LANE DEPARTURE WARNING SYSTEM USING VANISHING POINT BASED RANDOMIZED HOUGH TRANSFORM

PEERAWAT MONGKONYONG

A THESIS REPORT SUBMITTED IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF ENGINEERING IN COMPUTING IN ENGINEERING SYSTEM
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THESIS TITLE	Lane Departure Warning System using Vanishing Point Based Randomized Hough Transform
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ABSTRACT

Road accidents cause a tremendous loss of lives and properties. It tends to increase because of the population growth. Many reports in the past showed the causes of the road accident. One of the important cause is unintended lane changing. Lane departure warning system (LDWS) is presented to reduce the road accident rates. It will warn the driver when the vehicle is in the unintended lane changing state. Many researchers use the standard Hough transform (SHT) to operate LDWS. However, SHT consumes a lot of computational time because it uses all of the data in the image. Therefore, the randomized Hough transform (RHT) is presented to counter that drawback because it uses only some subset of the image. For the good performance, we propose the technique called the vanishing point based randomized Hough transform (VP-RHT). The proposed VP-RHT contains many parts: the image preprocessing, vanishing point section, lane boundary detection and tracking. The final is lane changing detection. It will warn the driver when the image is in the lane changing state with sound. To identify the unintended lane changing situation, the system should cooperate with the turn signal. By simulation, a new lane departure warning system using VP-RHT also faster than RHT and SHT method (0.13 sec/frame) but still cannot achieve the real-time performance. The results showed that the proposed system can accurately detect and track lanes in normal condition (99%) and lane changing condition (99%), obviously better than the compared methods. And it also achieves very good performance on nighttime condition (99%), curve road (95%) and congested condition (92%). However, it has some problems with heavy rain condition (79%).

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Peerawat Mongkonyong

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Background

Nowadays, more demand for vehicles is increasing because of the rapid population growth. This leads to the major causes of higher road accidents [1]. Nearly 3,500 people die on the road every day. It is found that the unintended lane changing is responsible for most of the accidents.

According to a report by the Royal Thai Police as shown in figure 1.1, lane changing without consciousness is one of the most accident causes. To solve the problem, many researchers evaluate the image from the car camera using the computer vision. Computer vision is the field that deals with how computers can be made for gaining high-level understanding from digital image or video. It is used in the system that finds lane boundary and warns the driver in case of unintended lane changing called lane departure warning system (LDWS).

The advantage of LDWS should be an optional tool to relieve such disaster. LDWS analyzes input frame from the car camera to detect lane markers, estimate lane from detected lane marker and warns the driver when the vehicle is in the lane changing state.

To detect the lane marker, many researchers use Standard Hough transform (SHT) to detect a line in the image first. SHT is a feature extraction technique that used to detect straight lines in the image by vote procedure.

Randomized Hough transform (RHT) is different from SHT in that it tries to avoid conducting the computationally expensive voting process for every nonzero pixel in the image by taking advantage of the geometric properties of analytical curves, and thus improve the time efficiency and

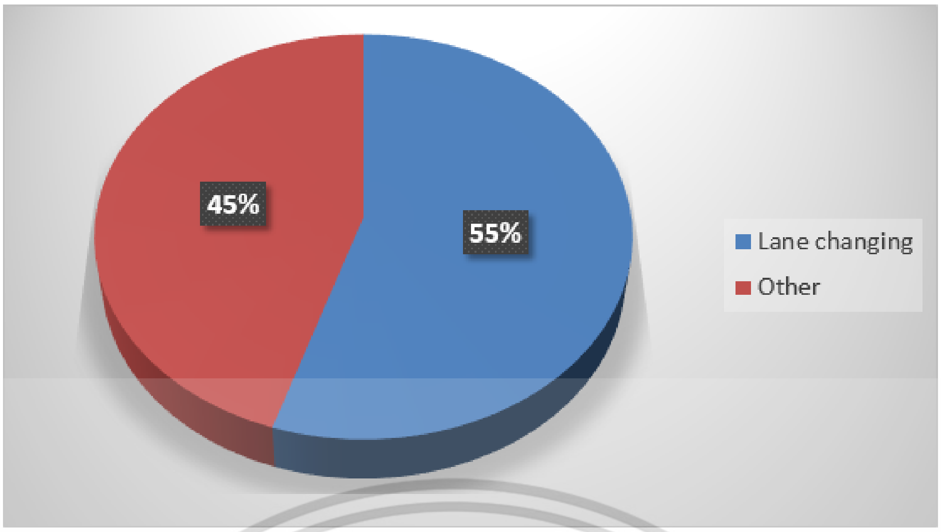

Figure 1.1: The number of traffic accident causes in Thailand between 2013 - 2015

reduce the storage requirement of the original algorithm.

However, the drawbacks of RHT are hard to control the random points and the system will randomly choose the pixel outside the region of the interest (ROI) in the method. To solve the problems, a vanishing point based randomized Hough transform (VP-RHT) is presented.

The vanishing point is the point on the image plane of a perspective drawing where the two-dimensional perspective projections (or drawings) of mutually parallel lines in three-dimensional space appear to converge.

In the RHT, it randomly picks two points and converts them into polar coordinate. On the contrary, the proposed VP-RHT assumes one point in random method to be the vanishing point after votes the accumulator. This will increase the accuracy in voting method.

1.2 Objectives and Scope of Work

The objective of the system is the comparison between SHT, RHT and VP-RHT in respect to the accuracy and computational time. For the accuracy part, it is divided into two parts: normal state and lane changing state in the clear condition (no heavy rain). For the last part, the result of computational time is divided into the first frame and the other frames. Because the VP-RHT should detect the vanishing point in the first frame.

The scope of this work is about the input image. It should be appropriated. If the position of the camera is not the middle of the car, it will change the position of the lane changing region. The angle of the camera is also important. If the road surface in the image is reduced, the pixel of the lane marker in the detected image will reduce. To solve this problem, the system should be trained before testing. This will make the system works in good performance.

1.3 Thesis Outline

Chapter 1 is about the introduction, objectives, scope of work and thesis outline. Then, the literature review is shown in Chapter 2. Chapter 3 is the background knowledge that uses in this thesis. The chapter will move on the proposed system in Chapter 4. It will consist of four parts: image preprocessing, vanishing point section, lane boundary detection, and lane changing detection. Validation will be shown in Chapters 5. The results of the proposed system in different road condition will also be shown. Finally, the conclusion will be presented in Chapter 6.

Chapter 2

Literature Review

2.1 Literature Review

This chapter includes past studies and theories of this proposed system. The last past is shown the objective and scope of work of this proposed system.

2.1.1 Single Camera Lane Detection and Tracking

Schreiber et al. [2] presented a lane detection that the vanishing points were discussed. Vanishing points were detected using SHT. This method was used the vanishing point to detect straight line segments. Canny edge detection was applied in this image preprocessing section.

However, the use of vanishing point also can remove the unwanted area, reduced the computational time. In edge detection, we introduced the Sobel edge detection that faster than Canny edge detection in case of time-consuming [3].

2.1.2 A Lane Detection Method for Lane Departure Warning System

He et al. [4] presented a lane detection method. The Canny algorithm was determined as the edge detection method according to the experiment comparison, and SHT was selected as the efficient way to detect the beeline. To meet the real-time requirement, the region of interest ROI was defined to reduce noise for rising accurately, and to enhance the processing speed. At last, experiment results indicated that the lane detection method can extract lane information from road images acquired efficiently and accurately.

This work also talked about Sobel edge detection that better than Canny edge detection in case of computational time. However, they applied the Canny edge detection because it was the most effective method for edge detection.

2.1.3 Lane Departure Detection and Transmission using Hough Transform Method

This lane departure detection was presented by Habib et al. [5]. The system operated lane departure detection using Hough transform and also used the Canny edge detection in the edge detection method. The interesting one was they tested the system in four categories: normal daylight, night under the vehicles beam light, under the tunnel dim light and general system performance.

In term of the computational time, Sobel edge detection was better than Canny edge detection in case of computational time. We also applied the road condition in our work such as night, heavy rain, curve and congest condition.

2.1.4 Lane-vehicle Detection and Tracking

Lim et al. [6] performed lane-vehicle detection and tracking. Vertical mean distribution was used to remove the sky region by averaging the gray values of each row on the image. A big jump of this method indicated the line that divided the image into the sky region and road region.

However, the result would be an error if some part of the car appeared in the image such as a console. Because the averaged value would have changed. To solve this problem, the vanishing point detection was used for this section.

2.1.5 Lane Recognition Algorithm using The Hough Transform with Applied Accumulator Cells in Multi-channel ROI

Cho et al. [7] applied the Hough transform with optimized the accumulator cells in the four ROI in parallel and detected lanes with highly efficient. By finding the two ROI at the bottom the image. Then, they applied the position of that two ROI in the other ROI at the middle of the image.

For the good performance, they should find the vanishing point for the efficiency in multi-channel ROI. This can reduce the computational time and remove some pixels in the image.

2.1.6 LDWS for Smart Vehicles using Image Processing Based on Hough Transform

Gulve et al. [8] applied LDWS using Hough transform and showed the advantage of the Hough transform: easy to use, low cost and also effective in detected lines from the image. Their work did not focus on computational time.

Because of this advantage, we applied the SHT in the vanishing point detection and also used the vanishing to remove area outside the region of the interest.

2.1.7 The Probabilistic and Non-probabilistic Hough Transforms Overview and Comparisons

Kalviainen et al. [9] presented the probabilistic and non-probabilistic Hough transforms overview and comparisons. They compared a lot of algorithms such as SHT, RHT, Dynamic RHT and Window RHT. They tested those algorithms in line detection with synthetic and real-world image demonstrate the high speed and low memory usage.

The presented RHT was very interesting and they did not target on the lane detection. For this reason, we combined RHT with the vanishing point and applied it to lane detection.

2.1.8 Randomized Hough Transform (RHT)

Kultanen et al. [10] introduced the RHT. The mechanisms of a random sampling of point pairs from the x - y plane, converted to the ρ - θ plane and voted the accumulator.

In the lane marker detection, the accuracy of this method can increase by assuming the one point of the pair to be the vanishing point. Because the vanishing point was the part of the straight line that intersects in the image. The vanishing point also can remove some pixels and reduce the computational time of that method.

	Sobel edge	Vanishing point detection	RHT	Other road condition
Ref. No. 2	X	O	X	X
Ref. No. 4	X	O	X	X
Ref. No. 5	X	X	X	O
Ref. No. 6	X	O	X	X
Ref. No. 7	X	X	X	X
Ref. No. 8	X	X	X	X
Ref. No. 9	X	X	O	X
Ref. No. 10	X	X	O	X
Ref. No. 11	X	O	X	X
Proposed system	O	O	O	O

Table 2.1: The overall of literature

2.1.9 Lane Detection and Tracking using B-snake

Wang et al. [11] presented a B-snake based lane detection and tracking algorithm without any parameters of the camera. This article used Canny/Hough estimation of vanishing points (CHEVP) to find a good initial position for the B-snake.

However, it also got some drawback such as it often set in local minima states which can be counteracted by simulated annealing techniques, minute features were often ignored during energy minimization over the entire contour and their accuracy was governed by the convergence criteria used in the energy minimization technique.

2.2 Conclusions

After reviewing many researches, they have some different point in their methods as shown in table 2.1.

Chapter 3

Background Knowledge

This chapter introduces various concepts related to this study and briefly clarifies important points which are foundations that this study is based on. It includes the Gaussian blur, edge detection, vanishing point, SHT and RHT.

3.1 Gaussian Blur

In image processing, a Gaussian blur is the result of blurring an image by a Gaussian function. It is a widely used effect in graphics software, typically to reduce image noise and reduce detail. Gaussian smoothing is also used as a preprocessing stage in computer vision algorithms in order to enhance image structures at different scales. Gaussian function at every point on the image will be non-zero, meaning that the entire image would need to be included in the calculations for each pixel.

Mathematically, applying a Gaussian blur to an image is the same as convolving the image with a Gaussian function. The equation of a Gaussian function in one dimension is

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}}, \tag{3.1}$$

in two dimensions, it is the product of two such Gaussian, one in each dimension:

$$G(x) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}, \tag{3.2}$$

where x, y are the coordinates corresponding and σ is the standard deviation of the Gaussian distribution.

3.2 Edge Detection

Edge detection is a fundamental tool in image processing and computer vision, particularly in the area of feature detection and feature extraction. It has been used for identifying a point in a digital image at which the image brightness changes sharply, or more formally, has discontinuities.

There are many edge detection available. However, this proposed system uses the Sobel edge detection. It has some smoothing effect on the random noise of the image resulting in thick and bright edges. It is based on convolving the image with a small, separable and integer-valued filter in horizontal and vertical direction. Therefore, it is relatively inexpensive in term of computations.

Mathematically, the detection approximates two derivatives (vertical and horizontal). For the source image, G_x and G_y are two matrices, which at each point contain the horizontal and vertical derivative approximations. At each point in the image, the resulting gradient approximations can be combined to give the gradient magnitude as in the following:

$$G = \sqrt{G_x^2 + G_y^2}, \tag{3.3}$$

and the gradient's direction:

$$\theta = atan(\frac{G_y}{G_x}), \tag{3.4}$$

the resulted image will be a binary image with the edge feature.

3.3 Vanishing Point

A vanishing point is a point on the image plane of a perspective drawing where the two-dimensional perspective projections (or drawings) of mutually parallel lines in three-dimensional space appear to converge. When the set of parallel lines is perpendicular to a picture plane, the construction is known as one-point perspective, and their vanishing point corresponds to the oculus, or “eye point”, from which the image should be viewed for correct perspective geometry.

3.4 Standard Hough Transform

The Hough Transform is a feature extraction technique used in image analysis, computer vision, and digital image processing. The purpose of the technique is to find imperfect instances of objects within a certain class of shapes by a voting procedure. This voting procedure is carried out in a parameter space, from which object candidates are obtained as local maxima in a so-called accumulator space that is explicitly constructed by the algorithm for computing the Hough transform.

The classical Hough transform was concerned with the identification of lines in the image, but later the Hough transform has been extended to identifying positions of arbitrary shapes, most commonly circles or ellipses. The Hough transform as it is universally used today was invented by Richard Duda and Peter Hart in 1972, who called it a “generalized Hough transform” [12] after the related 1962 patent of Paul Hough [13]. The transform was popularized in the computer vision community by Dana H. Ballard through a 1981 journal article titled “Generalizing the Hough transform to detect arbitrary shapes” [14].

In an automated analysis of digital images, a subproblem often arises of detecting simple shapes, such as straight lines, circles or ellipses. In many cases, an edge detector can be used as a preprocessing stage to obtain image points or image pixels that are on the desired curve in the image space. Due to imperfections in either the image data or the edge detector, however, there may be missing points or pixels on the desired curves as well as spatial deviations between the ideal line/circle/ellipse and the noisy edge points as they are obtained from the edge detector. For these reasons, it is often non-trivial to group the extracted edge features to an appropriate set of lines, circles or ellipses. The purpose of the Hough transform is to address this problem by making it possible to perform groupings of edge points into object candidates by performing an explicit voting procedure over a set of parameterized image objects [12].

The simplest case of Hough transform is detecting straight lines. In general, the straight line

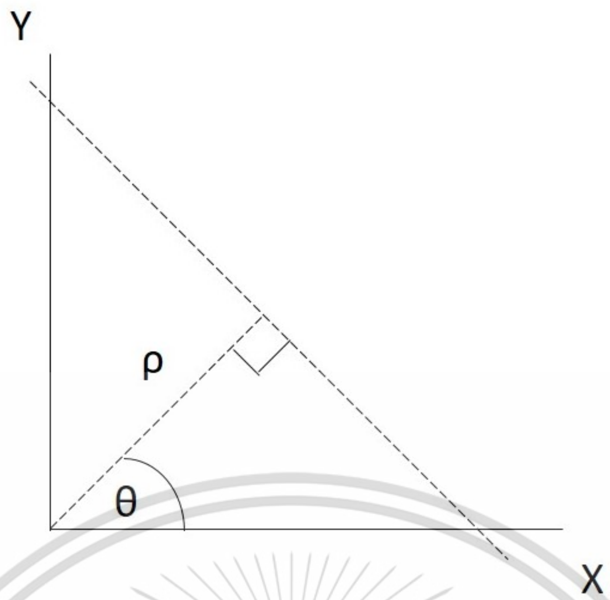

Figure 3.1: Hough transform converting

can be solved by equation 3.5.

$$y = mx + c, \tag{3.5}$$

where x, y are the coordinates corresponding, m is the slope and c is the y-axis intersection.

To avoid the calculation of m in the vertical line case, the system assumes all of the white pixels of the image to be the points and converts them into ρ - θ plane. Each point in the x - y plane will have the infinity lines that pass the point. Those lines are converted by the equation 3.6 and shown in figure 3.1.

$$\rho = x_0 cos\theta + y_0 sin\theta, \tag{3.6}$$

where x_0, y_0 are the coordinates corresponding to the theta, ρ is the line connecting the polar coordinate to the origin and θ is the angle between ρ and x-axis.

The line plot of those lines will be the sets of the point in the ρ - θ plane. So, the point connection will be the sinusoidal wave for each point in x - y. The intersection of the line in a ρ - θ plane that

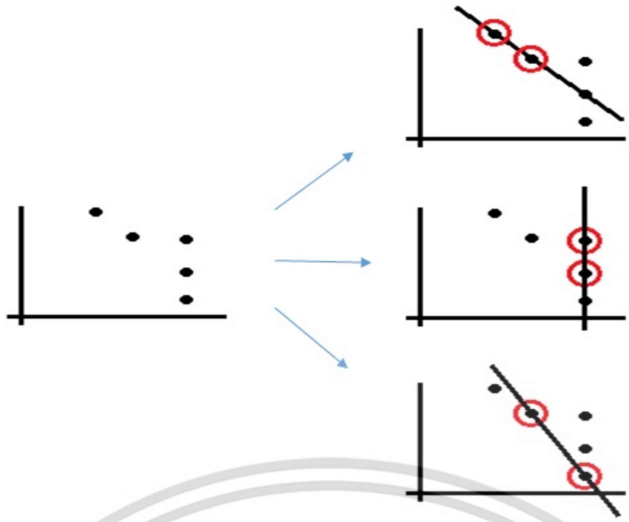

Figure 3.2: Random points method

means they have the same value of ρ - θ. By voting θ in the accumulator will get the set of point in an x - y plane that has the high possibility to be on the same line.

3.5 Randomized Hough Transform

RHT is different from Hough transform in that it tries to avoid conducting the computationally expensive voting process for every nonzero pixel in the image by taking advantage of the geometric properties of analytical curves, and thus improve the time efficiency and reduce the storage requirement of the original algorithm.

On the contrary, The RHT computation consists of selecting two random pixels from edge image and calculating the parameter from the line of the point connection as shown in figure 3.2, accumulating and voting the data in the accumulator, extracting the line segments from that data. The RHT algorithm lies in the fact that each point in ρ - θ plane can be expressed with two points or one line from the original binary edge image. RHT is different from SHT in that it tries to avoid conducting the computationally expensive voting process for every nonzero pixel in the image by taking advantage of the geometric properties of analytical curves, and thus improve the time efficiency and reduce the storage requirement of the original algorithm.

Chapter 4

Methodology

The proposed lane departure warning system using VP-RHT contains many parts including image preprocessing, vanishing point section, lane boundary detection, and tracking and the final is lane changing detection as shown in figure 4.1.

4.1 Image Preprocessing

Image preprocessing is the technique that uses to prepare the image for further processing from the original image as shown in figure 4.2. It is divided into three parts, i.e. sky region removing, grayscale image converting and image smoothing.

4.1.1 Sky Region Removing

The proposed sky region removing is the technique that removes the upper half of the image as shown in figure 4.3. This method can remove the pixel outside the ROI and reduce the computational time in the following method. Equation 4.1 also shows the position of the divided line.

$$\text{The position of the divided line} = \frac{\text{The number of pixels in vertical}}{2}, \tag{4.1}$$

4.1.2 Grayscale Image Converting

The input image is usually an RGB image. Consequently, this method converts the intensity

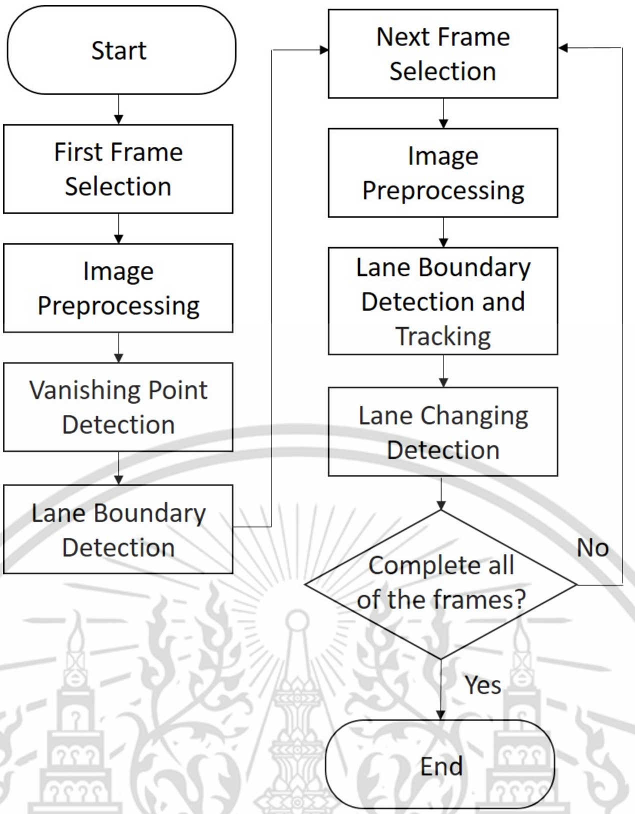

Figure 4.1: Overall of the proposed system

Figure 4.2: Original image

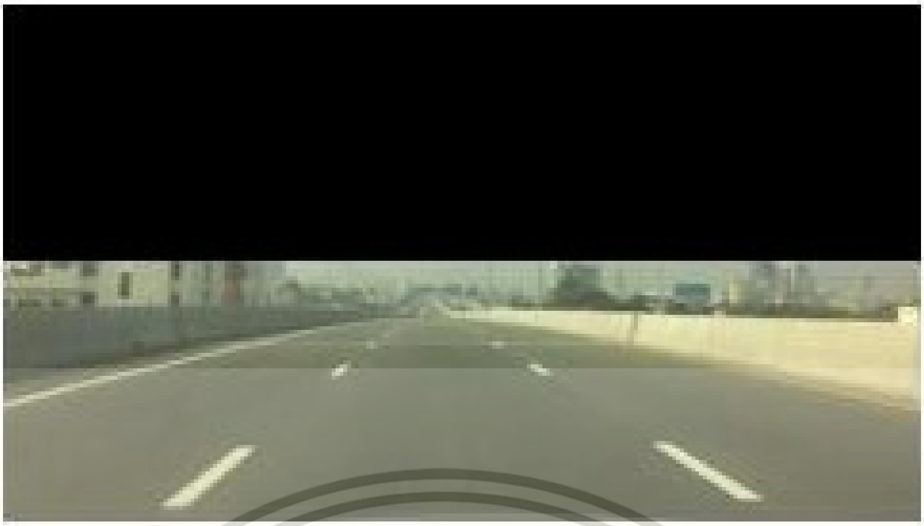

Figure 4.3: Sky region removing method (the black area should be removed)

Figure 4.4: Grayscale image converting method

value of the image into 0 to 255 and reduces the dimension of the image to two as shown in figure 4.4. Equation 4.2 also shows the conversion from RGB to intensity value in grayscale image.

$$\text{Intensity} = 02989 * R + 0.5870 * G + 0.1140 * B, \tag{4.2}$$

where R is the red component, G is the green component and B is the blue component.

4.1.3 Image Smoothing

After the image is converted to a grayscale image, this method uses Gaussian blur or Gaussian smoothing to blur the image as shown in figure 4.5. It is a widely used effect in graphics software, typically to reduce image noise. However, the image's detail will be reduced as well. The equation

Figure 4.5: Image smoothing method

Figure 4.6: Edge detection method

of a Gaussian function is shown in equation 3.2.

4.2 Vanishing Point Section

A vanishing point is a point intersection of the parallel lines projections in the image. The proposed vanishing point section contains two parts including edge detection and vanishing point detection.

4.2.1 Edge Detection

At this stage, edge detection is applied. Edge detection is a fundamental tool in image processing, machine vision, and computer vision, particularly in the areas of feature detection and feature extraction. There are many edge detection proposed in the literature [5]. However, Sobel edge detection has been chosen to use in this thesis. The result of the image is shown in figure 3.2.

4.2.2 Vanishing Point Detection

Vanishing point is a point intersection of the parallel lines projections in the image as shown in

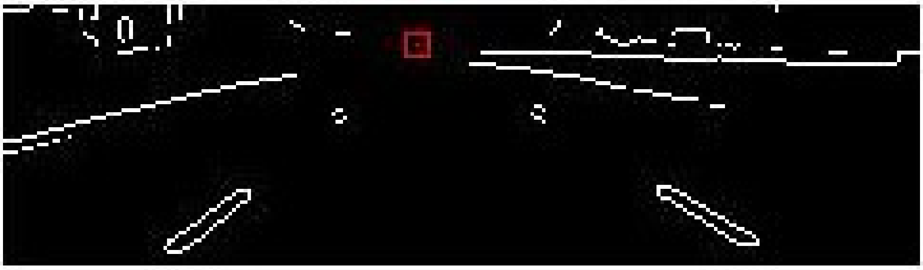

Figure 4.7: Vanishing point detection method

figure 4.7. The proposed system detects the vanishing point using SHT to find the lines because SHT use all of the pixels in the image and it also consumes some computational time. However, this method operates only one time in the first frame and the data of vanishing point is also used to reduce the computational time of another method. The intersection point of the lines that obtain from SHT will assume to be the vanishing point of this image.

For the good performance, the proposed method updates the value of the vanishing point every 20 frames. If new vanishing point is too far from the previous one, the proposed method will use that vanishing point to be the current vanishing point. On the other hand, if the value of a new vanishing point is near the previous one, the value of vanishing point will be averaged.

4.3 Lane Boundary Detection

The proposed lane boundary detection is the technique that uses vanishing point to find lane boundary in the image. It is divided into three parts, i.e. irrelevant area removal, vanishing point based randomized Hough transform (VP-RHT) and lane selection.

4.3.1 Irrelevant Area Removal

Although, the vanishing point in an image are found. The proposed irrelevant area removal is the technique that removes the area using the data of vanishing point. The system creates two line connections between vanishing point and two bottom corner in the image. Then, the system removes the upper part as shown in figure 4.8. This can reduce some noise and computational time of the system.

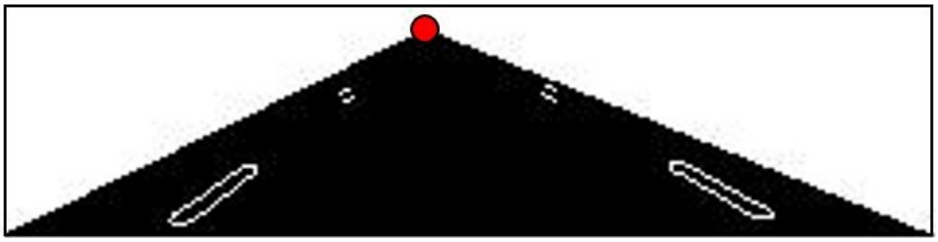

Figure 4.8: Irrelevant area removal (the white area should be removed)

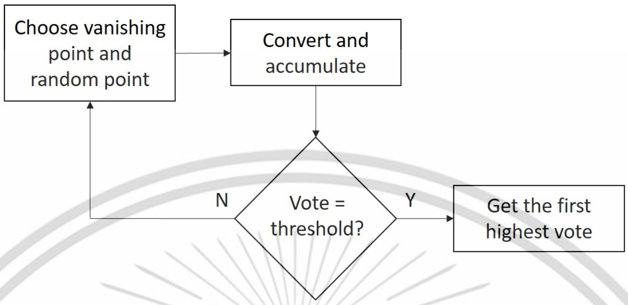

Figure 4.9: Block diagram of the vote type in accumulator

4.3.2 Vanishing Point Based Randomized Hough Transform

Since, the geometry of the lane on the road is actually a line. Thus, the algorithm that can detect lines should be used for lane detection. For this reason, the proposed VP-RHT is chosen and applied for lane detection. It uses the vanishing point in the random part of RHT. This randomly chooses two points (vanishing point and random point) from irrelevant area removal method. The random type is uniformly distributed pseudorandom integers. It converts those two points into a polar coordinate and accumulates them in the accumulator. Then, this method returns to randomly choose two points again until the number of votes in the accumulator is equal to the threshold value. Threshold value should be appropriate because a high value of threshold will consume a lot of computational time for loop as the block diagram in figure 4.9. This means a lot of pixels of the line will get the high possibility to firstly complete the vote condition.

4.3.3 Lane Selection

For this method, it identifies the lane marker from the detected lines. First, it divides the image using the vanishing point into two parts (left and right parts) as shown in figure 4.10. This makes the image easy to detect the lane marker.

Figure 4.10: Divided image

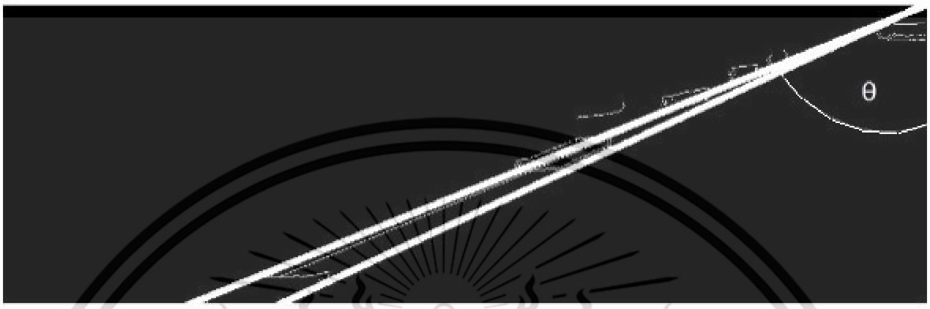

Figure 4.11: Lane selection method

Then, this method will select the lowest θ line and assume it to be the lane marker of the image as shown in figure 4.11. Generally, the lane marker should locate near the middle of the road surface.

4.3.4 Lane Boundary Detection and Tracking

The proposed lane boundary detection and tracking method also operates the image preprocessing method and detects the lane marker line using VP-RHT. It uses the data of vanishing point and the lane boundary of the previous frame to create the gap as shown in figure 4.12. This will reduce the pixel of the image and also reduce a lot of computational time of the system.

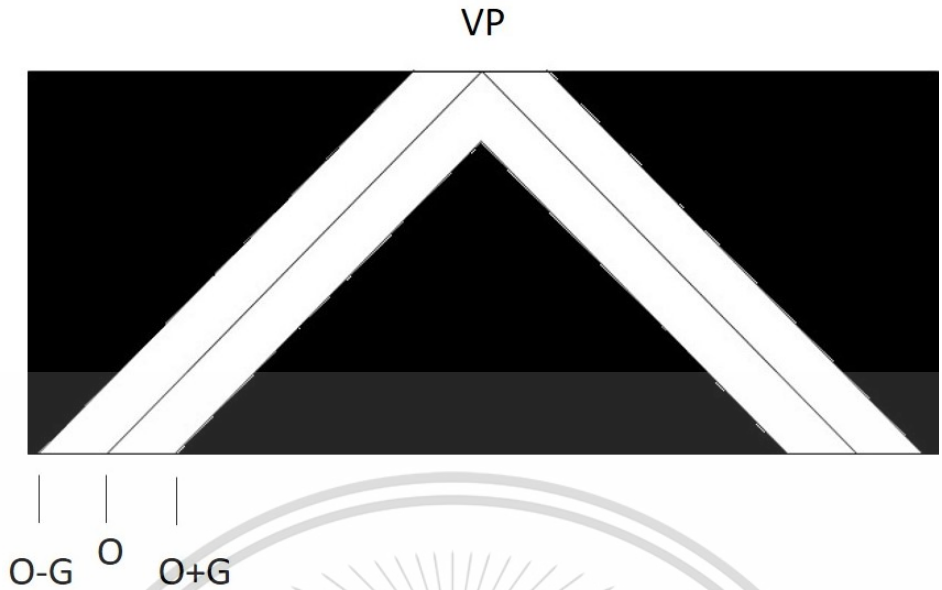

Figure 4.12: Lane boundary detection and tracking method

Where O is the intersection between the previous lane marker line and the x-axis, G is the constant value for the lane changing region. This process only the gap area O-G to O+G and the other area should be black.

4.4 Lane Changing Detection

This proposed method will warn the driver when the image is in unintended lane changing condition. The meaning of unintended lane changing is the driver should not use the direction signal. The proposed method warns the driver using sound and the block diagram as shown in figure 4.13.

The proposed condition testing classifies the image into four states: normal state, out of lane state, lane changing state and completed state as shown in figure 4.14.

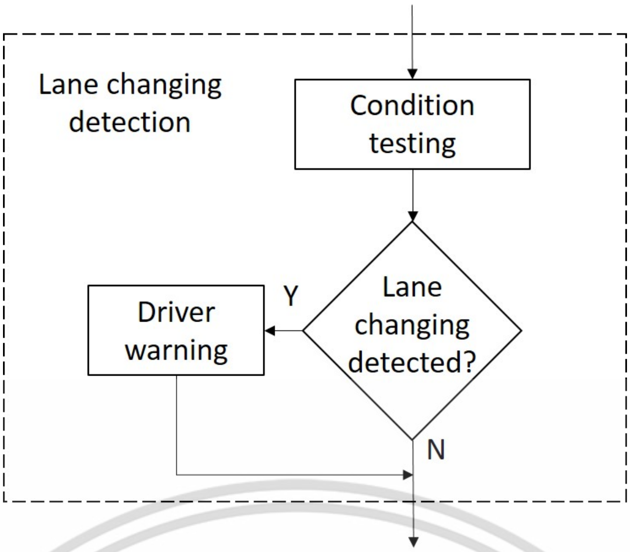

Figure 4.13: Lane changing detection block diagram

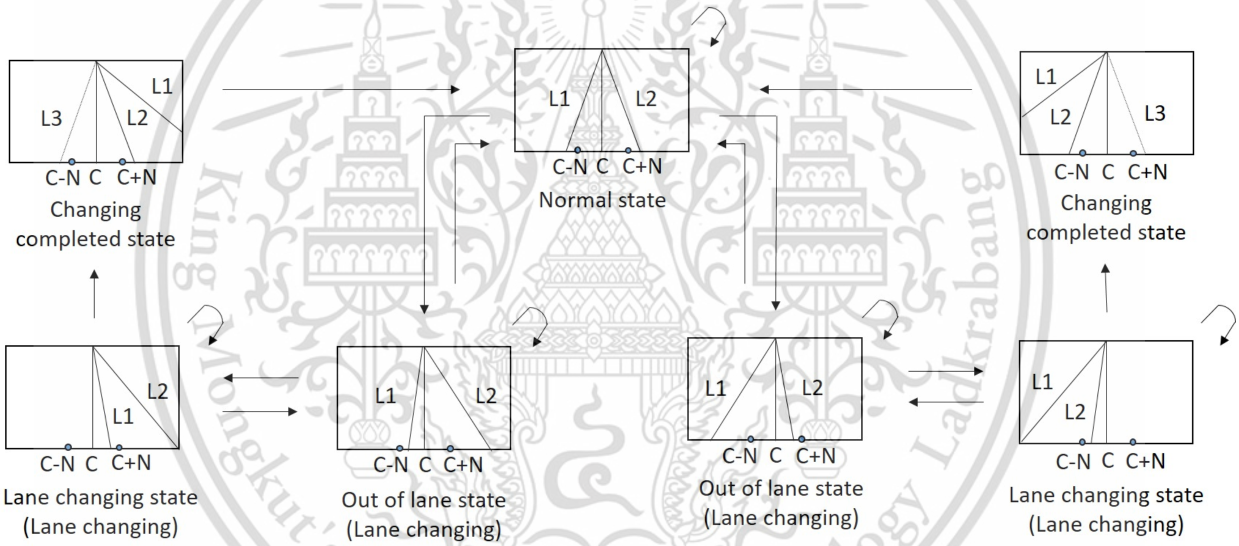

Figure 4.14: Condition testing method

Where C is the intersection between vanishing point line and the x-axis, L1 is the left lane marker line, L2 is the right lane marker line and L3 is the additional lane mark line. N is the constant and it is used to create lane changing region C-N to C+N.

The result of lane changing state depends on the position of the left and right lane marker lines. The method operates in both parts (left and right lane changing). However, this work will show only left lane changing for the convenience.

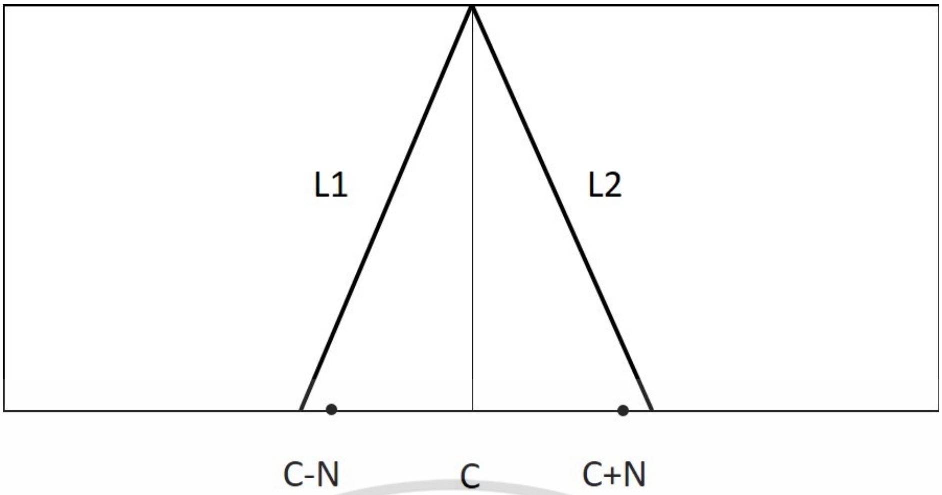

Figure 4.15: Normal state

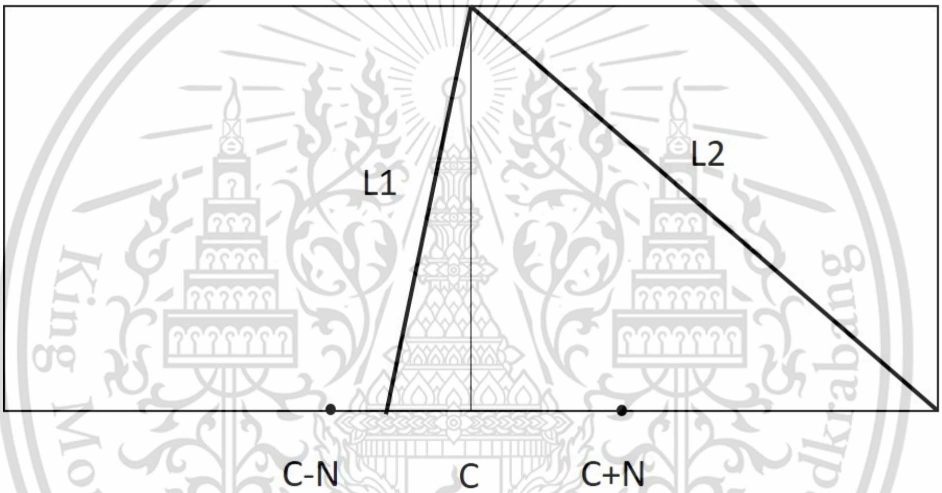

Figure 4.16: Out of lane state

4.4.1 Normal State

For this state, line L1 is lower than C-N and line L2 is higher than C+N as shown in figure 4.15. The warning doesn't operate and the next frame still can continue in this state.

4.4.2 Out of Lane State

For this state, line L1 drop into lane changing region C-N to C and the position of line L2 is still higher than C+N as shown in figure 4.16. However, the warning will operate and the next frame still can continue in this state.

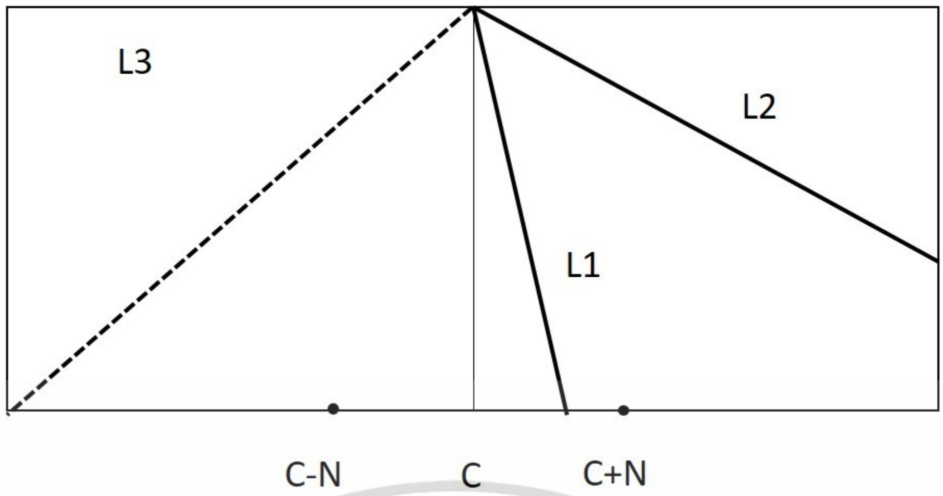

Figure 4.17: Lane changing state

4.4.3 Lane Changing State

This proposed state, the position of line L1 drop into lane changing region C to C+N and line L2 is still higher than C+N as shown in figure 4.17. However, this state detects the additional line in the left-hand side using VP-RHT. The meaning of L3 line is new lane marker line. The system still warns the driver and the next frame can continue in this state.

4.4.4 Changing Completed State

For this proposed changing completed state, L1 and L2 lines are outside the lane changing region C-N to C+N as shown in figure 4.18. This assumes L2 line to be the L1 and L1 line to be L3. The warning does not operate in this state.

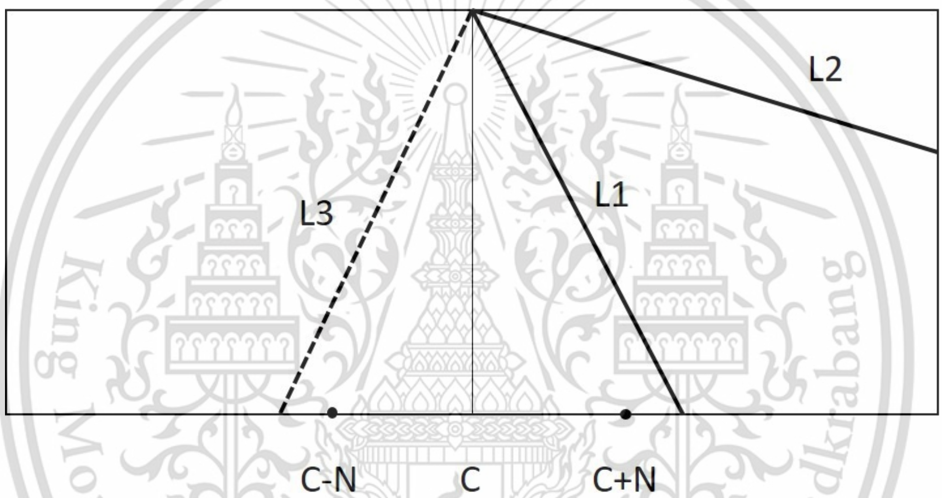

Figure 4.18: Changing completed state

Chapter 5

Results and Discussions

5.1 Datasets

The datasets of this thesis had five videoes. the first video was the comparison between VP-RHT, RHT and SHT. The second video was the night condition. The third video was the heavy rain condition. the fourth video was the curve condition and the final video was the congested condition. They were recorded by the front car camera as shown in figure 5.1. The overall of the datasets were shown in table 5.1.

5.2 Experimental Setup

The proposed system run on the experiment as shown in table 5.2. The video is recorded at 4 p.m. in the highway environment and it was also recorded in the normal and lane changing state.

The proposed system had a comparison between VP-RHT, RHT and SHT. The performance indicators of this system were lane detection accuracy, lane changing warning accuracy and time of processing.

Software	MATLAB R2013a
Video input	From front car camera 30 fps about 15 sec
Size	1920x1080 (resized to 240x135)

Table 5.1: Dataset

Figure 5.1: Camera installation

Model	ASUS K550J
CPU	Intel Core i7-4710HQ up to 3.5 GHz
RAM	8 GB

Table 5.2: Hardware system

Hough transform types	Accuracy (%)	
	Normal	Lane changing
SHT	79.40	56.00
RHT	30.00	26.67
VP-RHT	99.97	99.87

Table 5.3: Result of the accuracy

Hough transform types	Computational time (s)	
	First frame	Other frame
SHT	0.1988	0.1983
RHT	0.1804	0.1788
VP-RHT	0.2335	0.1391

Table 5.4: Result of the computational time

5.3 Comparison Results

The result of the comparison was shown in table 5.3. The accuracy of SHT was 79.40% in a normal state and 56.00% in lane changing state. The accuracy of RHT was 30.00% in a normal state and 26.67% in lane changing state. The final, the accuracy of VP-RHT was 99.97% in a normal state and 99.87% in lane changing state.

In case of computational time as shown in table 5.4, SHT was 198.8 millisecond in the first frame and 198.3 milliseconds in the other frame. The computational time of RHT was 180.4 millisecond in the first frame and 178.8 milliseconds in the other frame. The final, the computational time of VP-RHT was 233.5 millisecond in the first frame and 139.1 milliseconds in the other frame.

5.4 Different Road Conditions

The proposed VP-RHT was tested in the different road conditions such as night condition, heavy rain condition, curve condition and congested condition with the same dataset and experimental setup as the Hough transform comparison.

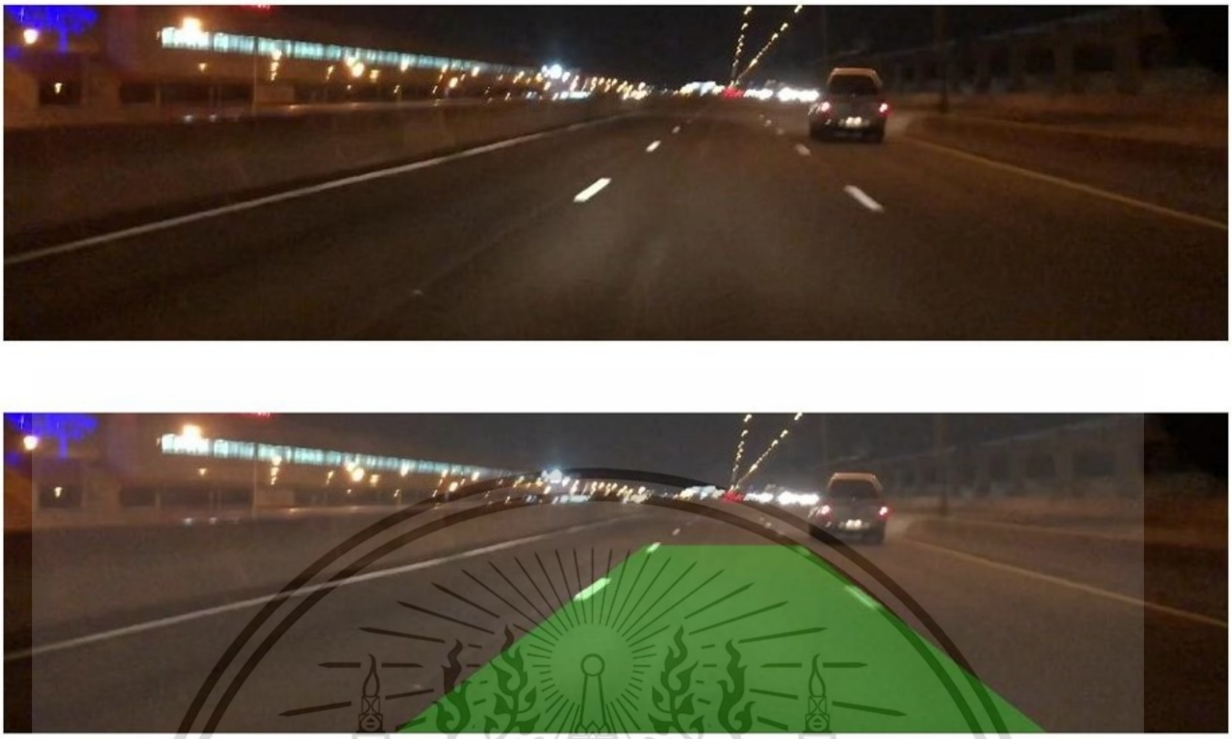

Figure 5.2: Night condition

5.4.1 Night Conditions

In this condition, the noise should increase because of the light. However, the VP-RHT still can detect the lane boundary as shown in figure 5.2.

5.4.2 Heavy Rain Conditions

In heavy rain condition, the proposed system obtained the noise from the rain on the road surface and the rain on the windshield. Not only that, but it also got the noise from the windshield wiper as shown in figure 5.3.

5.4.3 Curve Conditions

This method divided road surface of the input image into two parts as shown in figure 5.4. In area number 1, the curve did not change the lane marker of the image. On the other hand, the lane marker of the area number 2 tended to be the curve. For this reason, the proposed system should process only the pixels in area number 1 to avoid the effect of the curve road. However, the

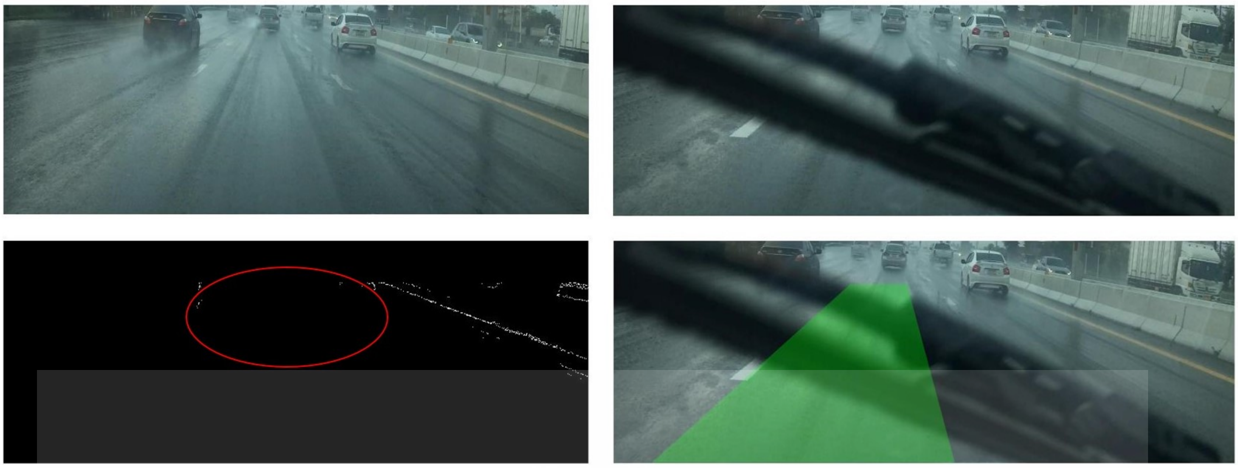

Figure 5.3: Heavy rain condition

Road condition types	Accuracy (%)
Night	99.45
Heavy rain	79.20
Curve	95.45
Congested	92.33

Table 5.5: Result of the different road condition

vanishing point also can be changed in this condition. This will change the position of the gap area in lane boundary detection and tracking and the proposed method will lose some pixel. To avoid this problem, the system should update the vanishing point every some set of the frame.

5.4.4 Congested Conditions

This condition meant there was more vehicle on the image. This will increase the noise pixel. The noise from the vehicle will effect to the vanishing point detection and the lane marker detection method. The system also can get more noise when the vehicle was on the lane marker pixel as shown in figure 5.5.

The result of LDWS using VP-RHT in different road condition was shown in table 5.5.

5.5 Discussions

From the table 5.3, the accuracy of RHT was lower than SHT because of the uncontrolled

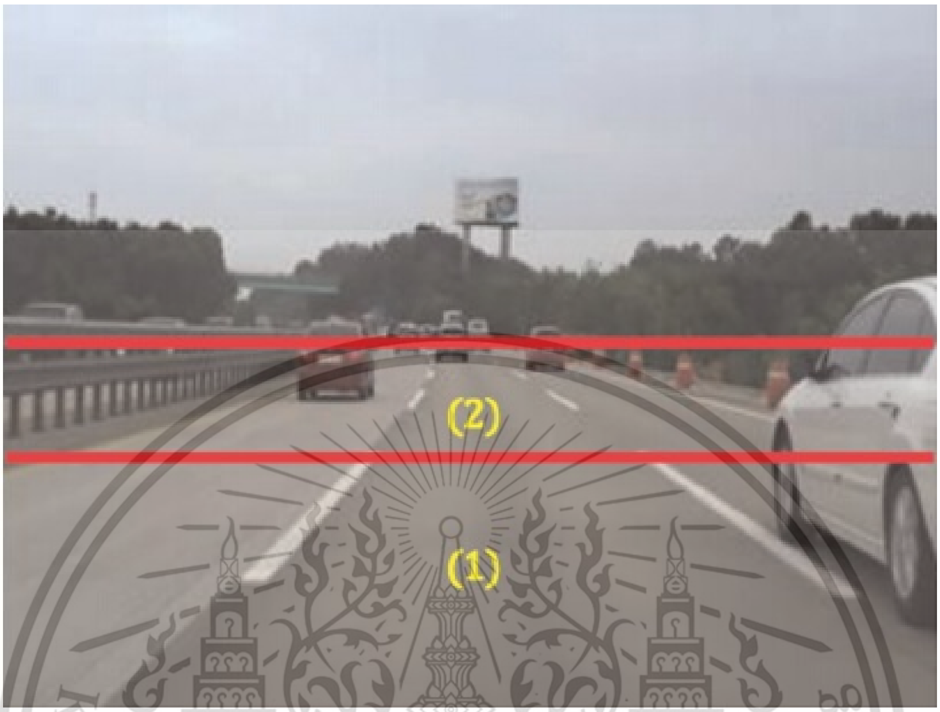

Figure 5.4: Curve condition

Figure 5.5: Congested condition

random point. The proposed VP-RHT was very good in normal and lane changing state because of the vanishing point detection method.

In addition, the computational time of RHT as shown in table 5.4 was lower than SHT in both frame condition because the RHT used only some subset of SHT. The computational time in the first frame of VP-RHT was higher than RHT and SHT because it should spend the time for the vanishing point detection method. Whereas, the vanishing point detection operated only the first frame of VP-RHT. However, the computational time of VP-RHT in the other frame was lower than RHT and SHT.

Finally, the table 5.5 shown the accuracy result of VP-RHT. The night condition was the highest accuracy because the lane marker also cleared by the car light. On the other hand, the congested condition was the lowest because of the noise from the other vehicle.

Chapter 6

Conclusions

6.1 Conclusions

The aim of the thesis is to reduce the road accident rate caused by unintended lane changing. This is done by developing a new driver warning system. This will warn the driver as they unintentionally change driving lane.

The system starts by obtaining a set of the image from video taken by the front car camera. These images are processed by appropriate image preprocessing, vanishing point section and lane boundary detection i.e. sky region removing, grayscale image converting, image smoothing, edge detection, vanishing point detection, irrelevant area removal, vanishing point based randomized Hough transform, lane selection, lane boundary detection and tracking. The lane changing detection will determine whether the car is changing lane or not. If the car is changing lane, the system will warn the driver in form of sound. For accuracy purposes, the position of the camera should be installed on the windshield of the car and facing to the road.

A new LDWS using VP-RHT is presented. It also proposes the VP-RHT based lane detection and tracking and lane changing detection using vanishing point. The computational time of this proposed VP-RHT is also faster than compared method (0.13 sec/frame) but still cannot achieve the real-time performance. The proposed system can accurately detect and track lanes (99%) in the simulation, obviously better than the compared method and also achieve very good performance on curve road and nighttime condition (99%) but has some problems with heavy rain condition (79%) in the simulation.

For the future work, this system could be optimized to reduce the time it takes for real-time processing. In image smoothing, the filter could be optimized to reduce the time it takes to process and reduce the noise. It still has many methods or techniques to find the vanishing point in the vanishing point detection. In the edge detection, other techniques could be applied to reduce more time of processing or remove some noise. Also the position of the camera could be experimented with, placing it on the center of the windshield could improve the accuracy for area removing part. In lane boundary detection, other Hough transform techniques can be experimented with, to optimally find the lane boundary. The other road condition such as the snow condition could be simulated on the future work.

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APPENDIX A :

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Lane Detection using Randomized Hough Transform International Conference on Mechanical Engineering (TSME-ICoME)

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Abstract. According to the report of the Royal Thai Police between 2006 and 2015, lane changing without consciousness is one of the most accident causes [1]. To solve this problem, many methods are announced. Lane Departure Warning System (LDWS) is considered to be one of the solving methods. LDWS is a mechanism designed to warn the driver when the vehicle begins to move out of its current lane. LDWS contains many parts including lane boundary detection, driver warning and lane marker tracking. This article focuses on the lane boundary detection part. The purposed lane boundary detection detects the lines of the image from the input video and selects the lane marker of the road surface from those lines. Standard Hough Transform (SHT) and Randomized Hough Transform (RHT) are purposed for this article. They are used to extract lines of an image. SHT extracts the lines from all of the edge pixels. RHT extracts only the lines randomly pick the point pairs from edge pixels. RHT algorithm reduces the time and memory usage when compared with SHT. The increasing of the threshold value in RHT will increase the voted limit of the line that has a high possibility to be the lane marker, but it also consumes the time and memory.

By comparison between SHT and RHT with the different threshold values, 500 frames of input video from the front car camera will be processed. The accuracy and the computational time of RHT are similar to SHT in the result of the comparison.

1. Introduction

Nowadays, more demands on vehicles are increasing because of the rapid population growth. This leads to the major causes of higher road accidents. Nearly 3,500 people die on the road every day. It is found that the lane changing is the most accident causes. The advantage of LDWS should be an optional tool to relieve such disaster. LDWS is one of the methods that purposed to solve the problem. LDWS uses the image processing mechanism to detect the lines of the image, selects the current lane markers, warn the driver when the vehicle leaves the current lane and tracks the lane marker for the next frame. In this article, an overview of SHT and RHT are presented and the algorithms are briefly introduced and compared.

Kalviainen et al. [2] presented the probabilistic and non-probabilistic Hough transforms overview and comparisons. They compared a lot of algorithms such as SHT, RHT, Dynamic RHT and Window RHT. They tested in line detection with synthetic and real-world image demonstrate the high speed and low memory usage. The result of the comparison was a good model for the road image.

Lim et al. [3] performed lane-vehicle detection and tracking. Vertical mean distribution was used to remove the sky region by averaging the gray values of each row on the image. A big jump of this method indicated the line that divided the image into sky region and road region. But the result would be error if some part of the car appeared in the image such as a console. Because the averaged value would have changed. To solve this problem, the vanishing point detection was used for this section.

Schreiber et al. [4] presented the lane detection that the vanishing points were discussed. Vanishing points were detected using Hough Transform (HT). This method was used the vanishing point to detect straight line segments. But the vanishing point also can remove the unwanted area to reduce the computational time. In edge detection, Canny edge detection was used in image preprocessing section. In case of computational time, some type of edge detection was better than Canny edge detection [5].

Kultanen et al. [6] introduced the RHT. The mechanisms of a random sampling of point pairs from the x - y plane, converted to the ρ - θ plane and voted the accumulator. In the lane marker detection, the accuracy of this method can increase by assuming the one point of the pair to be the vanishing point. Because the vanishing was the part of the straight line in the image.

Wang et al. [7] purposed a B-Snake based lane detection and tracking algorithm without any parameters of the camera. This article used Canny/Hough estimation of vanishing points (CHEVP) to provide a good initial position for the B-Snake. The snake got drawbacks. It often stuck in local minima states which can be counteracted by simulated annealing techniques. Minute features were often ignored during energy minimization over the entire contour. And their accuracy was governed by the convergence criteria used in the energy minimization technique.

To solve the problems, a lane detection is proposed in this article as the flow diagram in figure 1. Lane boundary detection is divided into 3 parts. The image that obtained from the camera has many ingredients. The image preprocessing is applied to make it appropriate for processing. Image preprocessing is performed on the road image to locate the left-right lane edges by separating the sky region and analyzing road region known as the region of the interest (ROI) in this article to extract the prominent road features such as lane markers. The information of the vanishing point is used to limit the area in line detection and refer the point in RHT. Lane marker detection part attempts to identify the lane marker from the detected lines.

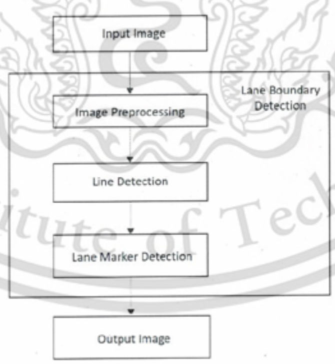

Figure 1. System overview.

This article is organized as follows. Section 2 discusses about the lane boundary detection and explains the detection technique. Some simulation results are shown in section 3 followed by the conclusion and future works.

2. Lane Boundary Detection

Lane boundary detection consists of 3 parts, i.e. image preprocessing prepares a proper image for further processing from the original image as shown in figure 2, line detection to extract the lines contained in the images and lane marker detection to detect the current lane markers.

Figure 2. Original image.

2.1. Image preprocessing

The purposed image preprocessing includes the grayscale image converting, image filtering, image morphology as shown in figure 3, Sky region removing applies some technique to remove some part of the image outside the ROI. This can reduce the computational time in the vanishing point detection method. In this article, the sky region removing removes the upper half of the image as shown in figure 4. Consuming some part of the road surface is unnecessary because this method focuses on the lane markers.

Figure 3. The result of image preprocessing.

Figure 4. The result of sky region removing.

pseudorandom integers. Then, create the line from that two points using linear equation. This method also uses the equation (1) to convert it. After that, the data are accumulated in the accumulator. The vote has 2 types. Firstly limiting the number of input θ and picking the highest one after voting. Secondly, limiting the vote and picking the first θ that equal the vote. This article uses the second one because the user can adjust the computation time. In the other hand, SHT is used the first one to vote the accumulator but the limit of the input is all of the data. So, the computation time of RHT should be lower than SHT because it uses only some point of the image.

The main difference between SHT and RHT is that while in SHT a single pixel in the original image is mapped to a curve in ρ - θ plane, in RHT a pair of pixels is mapped to a single cell in ρ - θ plane. SHT generates all parameter combinations, but RHT generates only a small subset of all parameter combinations.

After that, the area removing uses the information of vanishing point to further remove the unwanted area. Changing the value of that pixel to 0 (black pixel), it can reduce some computational time and some error for this method as shown in figure 10. After the vanishing point and other 2 points at the corner are specified. The corresponding linear equation can be found, i.e.

$$y = mx + c \tag{2}$$

Where m is the slope and c is the y-axis intersection. The vanishing point also can be used to divide the image into the left-hand side and the right-hand side. This method detects the lane marker of two sides as shown in figure 11 and figure 12.

Figure 10. The result of area removing. The image shows only the ROI.

Figure 11. The right-hand side image that divided by the vanishing point.

Figure 12. The left-hand side image that divided by the vanishing point.

2.2. *Line detection*

The line detection part consists of the edge detection that includes a variety of mathematical methods that aim at identifying points in a digital image at which the image brightness changes sharply as shown in figure 5. Many edge enhancement algorithms have been proposed. The Sobel edge detection is used for this article because it is better than Canny edge detection in term of time-consuming [5]. After edge detection method, the image has only white and black pixel.

Figure 5. The result of edge detection.

A vanishing point is a point intersection of the parallel lines projections in the image as shown in figure 6. HT can evaluate the vanishing point by detecting the lines and the intersection point of those lines in the image.

The objective of HT is finding lines in an image it is applied. They are 2 types of HT to be considered in this article, i.e. SHT and RHT. They are different mainly in the resource usage which is one of the concerned issues for the researchers.

2.2.1 Standard Hough Transform

The SHT computation consists of calculating the parameter and accumulating the data in the accumulator, finding the local maxima which represent line segments of the image and extracting the line segments from the maxima positions. The disadvantage of SHT are its computational complexity and huge storage memory consumption.

It assumes all of the white pixels of the image to be the points and converts them into ρ - θ plane. ρ is the line connecting the polar coordinate to the origin where the x-axis intersects the y-axis. θ is the angle between ρ and x-axis as shown in figure 7. Each point in the x - y plane will have the infinity lines that pass the point. Those lines are converted by the equation (1).

$$\rho = x_0 \cos\theta + y_0 \sin\theta \qquad (1)$$

Where x_0 and y_0 are the coordinates corresponding to the angles θ (x_0 , y_0). The line plot of those lines will be the sets of point in the ρ - θ plane. So, the point connection will be the sinusoidal wave for each point in x - y as shown in figure 8. The intersection of the line in a ρ - θ plane that means they have the same value of ρ - θ. By voting θ in the accumulator will get the set of point in an x - y plane that has the high possibility to be on the same line.

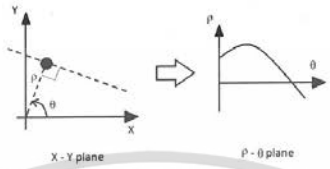

Figure 7. Principle of Hough transform. A point in x - y plane is converted into a curve in ρ - θ plane.

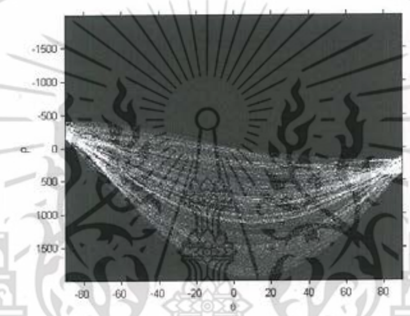

Figure 8. Data voting in ρ - θ plane.

2.2.2 Randomized Hough Transform

On the contrary, The RHT computation consists of selecting 2 random pixels from edge image and calculating the parameter from the line of the point connection as shown in figure 9, accumulating and voting the data in the accumulator, extracting the line segments from that data. The RHT algorithm lies in the fact that each point in ρ - θ plane can be expressed with 2 points or 1 line from the original binary edge image. The advantage of RHT are high parameter resolution, the infinite scope of the parameter space, small storage requirements and fast speed.

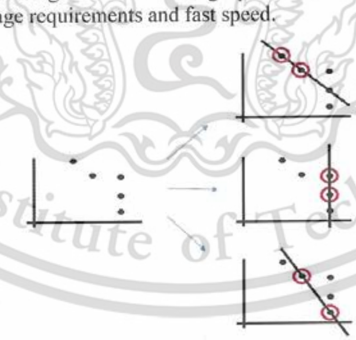

Figure 9. The random point pair method in RHT.

A line detection using the RHT will pick two points from the edge detection. The first point is the vanishing point and the second point is the random point. The random type is uniformly distributed

In case of curve and junction, the different between straight and curved road is some area under the vanishing line as shown in figure 13.

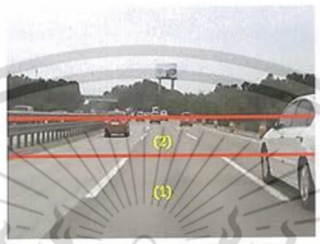

Figure 13. (2) is the area that effected by curved road and (1) is the area that not effected by curved road.

However, the high possibility lines would be the lane markers because of the number of the lane marker pixels.

2.3. Lane marker detection
After line extraction, the lane marker detection will select the lowest θ value of each side. They are assumed to be the lane marker as shown in figure 14.

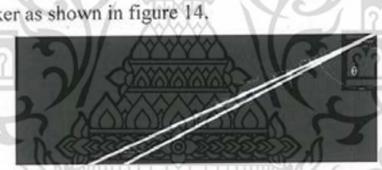

Figure 14. The lowest θ will get the high possibility to be the lane marker.

Generally, the lane marker should have located at the middle of the road surface and bottom of the image. For each side, the system needs to find at least two different θ from the vote and compares them. The lowest θ will have the high possibility to be the lane marker of that side.

3. Result
The system runs on MATLAB R2013a on ASUS K550J CPU Intel Core i7-4710HQ, up to 3.5 GHz RAM 8 GB. A video input was captured under clear condition sunny day about 4 p.m. in a highway environment using iPhone 6 camera.

The accuracy in table 1 is calculated from the correct image of 500 frames input video. The correct image is the image that has the edge of current lane region on the lane marker as shown in figure 15. The result of computational time is from MATLAB function that calculates the processing time of the project.

Table. 1 The comparison table.

Type	Accuracy (%)	Computational time (s)
1. SHT	93.0	150.146
2. RHT (threshold = 5)	93.6	142.488
3. RHT (threshold = 10)	93.8	142.639
4. RHT (threshold = 15)	95	146.587
5. RHT (threshold = 20)	95.2	150.047

Figure 16 shows that the pixels of the shadow are longer than the right lane marker. This means that the system has the higher possibility to random the point on the shadow and assume it to be a lane marker. To solve this problem, some additional methods for image preprocessing such as image filtering, another type of edge detection and the threshold of RHT can be applied. However, this would increase computation time of the system.

Figure 15. The result of the correct image.

Figure 16. The mistake from the detection because of the heavy shadow.

The threshold increasing in RHT will increase the accuracy and computational time. At the higher threshold, the value of accuracy tends to be stable as shown in figure 17. In the other hand, the system tends to consume a lot of computational time in the higher threshold state as shown in figure 18.

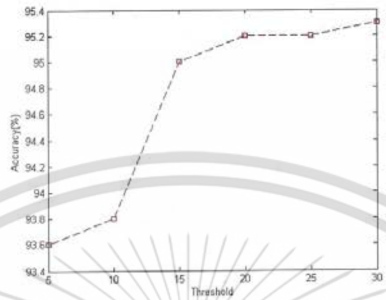

Figure 17. The accuracy of each threshold in RHT.

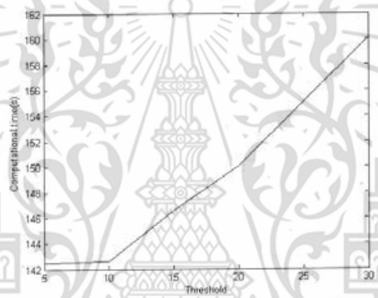

Figure 18. The computational time of each threshold in RHT.

4. Conclusion

Lane detection has been presented in this article image preprocessing, line detection and lane marker detection. It has been shown that the main advantage of the RHT method over the SHT is computational time. The different of computational time between SHT and RHT with 5 threshold is about 5.1 percent, RHT with 10 threshold is about 4.99 percent, RHT with 15 threshold is about 2.73 percent and RHT with 20 threshold is about 0.06 percent from table 1.

The system still has two further parts to complete, i.e. the warning part that finds the condition of lane changing and the tracking part that reduces the computational time of the current frame using the information of the previous frame.

In the future work, the developer can develop the system into the application of the smartphone and attach it to the front of the car.

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