System test	53
	4.5.1 Effects of accuracy and predictability	54
	4.6 Discussion	56
	4.6.1 Image processing and feature extraction	56
	4.6.2 Artificial neural network	57
	4.6.3 Overall road recognition system	57
	4.7 Summary	58
CHAPTER 5	**CONCLUSION & RECOMMENDATION**	**59**
	5.1 Justification of the objectives	59
	5.2 Research efforts	60
	5.3 Recommendations	62
REFERENCES		**63**
APPENDIX		

LIST OF TABLES

2.1	Comparison of types of sensors	9
2.2	Comparison of previous works	22
3.1	Representation of road patterns	40
4.1	Results of performance of different threshold value	44
4.2	Confusion matrix results for 300-n-4 ANN with 70 sample data	47
4.3	The results for ANN structure of 300-n-n_o with varying number of hidden neurons and output neurons, using 70 sample data	49
4.4	Best performed ANN structure for each number of output neuron	49
4.5	Results of ANN of different settings tested using 1297 frames of the real data collected	53
4.6	Overall performance for ANN 300-35-3	56

LIST OF FIGURES

2.1 Scopes of literature review 4

2.2 Data processing flowchart [18] 9

2.3 Image division in groups [20]. 11

2.4 Canonical system of a camera with two lenses. **f** is focal length, **B** is the distance between the lens [22] 11

2.5 Three consecutive laser data points on a flat road surface [5] 13

2.6 Simulation results [5]. (a) Synthetic collinear data, (b) Results of filtering segmentation and line fitting. 14

2.7 Overview of the proposed method [18] 15

2.8 A piecewise-linear road model (un-branched road model) [18] 15

2.9 Neural network architecture for autonomous driving [21] 17

2.10 Illustration of the pure pursuit" model of steering [21] 18

2.11 Features generation stages [22]. (a) Original image. (b) Image transformed into sub-images. (c) Road classified in red squares. 19

2.12 The System Architecture [22]. 19

2.13 ANN topology [22]. 20

2.14 Classification sample [22]. (a) Colour image. (b) Classification results. 20

2.15 Schematic drawing of biological neurons [27] 24

2.16 Single-input neuron [27]. 24

3.1 Methodology flowchart 29

3.2 System procedure 30

3.3 Logitech HD Pro Webcam C920 31

3.4 Webcam attached to windscreen 31

3.5 Camera alignment 32

3.6 (a) Region of interest; (b) Cropped image. 33

3.7 (a) Cropped Image, (b) Extracted road feature, 34

3.8 Frames of images 35

3.9 Two-layer network [27] 36

3.10 Seven road patterns (a) straight, (b) left curve, (c) right curve, (d) T junction, (e) left junction, (f) cross junction, and (g) right junction 37

3.11 Experiment flowchart 38

4.1 (a) Original image, (b) Extracted road feature in white color 43

4.2 (a) original image; (b) extracted road feature in white color 44

4.3 Labeling of ANN structure 45

4.4 ANN structure of 300-n-4 [29] 45

4.5 Confusion matrix for ANN structure of 300-5-3 with 70 sample data 46

4.6 ROC for ANN structure of 300-5-3 with 70 sample data 47

4.7 Plot of average correct (%) to the no. of hidden neuron, 48

4.8 ANN structure of 300-n-n_o (n_o is 3 to 7) [29]. 48

4.9 Results of different number of output neuron and hidden neuron using 70 sample data 50

4.10 ROC for the selected ANN structure 51

4.11 Graphical user interface 52

4.12 Plotted Results of ANN referring (Threshold = 30). 54

4.13 ROC plots for ANN 300-35-3. (a) ROC for accuracy of 70%, (b) ROC for accuracy of 97.1%, (c) ROC for accuracy of 97.1%, (d) ROC for accuracy of 100%. 55

LIST OF SYMBOLS AND ABBREVIATIONS

a	-	Neuron output
b	-	Bias
$\boldsymbol{B}$	-	Distance between lens
f	-	Transfer function
i	-	Row position of pixels
$\boldsymbol{I}$	-	Image value vector for ANN
j	-	Column position of pixels
n	-	Number of hidden neuron
n_o	-	Number of output neuron
p	-	Input for ANN
$\boldsymbol{p}$	-	Input vector for ANN
S^n	-	Number of neuron in the n-th layer
SD	-	and standard deviation
th	-	Threshold value
w	-	Weight
2D	-	Two-dimensional
ADAS	-	Advanced driving assistance systems
ALVINN	-	Autonomous Land Vehicle In a Neural Network
ANN	-	Artificial Neural Network
AUC	-	Area under the curve
DARPA	-	Defense Advanced Research Projects Agency
GPS	-	Global Positioning System
HSV	-	Hue, saturation and value for brightness
LADAR	-	Laser Detection and Ranging
LIDAR	-	Light Detection And Ranging
MLP	-	Multilayer perceptron
MSE	-	Mean Square Error

NASA	-	National Aeronautics and Space Administration
Radar	-	Radio detection and ranging
RGB	-	Red, green and blue
ROC	-	Receiver operating characteristics
SCARF	-	Supervised classification applied to road following
SNR	-	Signal to noise ratio
UNSCARF	-	Unsupervised classification applied to road following
UTHM	-	University of Tun Hussein Malaysia
YCrCb	-	Luma component, blue-difference and red-difference chroma components

LIST OF APPENDICES

APPENDIX	TITLE
A	Logitech HD Pro Webcam C920 Datasheet
B	Laptop GE620 Specifications
C	MATLAB Neural Network Pattern Recognition Tool
D	Intelligent Road Recognition System code in MATLAB

CHAPTER 1

INTRODUCTION

Many works [1] have been done for the past decades on the advanced driving assistance systems (ADAS) to help make road transport safer and more comfortable. Even in developed country, road traffic accidents can claim tens of thousands of lives, few million injured and cost few hundred billion yearly. Most accident are caused by human-inherent errors such as distraction, emotion, fatigue or drowsiness. In view of this, advanced driving assistance systems (ADAS) has become a strong interest for many researchers. Many research groups, publicly funded [2] entities, and automobile manufacturers are searching for advanced driver assistance systems and smart autonomous vehicle to make roads safer. ADAS can range from anti-lock brakes to radar-based adaptive cruise, and with the integration of drive-by-wire components such as electronic gas pedals, brakes and steering systems [3]. However these are low-level vehicle control. High-level vehicle control tasks to make real-time decision, and the executing driving maneuvers are still in research. To develop this high-level vehicle control [4], the ability to 'see' and 'perceive' the road environment, path planning and decision making, and to communicate between vehicles are important.

In their paper [5] written by cadets of Systems Engineering and Engineering Management at the United States Military Academy, autonomous surface rovers in largely un-navigated solar system are still one of the NASA's strategic goals. The main focus of their research is the use of advanced sensor technologies for remote and unmanned systems, especially for autonomous space landers and autonomous surface rovers. Among the identified operational functionality of the vehicle are the ability to make decisions regarding hazard prevention and path routing, minimum ground clearance to navigate terrain and hazards, small in size, low power consumption, and others [6].

Other areas [7] where autonomous vehicle are used are rice planting and agricultural vehicles, autonomous driving for urban areas, security and surveillance, and also exploration of any place or work where is considered hazardous and risky to human life like a mine or a place with fire adventure.

1.1 Problem statement

An autonomous vehicle without human-like perception and intelligence on road environment will not be able to move with flexibility or to adapt to new road environment. To be able to fully assist human, the autonomous vehicle needs to have a vision-like sensory feedback and suitable intelligence to recognize various road conditions.

1.2 Aim

The aim of this project is to design an intelligent visual perception system for an autonomous vehicle.

1.3 Objectives

The following are the objectives of this project:

i. To obtain the image data of the road environment.
ii. To extract features from the image data captured.
iii. To design an intelligent road recognition.

1.4 Scopes

The following are the scopes of this project:

i. The system is limited to recognize ideal road condition which is the tar road.

ii. The weather condition must be good, with good lighting and minimum shadows on the road.
iii. The speed of the vehicle is limited to less than 20km/h.

1.5 Outline of the thesis

In this thesis, an intelligent visual perception and road recognition system for an autonomous vehicle is proposed. The obtained images of the road are processed and the image features of the road area are extracted for the road pattern recognition.

Chapter 2 reviews the related works on road recognition for autonomous vehicle. The working principle of artificial neural network (ANN) is also included.

Chapter 3 demonstrates the methodology of the research. The procedures of the intelligent visual perception system are presented. The hardware setup, image acquisition, image processing and the application of ANN in road pattern recognition are described.

Chapter 4 demonstrates the result and analysis of this project regarding the image processing, ANN design and the overall system. The experiments study the output performance of the system by varying key variables. The best performed setting of the variables will be selected for the rest of the study.

Chapter 5 justifies the achievement of the project. Further research recommendations are proposed.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter will review the previous literatures on intelligent road recognition system for autonomous driving. Figure 2.1 shows the flow on the review of the previous literatures.

The review begins with the introduction to autonomous vehicle. The section followed will review the range of sensors being used by the autonomous vehicle for road detection. The next section reviews the data processing for certain sensors if needed. Next, types of intelligent algorithms for road recognition will be reviewed.

Lastly, further literature on the theory of artificial neural network will be reviewed.

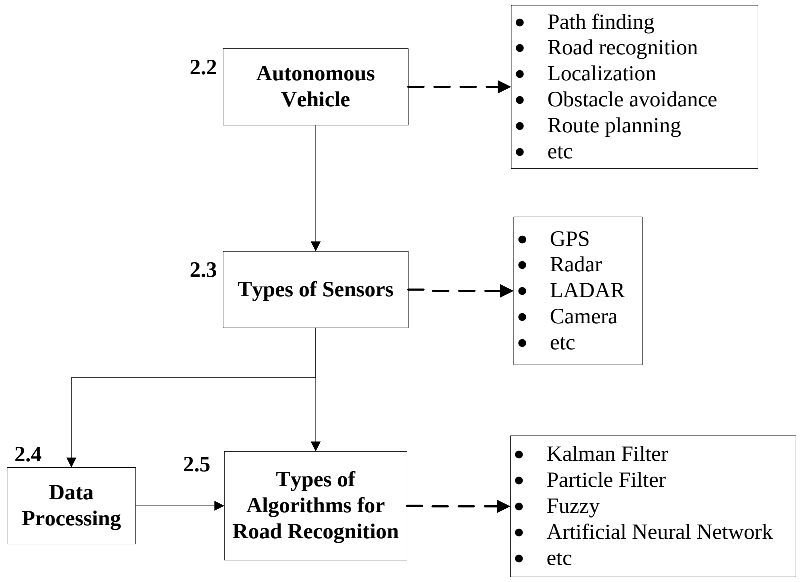


Figure 2.1: Scopes of literature review

2.2 Autonomous driving vehicle

Autonomous systems are developed to assist humans in everyday tasks with the advantages of eliminating errors and reducing the need for human observation [8].

An autonomous vehicle is a self-pivoted vehicle [7], requires no operator to be involved in performing the set tasks. An autonomous is also un-tethered [9], in which there is no need for communication with the vehicle during operation. Therefore, an autonomous vehicle must be able to recognize the environment and the potential problems and respond independently, without human intervention. Other necessary capabilities needed of an autonomous vehicle are obstacle avoidance, path planning, road recognition, and others.

Autonomous vehicle control system is a complex task [9], involving all the components and subsystems to work together. To implement 'human-like' reasoning to problems such as motion control, path planning, and obstacle avoidance may require the combination of artificial intelligence, computer vision, vehicle navigation, and graph theory. A fully autonomous vehicle should have functions [10] such as route planning, localization, road detection and following, and obstacle avoidance.

2.3 Types of sensors

In autonomous driving system, a variety of sensors have been used for different autonomous tasks for sensing, measuring, recognition, navigation and object manipulation [11]. One of the common sensors [12] used are Global Positioning System (GPS), laser range finders, radar as well as very accurate maps of the environment. However, each method has its limitations. For example, the use of GPS cannot guarantee safe navigation without local information of the road [10]. Range sensors are also used due to its ability to detect and measure the object's distance. As presented in [13], a numbers of range sensors are needed for an effective autonomous driving.

Hybrid forms of sensors are also used to complement each other and to act as a redundancy guard in case that one fails [6]. In certain situations where a vision system is used, an obstacle may not be detected due to glary lighting, colour of the object or many other factors. This leads to the employment of hyrbid forms of sensors to ensure that hazards are always detected. The selection of sensors is dependent on the function, power requirement and size of the vehicle.

A few important sensors are being studied and reviewed. There are the radar sensor, laser-based sensor, mono and stereo camera. Lastly these sensors are compared.

2.3.1 Radar

Sridhar Lakshmanan, Kesavarajan Kaliyaperumal and Karl Kluge [14] uses radio detection and ranging (Radar) to detect roads and obstacles in all weather condition. Radar can work in all weather condition, not easily affected by rain, fog, snow, darkness, or other weather condition. However, radar image is difficult to interpret due to its modality, resolution and perspective. To overcome this, the road boundaries and obstacles are detected from the radar image using an algorithm called likelihood-based experiments evaluating the efficacy of Radar. This algorithm is able to estimate the road shapes and detect potential obstacles.

2.3.2 Laser Detection and Ranging (LADAR)

Laser Detection and Ranging (LADAR) or also known as Light Detection And Ranging (LIDAR) is used to measure the distance of a target from the LADAR instrument. The instrument transmits a laser beam to a target. The measurement is made by analyzing the reflected light [15]. It is an active sensor technology with low resolutions, slower scanning speeds, and tends to interfere with each other in close proximity. Operating at millimeter wavelength, it has the advantages to be able to provide an alternate high-quality image of a road scene ahead over longer distances (1 - 80m) in snow, haze, dust, rain, and is not susceptible to ambient light. Having better cost, packaging ease, operating power, signal clutter and size considerations makes LADAR a preferable choice [2] over normal radar.

In their paper [2], Wijesoma, Kodagoda, and Arjuna P. Balasuriya used two-dimensional (2D) LADAR measurement system as a range-measuring device and extended Kalman filtering to detect and track road curbs. The LADAR data will segmented and filtered for extraction of straight-line features using an extended Kalman filter (EKF) approach. This technique using LADAR is simpler and computationally more efficient compared with the Radar methods. However, the condition requires that the minimum height for the road curb is 25mm. Heavy rain is found to be affecting the performance of LADAR sensing capability.

2.3.3 Camera

A camera is the light sensing element that sense light. It is a device that converts an optical image into electronic signal. There are three types of camera: vidicons, charge coupled devices and Complementary metal–oxide–semiconductor (CMOS) camera. The signals received will be processed with image processing and computer vision techniques. These techniques are implemented in computer software such as C++ and Java™. Mathematical systems have been developed to provide low-level functionality and data visualization schemes before the development of application code. These mathematical softwares are Mathcad, matrix laboratory (MATLAB) and others [16]. Visual sensing with camera is difficult to be applied in robotics applications [12], due to its complexities [8]. For a robot to move autonomously visually will allow great flexibility, and ability to adapt to new environment [17]. Applying vision and the interpretation of vision to robots to carry human tasks in driving vehicle can possibly save lives and cost, and are more efficient. For the past years, vision has been applied in autonomous vehicles. It has been used for road boundary detection [18], or road regions [19].

As shown in the research done by P. Y. Shinzato and D. F. Wolf [20] where camera is used to capture images for road region recognition from image features extracted. Another approach was conducted with camera sensing by Dean A. Pomerleau [21], which use the images captured to make steering decision based on pre-learned images.

Camera, a passive non-invasive sensor [2], has become a popular sensing device used as an automotive road sensor due to its high information content, lower costs and operating power, and absence of a sweep time. However, it is still has difficulty to detect curb under poor illumination, bad weather, and complex driving environments. Shadows, complex driving environments, inconspicuous or missing lane/curb markings, and lower signal-to-noise ratio (SNR) make extraction of road features using vision alone extremely difficult .

2.3.4 Stereo camera

Camera sensing mentioned in previous section provides 2 dimensional images. A further approach known as stereo camera, uses two or more lenses together with separate image sensor. Stereo vision which allows the calculation of disparity or depth information can be used to make 3D images or range imaging [22]. Disparity or depth images can help solve misclassification of near obstacles with similar colours. This can be used for obstacle detection and range measurements, as demonstrated by P. Y. Shinzato and D. F. Wolf [22] with F. S. Osorio who further their previous work using stereo vision to calculate disparity.

2.3.5 Comparison of types of sensors

Table 2.1 shows the comparison of types of sensors used with their advantages, disadvantages and their application. It can be observed that each sensor has its own purpose and capability.

Some sensors like the LADAR is a simple laser range detecting sensor with the ability to measure the distance of a target. With the laser technology it has make unsusceptible to shadows, bad lighting, and dirty road condition. Such sensors however require high computation to extract the information from the signal data. Its disadvantage is also its inability to sense more information content from the road environment, making its implementation limited to relying road curb detection for road recognition. Similar to radar, LADAR have difficulty sensing object like pedestrian or vehicle, and are not really suitable for road detection due to its low information content.

Another sensor used is image sensor of a camera, where it is dependent on the amount of reflected light captured from objects. Thus, it requires good lighting. Camera can capture image in two dimension with high information content but requires complex image processing to extract information from the image. Unlike LADAR, camera cannot measure distance of an object. However, with another additional camera, stereo images can be captured to calculate the disparity. Disparity allows the determination of object distance.

Table 2.1: Comparison of types of sensors

TYPES OF SENSORS	ADVANTAGES	DISADVANTAGES	SUITABILITY
Radar [14]	Works in all weather condition. Good distance detection. Short and long range detection.	Difficult to interpret. Does not detect every object well.	Obstacle detection.
LADAR [2]	High-quality image (1 - 80m) in snow, haze, dust, rain, and is not susceptible to ambient light. Better cost, packaging ease, operating power, signal clutter and size considerations compared to radar.	High computation. Does not detect every object well.	Road curb detection
Camera [18–21]	High information content. Lower costs and operating power, and absence of a sweep time.	Complex image processing. Requires good lighting.	Road recognition
Stereo camera [22]	Obstacle detection and range measurements		Object detection Road curb detection

2.4 Data processing

After acquiring data from the physical conditions of the real world with sensors, often these signals need to be processed according to the need of the system. For example, types of data processing are image processing, speech signal processing, video processing and others. Figure 2.2 shows the flow of a typical data processing process.

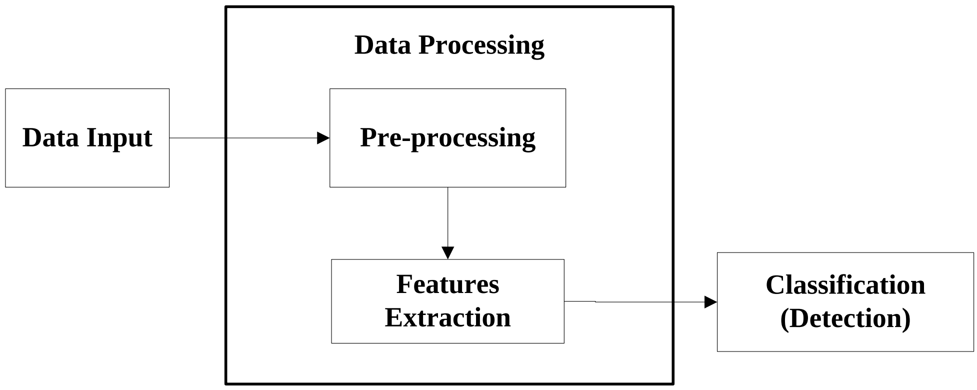


Figure 2.2: Data processing flowchart [18]

The data collected will be pre-processed to produce better images for optimum information extraction later. After pre-processing images, features will be extracted from the pre-processed images. Next, classification or detection of certain information will be done with the image features extracted. This section review the method of data processing done by previous researchers, prior to the training of road recognition.

2.4.1 Image feature extraction

Image feature extraction is applied when a camera is used as sensor. Images captured will be processed to detect and isolate various desired features before it is applied to the algorithms for road recognition.

This paper [18] extracts image features from colour, edge, and height information obtained from a stereo camera to sense the road boundaries. Three types of gradient image will be generated, i.e. colour, intensity and height. The colour gradient image is generated by road region colour model estimation and gradient calculation. The intensity gradient image is generated by applying median filter, Sober filter with Gaussian smoothing to the input image. The height gradient image is generated through the conversion of the input stereo depth image into a height image and differentiate with a Gaussian smoothing. The features extracted will then be processed by weight calculation and particle filter to recognize the road, which will be reviewed in Section 2.5.3.

Another different approach was done by P. Y. Shinzato and D. F. Wolf [20] using statistical measures such as Shannon Entropy, energy, and variance. In their paper, the image is sliced into groups, as shown in Figure 2.3. Each group will be represented by a value such as the average of the Red Green Blue (RGB), entropy and others features. Hue (H), saturation (S) and value for brightness (V), are also taken for the generation of the average, entropy and energy. A block-based classification method is then used to treat and evaluate a collection of pixels directly connected, neighbors, as a group. For example, the classification based in RGB colour space is the weighted average of the pixel occurrence in pixel-block. Each of these block will be used as the inputs for ANN.

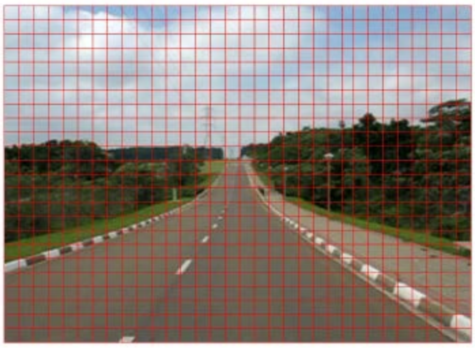


Figure 2.3: Image division in groups [20].

In their later work [22], they modified the method by adding disparity information from images captured with a stereo camera. The stereo camera captures a pair of images which contain a shift between parts of an image that is proportional to the distance of the lens. This enables the depth of a point to be determined. Figure 2.4 shows the canonical system of a camera with two lenses. Referring to point p in left image and point p' in right image. Disparity is the distance between these two points, which will calculated with match algorithm. The calculation of disparity solves misclassification of near obstacles with similar colours. Other extra features used are taken from YCrCb colour channel in addition to RGB and HSV. Y is the luma component and CB and CR are the blue-difference and red-difference chroma components. These features will be used as input of the ANN to identify the road region.

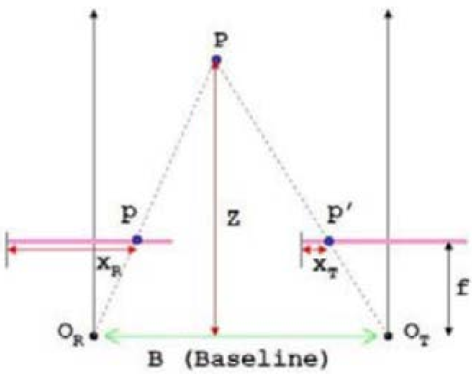


Figure 2.4: Canonical system of a camera with two lenses. **f** is focal length, **B** is the distance between the lens [22]

2.5 Types of algorithms for road recognition

There are various approach to road recognition, from pure mathematical approach, image processing, fuzzy logic, and the artificial neural network. This section review the algorithms used by previous researchers in the study of road recognition for an autonomous vehicle.

2.5.1 Image processing algorithm

This paper [23] presents the use of image processing algorithm for road recognition. The process ranges from re-projecting image, edge detection, determining road curvature, determining road boundaries and road colours. This technique gives good results but longer computing time, which is not suitable for real-time application, but much better when compared to unsupervised classification applied to road following (UNSCARF) and supervised classification applied to road following (SCARF) method. It works in well-structured road.

Another approach [24] that use image processing algorithm for road recognition and object detection, uses process range from remapping, threshold-ding, and superimposed onto the original image. The stereo camera is used only for detecting object that raises out from the road plane. This method was tested successfully on extra-urban roads and freeways with clear road markings.

2.5.2 Kalman filter

Kalman filter is an estimator for the linear-quadratic problem. It is often applied to the control of complex dynamic systems. Its advantages are to be able to infer missing information from indirect and noisy environments, and able to predict the likely future courses of dynamic systems [25].

This paper [2] used the Kalman filtering for fast detection and tracking road curbs using range/bearing readings obtained from a scanning two-dimensional (2D) LADAR measurement system. A laser spot beam will scan from right to left to the road surface. Road surface, curb surface, pavement surface or other types of region is described approximately by a straight line over a small window. A straight-line process model is used to predict the next range data (d_{i+2}) given the past two range measurements (d_i, d_{i+1}) obtained at equal angular separation (see Figure 2.5).

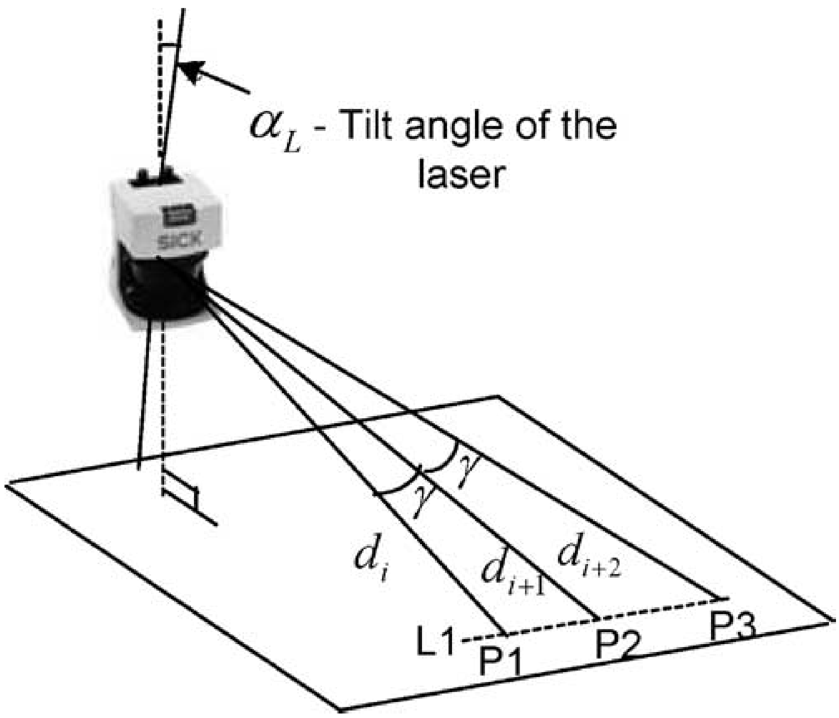
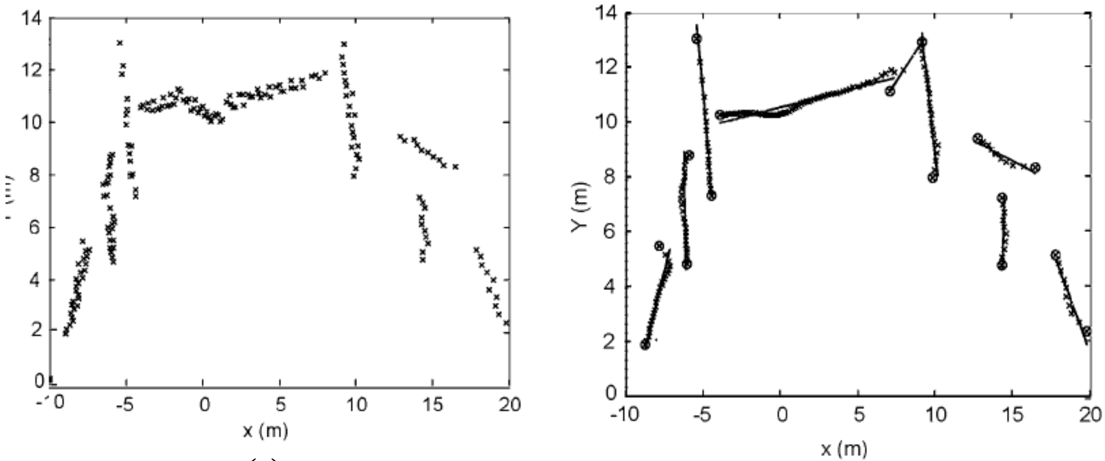


Figure 2.5: Three consecutive laser data points on a flat road surface [2]

The prediction error would be significant from the measured data at the boundary separating two contiguous regions (pavement surface to curb surface). The magnitude of the prediction error will be computed at a particular data point. If the prediction error exceeds a threshold at a particular data point, endpoints of the segment are reached and a new process model will start. Straight lines are then fitted to the segmented data sets. These edge lines are analyzed for possible curbs. The extracted curbs are then tracked using a Kalman-filter-based technique.

Figure 2.6 (a) shows white noise corrupted data sets. The circles indicate start and end of each data segment, as detected by the algorithm. The “x” in Figure 2.6b denotes the filtered data using the Extended Kalman Filter (EKF). Lines are fitted to the segmented collinear sets of data points by using a robust eigenvector technique, shown in Figure 2.6 (b).



(a) (b)

Figure 2.6: Simulation results [2]. (a) Synthetic collinear data, (b) Results of filtering segmentation and line fitting.

2.5.3 Particle filter

Particle filters perform sequential Monte Carlo (SMC) estimation based on point mass representation of probability densities. Particle filters are mostly used in tracking application. Unlike the Kalman filter, it is not limited to a relatively restricted class of linear Gaussian problems [26].

This paper [18] adopts a particle filter where particle represents road hypotheses. After sensor data have been processed, e.g. through image feature extraction and other methods. The processed data will be applied to the particle filter. Figure 2.7 shows the overview of the method. The right side of the figure is the iteration of particle filter, while the left side shows the sensor data processing.

The robot position and road parameters with respect to previous position are represented by the state vector. State vector is consists of robot ego-motion, parameters of the boundaries, local curvature, and the width of the road. The road model are made up of road segments (Figure 2.8). The gaps between the boundaries are then estimated. After normalizing the gradient images, likelihood calculation is made. This is done by taking the averaged gradient value under the mapped boundary of the road model and the gradient image. This transformed averaged value using sigmoid function is the likelihood value. The product of all the likelihood values is the importance weight of a particle. The particle filter transforms a set of particles to another set by robot ego-motion estimate and road model update. To only generate particles when it is likely to approach, the trends of the likelihood values for the intensity gradient, colour gradient, the height gradient, and the direction of the road is examined beforehand.

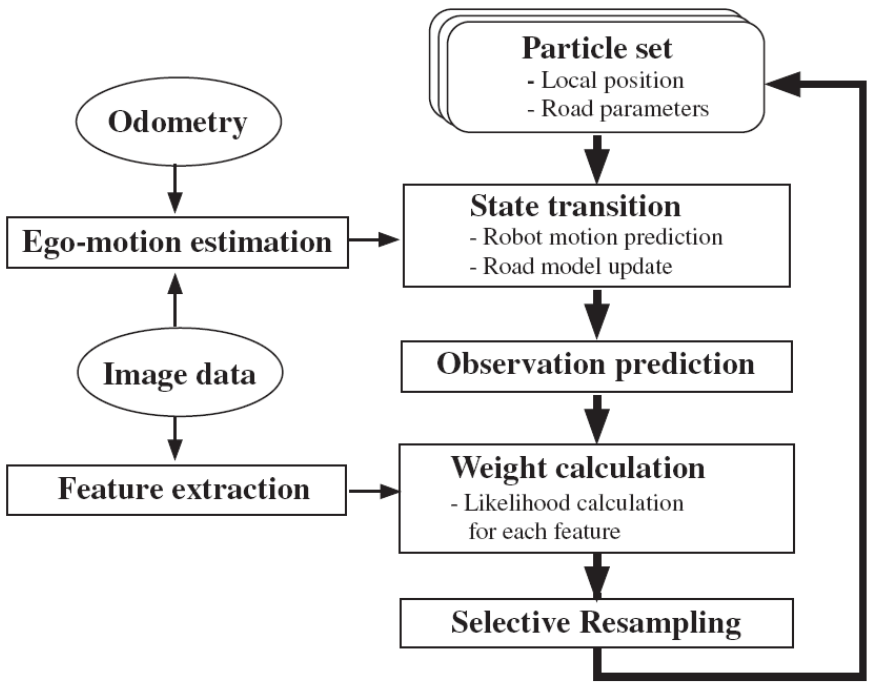


Figure 2.7: Overview of the proposed method [18]

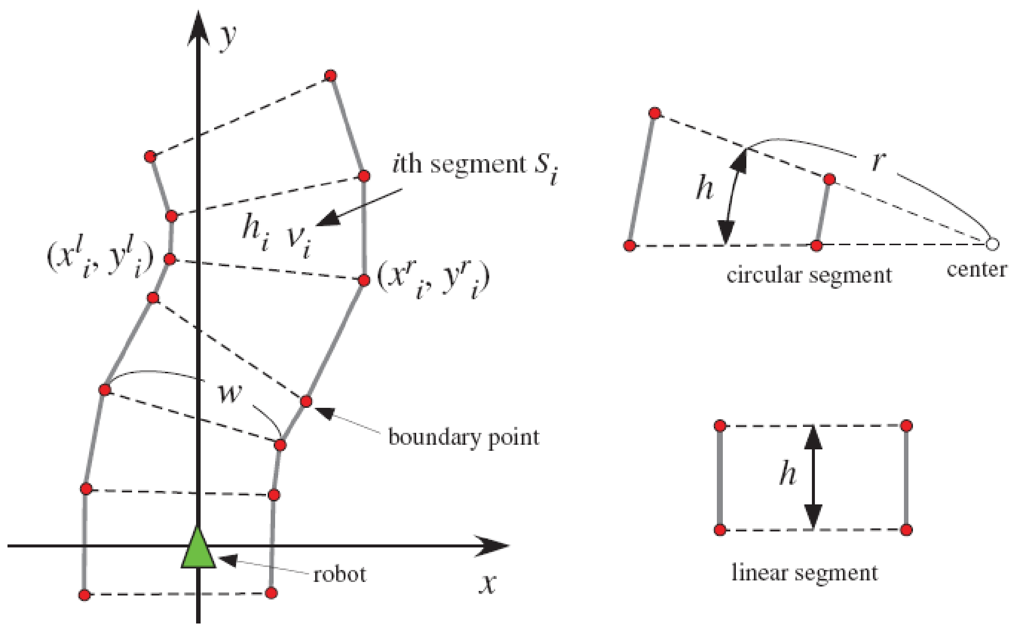


Figure 2.8: A piecewise-linear road model (un-branched road model) [18]

The autonomous robot made up of an electric wheelchair controlled by a laptop PC is tested and the speed is 0.7 m/s [18]. This method using particle filter requires lots of calculation and high computing power, resulting in slow moving autonomous robot. This paper did not have collision prevention. If further works on collision prevention is conducted, consideration of weather and other variables, the system will become much more heavier to run.

2.5.4 Artificial neural network

The ANN is a mathematical model which is inspired by the characteristics of brain function. The advantage of ANN is the ability to be 'taught' and 'learn' from observed data [27]. The basic theory of ANN are reviewed in Section 2.7.

In their paper, P. Y. Shinzato and D. F. Wolf [20] use ANN for road recognition. After extracting the image features, they select few combinations of features to be used as input for the ANN. The ANN model used is a multilayer perceptron (MLP) with back propagation technique. The network used has five neurons in hidden layer and one neuron on the output layer. The input layer depends on the combination of evaluated features. This paper is tested and evaluates different combinations of network topologies in realistic environments. Though results are satisfactory, all the networks had errors at the edges, traffic lane, parking areas, and dirty road.

To solve real world problems that require a degree of flexibility without using hand programmed algorithms, Dean A. Pomerleau [21] introduced a machine learning system, called ALVINN (Autonomous Land Vehicle In a Neural Network). Due to the noise and variability presence in the real world scenes, many image processing and pattern recognition techniques could not fully perform well. Results show that ALVINN networks perform four times faster than sensor-based autonomous system.

ALVINN system is a single hidden layer feedforward neural network (Figure 2.9). The 30 unit output layer linearly represents the currently appropriate steering direction. The "travel straight ahead" condition is represented by the centremost output unit, while the left and right turns are represented by the units to the left and right respectively. The steering command is determined by the centre of mass of activation.

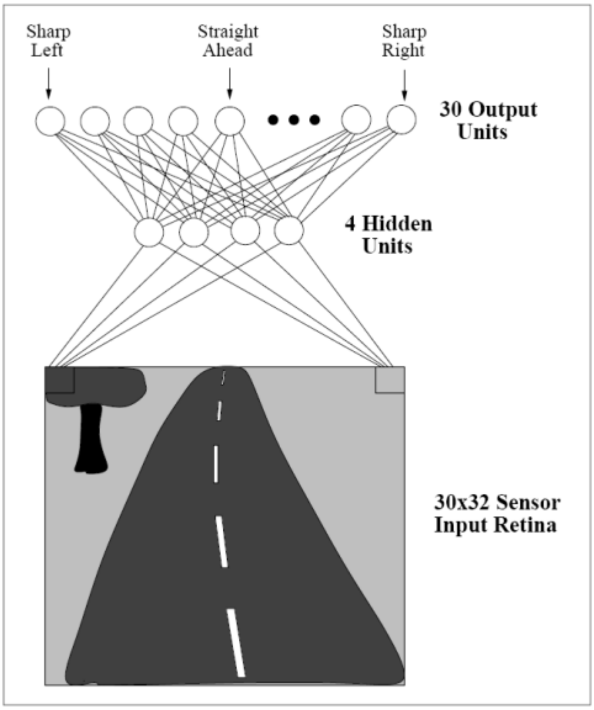


Figure 2.9: Neural network architecture for autonomous driving [21]

The network is trained using the back-propagation learning algorithm. The teaching signal is taken directly from the human driver's current steering direction. The network is carefully being trained with full training data with lots of possible situations. Doing so will need manual input to turn the learning on and off for certain events, and it is time consuming and dangerous to do so on the road. Pomerleau solved these by developing few solutions. Firstly, the images sensed is transformed to create additional training exemplars. After transforming the images, the pixels which is missing are extrapolated. After that, the second step is to transform the steering direction for each of the transformed images. The model used to do the transformation is called pure pursuit steering [28]. The concept of the model is illustrated in Figure 2.10. The radius of the steering arc is $r = \frac{l^2+d^2}{2d}$. The parameter l is the distance ahead of the vehicle to select a point to steer towards. Pomerleau empirically set 2.3 seconds for the vehicle to travel the look ahead distance.

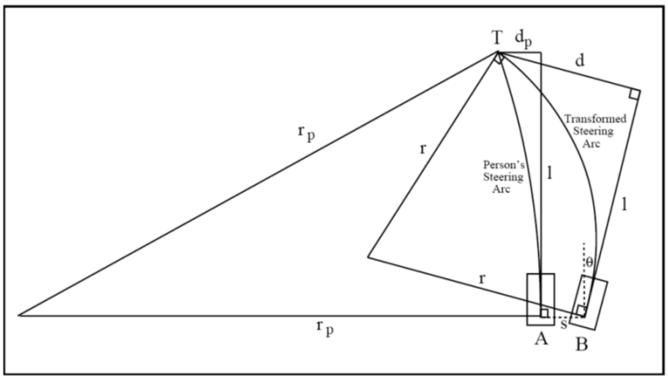


Figure 2.10: Illustration of the pure pursuit" model of steering [21]

Thirdly, to solve the repetitive exemplars, the training set is diversify through buffering. The four techniques include replacing oldest patterns, randomly choose old patterns to be replaced by new ones, replace patterns on which the network was making the lower error, and to add a random replacement probability to all patterns in the training buffer. Lastly, Pomerleau add training details such as the number and magnitude of transformations to use for the training network.

Compare to hand programmed systems where features for the particular driving domain is to be determined, detectors program for finding these features are needed and algorithm needs to be developed to determine the direction, ALVINN saves more time in developing and is more flexible.

The disadvantage of ALVINN is that it could not drive on road types that it has not been trained [22]. Its weakness is in its poor distinction between the road and the non-road, rely heavily on image feature consistently. The network can become erratic and swearing from side to side when face with unfamiliar image.

In their paper [22], P. Y. Shinzato, D. F. Wolf, and F. S. Osorio used image features extracted are then applied to the input of ANN for recognition of road, represented in red squares in Figure 2.11(c). By using ANN, the amount of data can be reduced, and processing and obtaining information like texture from sub-images will become faster. There are total a group of 49 features generated for the inputs of ANN. The selection of features uses "CFS" method. The process is shown in Figure 2.12. Given a pair of images, the disparity is calculated. After that, disparity and colour image are transformed into a set of sub-images that will be classified by ANN. The control of the vehicle is done with a control algorithm.

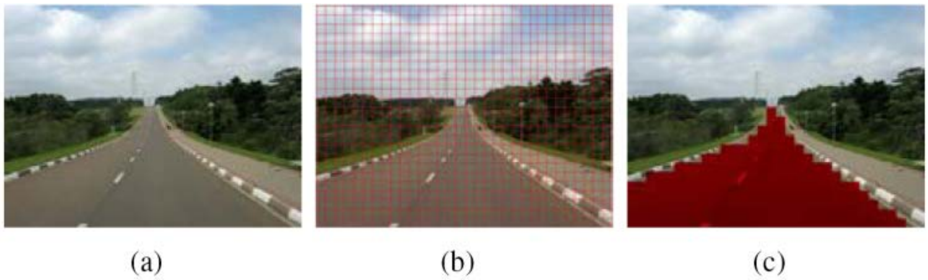


Figure 2.11: Features generation stages [22]. (a) Original image. (b) Image transformed into sub-images. (c) Road classified in red squares.

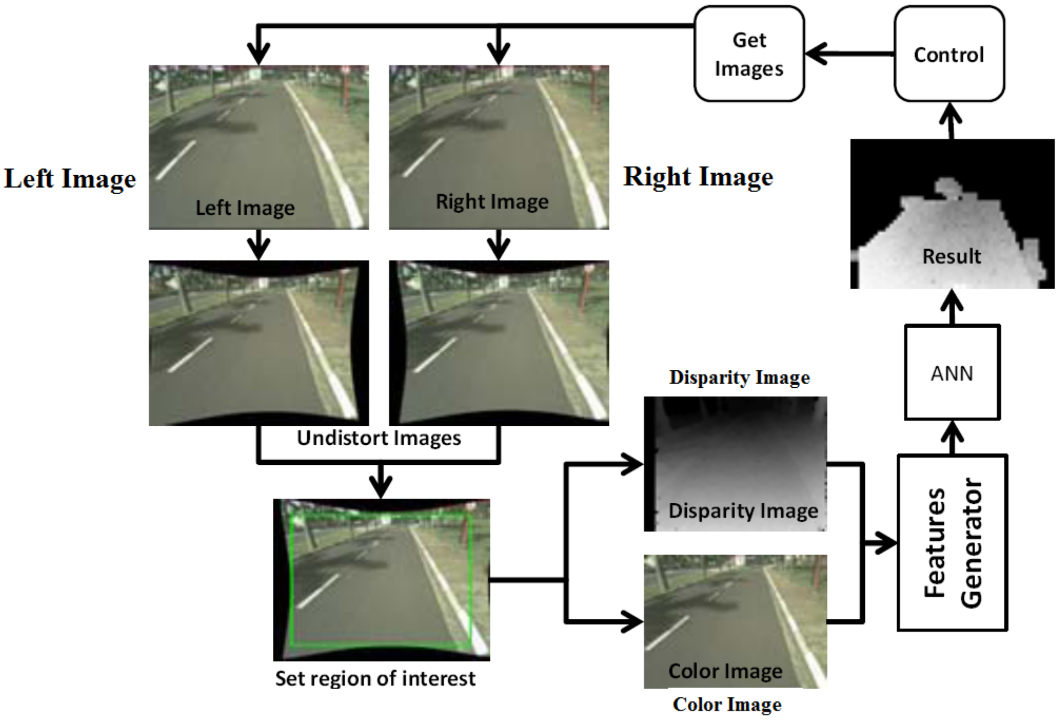


Figure 2.12: The System Architecture [22].

The type of ANN used is a multilayer perceptron (MLP) (Figure 2.13), a feedforward neural network model. The ANN uses some features, not all, to classify the sub-image between belonging to a road class or not. The back propagation technique is used to estimates the weights based on the amount of error in the output compared to the expected results. To evaluate the convergence, "Mean Square Error" ("MSE") and "Hit Rate" metrics are used. A method known as area under a receiver operating characteristics (ROC) curve (AUC) is later used to help define a good precision to interpret the ANN output.

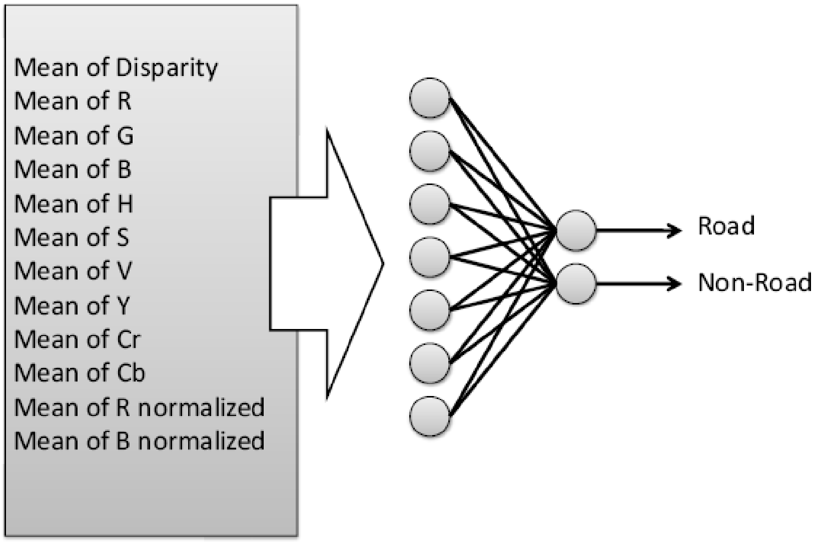


Figure 2.13: ANN topology [22].

Finally the system generate a visual navigation map (VNMap), shown in Figure 2.14 (b), to filter the resulting image with a growth algorithm. Black represents non-road class, white represents road class and the gray represents the intermediate values. Though the system is able to distinguish the road from the sidewalk and other items, small errors were obtained when running on traffic lanes that have very different colours of asphalt. Errors were also accumulated with the loss of accuracy at the edges.

(a) (b)

Figure 2.14: Classification sample [22]. (a) Colour image. (b) Classification results.

Unlike ALVINN, this method does not need to be retrained due to the generalization capacity. ANN is used for road and non-road recognition. The ability to recognize road means training data in variety of roads is no longer required. On the other hand, the vehicle control is achieved with control algorithm, thus eliminating the need for training with human assist and image transformation work to create additional training exemplars.

2.6 Comparison of the types of algorithms for road recognition

Table 2.2 shows the comparison of different type of algorithm, ANN model and other method used for road recognition. Few main different approaches are chosen and organized for this comparison. The table are categorized according to the author, year, type of sensors, type of algorithm used for road recognition, the advantages and the disadvantages.

In road recognition, camera has been the favoured by many researchers. There are other researchers who has used LADAR, a laser range detector to detect road curb and then calculate the road area. It was successfully tested on real road environment, without being affected by leaves, dirt, shadows or by the weather condition. This system comes with a requirement that the road has to have road curb and of a minimum height. Such requirement limits this system mostly to city roads, where roads with curb are mostly found. Camera for image sensing on the other hand, is easily affected by environment's lighting, shadows, weather, bad road condition and inconspicuous markings. This makes its implementation a complex task. Nevertheless, it still produces good results in road recognition with better flexibility. Stereo Camera are sometimes used instead of the usual mono camera due to the ability to extract disparity or depth image from the stereo image it captured.

For the algorithm for road recognition, there has been few main approaches. The use of ANN has been attempt, as shown by ALVINN in the early years. Though successfully tested on real road environment, it can only drive on roads that it has been trained. Other researchers also used ANN for road recognition with good results. Besides ANN, there are also mathematical algorithm such as particle filter, Kalman filter, image processing algorithm and others. Mathematical algorithm has shown good accuracy in road recognition. To implement such algorithm needs high computing capability, which means such approach will slow down the autonomous vehicle, making it currently unsuitable for real-time application.

Table 2.2: Comparison of previous works

AUTHOR	YEAR	SENSORS	AI ALGORITHM / CONCEPT	ADVANTAGES	DISADVANTAGES
Patrick Yuri Shinzato, Denis Fernando Wolf [22]	2011	Stereo Camera	Image feature extraction. a. RGB Colour Spaces b. HSV Colour Spaces c. YCrCb Colour Spaces d. Disparity ANN (multilayer perceptron, back propagation technique).	Tested on roads. Able to distinguish the road from the sidewalk and other items. Calculation of disparity that helped solve misclassification of near obstacles with similar colours.	Small errors when running on traffic lanes that have very different colours of asphalt. Accumulated errors with the loss of accuracy at the edges.
Takeshi Chiku, Jun Miura, Junji Satake [18]	2011	Stereo camera.	Image feature extraction. a. RGB Colour Spaces. b. HSV Colour Spaces Particle filter.	Tested on variety of empty road scenes and conditions.	Heavy computing. Speed of 0.7 m/s.
Patrick Yuri Shinzato, Denis Fernando Wolf [20]	2010	Camera, (320 x 240) pixels with 30 FPS.	Image feature extraction. ANN (multilayer perceptron, back propagation technique).	Tested on paved street, walkways and vegetation. Blue average or hue entropy or saturation entropy obtained better results.	Few errors at the edges, traffic lane, parking areas, and dirty road.
W. S. Wijesoma, K. R. S. Kodagoda, and Arjuna P. Balasuriya [2]	2004	1) Two-dimensional (2-D) Laser Detection and Ranging (LADAR) sensor 2) wheel encoder 3) fiber-optic gyroscope	Extended Kalman filter	Tested on road with minimum curb height of 25mm. System not affected by leaves and dirt on and around the curbs.	System affected by specular reflections cause by water layer. Curb required for road detection.

(Continued) Table 2.2 Comparison of previous works

W. S. Wijesoma, K. R. S. Kodagoda, and Arjuna P. Balasuriya [2]	2004	a. Two-dimensional (2-D) LADAR sensor b. wheel encoder c. fiber-optic gyroscope	Extended Kalman filter	Tested on road with minimum curb height of 25mm. System not affected by leaves and dirt on and around the curbs.	System affected by specular reflections cause by water layer. Curb required for road detection.
Yinghua He, Hong Wang, and Bo Zhang [23]	2004	Camera	Image processing algorithms	Tested on urban traffic road or campus' semi-structured road.	Long computing time. Not suitable for real-time application.
Massimo Bertozzi, and Alberto Broggi [24]	1998	Stereo Camera (Stereo for obstacle detection)	Image processing algorithms	Tested on extra-urban roads and freeways with clear road markings.	Works on flat roads and with clear marking
A. Pomerleau [21]	1996	Camera	Autonomous Land Vehicle In a Neural Network (ALVINN)	Drove in a different roads ranging from single-lane paved and unpaved roads, multilane lined and unlined roads, and obstacle-ridden on- and off-road environments, at speeds of up to 55 miles per hour.	Could not drive on road types that it has not been trained.

2.7 Theory of ANN

Hagan [27] explained that the ANN are inspired by the characteristics of brain function. The brain consists of highly connected elements called neurons. Neurons have three principal components consisting of the dendrites, the cell body and axon. The dendrites carry electrical signals into the cell body. The cell body then sums and thresholds these signals. The produced signal will be carried by the axon from the cell body out to other neurons. The point of connection between neurons is called synapse. The arrangement of neurons and the strengths of the individual synapses, determined by complex chemical process, that establishes the function of the neural network. The simplified diagram of the biological neurons is shown in Figure 2.15 below.

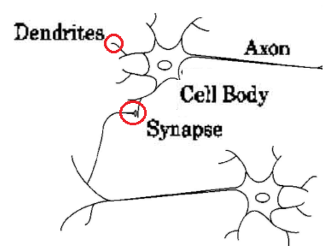


Figure 2.15: Schematic drawing of biological neurons [27]

In mathematical notation, weight *w* corresponds to the strength of a synapse, the cell body is the summation and the transfer function and axon is the neuron output *a*. The architecture of the single-input neuron is shown in Figure 2.16.

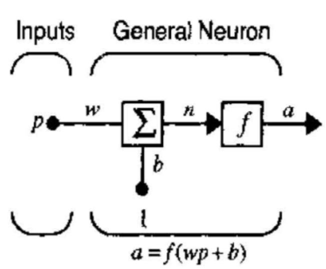


Figure 2.16: Single-input neuron [27].

The neuron output is calculated as

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