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Vision Based Road Lane Detection System for Vehicles Guidance

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Abstract: Driver support system is one of the most important feature of the modern vehicles to ensure driver safety and decrease vehicle accident on roads. Apparently, the road lane detection or road boundaries detection is the complex and most challenging tasks. It is includes the localization of the road and the determination of the relative position between vehicle and road. A vision system using on-board camera looking outwards from the windshield is presented in this paper. The system acquires the front view using a camera mounted on the vehicle and detects the lanes by applying few processes. The lanes are extracted using Hough transform through a pair of hyperbolas which are fitted to the edges of the lanes. The proposed lane detection system can be applied on both painted and unpainted roads as well as curved and straight road in different weather conditions. The proposed system does not require any extra information such as lane width, time to lane crossing and offset between the center of the lanes. In addition, camera calibration and coordinate transformation are also not required. The system was investigated under various situations of changing illumination, and shadows effects in various road types without speed limits. The system has demonstrated a robust performance for detecting the road lanes under different conditions.

Key words: Lane detection, Computer vision, Intelligent Vehicles, Hough Transform Visual Guides

INTRODUCTION

Advanced Driving Assistance Systems (ADAS) require the ability to model the shape of road lanes and localize the vehicle with respect to the road. Although, the main reason to build intelligent vehicles is to improve the safety conditions by the entire or partial automation of driving tasks. Among these tasks, the road detection took an important role in driving assistance systems that provides information such as lane structure and vehicle position relative to the lane. However, vehicle crashes remains the leading cause of accident death and injuries in Malaysia and Asian countries which 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. The United Nations has ranked Malaysia as 30th among countries with the highest number of fatal road accidents, registering an average of 4.5 deaths per 10,000 registered vehicles (Benozzi *et al.*, 2002). Therefore, a system that provides a means of warning to a driver for a danger has been considered as a potential way to save a considerable number of lives. One of the main technology involves in these tasks is computer vision which becomes a powerful tool for sensing the environment and has been widely used in many applications by the intelligent transportation systems (ITS). In some proposed systems such as Tsugawa and Sadayuki, (1994), the lane detection consists of the localization of specific primitives such as the road markings of the surface of painted roads. Some systems achieves good results, but detecting the road lane remains a challenging task under adverse conditions (heavy rain, degraded lane markings, adverse meteorological and lighting conditions) that are often met in real driving situations. Under such conditions, the system should at least switch off automatically and not report a false detection, nevertheless, two situations can disturb the process. The presence of other vehicles on the same lane may occlude partially the road markings ahead of the vehicle are the presence of shadows caused by trees, buildings etc. This paper presents a vision- based approach which is capable of reaching a real time performance in detecting and tracking of structured road boundaries (painted or unpainted lane markings) with slight curvature and shadow conditions. Road boundaries are detected by fitting a parallel hyperbola pairs to the edges of the lane after applying the edge detection and Hough transform. The vehicle is supposed to move on a flat and straight road or with slow curvature.

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***Related Work*:**

A large number of researchers are working cooperatively with a goal to build autonomous vehicles and many government institutions have also lunched various projects worldwide. These efforts have produced several prototypes and solutions, based on slightly different approaches Richard, (1997). In Europe the PROMETHEUS program (Program for European Traffic with Highest Efficiency and Unprecedented Safety) pioneered this exploration. More than 13 vehicle manufactures and several research institutes from 19 European countries were involved. Several prototype vehicles and systems such as (VaMoRs, VITA, VaMP, MOB-LAB, and GOLD) were designed as a result of these projects. Although the first research efforts on developing intelligent vehicles were seen in Japan on the 1970's, significant research activities were triggered in Europe in the late 1980's and early 1990's. MITI, Nissan and Fujitsu pioneered the research in this area by joining forces in the project "Personal Vehicle System" Broggi, (1998). In US, a great deal of initiatives has been launched to address this problem. The National Automated Highway System Consortium (NAHSC) was established in 1995 and the Intelligent Vehicle Initiative (IVI) in 1997 Kreucher, *et al.*, (1998). At present many different vision-based road detection algorithms have been developed and deployed in these autonomous vehicles. Among these algorithms, the GOLD system developed by Broggi uses an edge-based lane boundary detection algorithm Chen *et al.*, (2004). The acquired image is remapped in a new image by representing a bird's eye view of the road where the lane markings are nearly vertical bright lines on a darker background. Specific adaptive filtering is used to extract quasi vertical bright lines that concatenated into specific larger segments. Kreucher C. proposed in Ran and Xianghong, (2002) the LOIS algorithm as a deformable template approach. A parametric family of shapes describes the set of all possible ways that the lane edges could appear in the image. A function is defined whose value is found proportional to a particular set of lane shape parameters matches the pixel data in a specified image. Lane detection is performed by finding the lane shape that maximizes the function for the current image. The Carnegie Mellon University proposed the RALPH system, used to control the lateral position of an autonomous vehicle John and Donald, (1999). It used a matching technique that adaptively adjusts and aligns a template to the averaged scan line intensity profile in order to determine the lane's curvature and lateral offsets. The same university developed another system called AURORA which tracks the lane markers present on structured road using a color camera mounted on the side of a car pointed downwards toward the road Kreucher and Lakshmanan, (1999). A single scan line was applied in each image to detect the lane markers. An algorithm defined for painted or unpainted road is described in Kluge, (1994). Some color cues were used to conduct image segmentation and remove the shadow. Assuming that the lanes are normally long with smooth curves then theirs boundaries can be detected using Hough transformation applied to the edge image. A temporal correlation between successive images was used in the following phases. Three-feature based automatic lane detection algorithm (TFALDA) Chen *et al.*, (2006) was primarily intended for automatic extraction of the lane boundaries without manual initialization or a priori information under different road environments and real-time processing. It was based upon similarity match in a three dimensional (3-D) space spanned by the three features of a lane boundary starting position direction (or orientation), and its gray level intensity features comprising a lane vector are obtained via simple image processing. LANA algorithm Graham *et al.*, (2001) was based on novel set of frequency domain features those captured relevant information concerning the magnitude and orientation of spatial edges extracted by 8*8(DCT). The hyperbola-pair model was deformable template, and was developed on the basis of Kluge's work Gernot, Hoffmann, (2001). The original model was suitable for single-side lane markings firstly, but in the work by Wang and Chen Kristijan Macek, *et al.*, (2002), it was emphasized that some parameters of the model were the same, if the lanes were parallel on the same road. The considerable feature is also used in proposed algorithms, to form an extended equation to fit the road shape.

Environmantal Variabilty:

In addition to the intended application of the vision lane detection system, it is important to evaluate the type of conditions that are expected to be encountered. Road markings can vary greatly between regions and over nearby stretches of road. Roads can be marked by well-defined solid lines, segmented lines, circular reflectors, physical barriers, or even nothing at all. The road surface can be comprised of light or dark pavements or combinations. An example of the variety of road conditions is presented in Figure 1. Some roads are relatively simple scene with both solid lines and dashed lines lane markings. Lane position in this scene can be considered relatively easy because of the clearly defined markings and uniform road texture. But in other complex scene in which the road surface varies and markings consist of circular reflectors as well as solid lines, the lane detection would not be an easy task. Furthermore, shadowing obscuring road markings makes the edge detection phase more complex. Along with the various types of markings and shadowing, weather conditions, and time of day can have a great impact on the visibility of the road surface as shown in Figure 1. All these circumstances must be efficiently handled in order to achieve an accurate vision system.

Fig. 1: Two road scenes in different circumstances

The Proposed Algorithm:

The proposed algorithm structure is shown in Figure 2. A CCD camera is fixed on the front-view mirror to capture the road scene. To simplify the problem, the baseline is assumed to be setup as horizontal, which assures the horizon in the image is parallel to the *x*-axis. Otherwise, the image of the camera can be adjusted using the calibration data. Each lane boundary marking, usually a rectangle (or approximate) forms a pair of edge lines.

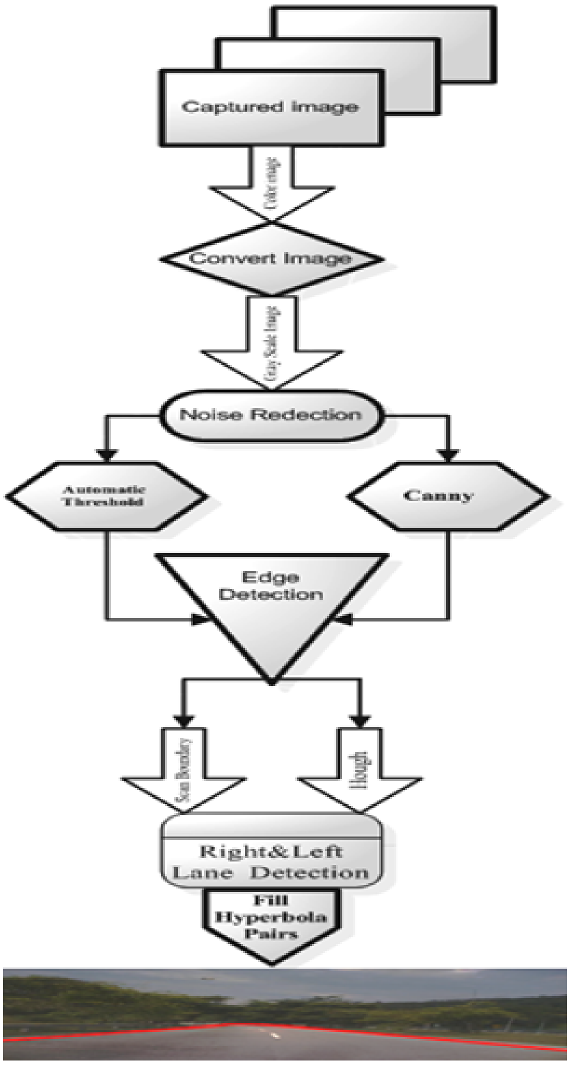

Fig. 2: An over view of the proposed algorithm

In this paper, it was assumed that the input to the algorithm was a 620x480 RGB color image. Therefore the algorithm works to convert the image to a grayscale image in order to minimize the processing time. Secondly, in presence of noise, the image will hinder the correct edge detection. Hence, F.H.D algorithm Mohamed Roushdy (2007) was applied to make the edge detection more accurate. Then the edge detector was used to produce an edge image by using canny filter with an automatic thresholding to obtain the edges. It has reduced the amount of learning data required by simplifying the image edges considerably. Then edged image has been sent to the line detector which produces a right and left lane boundary segment. The projected intersection of these two line segments was determined and was referred to as the horizon. The lane boundary scan used the information in the edge image detected by the Hough transform to perform the scan. The scan returned a series of points on the right and left side. Finally pair of hyperbolas were fitted to these data points to represent the lane boundaries. For visualization purposes the hyperbolas are displayed on the original color image.

A. Image Capturing:

The input data was a color image sequences taken from a moving vehicle. A color camera was mounted inside the vehicle at the front-view mirror along the central line. It took the images of the environment in front of the vehicle, including the road, vehicles on the road, roadside, and sometimes incident objects on the road. The on-board computer with image capturing card captured the images in real time (up to 30 frames/second), and saved them in the computer memory. The lane detection system read the image sequences from the memory and started processing. A typical scene of the road ahead is depicted by Figure 1.

B. Conversion to Gray Scale:

To retain the color information as well as to segment the road from the lane boundaries using the color information, edge detection becomes difficult and consequently effects the processing time. In practice the road surface can be made up of many different colors due to shadows, pavement style or age, which causes the color of the road surface and lane markings to change from one image region to another. Therefore, color image were converted into grayscale. However, the processing of grayscale images became minimal as compared to a color image. This function transformed a 24-bit, three-channel, color image to an 8-bit, single channel grayscale image. The function formed a weighted sum of the Red component of the pixel value * 0.3 +Green component of the pixel value * 0.59 + Blue component for the pixel value *0.11 and the output is the gray scale value for the corresponding pixel (www.themalaysian.blogspot.com).

C. Noise Reduction:

Noise is a real world problem for all systems including computer vision processing. The developed algorithms must either be noise tolerant or the noise must be eliminated. As presence of noise in proposed system will hinder the correct edge detection. Hence noise removal is a pre requisite for efficient edge detection with the help of (F.H.D.) algorithm Mohamed Roushdy, (2007) that removed strong shadows from a single image. The basic idea was that a shadow has a distinguished boundary. Hence removing the shadow boundary from the image derivatives and reconstructing the image was applied. A shadow edge image has been created by applying edge-detection on the invariant image and the original image. By selecting the edges that exist in the original image but not in the invariant image and to reconstruct the shadow free image by removing the edges from the original image by using a pseudo-inverse filter has been implemented.

D. Edge Detection:

Lane boundaries are defined by sharp contrast between the road surface and painted lines or some types of non-pavement surfaces. These sharp contrasts are edges in the images. Therefore edge detectors are very important in determining the location of lane boundaries. It also reduces the amount of learning data required by simplifying the image considerably, if the outline of a road can be extracted from the image. The edge detector was implemented for this algorithm. The one that produced the best edge images from all the evaluated edge detectors was the ‘canny’ edge detector.

It was important to have the edge detection algorithm that could be able to select thresholds automatically However, the automatic threshold used in the default Canny Algorithm produced edge information that is far from actual threshold. A slight modification to the edge detection in canny has produced more desirable results. The only changes necessary were to set the amount of non-edge pixels of the highest and lower thresholding to the best value that has provided more accurate edges in different conditions of image capturing environment. The process is given in equation (1) and an image detected by modified Canny Algorithm is presented in Figure 3.

Fig. 3: An image detected by modified Canny Algorithm

$$T_1 = \min_{\substack{x=0,1,\ldots\ldots,m \\ y=0,1,\ldots\ldots,n}} \{ f(x,y) \} \, and, T_2 = \max_{\substack{x=0,1,\ldots\ldots,m \\ y=0,1,\ldots\ldots,n}} \{ f(x,y) \} \tag{1}$$

The canny edge detector also has a very desirable characteristic that it does not produce noise like the other approaches.

E. Line Detection:

The line detector used is a standard Hough transform Chen and Wang, (2006) with a restricted search space. The standard Hough transforms searches for lines are shown in Figure 4.

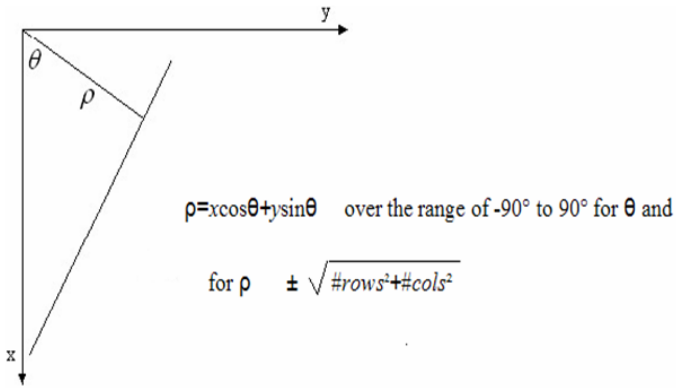

Fig. 4: Hough Transform searching methods

In reality, any line that falls outside a certain region can be neglected. For example a horizontal line is probably not the lane boundary and can be rejected. The restricted Hough transform was modified to limit the search space to 45° for each side. Also the input image is splitted in half yielding a right and left side of the image. Each the right and left sides are searched separately returning the most dominant line in the half image that falls with in the 45° window. The horizon is simply calculated using the left and right Hough lines and projecting them to their intersection. The horizontal line at this intersection is referred to as the horizon

F. Lane Boundary Scan:

The lane boundary scan phase uses the edge images, the Hough lines and the horizon line as input. The edge image is what is scanned and the edges are the data points it collects. The scan begins where the projected Hough lines intersect the image border at the bottom of the image. Once that intersection is found, it is considered the starting point for the left or right search, depending upon which intersection is at hand. From the starting point, the search begins a certain number of pixels towards the center of the lane and then proceeds to look for the first edge pixel until reaching a specified number of pixels after the maximum range. The range will be set to the location of the previously located edge pixel plus a buffer number of pixels further

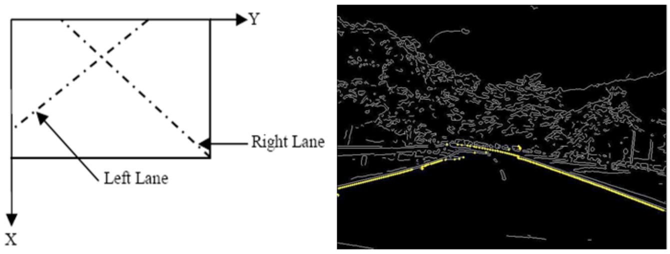

Fig. 5: Image coordinates

For the starting condition, the search will already be at the left- or right-most border, as shown in Figure 5, so the maximum range will be the border itself. The extra buffer zone of the search will help facilitate the following of outward curves of the lane boundaries. The lane points are organized into two lists expressed as $L(l)$ and $L(r)$ as follows

$$L^{(l)} = \left\{(u_1^{(l)}, v_1^{(l)}), (u_2^{(l)}, v_2^{(l)}), \ldots\ldots\ldots\ldots, (u_m^{(l)}, v_m^{(l)})\right\} \qquad (2)$$

$$L^{(r)} = \left\{(u_1^{(r)}, v_1^{(r)}), (u_2^{(r)}, v_2^{(r)}), \ldots\ldots\ldots\ldots, (u_m^{(r)}, v_m^{(r)})\right\} \qquad (3)$$

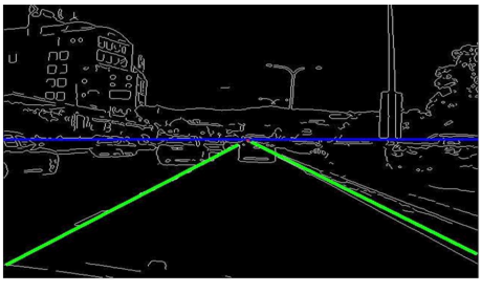

Fig. 6: Lane boundary detection

G. Hyperbola Fitting:

The hyperbola pair fitting phase uses the two vectors of data points from the lane scan as input. A least squares technique is used to fit a hyperbola to the data. 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 as shown in Figure 7. The formula for expressing the lane boundary as a hyperbola Kristijan Macek, *et al.*,(2002) given the road boundary point (u, v) in image plane:

$$u = \frac{k}{u-h} + b(v-h) + c \qquad (4)$$

u and v are the x- and y-coordinate in the image reference frame, h is the Y-coordinate of the horizon in the image reference frame, and k, b and c are the parameters of the curve, which can be calculated from the shape of the lane

Expermental Setup:

A CCD camera is mounted behind the driving mirror on the experimental passenger vehicle and it is used to monitor continuously the traffic scenes at the driving speed between 30km/hr and 120km/hr. The vibration problem has been ignored in experiment since the stability of the vehicle and the camera can be achieved by some mechanisms now a days. The captured frame (620X480) were broken up into 30 frames per second (30 fps) then delivered to the mobile computer which is equipped with Intel ® Core TM (2) 2.0 GHz processor and 2GB. The system has been experimentally evaluated under different weather and lighting conditions as described below:

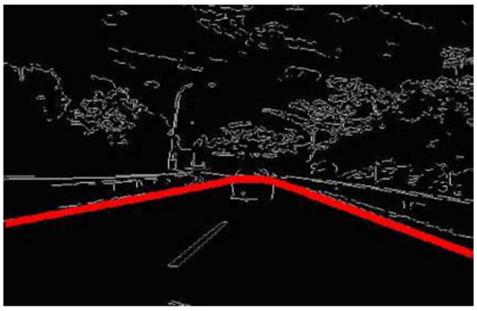

Fig. 7: Hyperbola fitting

Experiment 1: Edges and Boundaries Detection:

To improve the performance of the algorithm different values of the non-edge image pixels were tested by assuming different intensities values as used to set the automatic thresholding for each frame is shown in Figure 8. Set A describes the accuracy rate of the edge detection using different levels of non-edge pixels during day time in different locations. This Figure shows that at 80% of non-edge pixels, the accuracy of the detection rate approaches the highest level indicating that this value is the best to help us to prevent excessively noise edge detection. Similarly, using the Set B where the frames at night in different conditions improve the accuracy rate of the edge detection gradually until point 12, and then the detection decreased sharply after that point as demonstrated in Figure 8.

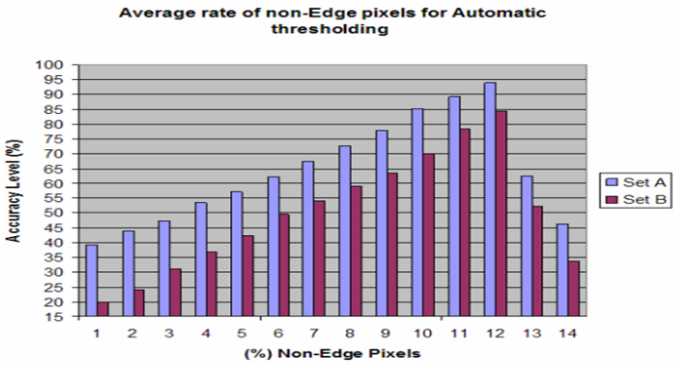

Fig. 8: Average rate of edge detection using different non-edges.

Experiment 2: Hough Transform Processing:

In order to increase robustness of the estimated lane position, the image has been divided into halves and then limiting the range of the search angle to 45º to the left side and 135º to the right side. Each of these sides was searched separately returning the most accurate line that falls within the particular angle. Figure 9 shows the detection accuracy rate of lines using restricted Hough transform during day time. However, this approach has great impact on the line detection results compared to the preliminary results. From Figure 9, it can be noticed that the detecting of lines using this approach under different road structure such as clear and straight line marking segment or dashed lane markings were good. For clear road marking during day time, it can be seen the best accuracy obtained is 97% in straight single road and 95% in straight highway. For dashed road markings, it can be seen that the best accuracy obtained is 89% in straight single road and 90% in straight highway.

Experiment 3: Window size:

In order to search out for the left and right vectors points which represent the road lanes, the lane scan boundary phase uses the edge image and the left and right Hough lines and the horizon line as inputs to allocate road boundary. In addition, the scan will select points for each row by choosing the most inward edge point within a window of a prior row's chosen boundary points. The window has a total width of pixels, corresponding to Figure 10, the accuracy of the lane detection has given different results depending on the size of the window. The window size was changed from 5 to 30pixel of size and the corresponding point's detection accuracy rate was measured. It can be deduced from Figure 10 that the performance increases when the window size is increased. The efficiency reaches its highest point when window size increased to 20, achieving a rate of 89% in a single lane road and 91% in multiple lanes road which is considered as the most optimal size for the window to obtain the points that correspond to the road lanes.

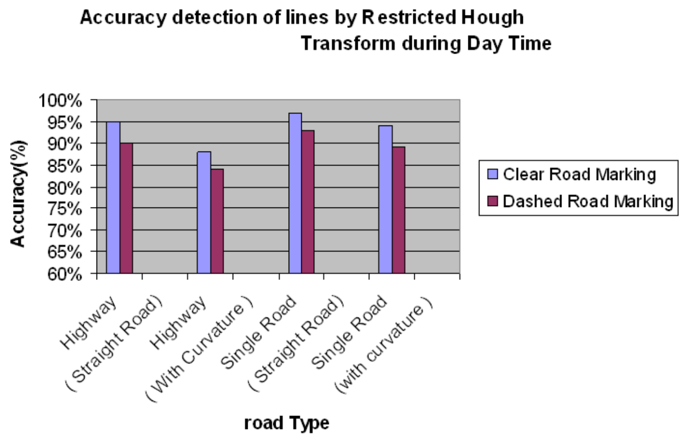

Fig. 9: Accuracy detection of lines by restricted Hough transform during day time.

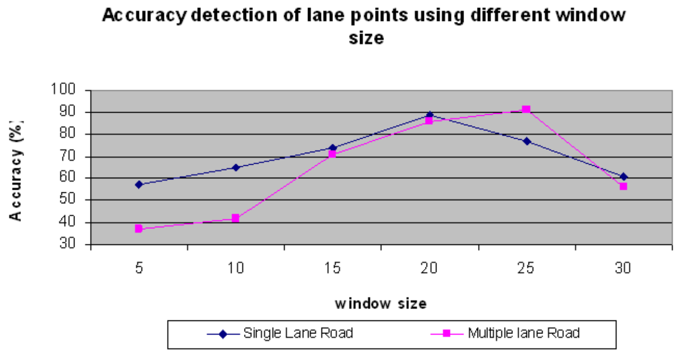

Fig. 10: Accuracy for detection of road lanes using different window size

RESULTS AND DISCUSSION

This section evaluates the overall performance of the system, after solving most of the problems discovered in earlier developed stages of the scheme. The performance of the algorithm is evaluated qualitatively 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 a vehicle could conceivably navigate with the output hyperbola pairs. It has been developed from the algorithm where accurate lane detection is marked by a red line at 2 and once it drops down to 1 it indicates the fault lane detection at that frame sequence.

Fig. 11: Curved and straight road lane detection in a highway during day.

However, the evaluation ranged from straight highway to curved normal country roads, during day and night. A few frames had been shown as traffic in road types, Railway Bridge, and critical weather condition such as heavy rain and cloudy sky as shown in Figure 11.

Fig. 12: Curved and straight road lane detection in a highway during night.

The final summary of the best results obtained in different road conditions in this project were shown in Figure 12 where the detection rate per frame achieved 96.6% during day time and 92.6% at night time as presented in Figures 13 and 14. The results is considered to be satisfactory after avoiding most of the light reflection problems that caused to have a very disappointing results at the preliminary stage.

Fig. 13: Lane detection in highway during day time per single frame

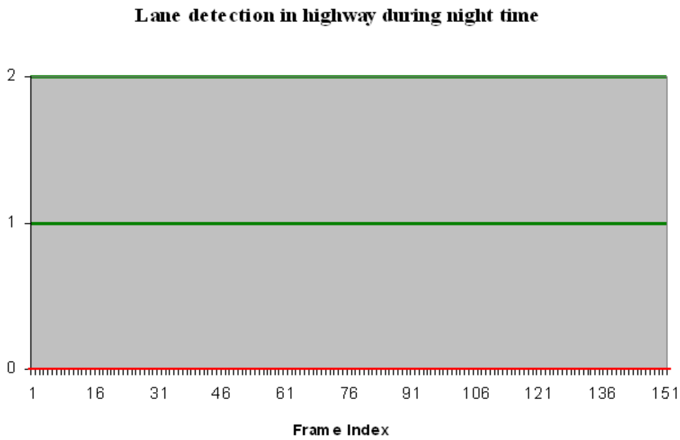

Fig. 14: Lane detection in highway during night time per single frame

A successful completion of the algorithm has been shown in Figure 15 where the lanes were disturbed by variety of noses ranging from shadows in the lane to vehicle on the road causing the lanes to be indistinguishable. Sharp curves caused some frames to fail during detection. The failures in the test frames came from a multitude of sources including line extraction problems as well as problems in finding the lane boundary pixels. However, the lane detection rate was still in stable condition obtaining above 95% with different noise cases showing the strength of the algorithm in handling noise as depict in Figure 16.

There are satisfactory results for critical weather conditions such as cloudy or rainy, as presented in Figure 17 where the lanes were detected in cloudy weather and during heavy rain. The lanes were scarcely distinguished in the road. The most elusive problem causing low detection is the moving wiper of the windshield. However, the system is accurately detecting the lanes after the wiper moves up or down, meaning it still produces acceptable results under the poor visibility condition approaching 75% per frame. Figure 18 illustrates the above mentioned detection rate.

Fig. 15: Road lane detection under different nose conditions

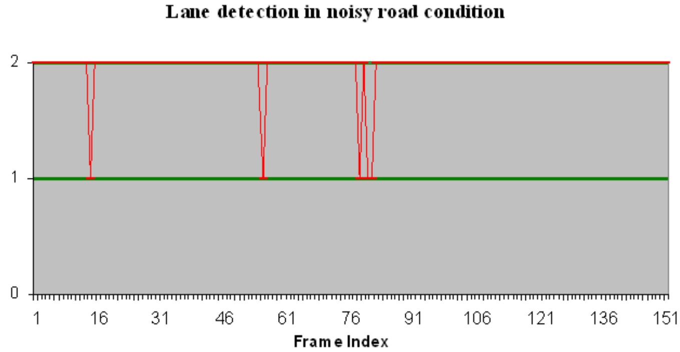

Fig. 16: Lane detection in noise road condition per single frame

Fig. 17: Road lane detection under cloudy and rainy weather

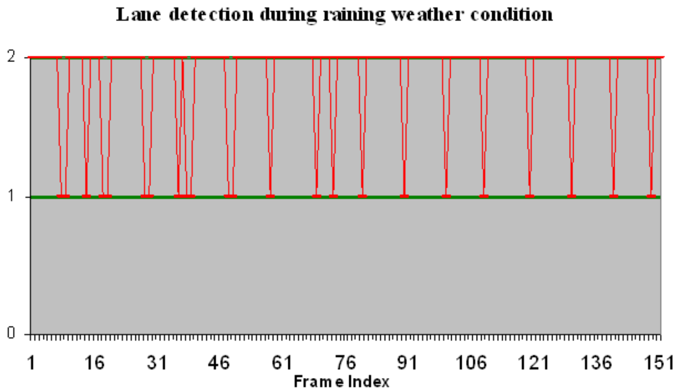

Fig. 18: Lane detection during bad weather condition per single frame

Conlusion:

In this paper, A real time vision-based lane detection method was proposed. Image segmentation and remove the shadow of the road were processed. Canny operator was used to detect edges that represent road lanes or road boundaries. A hyperbola-pair road model used to deal with the occlusion and imperfect road condition. A series of experiment showed that the lanes were detected using Hough transformation with restricted search area and the projection of their intersection will form the last scan point called the horizon. Furthermore, In order to search out for the left and right vector points that represent the road lanes, the lane scan boundary phase uses the edge image and the left and right Hough lines and the horizon line as inputs, to effectively allocate the lane points. That was demonstrated by two hyperbola lines. The experimental results showed that the system is able to achieve a standard requirement to provide valuable information to the driver to ensure safety.

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