*Research Report

Vision-Based Road Detection for Autonomous Intelligent Vehicle

UIAM 0000389

Project Leader: Prof. Dr. Othman O. Khalifa

Department of Electrical and Computer Engineering

Kulliyyah of Engineering

International Islamic University Malaysia

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ABSTRACT

Increasing safety and reducing road accidents is one of the primary interests of Advanced Driver Assistance Systems. Apparently, among the complex and challenging tasks of future road vehicles is road lane detection or road boundaries detection. The problems are inherent in lane detection which includes the localization of the road, the determination of the relative position between vehicle and road, and the analysis of the vehicle's heading direction. One of the principal approaches to detect road boundaries and lanes is by using vision-based systems on the vehicle. However, lane detection is a difficult problem because of the varying road conditions that one can encounter while driving. In this project, a vision-based lane detection approach capable of reaching real time operation with robustness to lighting change and shadows is presented. The system acquires the front view using a camera mounted on the vehicle then the developed pre-processing phase in which data is subjected to grayscale conversion, noise removal, edge detection with automatic thresholding to obtain the edges. Next, lines are extracted using Hough transform within a restricted search area and a lane boundary scan uses this information to return a series of points on the right and left side which are representing the lines or boundaries of the road. Finally, a pair of hyperbolas is fitted to these data points to represent the lane boundaries. The proposed lane detection system can be applied on both painted and unpainted road as well as curved and straight road in different weather conditions. The system is implemented on MATLAB2010 using the Prosilica GX1910 Gigabit Ethernet camera. This approach was tested and the experimental results show that the proposed scheme is robust and fast enough for real time requirements.

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

In the last few decades a great deal of research in the domain of transport systems has been conducted to improve the safety conditions by the entire or partial automation of driving tasks. Among these the road detection which took an important part in driving assistance systems that provides information such as lane structure and vehicle position relative to the lane. However, there are many areas in which vehicles has to follow a road autonomously could be deployed for humanitarian or economic benefit.

The main objective of the intelligent transportation systems (ITS) that integrates the technology to achieve the fully automating or partially automating driving tasks such as, following the road and keeping within the correct lane, regulating the vehicle speed in accordance with current traffic conditions, planning a route to arrive at a desired end location from a known starting location and detecting obstacles in the vehicles path and reacting to such obstacles. One of the main technologies involves in these takes computer vision which become a powerful tool for sensing the environment and has been widely used in many applications by the intelligent transportation systems (ITS).

Road lane detection is considered as one of the most challenging tasks in the field of autonomous vehicles (AV) using computer vision. There are a number of techniques have been suggested using different methodologies and achieving diverse detection rates. In the mean time, the challenge is to design a system that works for variety of environmental situations which may disturb the process of detection such as the presence of other vehicles on the same lane occluded partially the road markings ahead of the vehicle (M. C,1998). or the presence of shadows caused by trees, buildings, or in other situations such as weather changing in terms of rain fogy or sunny. Despite the fact that millions of people are driving their vehicles daily but fully autonomous driving system in not commercially presented.

1.2 PROBLEM SIGNIFICANCE

The most compelling reason for adding autonomous capability to vehicles is to ensure the safety requirement. Many lives were lost due to vehicle roadway accident therefore vehicle crashes remain the leading cause of accident death and injuries in Malaysia and Asian countries claiming tens of thousands of lives and injuring millions of people each year. Most of these transportation deaths and injuries occur on the nation's highways. Currently, approximately 90% of all traffic accidents are caused by driver error. The United Nations has ranked Malaysia 30th among countries with the highest number of fatal road accidents, registering an average of 4.5 deaths per 10,000 registered vehicles.

1.3 MOTIVATION

The scenario of accident types in Figure 1.1 shows the type of accident that should be avoided using road lane detection system. In the first accident type (a) unintentional lane departure to the left or right road boundaries may lead to deadly accident due to the driver drowsiness or sleepiness, and in the (b) type the vehicle is entering a curved road too fast which will cause the vehicle to lose its balance on the road ,in the (c) and (e) types the vehicle is going out of the road path due to the unawareness or driving in high speed or not clear vision for instance at night may lead to a bad accident as well ,regulating the vehicle speed is one of the objectives of the autonomous vehicle system and it is out of our scope in this thesis ,one of the most dangers action that normally happen on the single lane road is described in (d) when the vehicle moves to the other vehicle road which is going to crash both vehicles in head .Finally in (f),(g),(h) accident types the driver is moving to the other lane in multiple lane road which may cause the crash with the other vehicle in the same road or collagen with the infrastructure. In most of the previous scenarios the accident is going to be deadly. Therefore, the road lane detection system is going to give a great help and support to drivers on the road and decreasing the vehicle accident on the road as much as possible.

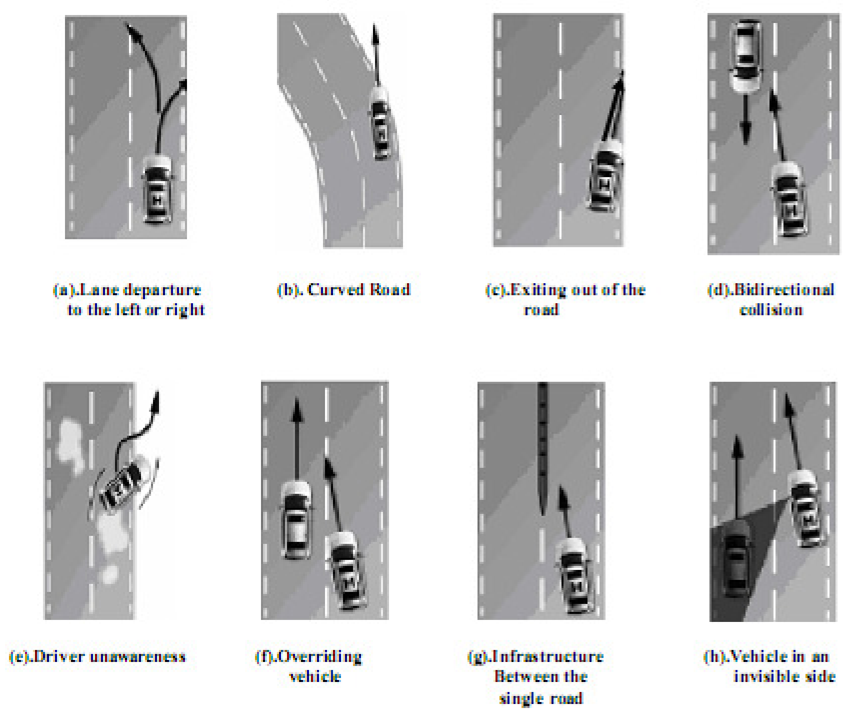


Figure 1.1- Road accident types

1.4 PROBLEM STATEMENT

There are some complexities that face the road lane detection system, which comes from several aspects. First, the system should be performed in real time; it requires efficient algorithms and high performance hardware. In addition, the complex outside conditions should be considered which include lighting (day, night) shadow reflections on the lane due to trees or building near by the lane, other type of noise (other vehicle or motorbike hiding the lanes) and different weather (sunny, rainy, foggy, etc) conditions all these factors are crucial issue that will be hindrances in detecting the road lanes.

1.5 PROJECT OBJECTIVES

In order to tackle the problem statement, the main objectives of the project are defined:

1. To develop an algorithm for efficient and effective road lane detection that can be used in an intelligent vehicle in real time applications.

2. To design a low cost lane detection algorithm based on video sequences taken from camera mounted in a vehicle.

3. The system must be capable to achieve high accuracy detection in different environment condition (Sunny, Cloudy, Raining) in the presence on noise on different road structure (Straight, Curvy) road. In addition, these conditions are evaluated during day and night period.

4. To simulate and test each processing step of the algorithm individually under different environmental conditions, and how efficiently could achieve the task.

5. To evaluate the overall performance of the system experimentally, and how robust is the system comparing to other systems developed.

CHAPTER 2

THEORETICAL BACKGROUND

2.1 COMPUTER VISION

Computer vision is the science and technology that gives a machine the ability to process and understand the view facing it. The organization of a computer vision system is highly application dependent. Some systems are stand-alone applications which solve a specific measurement or detection problem while other constitute of a sub-system for a larger design which for example, a system that contains sub-systems for control of mechanical, planning, information databases, man-machine interfaces, etc. Therefore, a vision system also has sub-systems that are processed in order to get to the final result. Figure 2.1 shows the diagram of typical vision system for road lane detection which consists of several stages from capturing the image to processing stage which is the most important stage, then the output stage either by screen display the detection or fully controlling the vehicle.

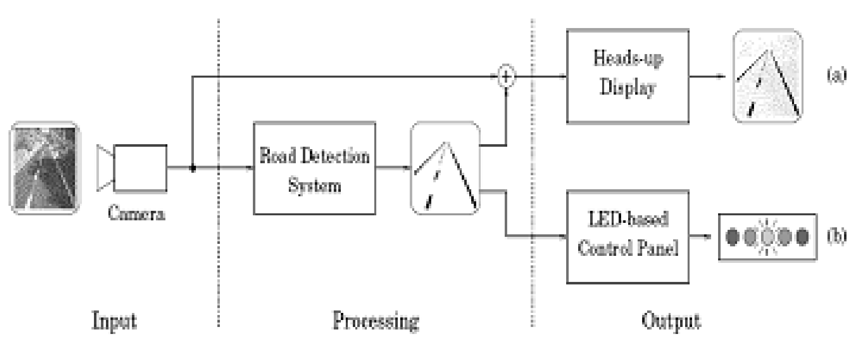


Figure 2.1- Typical vision system for road detection.

A majority of image processing applications concern the detection and recognition and they are typically consist of three subsequent parts: image acquisition, image data processing, and image understanding, as it is shown in Figure 2.2.The specific implementation of a computer vision system also depends if its functionality as pre-specified or if some part of it can be learned or modified during these subsequent functions in order to get the desired result from system over all.

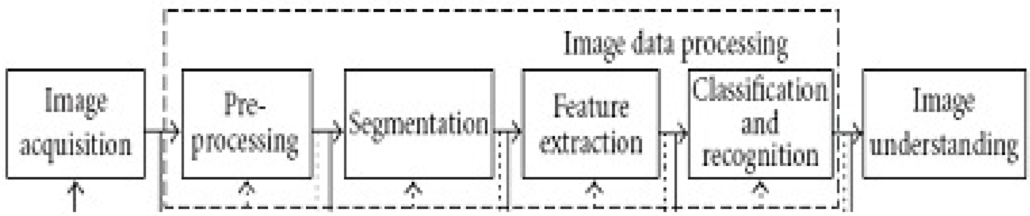


Figure 2.2- Vision system operations.

The accuracy of the final results is highly depending on the efficient of the output from the sub-sequence function.

2.2 RELATED WORK

In most modern systems (third-generation systems), feature-based approaches are used for road detection. This feature is derived by the detection of edges in the image and the organization of edges into meaningful structures lanes or lane markings (P. Charbonnier, 1998). Meaningful edges of the video image are located at a certain distance apart, in order to fit the lane-width model. GOLD system (M. Bertozzi, 1998) detects lane markings through a horizontal (linear) edge detector and enhances vertical edges via a morphological operator. A similar approach is used in (W. Kasprzak, 2001) for auto-calibration of the camera module to detect edges which are possible road boundaries. While the LANA algorithm (C. Kreucher, 1999) was based on novel set of frequency domain features that captures relevant information concerning the magnitude and orientation of possible road geometry for fitting in simple linear models (DA. Pomerleau, 1996). In general, feature driven approaches are highly dependent on the methods used to extract features and they suffer from noise effects and irrelevant feature structures.

In some approaches, windows of interest (WOIs) are determined dynamically by means of statistical methods. For example, the system developed at LASMEA selects the proper window according to the current state and previously detected WOIs (R. Chapuis, 2001). A system developed by the Robert Bosch GmbH research group, employs a model both for the road and the vehicle's dynamic to determine the road portion that most likely to find lane markings (J. Goldbeck, 1998). Similarly, a preliminary version of the lane detection system developed at The Ohio State University Center for Intelligent Transportation Research and also a system developed at The University Blaise Pascal relies on a polynomial curve to estimate road boundaries within a window (KA. Redmill, 1997). These approaches seem more robust and can deal with the noise present in most road detection scenarios. Furthermore, due to the limited search space, they operate faster and can thus achieve real-time operation.

2.3 OPEN ISSUES AND CHALLENGES

From an analysis of current literature and modern road detection modules for driver assist systems, the following open issues and challenges can be identified:

I. Location of the Camera: In case of most systems, the camera needs to be placed high on the top of the roof inside the vehicle. This serves two purposes

1. View of the camera increases with its distance from the ground.
2. The captured frame will be clearer in order to detect the road lanes.

II. Traffic Conditions: When the traffic is free flowing, vehicles are well separated. In this case, lane detection and tracking is relatively easy. When traffic is moving slowly, vehicles travel close to each other resulting into more occlusion events performance of most of the systems degrade in such situations.

III. Number of Lane: The lane marking on the road are different from one place to another, some roads with only two lanes but there is another with four or six lanes, so we must ensure what type of lane are we working on.

IV. Moving Shadows: Moving cast shadows of vehicles result into two or more vehicles merging into a single foreground object, thus reducing the accuracy of the system.

V. Lighting Conditions: Different algorithms are required for daytime and nighttime. And this factor is one of the most important one because once we deal with a vision system when we approach the detection phase the thresholding level is not easy to be implemented in different lighting condition.

VI. Weather Conditions: Reflection of the headlights on a wet road results into wrong lane detection counts. In case of a rain, segmenting the foreground becomes more difficult.

Many of these open issues and challenges are hoped to be overcome using the algorithm proposed and implemented in this project.

CHAPTER 3

ALGORITHM IMPLEMENTATION

3.1 PROPOSED ALGORITHM

In the proposed system, a camera is fixed on the front windshield to capture the road scene. The proposed algorithm which is shown in Figure 3.2, first converts the image to a grayscale. Next, due to the presence of noise in the image, the Finlayson-Hordley-Drew (FHD) algorithm is applied to make edge detection more accurate. After this, the edge detector is used to produce an edge image by a threshold canny filter. The edge image sent to the line detector after detecting the edges which will produce the right and left lane boundary segments. The projected intersection of these two line segments is determined and is referred to as the horizon.

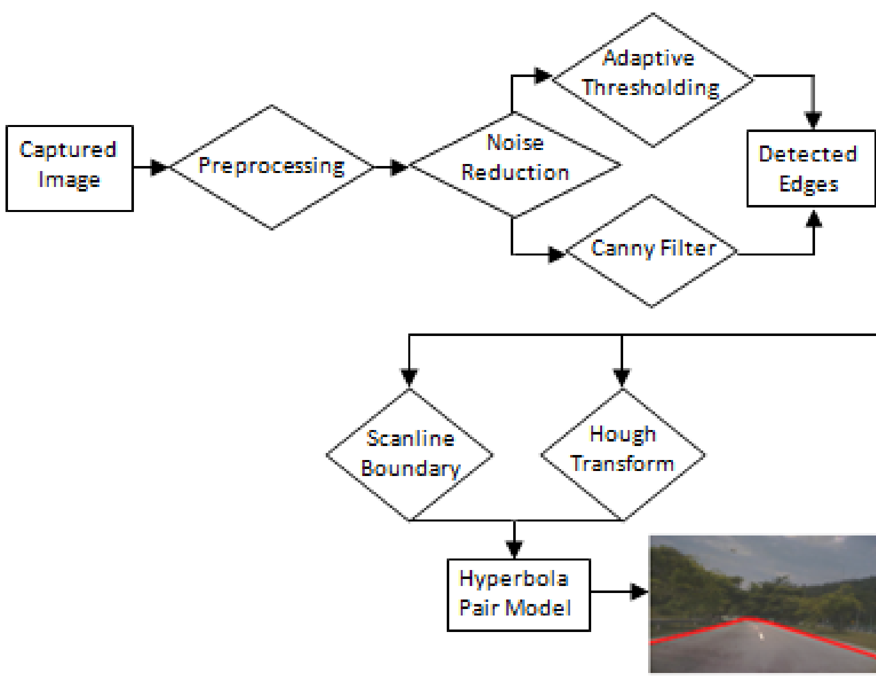


Figure 3.1- Overview of proposed algorithm.

The lane boundary scan uses the information in the edge image detected by the Hough transform to perform the scan. The scan returns a series of points on the right and left side. Finally, a pair of hyperbolas is fitted to these data points to represent the lane boundaries. For visualization purposes the hyperbolas are displayed on the original color image.

As presence of noise in our system will affect edge detection, noise removal is very important. The F.H.D. algorithm has been shown to remove strong shadows from a single image. The basic idea is that since shadows have a distinguished boundary, removing the shadow boundary from the image derivatives and reconstructing the image should remove the entire shadow. Lane boundaries are defined by sharp contrast between the road surface and painted lines or some type of non-pavement surface and obviously form edges in the image. Thus, a Canny edge detector was employed in determining the location of lane boundaries and its output is shown in Figure 3.3.

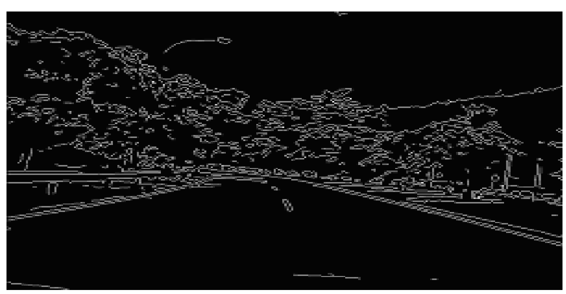


Figure 3.3- Canny edge detection.

The line detector used is a standard Hough transform that limits the search space to 45° for each side as shown in Figure 3.4. The rationale behind this restriction is that lane boundaries rarely ever approach lower angles such as a horizontal line. Further, the input image is split in left and right halves, with the horizon line being formed by the intersection of the lines detected in the sub-images.

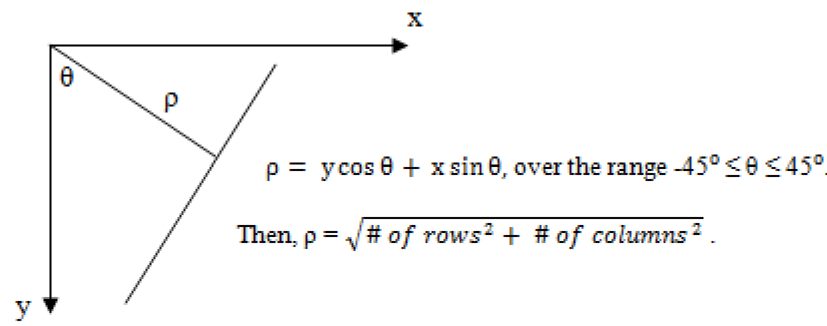


Figure 3.4- Restricted Hough Transform.

The lane boundary scan phase uses the edge image the Hough lines and the horizon line as input as shown in Figure 3.5. The scan begins at the bottom of the image, where the projected Hough lines intersect the image border. From this starting point, the search begins a number of pixels towards the center of the lane and looks for the first edge pixel within a certain distance. This occurs iteratively until reaching the centre of the image. An extra buffer zone of the search will help facilitate the following of outward curves of the lane boundaries.

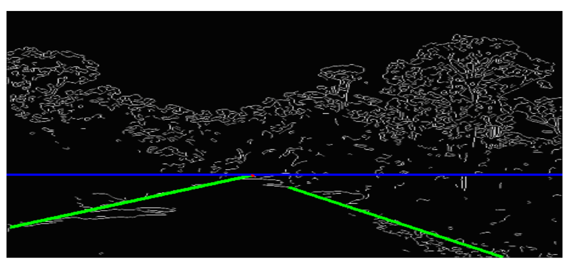


Figure 3.5- Horizon line and search area.

A method (Q. Chen, 2006) has been devised for determining and estimating the lane boundaries of a road by assuming that the lane boundaries themselves were pairs of hyperbolas in the left and right sub-images. The developed algorithm from the hyperbola-pair model (K. Kluge, 1994) helps to solve a specified hyperbola-pair described by Eq. 1, passing through point (*u, v*) in the image plane where the horizon line is h, with eccentricity k and curvature $b^{(l)}$ and $b^{(r)}$ for the left and right hyperbola pairs respectively.

$$u = \frac{k}{v-h} + b^{(l)}(v-h) + b^{(r)}(v-h) + h \tag{1}$$

Since the interpolation needs to be done for a large number of points, this model is cast into matrix form as in Eqs. (2)-(4) and solved numerically using a least squares technique. Convergence of the solutions will be the best proof of a correctly identified hyperbola-pair as both hyperbolas are on the image, and are thus assumed to have the same eccentricity and curvature.

$$\bar{A}\,\bar{X} = \bar{B} \tag{2}$$

$$\bar{A} = \begin{bmatrix} \dfrac{1}{v_i{}^{(l)} - h} & v_i{}^{(l)} - h & 0 & 1 \\ \dfrac{1}{v_{i+1}{}^{(l)} - h} & v_{i+1}{}^{(l)} - h & 0 & 1 \\ \dfrac{1}{v_i{}^{(r)} - h} & 0 & v_i{}^{(r)} - h & 1 \\ \dfrac{1}{v_{i+1}{}^{(l)} - h} & 0 & v_{i+1}{}^{(r)} - h & 1 \end{bmatrix} \tag{3}$$

$$\bar{X} = [k \quad b^{(l)} \quad b^{(r)} \quad c]^T \tag{4}$$

$$\bar{B} = [\,u_1{}^{(l)} \dots u_m{}^{(l)}, \qquad v_1{}^{(r)} \dots v_m{}^{(r)}]^T \tag{5}$$

The model parameters will be found after Eq. 2 has been solved iteratively for all edge pixels that were detected in the left and right sub-image from the restricted Hough transform.

3.2 IMPLEMENTATION

The system was implemented in real-time on MATLAB 2010Ra with the Image Acquisition toolbox using the high data rate GX1910 Prosilica camera, on a Sony Vaio laptop with Intel Core 2 Duo (2.8GHz) Processor and 6GB RAM (Figure 3.6). For offline processing, the camera can be interface directly to the laptop through the driver files and the Prosilica MATLAB 2010Ra adaptor.

However, for real-time processing in the car, a power inverter was used – Belkin AC Anywhere 300W – in order to provide a power supply for the camera inside the vehicle (Figures 3.7, 3.8).

Figure 3.6- Equipment set up for development.

Figure 3.7- Calibrating camera for real-time experimenting.

Figure 3.8- Calibrating camera for real-time experimenting.

All raw and processed video was recorded while the algorithm was working in real-time at highways and normal roads, with dashed markings; and straight and curved roads in different environmental conditions.

CHAPTER 4

EXPERIMENTAL RESULTS AND ANALYSIS

4.1 OUTLINE

This section demonstrates some of the tested image sequences that are able to highlight the effectiveness of the proposed detection system. These experimental results are obtained using the proposed detection algorithm that has been discussed in Chapter 3. The proposed algorithm includes image capturing, Conversion to Gray Scale, Noise Reduction, Edge Detection, Line Detection, Lane Boundary Scan and Hyperbola Fitting.. It has been tested with many off-line and real-time image sequences containing a moving vehicle. These experiments were carried out on traffic scenes, taken on highways and normal roads under different weather conditions. A number of different experiments were conducted as outlined in the following sections.

4.2 EXPERIMENT 1: IMAGE RESOLUTION, PROCESSING TIMES AND DETECTION RATE

The image resolution is one of the important factors, in such kind of implementation. Increasing the image resolution or decreasing it may affect the overall performance. Therefore, we decided to investigate the lowest resolution at which a road lane detection system still can achieve acceptable performance. The results are given in Table 3.1. The results are plotted in Figure 3.9 illustrating the impact of the resolution of the image on the processing speed, which found that the processing time is increasing slightly from 1 to 5 and at the point 6 the processing time is increasing sharply, for that reason we can say that we can select one of the points from 1 to 5 as shown in Figure 3.9, but we have to keep in mined that the lower resolution is going to make some of the image features not clear and that will be a drawback on the performance. Therefore, we investigate the sensitivity of the detection part depending on different image resolution as listed in Table 3.1. The most important standard indication is that with a higher resolution, the image looks better, and the road boundaries should also look clearer. Therefore, we experimentally tested the image sequence in different resolution levels and we found that the best performance could be achieved with the 640x 480 pixels as shown in Figure 3.10.

Table3.1- Image resolution and processing times and accuracy.

NO	**Input Image resolution**	**Processing Time**	**Detection rate**
1	128 by 128	20ms	65%
2	160 by 160	26ms	69%
3	314 by 235	33ms	73%
4	448 by336	38ms	87%
5	640 by480	46ms	89%
6	800 by600	1.1s	94%
7	1024 by768	1.8s	96%

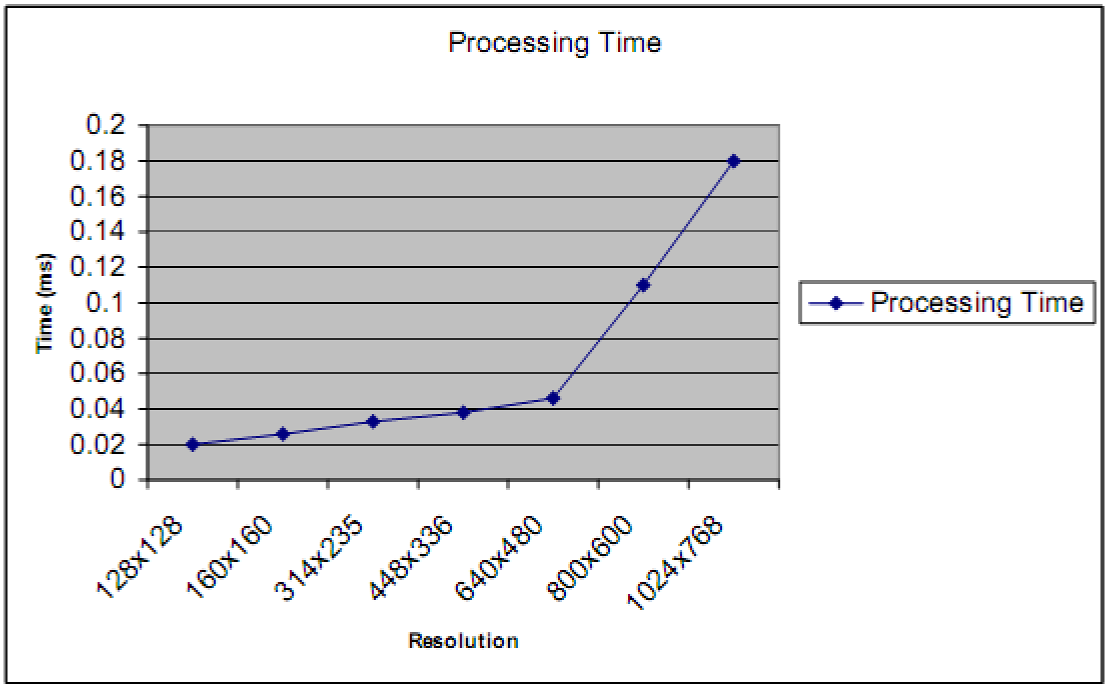


Figure 3.9- Image resolution and processing time.

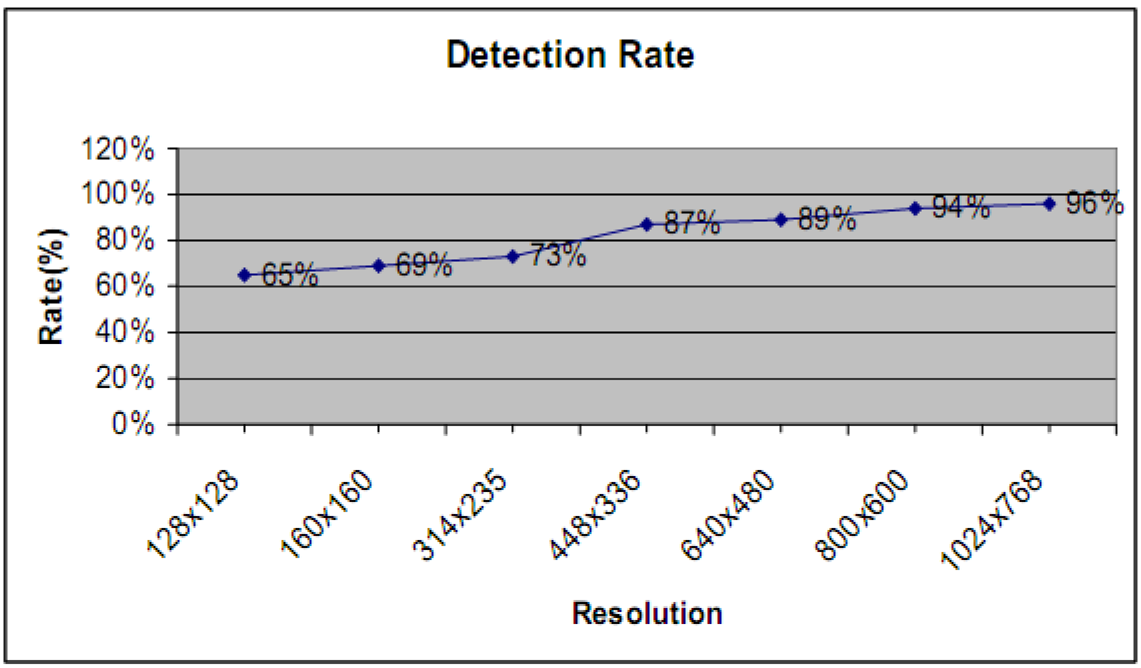


Figure 3.10- Image resolution and detection rate.

4.3 EXPERIMENT 2: NOISE REMOVAL

In this experiment we have tried to test few noise removal methods but the problems again some of these methods takes along time to remove the noise with will effect the over all performance. A high accuracy system with low error rate is required because in this work the clear image with lower noise is best input for the next phase and which will make the edge detection simpler. The frames were selected in a way that covers all possible conditions like different positions of the lanes on the road, different time of the day. The accuracy for the noise removal is shown in Table 3.2 and 3.3.

Table 3.2- Noise removal during day.

Road Type	Day			
	Frames	Success	Fail	Accuracy
Highway	120	102	18	85%
Single Lane	120	110	10	91.6%
Multi Lanes	120	97	23	80.8%

Table 3.3- Noise removal during night.

Road Type	Night			
	Frames	Success	Fail	Accuracy
Highway	120	94	26	78%
Single Lane	120	100	10	83.3%
Multi Lanes	120	81	39	67.5%

4.4 EXPERIMENT 3: RESTRICTED HOUGH TRANSFORM FOR DIFFERENT ROAD TYPES AND CONDITIONS

One essential part of the algorithm as discussed in Chapter 3 and outlined in some literature in Chapter 2 is the use of a restricted search technique to reduce the data processing time. In our proposed algorithm, the Restricted Hough Transform was used and its performance evaluated for different road types and conditions. The Hough line transformation computes the two most likely lines in the image and labels these two lines as the lane boundaries. It is assumed that the two lines discovered will be in the general lower left-hand and lower right-hand portion of the image and that if extended infinitely they will converge on a point roughly halfway up the image of the lane is calculated from the two extended line segments. This approach has given a great impact on the line detection results comparing to the preliminary results. The results as shown in Figure 3.11 shows that the detecting lines using this approach under different road structure such as smaller size line marking segment or dashed lane markings were good and even in congestion roads the lines were detected with a high accuracy rate. Figure 3.12 gives the corresponding detection rates during night.

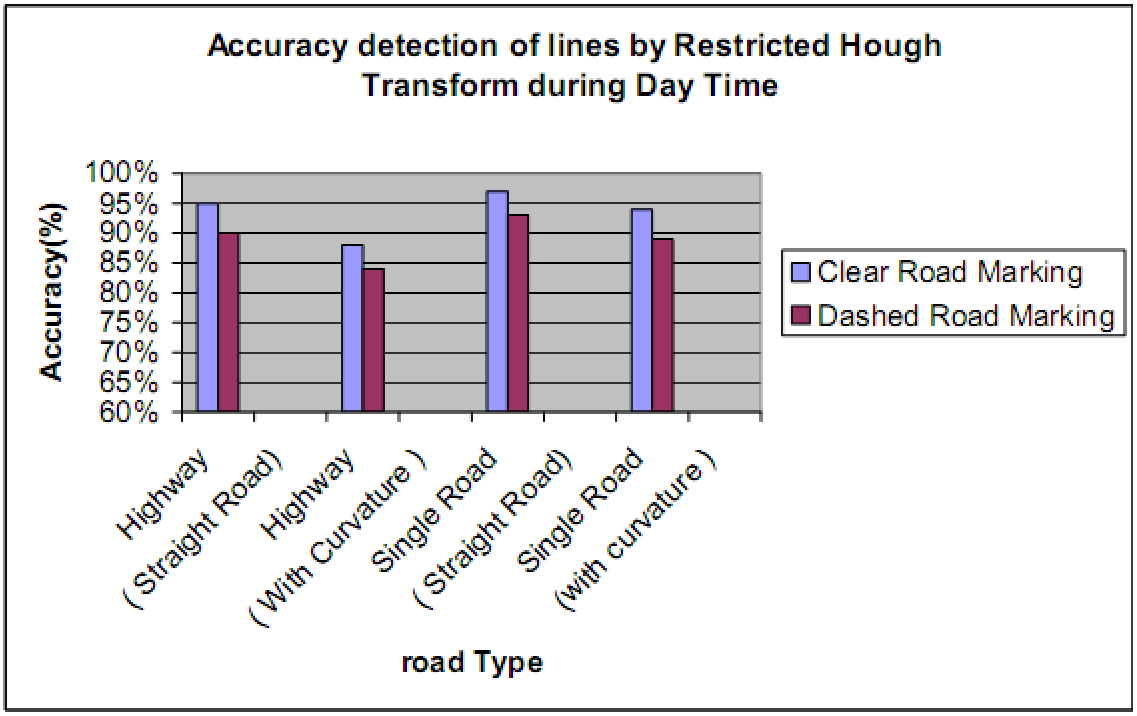


Figure 3.11- Restricted Hough Transform accuracy during day.

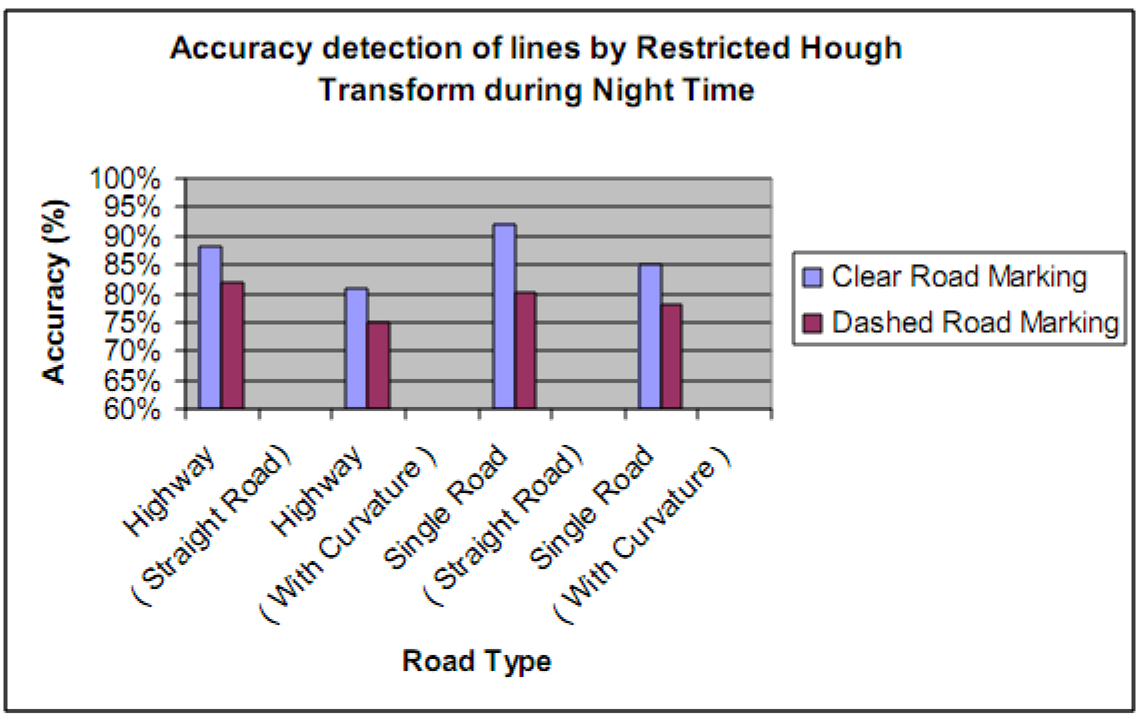


Figure 3.12- Restricted Hough Transform accuracy during night.

4.5 EXPERIMENT 4: WINDOW SIZE AND ACCURACY

Even after the Restricted Hough Transform is used to limit the search area, a window needs to be used in order to determine the closest pixels that will be processed and analyzed near the horizon line. This window size will also impact the accuracy of the algorithm, as certain candidate lines may be lost if they do not fall within the window. Thus, we ran a small experiment to determine the optimal window size within the restricted search space and the results are shown in Figure 3.13. The efficiency reaches its highest point when window size increase up to 20 achieving a rate of 89% in a single lane road and 91% is achieving in multiple road lane using 25 pixel window size. The lowest rates obtained using 5 window size where the average rate is 57% in a single lane, and 37% in multiple lanes and this is due to is small window size. Similarly, using bigger window size is not advisable as we can see that the average rate in a single lane using 30 pixel window size is 60%, and 55% at multiple lanes. Therefore, using 20 pixel window size is the best to be used to achieve the highest point detection.

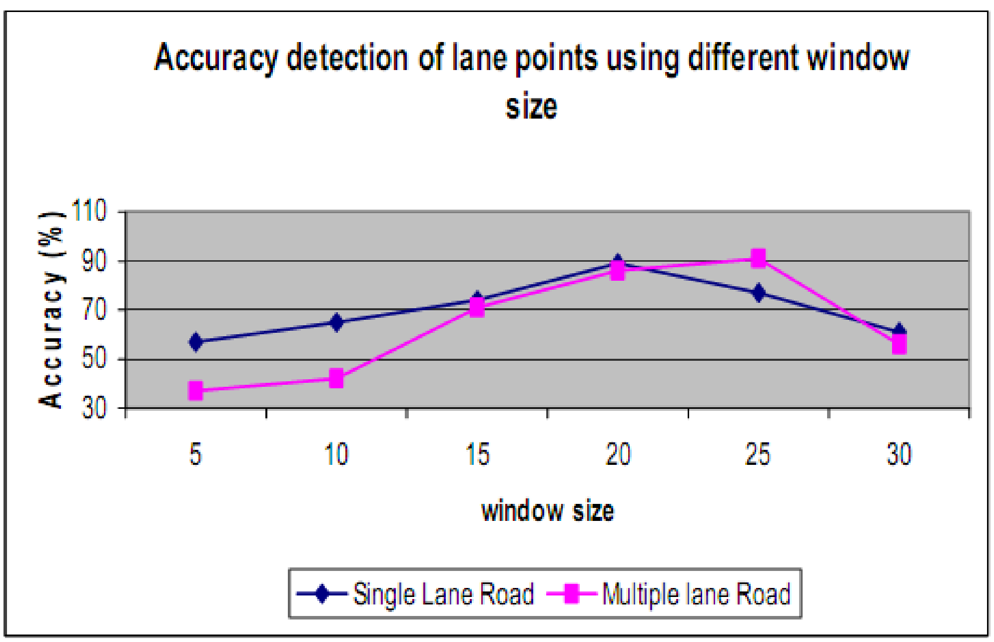


Figure 3.13- Window size and accuracy.

4.6 EXPERIMENT 5: HYPERBOLA PAIR FITTING

One hyperbola is fit to each of the vectors of data points. However, they are solved in simultaneously due to the fact that they are a pair model. The parameters of the two hyperbolas are related because they must converge to the same point, due to the geometry of the roadway. It is worth mentioning that the results shown in Table 3.4 which explain the accuracy of the fitting lines in different road conditions has given good results after some improvement to the point collection that represent the lane which is eliminating some of these points that falls out of a maximum and minimum range. This just to ensure if any edge points have been detected wrongly to represent the lane will be neglected. Figure 3.14 illustrates this results as the accuracy riches it highest average rate by 98% of lane detection in straight single road with a smooth traffic condition and 93% in a congested road. Similarly, straight highway road achieve 96% with smooth traffic and 91% with congestion condition. The accuracy rate has gradually dropped to 92% in a single road with curvature in smooth traffic and 85% in congestion road. This is followed by 88% for single road and 83% in congestion road respectively.

Table 3.4- Detection percentage with different road types.

	Smooth Road	Congested Road
Straight Single Road	98	93
Straight Highway	96	91
Single Road with Curvature	92	85
Highway with Curvature	88	83

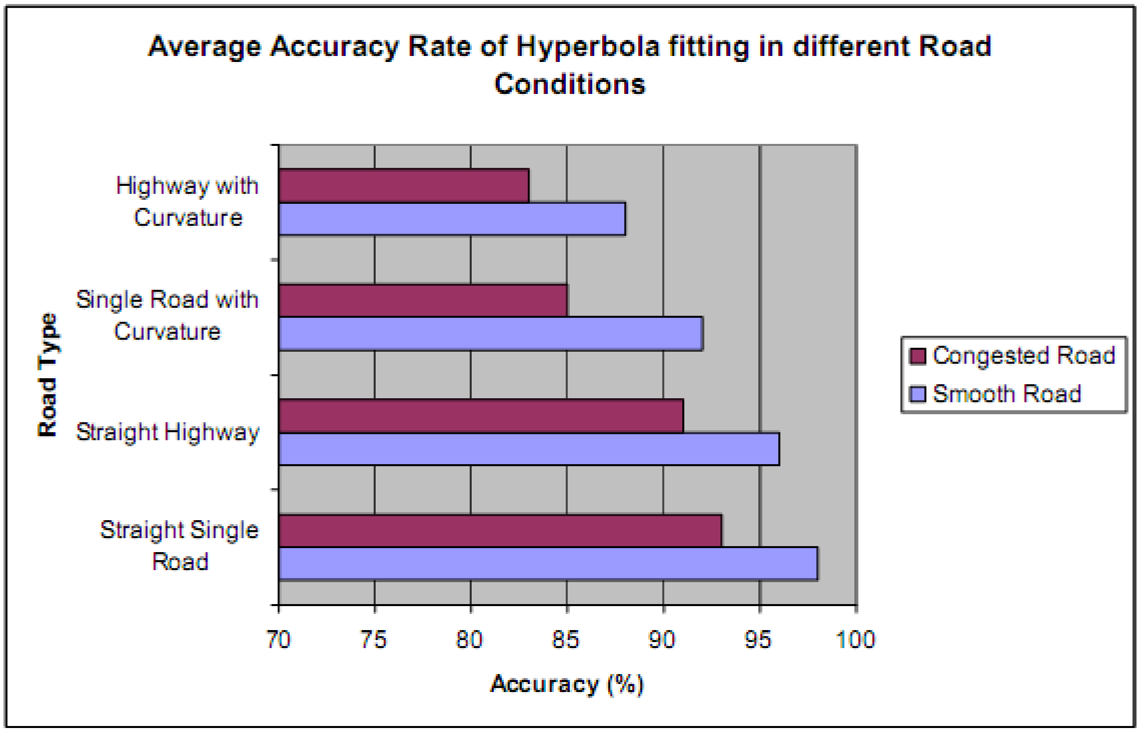


Figure 3.14- Hyperbola-pair fitting accuracy under different road conditions.

4.7 EXPERIMENT 6: REAL-TIME EXPERIMENTS

For the final evaluation of the algorithm, performance metrics were established on a two-tier basis for real-time experimentation and evaluation. The first tier measures whether or not the algorithm performs each processing phase accurately, and that has been illustrated in the previous sections. And the second tier evaluates qualitatively the performance of the algorithm in terms of accuracy in the localization of the lane boundaries for 150 frames in each case. This tier performance metric per input frame is strictly a pass/fail vote based on the likelihood that an autonomous vehicle could conceivably navigate with the output hyperbola pairs from the algorithm. The evolution ranged from straight highway scenes to curvy, during day and night. Also straight and curvy normal country road scenes during day and night. A few frames had traffic in both road types and on Railway Bridge, and even in critical weather condition such as heavy rain and cloudy sky has been demonstrated.

The final summary of the best results obtained in different road conditions in this project are shown in Figure 3.15 to Figure 3.26.

Firstly, in Figure 3.15 where we can see the highway road frames in straight and curvature condition during day time and similarly during night time in Figure 3.16, the lanes are detected accurately with slight error when the vehicle enter a sharp curve, however, the detection rate per frame achieved 96.6% as shown in Figure 3.17 during a day time and 92.6% during night time as in Figure 3.18 which considered to be good result after avoiding most of the light reflection problems that caused to have a very disappointing results at the preliminary stage.

Figure 3.15- Curved and straight road lane detection on highway during day.

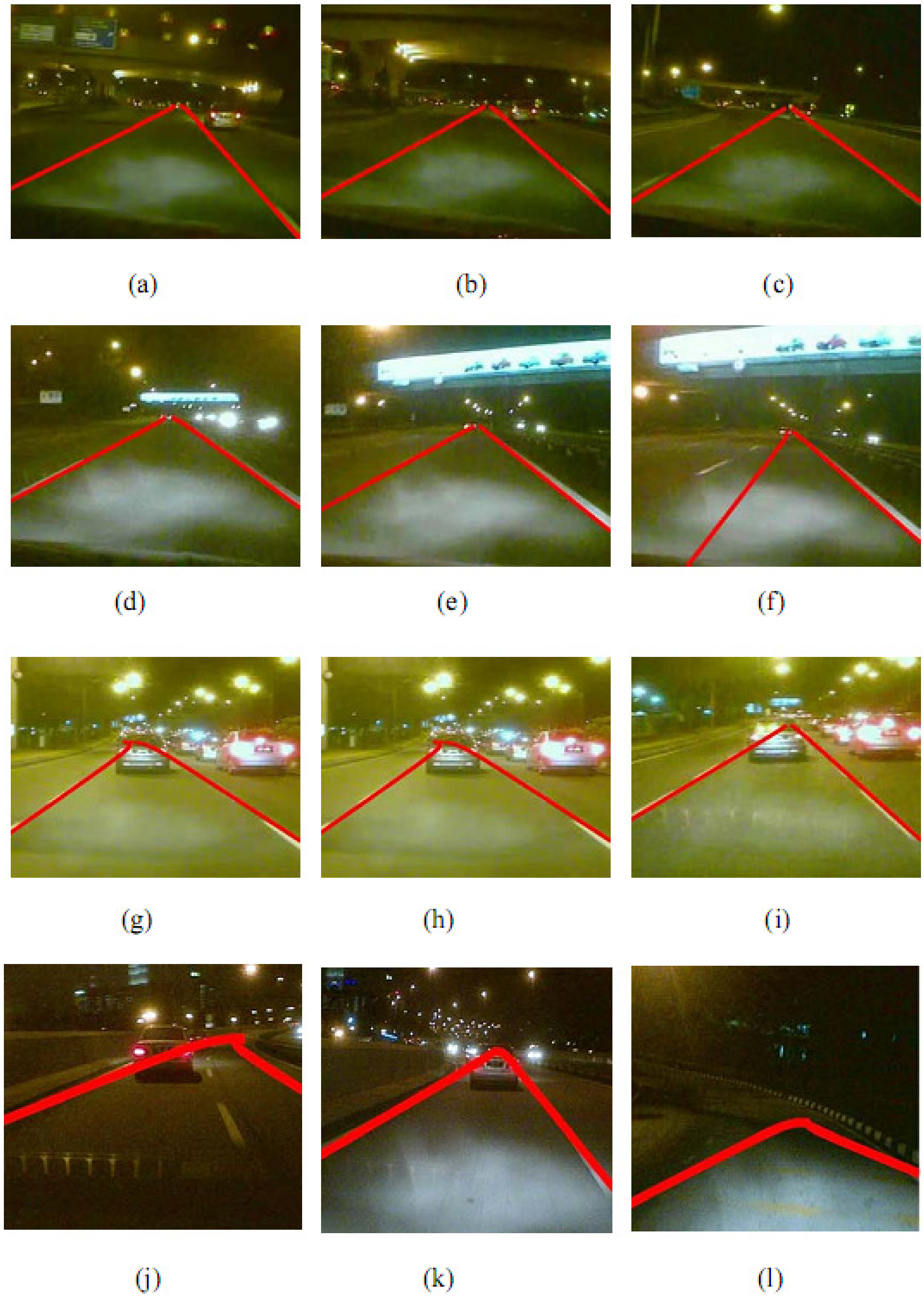


Figure 3.16- Curved and straight road lane detection on highway during night.

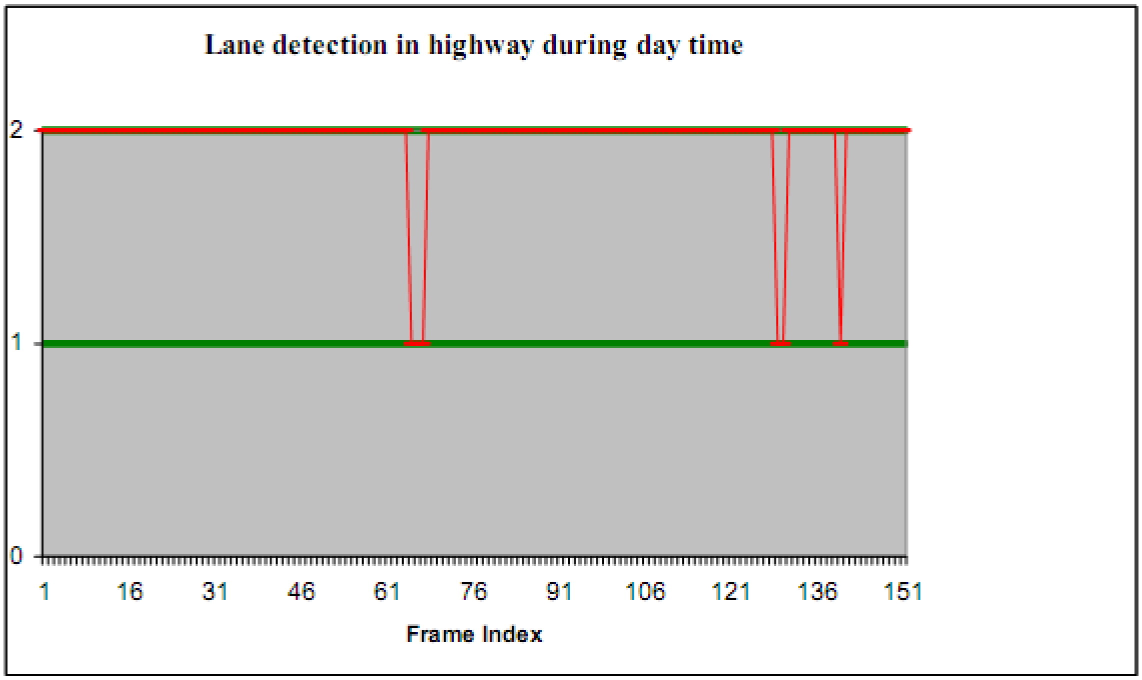


Figure 3.17- Highway lane detection during day per individual frame.

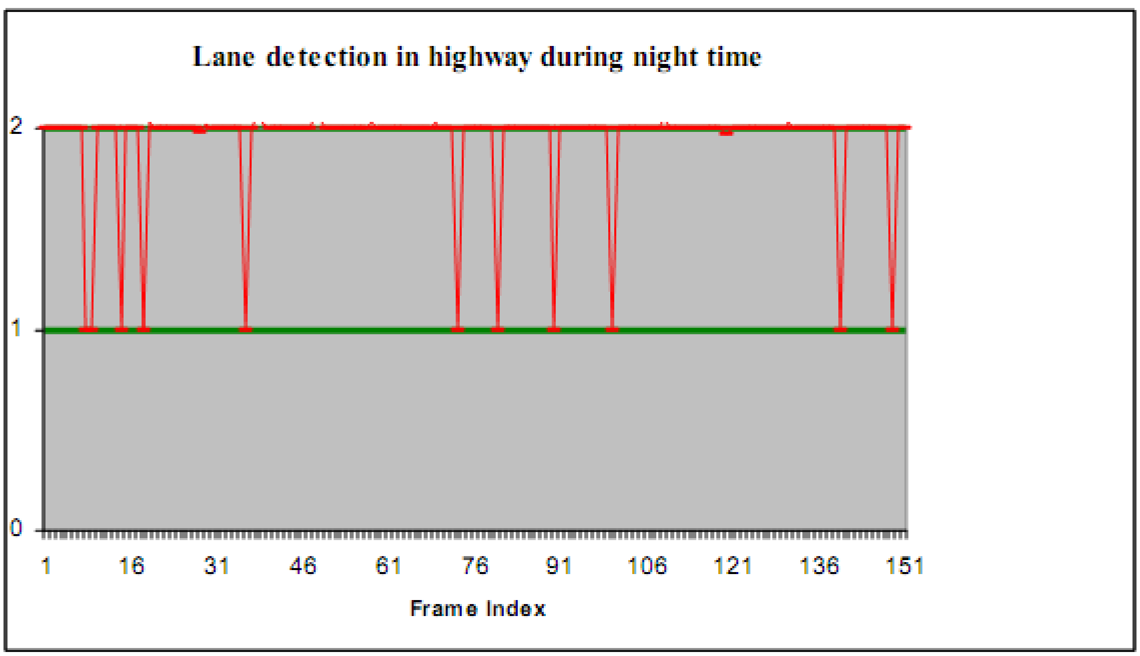


Figure 3.18- Highway lane detection during night per individual frame.

Figure 3.19 highlight the road lane detection in normal roads at the city which contain a lot of obstacle that may cause the lanes to be undetected. As for the test frames shown in Figure 3.19 the detection of lanes is clear in most of the cases during day time and even when the lighting condition is very poor during night Figure 3.20 the lane are recognized by the system accurately. Corresponding to Figure 3.23 the detection rate per frame in these cases is achieving its highest rate by 98% during day time and 94% during night time as shown in Figure 3.24. A successful completion of the algorithm is shown in Figure 3.21 where the lane of the road are disturbed by variety of nose ranging from shadows in the lane, and so many vehicles on the road causing the lanes to be indistinguishable, sharp curves, and this will cause some frames to fail the detection. The roots of the failures in the test frames ranged from a multitude of sources including line extraction problems as well as problems in finding the lane boundary pixels. However, the lane detection rare is still in stable condition obtaining 95% over different noise cases which shows how powerful the algorithm in handling noise and that is depict in Figure 3.25. The effect of critical weather conditions such as cloudy or rainy has given satisfactory results as we can see that in Figure 3.22 the lanes are detected in cloudy weather and during heavy raining, the lanes were scarcely distinguished in the road and the most tricky problem that causes the low detection is the moving wiper of the front window of the vehicle. However, the system is accurately detecting the lanes after the wiper moves up or down, which means that it still gives good results even in that kind of poor visibility condition approaching 75% per frame. Figure 3.26 illustrates the said detection rate.

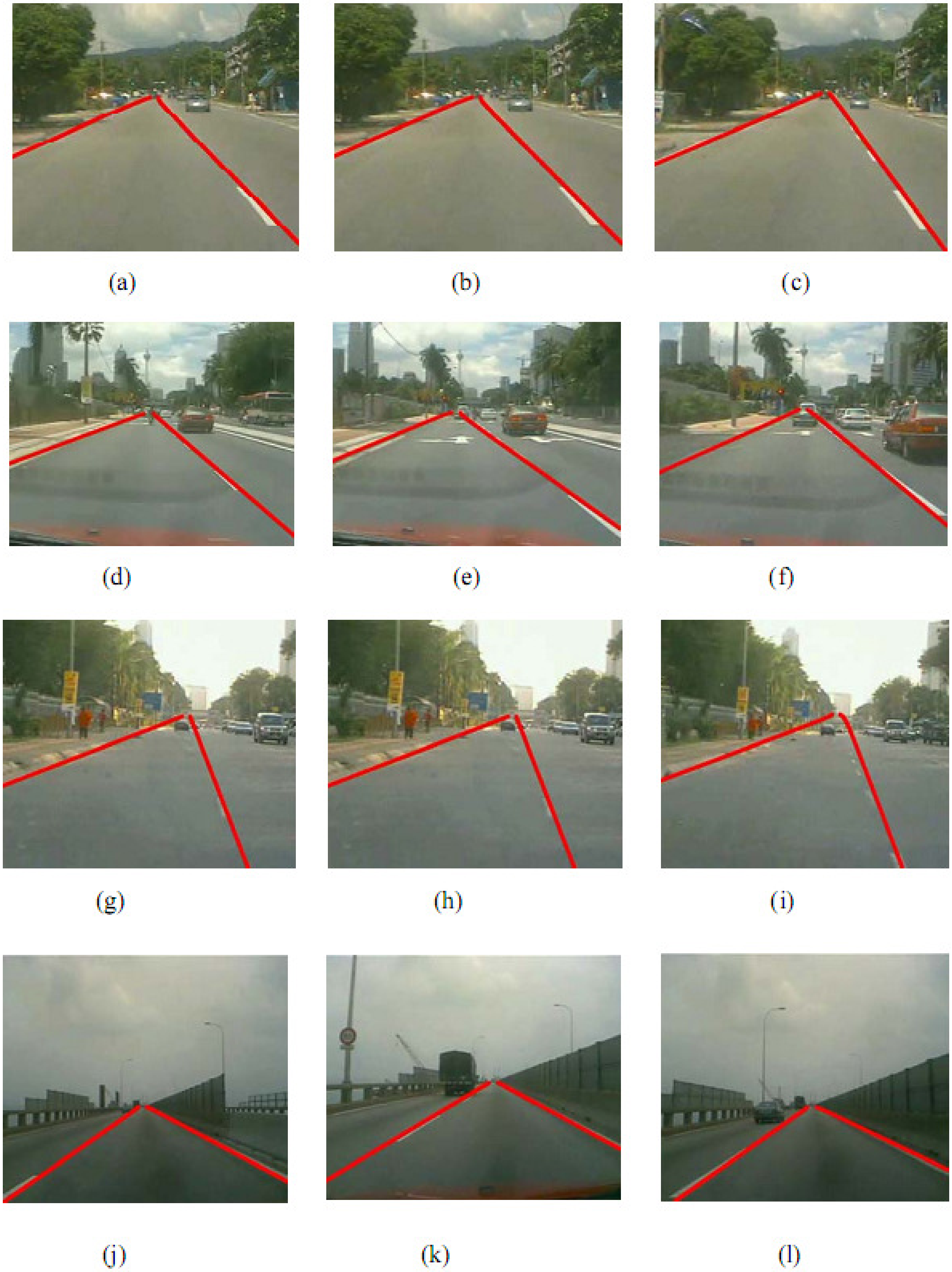


Figure 3.19- Curved and straight road lane detection on normal road and railway bridge.

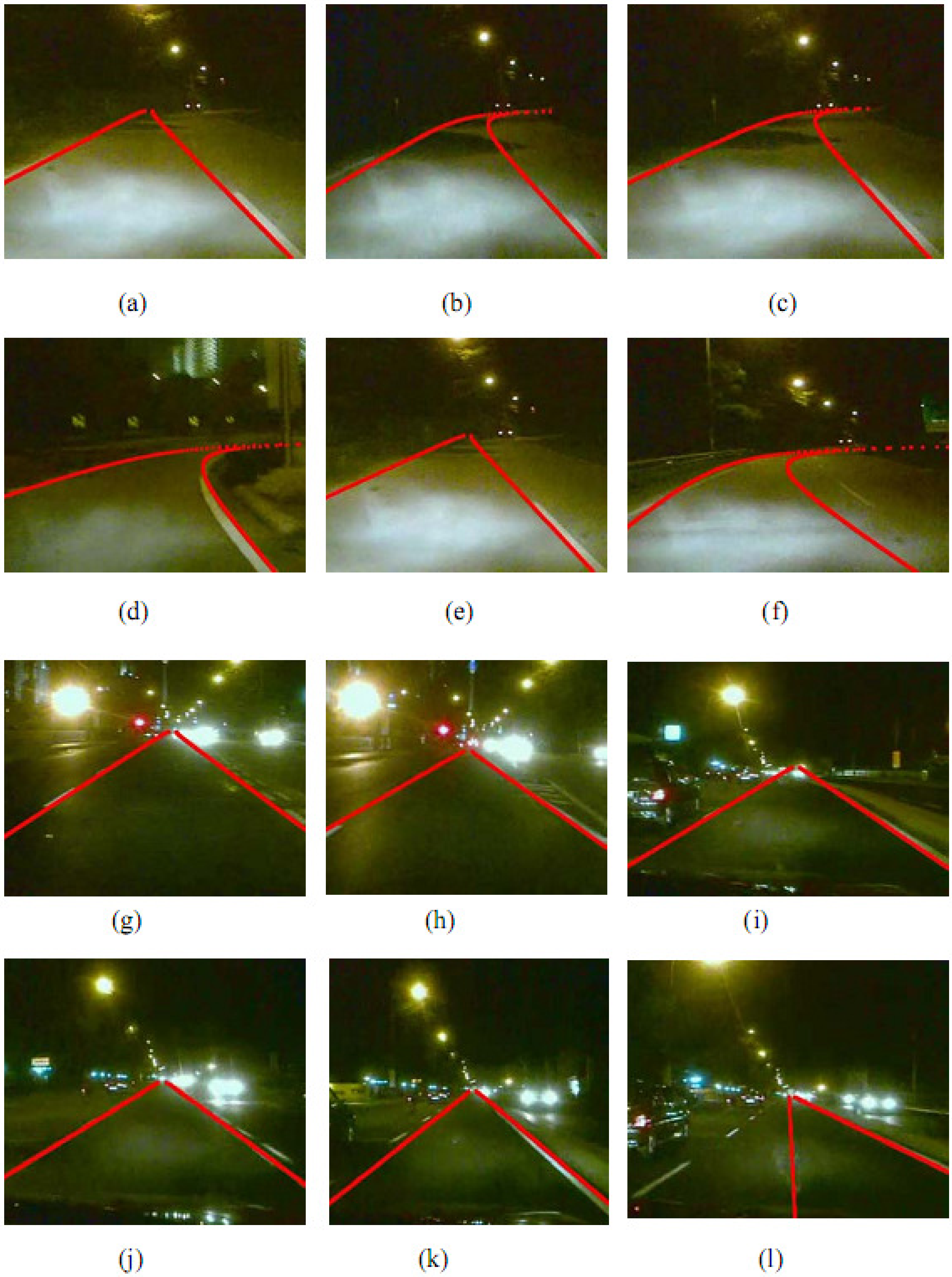


Figure 3.20- Curved and straight road lane detection at night.

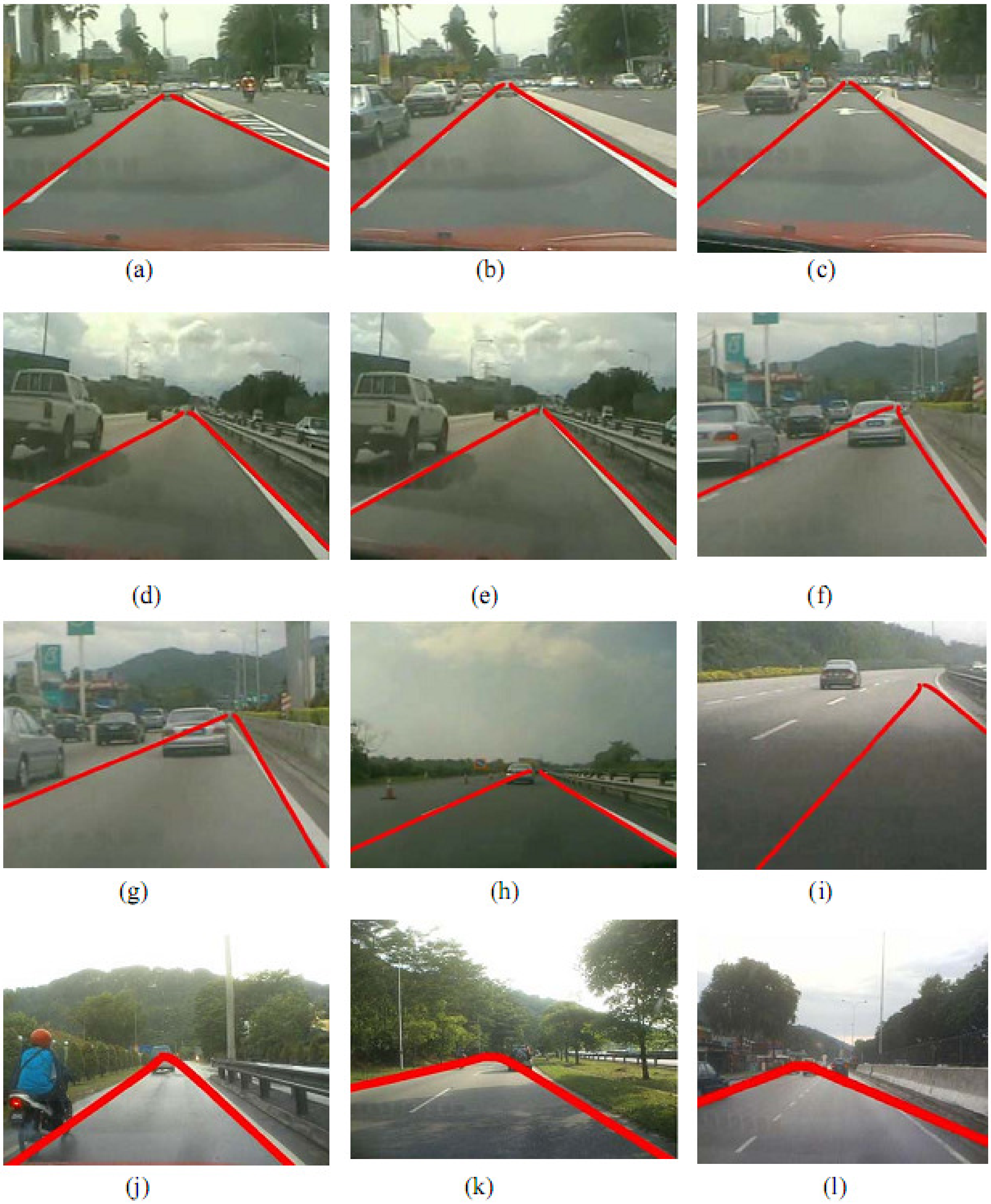
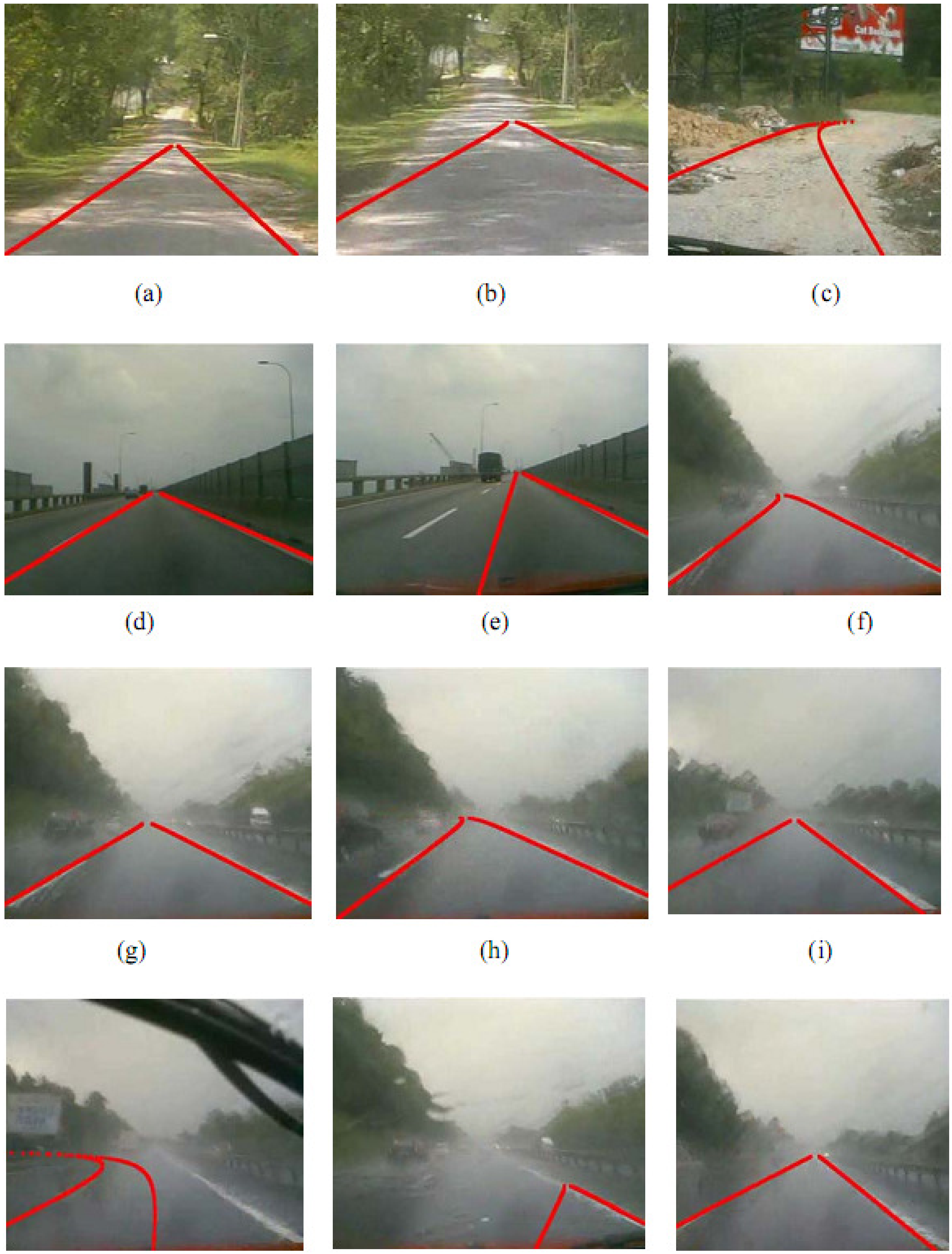


Figure 3.21- Road lane detection under different noise conditions.



(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

(j) (k) (l)

Figure 3.22- Road lane detection under different cloudy and rainy weather.

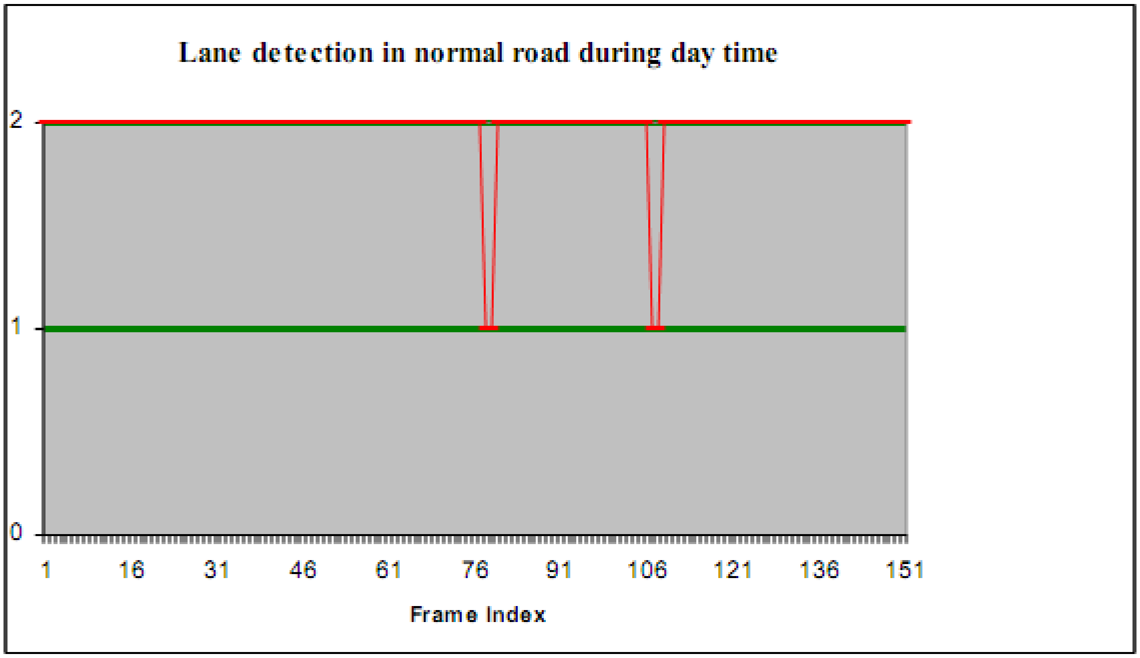


Figure 3.23- Road lane detection on normal road during day per individual frame.

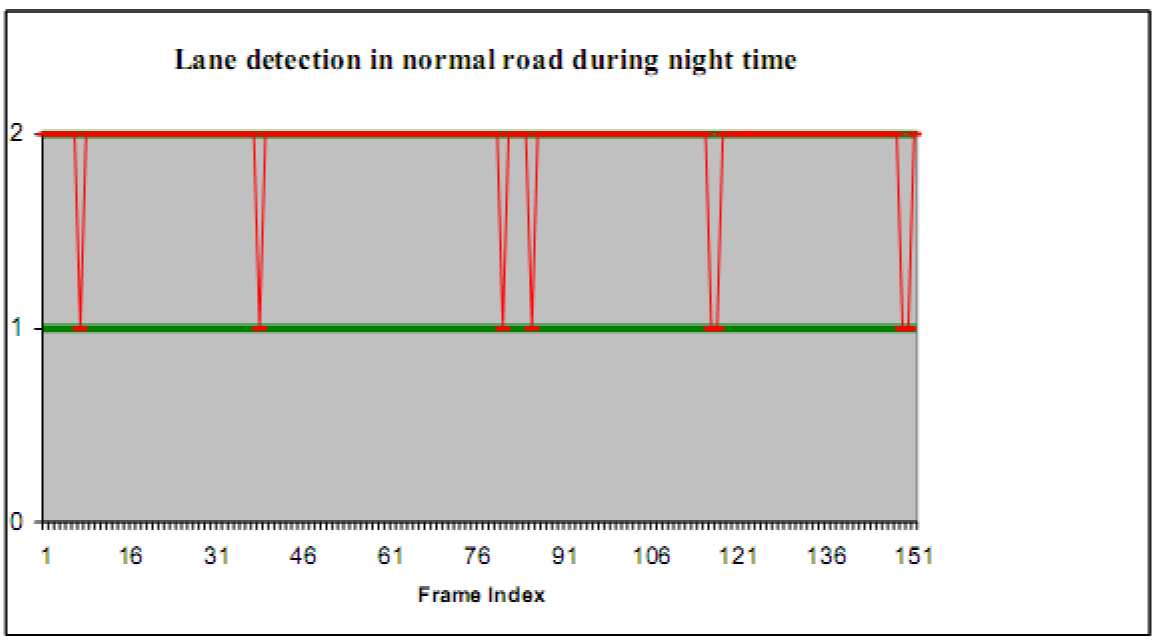


Figure 3.24- Road lane detection on normal road during night per individual frame.

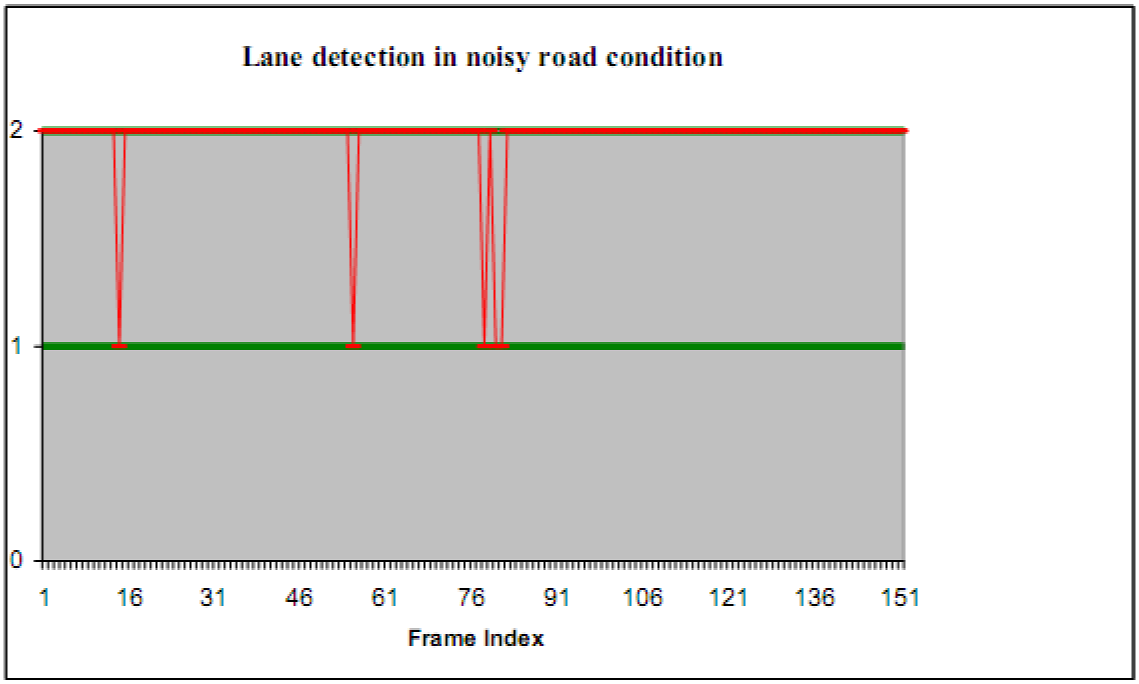


Figure 3.25- Road lane detection during noisy road condition per individual frame.

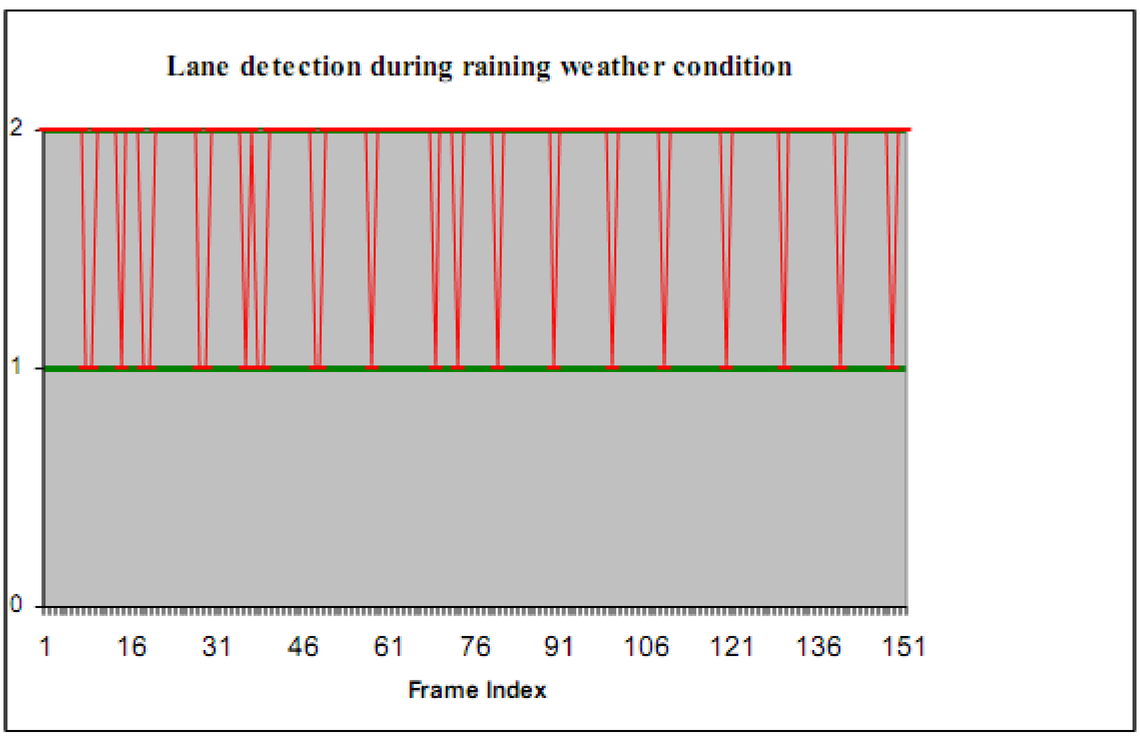


Figure 3.26- Road lane detection during raining weather condition per individual frame.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

The overall objectives of this project have been achieved. The algorithm proposed in this project was successfully implemented for the purpose of road and lane detection in autonomous vehicles. It has been shown to be robust and accurate, providing good lane detection results under various conditions (day, night, cloudy, rainy, etc) and for different types of lanes (single lane, double/multi-lane, no painted lane), where other algorithms are likely to provide less favourable results. It also is able to work fast enough for real-time processing. There were a number of technical problems through-out the project, especially concerning equipment supply and requirements mismatch. However, these were handled well in order to achieve the general design and implementation requirements of the project.

A future recommendation would be to implement the algorithm in hardware or customized FPGA boards in order to interface it with steering mechanisms for smart cars so that the autonomous vehicle's lane detection sub-system that has been developed would seamlessly integrate into the modern smart car concept.

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