

Design and Development of Spherical Camera based Deep Learning Enabled  
Auto Lane Width Measurement for Road Safety Grading System

**TAY CHOON KIAT**



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<b>Tajuk Projek</b>	Design and Development of Spherical Camera based Deep Learning Enabled Auto Lane Width Measurement for Road Safety Grading System						
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Signature : \_\_\_\_\_

Author : Dr. Lim Kim Chuan

Date : 10 July 2017

*For Michelle*

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## ABSTRACT

Design and Development of Spherical Camera based Deep Learning enabled Auto Lane Width Measurement for Road Safety Grading System is a project which provide a system that recognize the road objects using deep learning approach. This project is inspired by the Malaysian government commitment to provide a safer and higher quality road. Malaysian Institute of Road Safety Research (MIROS) funded this project RM100, 000 to develop a system that can used for road survey and road width measurement. Spherical camera is suggested in this project because front facing camera limits the receptive field of the survey video. Deep Learning is famous of their robustness in recognize object. Therefore, this project proposes a new method to recognize the car and road marking and represent it in distinct colors. The predicted lane marking will further be used by lane width measurement. Deep Learning network used by this project is SegNet from University of Cambridge, UK. To suit our application, we further train the model using the spherical images dataset. The final global test accuracy hits 78.9% on spherical video recognition. Road width measurement is accurate when the lane is detected in the bottom area on the video.

## ABSTRAK

Reka dan Pembuatan Pengukuran Kelebaran Jalan Raya dengan teknik Deep Learning untuk Sistem Periksa Jalan dengan Kamera Sfera merupakan projek yang menyediakan satu sistem boleh mengenali jalan dan kenderaaan. Project ini diinspirasi oleh komitmen dan berusaha kerajaan Malaysia yang ingin menjaga keselamatan dan kualiti jalan raya Malaysia. Institut Penyelidikan Keselamatan Jalan Raya (MIROS) menbiayai projek ini sebanyak RM100,000 untuk mencipta satu system yang boleh mengenali kenderaan dan boleh mengukur kelebaran jalan raya. Kamera Sfera dicadangkan dalam projek ini adalah untuk menangkap pandangan yang lebih luas berbandingkan dengan kamera biasa. Teknik Deep Learning ialah satu teknik perisian komputer yang terkenal dalam menganali benda dengan tepat. Oleh demikian, teknik perisian komputer ini digunakan untuk mengenali penanda jalan. Ramalan penanda jalan dari Deep Learning akan digunakan untuk mengukur kelebaran jalan raya. Perisian Deep Learning yang digunakan dalam projek ini bernama SegNet, adalah ciptaan dari University of Cambridge, UK. Untuk mengenali pandangan jalan raya dari kamera sfera, latihan lanjutan bagi SegNet perlu dibuat. Ketepatan ramalan SegNet terhadap gambar kamera sfera dapat 78.9%. Ukuran Jalan raya boleh diselesaikan apabila penanda jalan terdapat di tempat bawah video.



## TABLE OF CONTENTS

<b>ACKNOWLEDGEMENT .....</b>	<b>VI</b>
<b>ABSTRACT .....</b>	<b>VII</b>
<b>ABSTRAK.....</b>	<b>VIII</b>
<b>CHAPTER 1.....</b>	<b>1</b>
<b>INTRODUCTION .....</b>	<b>1</b>
<b>1.1 Project Background and Motivation.....</b>	<b>1</b>
<b>1.2 Objectives.....</b>	<b>5</b>
<b>1.3 Problem Statement.....</b>	<b>5</b>
<b>1.4 Scope of Project.....</b>	<b>5</b>
<b>CHAPTER 2.....</b>	<b>6</b>
<b>LITERATURE REVIEW .....</b>	<b>6</b>
<b>2.1 Lane Detection .....</b>	<b>6</b>
<b>2.2 Convolutional Neural Network .....</b>	<b>8</b>
<b>2.3 Deep Learning on Lane Detection .....</b>	<b>9</b>
<b>2.4 Deep Learning Semantic Segmentation .....</b>	<b>10</b>
<b>2.5 DeepLab .....</b>	<b>11</b>
<b>2.6 Fully Convolutional Network, FCN .....</b>	<b>12</b>
<b>2.7 SegNet.....</b>	<b>13</b>
<b>2.8 Conclusion .....</b>	<b>16</b>
<b>CHAPTER 3.....</b>	<b>17</b>
<b>METHODOLOGY .....</b>	<b>17</b>
<b>3.1 Flowcharts.....</b>	<b>17</b>
<b>3.1.1 Overall flowchart .....</b>	<b>Error! Bookmark not defined.</b>
<b>3.1.2 Dataset Preparation Flowchart .....</b>	<b>Error! Bookmark not defined.</b>
<b>3.1.3 Lane Width Measurement Flowchart .....</b>	<b>Error! Bookmark not defined.</b>
<b>3.1.4 Flowchart Description .....</b>	<b>Error! Bookmark not defined.</b>
<b>3.2 CamVid Dataset .....</b>	<b>21</b>
<b>3.3 Dataset preparation .....</b>	<b>22</b>
<b>3.3.1 Label dataset using MATLAB.....</b>	<b>22</b>

<b>3.4</b>	<b>Operation of each layer in SegNet.....</b>	<b>23</b>
<b>3.4.1</b>	<b>Input layer.....</b>	<b>23</b>
<b>3.4.2</b>	<b>Convolution layer.....</b>	<b>24</b>
<b>3.4.3</b>	<b>ReLU .....</b>	<b>25</b>
<b>3.4.4</b>	<b>Pooling Layer .....</b>	<b>26</b>
<b>3.5</b>	<b>Lane Width Measurement.....</b>	<b>26</b>
<b>3.5.1</b>	<b>Singular Value Decomposition (SVD).....</b>	<b>26</b>
<b>3.5.2</b>	<b>Calibration .....</b>	<b>27</b>
<b>3.5.3</b>	<b>Homography value.....</b>	<b>27</b>
<b>3.5.4</b>	<b>Road Width measurement in Python .....</b>	<b>30</b>
<b>3.5.5</b>	<b>Conclusion.....</b>	<b>Error! Bookmark not defined.</b>
<b>CHAPTER 4.....</b>		<b>31</b>
<b>RESULT AND DISCUSSION .....</b>		<b>31</b>
<b>4.1</b>	<b>SegNet with CamVid dataset.....</b>	<b>31</b>
<b>4.1.1</b>	<b>Training SegNet with CamVid Dataset 20k Iterations.....</b>	<b>32</b>
<b>4.1.2</b>	<b>Training SegNet with CamVid Dataset 40k Iterations.....</b>	<b>32</b>
<b>4.1.3</b>	<b>Prediction on normal video.....</b>	<b>33</b>
<b>4.2</b>	<b>Road Width Measurement using Predicted Road Marking.....</b>	<b>35</b>
<b>4.3</b>	<b>SegNet with spherical images dataset.....</b>	<b>38</b>
<b>4.3.1</b>	<b>Prediction on 360° Spherical Camera using CamVid Dataset..</b>	<b>38</b>
<b>4.3.2</b>	<b>Training SegNet with 500 spherical images dataset .....</b>	<b>40</b>
<b>4.3.3</b>	<b>Prediction on 360° Spherical Camera with 500 Spherical Images dataset</b>	<b>41</b>
<b>4.3.4</b>	<b>Training SegNet with 1000 spherical images dataset.....</b>	<b>43</b>
<b>4.3.5</b>	<b>Prediction on 360° Spherical Camera with 500 Spherical Images dataset</b>	<b>43</b>
<b>4.4</b>	<b>Conclusion .....</b>	<b>46</b>
<b>CHAPTER 5.....</b>		<b>47</b>
<b>CONCLUSION AND RECOMMENDATION .....</b>		<b>47</b>

<b>5.1</b>	<b>Conclusion .....</b>	<b>47</b>
<b>5.2</b>	<b>Recommendation .....</b>	<b>49</b>
	<b>REFERENCE.....</b>	<b>50</b>
	<b>APPENDIX .....</b>	<b>52</b>

**LIST OF TABLE**

<b>TABLE 1.1 PRE-SURVEY CONFIGURATION .....</b>	<b>3</b>
<b>TABLE 1.2 MAIN FEATURES ON THE PROPOSED SYSTEM.....</b>	<b>4</b>
<b>TABLE 2.1 COMPARISON BETWEEN NEURAL NETWORK IN TERMS OF ACCURACY[18].....</b>	<b>16</b>
<b>TABLE 3.1 PLANAR HOMOGRAPHY VALUE IN MATRIX.....</b>	<b>29</b>
<b>TABLE 3.2 PIXEL COORDINATE OF CALIBRATION RIG IN IMAGE.....</b>	<b>29</b>
<b>TABLE 3.3 REFERENCE COORDINATES OF CALIBRATION RIG .....</b>	<b>29</b>
<b>TABLE 4.1 COLOR REPRESENTATION FOR EACH 12 CLASSES IN CAMVID DATASET .....</b>	<b>32</b>
<b>TABLE 4.2 COLOR REPRESENTATION FOR EACH 10 CLASSES IN SPHERICAL IMAGE DATASET .....</b>	<b>38</b>

## LIST OF FIGURE

<b>FIGURE 1.1 MIROS ROAD SURVEY CAR .....</b>	<b>2</b>
<b>FIGURE 1.2 PROPOSED ROAD SURVEY CAR .....</b>	<b>2</b>
<b>FIGURE 1.3 PROPOSED SYSTEM BLOCK DIAGRAM.....</b>	<b>3</b>
<b>FIGURE 2.1 IPM ILLUSTRATION[6] .....</b>	<b>7</b>
<b>FIGURE 2.2 IPM SAMPLE[6].....</b>	<b>7</b>
<b>FIGURE 2.3 ARCHITECTURE OF ALEXNET[9].....</b>	<b>8</b>
<b>FIGURE 2.4 LANE BOUNDARY GROUND TRUTH[10].....</b>	<b>9</b>
<b>FIGURE 2.5 EXAMPLE OF OBJECT CLASSIFICATION IN SEMANTIC SEGMENTATION[11] .....</b>	<b>10</b>
<b>FIGURE 2.6 DEEPLAB MODELLING ILLUSTRATION[17] .....</b>	<b>11</b>
<b>FIGURE 2.7 ILLUSTRATION OF FCN MODEL[14] .....</b>	<b>12</b>
<b>FIGURE 2.8 SEGNET ARCHITECTURE, INPUT AND OUTPUT[18] .....</b>	<b>13</b>
<b>FIGURE 2.9 COMPARISON OF PERFORMANCE BETWEEN SEGNET AND OTHER SEMANTIC SEGMENTATION NETWORKS[18].....</b>	<b>15</b>
<b>FIGURE 3.1 OVERALL PROJECT FLOWCHART .....</b>	<b>18</b>
<b>FIGURE 3.2 DATASET PREPARATION FLOWCHART.....</b>	<b>19</b>
<b>FIGURE 3.3 LANE MEASUREMENT FLOWCHART .....</b>	<b>20</b>
<b>FIGURE 3.4 SEGMENTATION TRANSFORMATION FROM VIDEO FRAME TO SEGMENTATION.....</b>	<b>21</b>
<b>FIGURE 3.5 THE 360CAM FRAMES FOOTAGE .....</b>	<b>22</b>
<b>FIGURE 3.6 LABEL IMAGE ON MATLAB USING LIBLABEL.....</b>	<b>23</b>
<b>FIGURE 3.7 SEGMENTED DATASET, GROUND TRUTH .....</b>	<b>23</b>
<b>FIGURE 3.8 ILLUSTRATION OF CONVOLUTION LAYER.....</b>	<b>24</b>
<b>FIGURE 3.9 RELU ILLUSTRATED IN GRAPH .....</b>	<b>25</b>
<b>FIGURE 3.10 ILLUSTRATION OF MAX POOLING OPERATION .....</b>	<b>26</b>
<b>FIGURE 3.11 CALIBRATION RIG IN CALIBRATION IMAGE.....</b>	<b>ERROR!</b>
BOOKMARK NOT DEFINED.	
<b>FIGURE 3.12 MATRIX COMBINE PIXEL COORDINATES AND REFERENCE COORDINATES .....</b>	<b>28</b>
<b>FIGURE 4.1 TRAINING LOSS &amp; TEST ACCURACY VS. ITERATION (MAX. 20K ITERATION) .....</b>	<b>32</b>

<b>FIGURE 4.2 TRAINING LOSS &amp; TEST ACCURACY VS. ITERATION (MAX. 40K ITERATION)</b> .....	<b>33</b>
<b>FIGURE 4.3 INPUT FRAME (SEGNET + CAMVID DATASET)</b> .....	<b>34</b>
<b>FIGURE 4.4 OUTPUT FRAME (SEGNET + CAMVID DATASET)</b> .....	<b>34</b>
<b>FIGURE 4.5 INPUT FRAME BEFORE SEGNET INFERENCE</b> .....	<b>37</b>
<b>FIGURE 4.6 SEGNET INFERENCE WITH THE ROAD WIDTH MEASUREMENT</b> .....	<b>37</b>
<b>FIGURE 4.7 SPHERICAL INPUT FRAME (SEGNET + CAMVID DATASET)</b> .....	<b>39</b>
<b>FIGURE 4.8 SPHERICAL OUTPUT FRAME (SEGNET + CAMVID DATASET)</b> .....	<b>40</b>
<b>FIGURE 4.9 TRAINING LOSS &amp; TEST ACCURACY VS. ITERATION (MAX. 40K ITERATION)</b> .....	<b>41</b>
<b>FIGURE 4.10 SPHERICAL INPUT FRAME (SEGNET + SPHERICAL 500 IMAGE DATASET)</b> .....	<b>42</b>
<b>FIGURE 4.11 SPHERICAL OUTPUT FRAME (SEGNET + SPHERICAL 500 IMAGE DATASET)</b> .....	<b>42</b>
<b>FIGURE 4.12 TRAINING LOSS &amp; TEST ACCURACY VS. ITERATION (MAX. 80K ITERATION)</b> .....	<b>43</b>
<b>FIGURE 4.13 SPHERICAL INPUT FRAME ON HIGHWAY (SEGNET + SPHERICAL 1000 IMAGE DATASET)</b> .....	<b>44</b>
<b>FIGURE 4.14 SPHERICAL OUTPUT FRAME ON HIGHWAY (SEGNET + SPHERICAL 1000 IMAGE DATASET)</b> .....	<b>44</b>
<b>FIGURE 4.15 SPHERICAL INPUT FRAME TOWN AREA (SEGNET + SPHERICAL 1000 IMAGE DATASET)</b> .....	<b>45</b>
<b>FIGURE 4.16 SPHERICAL OUTPUT FRAME TOWN AREA(SEGNET + SPHERICAL 1000 IMAGE DATASET)</b> .....	<b>46</b>

## CHAPTER 1

### INTRODUCTION

This chapter will discuss about the project background and motivation, objectives, problem statement and the scope of the project.

#### 1.1 Project Background and Motivation

Road Assessment Program (RAP) established in 2000 by Europe Automobile Association to enhance road safety in developing and under-develop countries. International RAP (iRAP), an umbrella organization setup to promote the consistency of implementation of RAP globally[1]. Malaysia was selected as pilot country for iRAP in Asia region as Malaysia government's commitment on road safety. At year 2007, there were total 3600km of Malaysian road been surveyed. This survey led by Malaysia Institute of Road Safety Research (MIROS), JKR, JKJR, AAM, sponsored by UK charity organization FIA Foundation for Automobile and Society while the equipment were provided by RAPs members[2]. The system being used in 2007 shown in Figure 1.1 consists of 3 cameras facing in front road, a GPS module, and some other sensors. was not perfect and several improvements can be made, for example survey video quality and field angle of the survey video. There are limitations of this system, camera field only cover road in the front, road survey officer need to measure the lane manually using computer software.

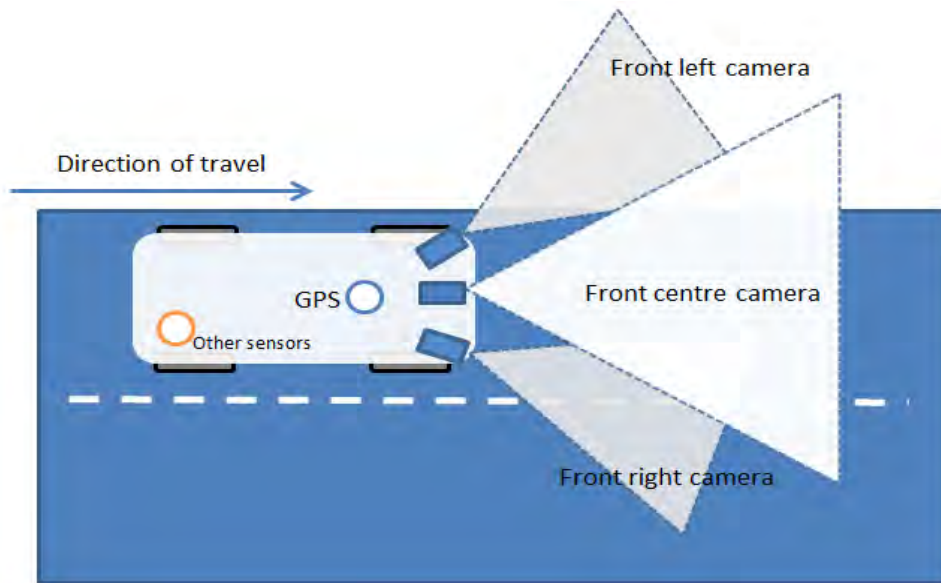


Figure 1.1 MIROS Road Survey Car

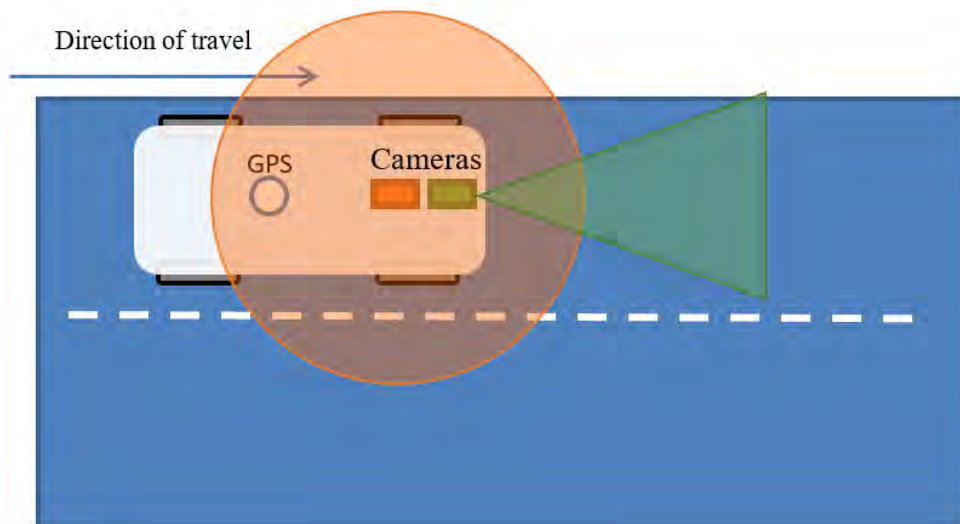


Figure 1.2 Proposed Road Survey Car



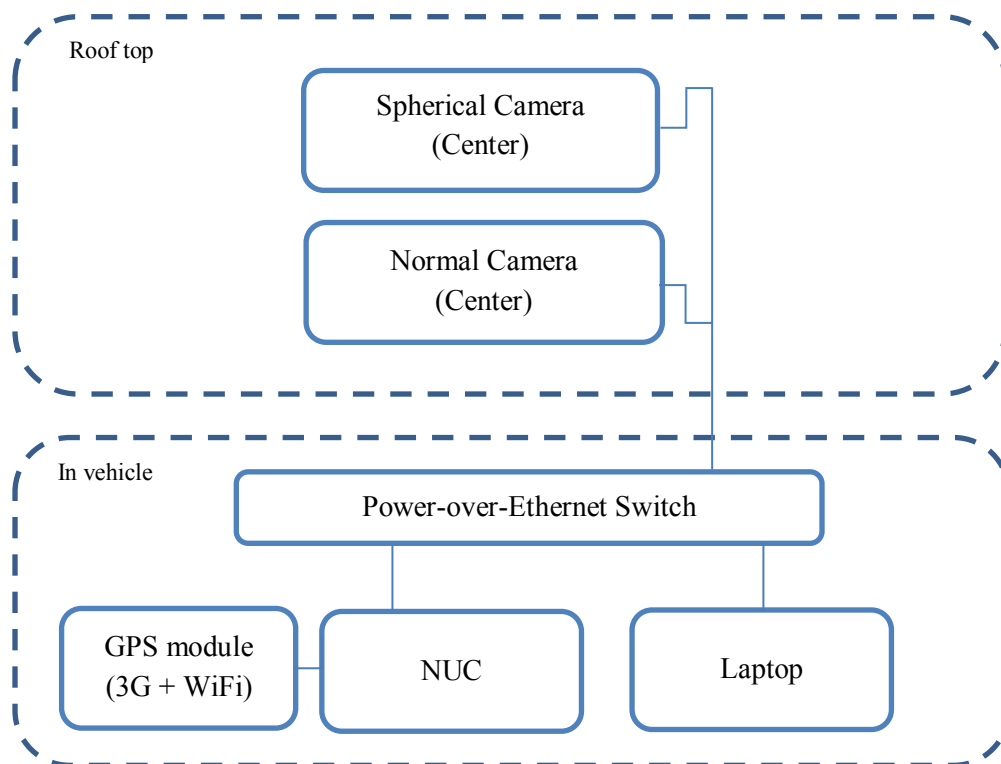


Figure 1.3 Proposed system Block Diagram

Table 1.1 Pre-survey configuration

Features	Detail
Highly portable camera mounting	Each of the roof top cameras is mounted with suction cup for easy install and portability.
Horizontal camera calibration module	The planar homography for subsequent lane width measurement is calibrated and recorded.
Power-over-Ethernet(PoE) connection	Spherical and normal camera will be powered by PoE network switch. Videos will be recorded to laptop connected to the switch.
Survey driver and route configuration	Detail of the survey vehicle driver and detail of the route to be surveyed is saved via the provided by GUI.

Table 1.2 Main features on the proposed system

Features	Detail
Road object recognition	Predict and present the road objects in different colour according to its class in video.
Lane width measurement	Measure the lane width by using the predicted road marking in the predicted frame.

Figure 1.3 shows the proposed system improved over the current MIROS road survey vehicle in Figure 1.1. In Figure 1.2 the green color rectangular block is the normal camera while orange color rectangular block is the spherical camera and the green triangle and orange circle indicate the field of view respectively. However, the field of view in Figure 1.1 and Figure 1.2 just for illustration purpose and no exact angle and distance. From Figure 1.3, the block diagram clearly shows the camera is mounted on top of the survey vehicle roof using vacuum suction cup. While the other equipment for the recording video footage such as laptop and network switch are placed in the vehicle for better management. Table 1.1 shows the preparation to take before every survey and Table 1.2 shows the main features of this proposed system.

For road survey purposes, road in front of the survey vehicle can only capture certain but not all road scene in the video. This limits the possibilities of road survey study. 360° spherical camera provides no blind spot to capture objects on the road. While the normal camera captures a higher definition and quality footage is suitable for predicting the road marking which is further needed in lane width measurement.

Deep learning is an artificial intelligence subset that mimics the neurons function in human brains. Deep learning is chosen for road object detection and road marking detection because of its robustness of various environment recognition. For example, the survey is done at Malacca but applicable in other cities. There are many approaches proposed by others but might be susceptible by the different ambients

The whole project is funded by MIROS with RM100, 000.

## 1.2 Objectives

- To evaluate the accuracy of existing deep learning based Road Scene Recognition CNN model.
- To further train the identified CNN model for better accuracy with spherical camera imaging.
- To automate the lanes width measurement with the result of deep learning.

## 1.3 Problem Statement

The conventional visual recognition methods for road mark detection required manual parameter, image processing parameters thresholding and hand tuning kernel. The hand tuning kernel are susceptible for environment lighting changing and occlusion.

A sustainable visual recognition method able to recognize multiple objects (lane detection, vehicle classification, pedestrian detection), with auto kernels tuning for successful visual recognition for road safety star rating is needed.

## 1.4 Scope of Project

- To test and validate the design and develop of lane marking measurement for common Malaysia road (1 to 4 lanes)

## CHAPTER 2

### LITERATURE REVIEW

This chapter will discuss about the related work done by other researchers.

#### 2.1 Lane Detection

Automating driving may help reduce this huge number of human fatalities. One useful technology is lane detection which has received considerable attention since the mid-1980s[3]. Techniques used varied from using monocular[4] to stereo vision [5]. Most of the techniques were focus on detection of lane marking on highway. Recently, Inverse Perspective Mapping (IPM) technique is used in lane detection for top-view of the image, and the image is filtered using selective Gaussian spatial filters that optimized to detects vertical lines[6]. Figure 2.1 shows how IPM theory illustration while Figure 2.2 is an example of IPM warping a picture from monocular to bird eye view.

RANSAC paradigm is also a famous technique used to get high accuracy and robust lane detection system, where it used to get the parameter of the hyperbola-pair model to detect the lane boundaries[7].

Another lane detection method are proposed by using active contour which providing a framework for parameterizing 2D curves along the image boundaries while balancing global smoothness constraints and local image features[8].

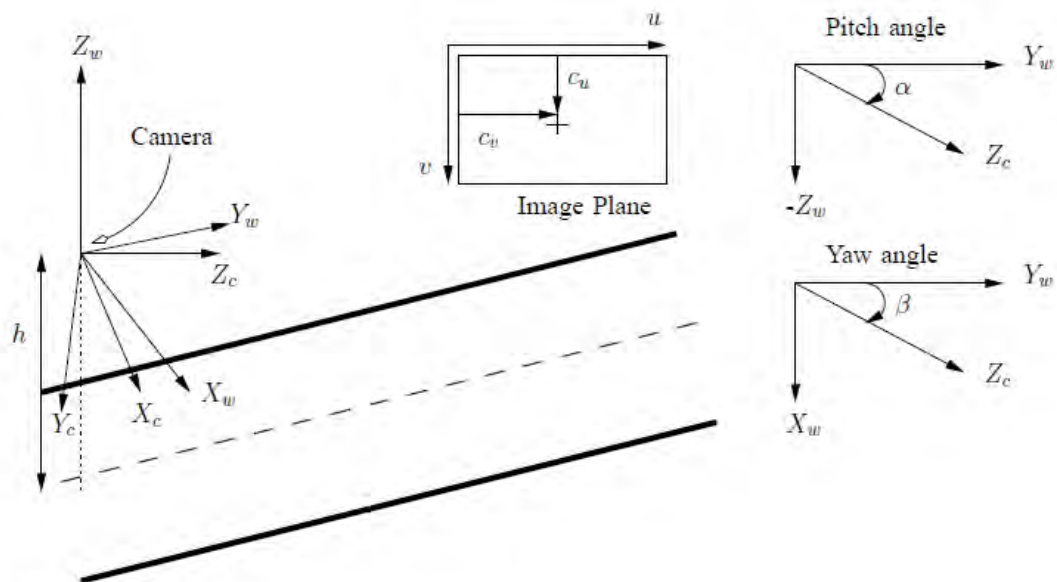


Figure 2.1 IPM illustration[6]



Figure 2.2 IPM Sample[6]

## 2.2 Convolutional Neural Network

Convolutional Lane detection is an operation that detect lane as the target object and outline the edge or highlight explicit road marking which detected or predicted. Current approaches to object recognition make essential use of machine learning methods. To improve their performance, we can collect larger datasets, learn more powerful models, and use better techniques for preventing overfitting[9]. In 2012, the state-of-the-art object recognition convolutional neural network (CNN) AlexNet won the ImageNet Large Scale Visual Recognition Competition 2012 by a significant margin, where the error rate of only 15.3% compared to 26.2% achieved by the second-best entry[9]. The distinct architecture of AlexNet considered “Deep” as it consists more than two convolutional neural network. Figure 2.3 shows the architecture of AlexNet, 5 convolutional layer, 3 Fully-Connected Layer and 1000 nodes of Softmax layer (Recognize 1000 different object). In machine learning term, the more dataset will produce better accuracy[9]. Dataset that trained on AlexNet contain 15 million labelled high resolution images and divided into 22,000 categories.

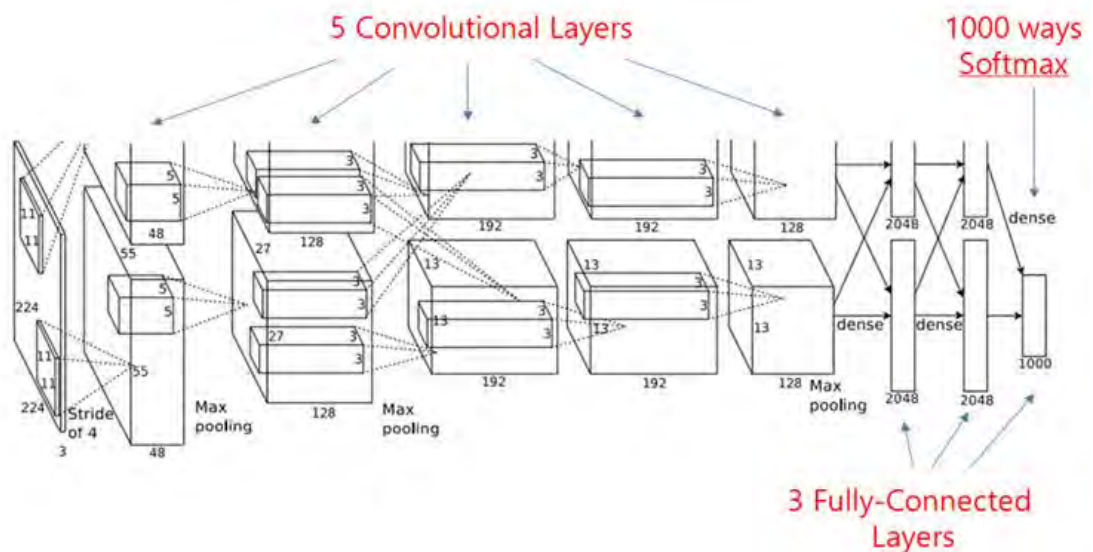


Figure 2.3 Architecture of AlexNet[9]

### 2.3 Deep Learning on Lane Detection

Deep convolutional neural networks are normally called “Deep Learning”. Since deep learning is well proven good performance of object detection and recognition, there are numerous groups have applied deep learning technique to computer vision problem in highway perception scenarios[10]. Advanced-driver assistance system (ADAS) and LIDAR are good performance piece of equipment to detects the lane on road, however the price is very expensive. On the other hand, deep learning based computer vision approach provide a robust solution on lane detection.

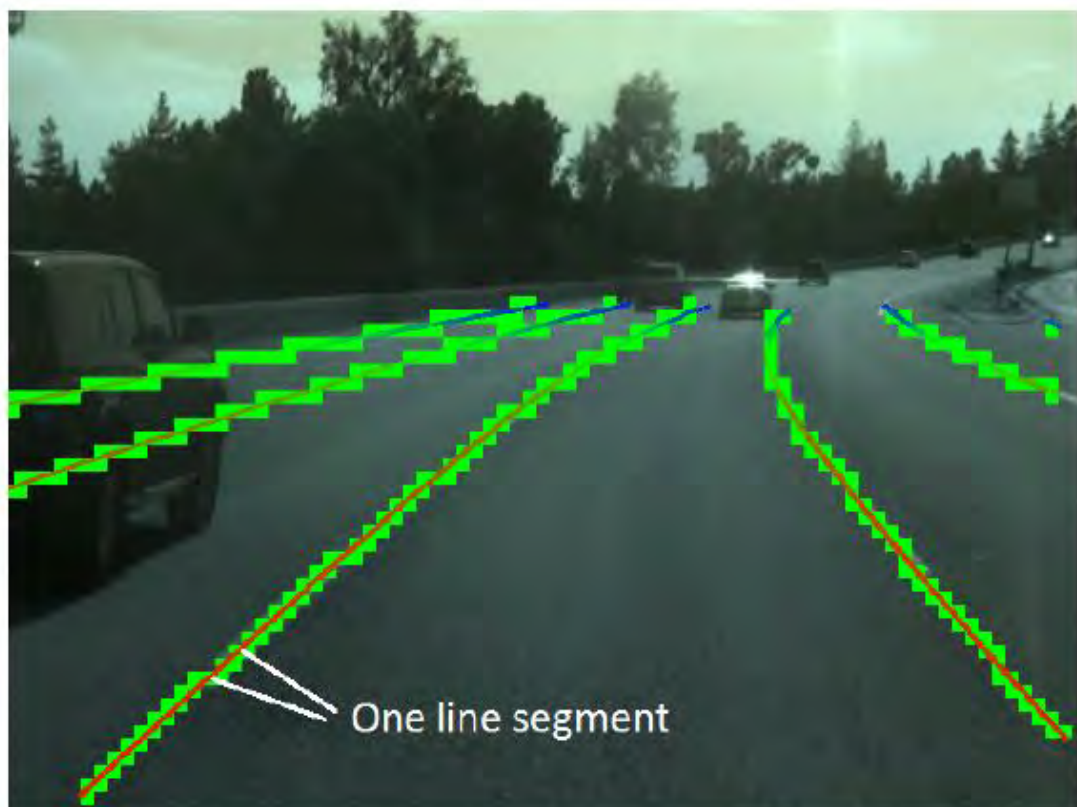


Figure 2.4 Lane boundary ground truth[10]

In Figure 2.4, the lane boundary ground truth label overlaid on an example image. The green tiles indicate locations where the detector is trained to fire, and the line segments represented by the regression labels are explicitly drawn. The line segments have their ends connected to form continuous splines. The depth of the line segments is color-coded such that the closest segments are red and the furthest ones are blue[10].

## 2.4 Deep Learning Semantic Segmentation

For road safety survey, lane detection alone is far from achieving the survey purpose. To teach computer to understand the road scene is the key to advance road surveying system. Scene labelling consists in labelling every pixel in an image with categories of the object belongs to[11].



Figure 2.5 Example of object classification in semantic segmentation[11]

Figure 2.5 shows the result of the Farabet Group[11] approach on semantic segmentation object classification. These are the result from proposed multiscale convolutional network and a flat Conditional Random Field (CRF).

The main idea is to use a convolutional network[12]operating on a large input window to produce label hypotheses for each pixel location. The first two layers of the network are composed of a bank of filters of size  $7 \times 7$  followed by tanh units and  $2 \times 2$  max-pooling operations. The last layer is a simple filter bank. The filters and pooling dimensions were chosen by a grid search. The input image is transformed into YUV space, and a Laplacian pyramid is constructed from it. The Y, U and V channels of each scale in the pyramid are then independently locally normalized, such that each local  $15 \times 15$  patch has zero-mean and unit variance. For these experiments, the pyramid consists of 3 rescaled versions of the input ( $N = 3$ ), in octaves:  $320 \times 240, 160 \times 120, 80 \times 60$ . The network is then applied to each 3-dimension input map  $X_s$ . This input is transformed into a 16-dimension feature map, using a bank of 16 filters, 10 connected to the Y channel, the 6 others connected to the U and V channels. The second layer transforms this 16-dimension feature map into a 64-dimension feature map, each map being produced by a combination of 8 randomly selected feature maps from the previous layer. Finally, the 64-dimension feature map is transformed into a 256-