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Lane Detection Based on Block-wise Hough Based Features and ANN

Khin Hsu Wai[1]* **May The` Yu[1]**

[1]*University of Computer Studies, Mandalay, Myanmar*
* Corresponding author's Email: khinhsuwai@ucsm.edu.mm

Abstract: Effective and automated lane marking detection system is one of the important part of many intelligent transportation systems. Many researches of lane detection techniques have been conducted on academic and automobile industry and applied in intelligent transportation systems. However, It is still a challenging problem because of the various environmental conditions such as shadows, lane occlusion and illumination invariance that can decrease the lane detection performance. To deal with these issues, a reliable lane marking detection system that use the block-wise Hough based features is proposed. We propose the Region of interest extraction that divides the image into sub-image blocks to detect the lane line and block-wise Hough Transform feature extraction approach to extract the lane line features. Artificial Neural Network (ANN) applys the extracted features to detect the lane. The efficiency and accuracy of our system is evaluated by using the Caltech lane dataset. The average correct detection rate is 94.67% and the computational time is 17.64 ms/frame by applying the proposed method.

Keywords: Lane detection, Block-wise features, Hough transform, ANN.

1. Introduction

Nowadays, road accidents are one of the biggest problems due to the many factor such as unintended lane departure. Several researches on Advanced Driver Assistance Systems (ADAS) have been conducted worldwide for a past decade to reduce the road accidents by providing the assistance to the driver [1]. Lane Detection (LD) is a main processing stage in ADAS and different lane detection systems have emerged in the past few years [2]. In most cases, lanes are the straight-line in the road image. Otherwise, they appear as the curves which can be detected by small straight lines [3]. The main process of LD system is detecting the lane line from the road image taken with the camera installed on the vehicle [4]. Previous lane detection methods distinguish lane markings from background noise based on the hardware resources or computer-vision techniques [5]. This research mainly focuses on computer-vision based LD system due to the lower cost and high detection accuracy. Most challenges faced by existing lane detection algorithms are caused by the noise such as shadow interference, partial occlusion and different lighting conditions [6-8]. These challenges will affect detection performance of the lane detection systems.

A lot of researches have been done to address these challenges by using difference approaches. Generally, lane detections are performed by employing two types of LD approaches: the feature-oriented approaches, the model-oriented approaches.

The feature-oriented approaches are usually applied to detect the lane by extracting the gradients of pixel information or the colour of patterns [9]. In previous studies, Sobel filter [10], Canny operator [11], local threshold [12], Gabor filter [13], color models [14] are usually used as feature detectors; after that, line detection algorithm such as Hough Transform [15], LSD [16], are used to detect the line segments. These approaches are the most primitive and extendable approaches for LD systems.

The model-oriented approaches use several mathematical lane models: straight line model, parabolic model, and spline model to recognize the lane markings [17] and RANSAC method [18, 19] has been widely used to fit the lane model. The model-oriented approaches are not affected by the noise but they require large computational resource [20]. Moreover, the drawback of model-oriented approaches is that the lane model constructed for one scene cannot detect the lane in other scenes [16].

This paper proposes the lightweight feature-oriented lane detection system to detect the current driving lane. In this proposed system, lane detection operation consists of three phases: image pre-processing phase, Hough Transform based feature extraction phase and ANN based detection phase.

The aims of our proposed lane detection system are as follows:

- to set the region of interest that exist the lane markings.
- to extract the lane marking features using block-wise HT feature extraction technique for lane detection.
- to provide the driving safety in various illumination conditions.

This paper proposes two contributions: (1) the region of interest (ROI) extraction method for extracting the lane region and dividing the ROI into sub-image blocks to reduce the computational complexity; (2) Hough Transform based feature extraction approach for extracting block-wise lane line features on each image block.

The remaining sections are organized as follows: the previous research works related with the LD system are described in section 2. Our proposed LD framework is discussed in section 3. In section 4, experimental setup and result analysis using public lane dataset is illustrated. The conclusion of this paper is mentioned in section 5.

2. Related works

In this section, previous research methods that related with the lane detection and tracking systems are described. There have been many researches that have proposed various computer-vision and machine learning based LD approaches.

Y. YenIaydin and K. W. Schmidt [21] proposed the novel neighbourhood AND operator to get the binary image and detect the lane pixels via maximum likelihood estimation in Gaussian probability density function. However, this approach used fixed ROI and the static thresholds. It can only detect the straight lane in clear conditions.

J. H. Yoo, S. W. Lee, S. K. Park, and D. H. Kim [22] proposed the vanishing point based LD framework in which LSD algorithm was used to extract the line segments. Lane markings are detected by filtering out the outlier line segments according to orientation constraints. However, the performance of their method may degrade in lane detection because irrelevant line segment is extracted because of the incorrectly detected vanishing point in noisy areas.

Q. Zou, H. Jiang, Q. Dai, Y. Yue, L. Chen, and Q. Wang [23] proposed the novel fusion strategy by integrating CNN and RNN for identifying the lane marking in continuous driving scenes. In this architecture, convolutional neural network (CNN) was used to abstract input frames into feature maps and LSTM take feature maps to predict the lane line. However, this method is time consuming.

J. Chen, Y. Ruan, and Q. Chen [24] proposed a lane line detection approach in which Gaussian Mixture Model (GMM) was used to generate the ROI region and detect the line segments by PPHT. After that, left lane and right lane are detected by clustering line segments according to slope and intercept features using K-Means algorithm. However, it cannot perform well in challenging and noisy environments.

Y. Kortli, M. Marzougui, B. Bouallegue, J. S. C. Bose, P. Rodrigues, and M. Atri [25] proposed the illumination-invariant LD system based on Otsu’s thresholding and Hough Transform algorithm where ROI is extracted using the vanishing point location and edge features are extracted by Sobel operator. This process aims to deal with the lighting problems for lane detection. However, this method can cause false detection for worn lane markings.

D. Liu, Y. Wang, T. Chen, and E. T. Matson [26] suggested the LD approach, which used the combination of colour filter and K-Means algorithm for to reduce the noise. Firstly, distortion correction was performed on the image and the edges are detected by Sobel method. Then, the edge image is enhanced using the proposed method and detect the lane line pixel by Hough Transform. However, it cannot correctly detect the lane in shadowy and illumination conditions.

M. Marzougui, A. Alasiry, Y. Kortli, and J. Baili [6] proposed a LD framework in which the region of interest is defined by using the Vertical Mean Distribution method. PPHT and K-mean clustering methods were employed for identifying the left and right lane. The orientation angle thresholds are defined to eliminate the outlier line segments and Kalmal filter track the lane markings.

S. Malmir and M. Shalchian [10] presented the FPGA-based LD system that combines with two lane detection algorithms to solve the real world challenges. The first algorithm detects the lane markers by using adaptive threshold and HT to detect the lane markers. Then, strip feature detection was activated to find the lane marks when HT fails to detect the lane. Although this system can efficiently detect the lane markings, it can cost the processing time and hardware resources.

S. Liu, L. Lu, X. Zhong, and J. Zeng [16] presented the road lane detection and tracking algorithm for detecting the right and left lane markers. Line Segment Detector (LSD) was applied on the right and left ROIs to detect the line and used the slope and length properties to eliminate the noisy line segments. Moreover, Kalman filter was used not only to track the ending and starting points of the lane but also to predict the next ROIs. The experiment was conducted on Caltech lane dataset.

T. Youjin, C. Wei, L. Xingguang, and C. Lei [20] proposed the vanishing point based lane detection system in which LSD method was employed to detect the candidate line segments, and proposed the direction priority search method and score function to eliminate the false line segments. This technique conducted the experiment on the Caltech lane dataset which contains the challenging road conditions. Although this system can detect the lane markings in complex road scenes, there are some detection failures due to the shadows and repaired marks on the road.

Most of the aforementioned LD systems mainly applied Hough Transform as the lane detector. They performed the post-processing operations to eliminate the outlier line segments by using the heuristic threshold value. Although deep-learning based LD system can increase the accuracy of the detection performance, they consume the hardware resource and computational complexity. To overcome these shortcomings, this paper proposed the lightweight lane detection system by using HT as a feature extractor to extract the block-wise lane line features and detect ego-lane according to the extracted features by using the supervised learning approach.

3. Proposed method

Our proposed lane detection framework is mainly composed of four main phases: ROI extraction and block division, Pre-processing, Feature Extraction and detection phases. Our proposed LD system architecture is illustrated in Fig. 1. Firstly, region of interest (ROI) are set from the input image frame sequences and divide the sub-region blocks to reduce the computational complexity by using the proposed ROI extraction technique. And then, pre-processing is performed to each image block to get the enhanced image. After that, block-wise lane line features are extracted by using the Hough Transform approach and extracted features are used as the inputs to the Artificial Neural Network (ANN) to detect the left and right lane markings.

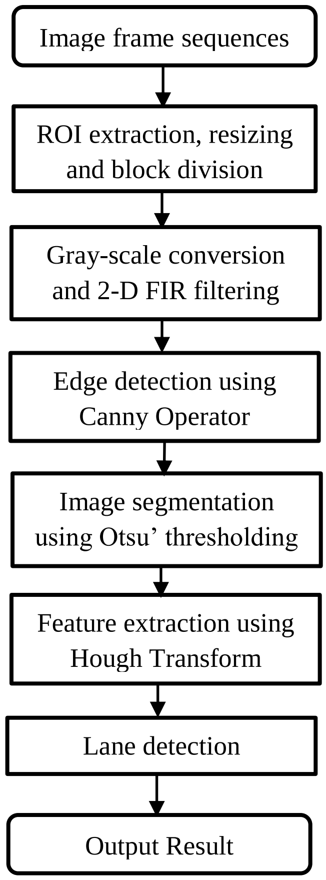

Figure. 1 Proposed lane detection system architecture

3.1 Region of Interest (ROI) extraction and block division

The input image contains the useless information that can affect detection performance. Therefore, extraction the ROI is important to minimize the computational complexity and get the better detection performance [27]. The input image contains the important lane markings, and other noisy parts such as sky, tree, etc. Thus, the region of interest extraction is performed to eliminate the noisy areas that can increase the false detection. The x and y coordinates of the ROI are calculated by using the Eq. (1) and Eq. (2) and the width and height of the ROI are 256 and 128 pixels respectively

$$x = ceil\left(\frac{w}{2}\right) - 128 \qquad (1)$$

$$y = ceil\left(\frac{h}{2.5}\right) \qquad (2)$$

Where w and h are width and height of the original image frame. After ROI is extracted, 64×64 image blocks are divided to extract the features and detect the lane as shown in Fig. 2. Since the size of ROI is 256×128 dimension, there are eight blocks of 64×64 sub-image blocks.

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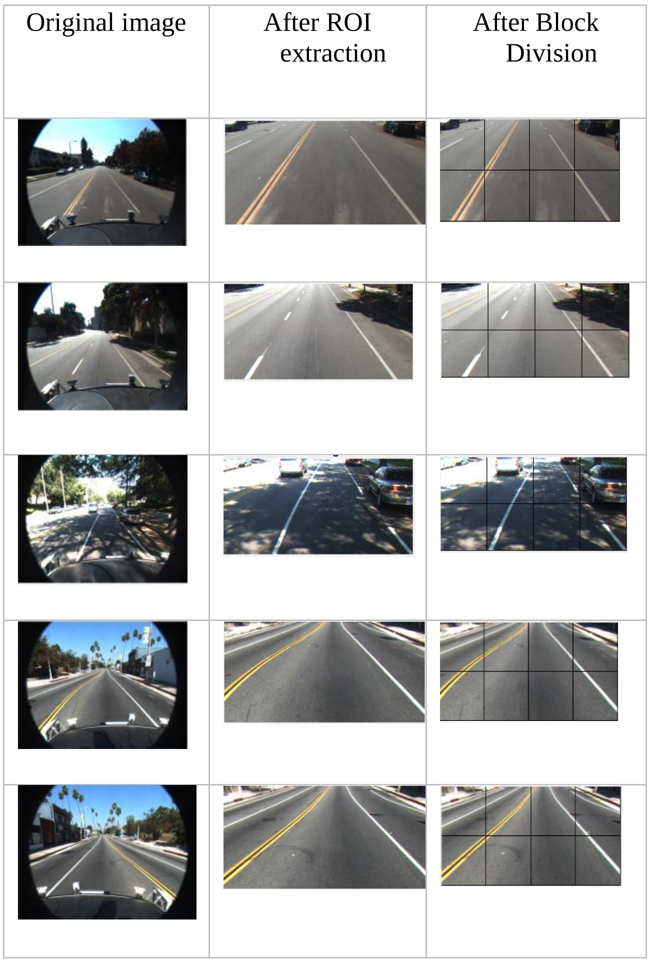

Figure. 2 ROI extraction and block division

4.1 Pre-processing

In this phase, some image processing techniques are performed to highlight the certain details of the image and smooth the image.

In this research, there are four main steps in pre-processing phase: gray-scale conversion, image smoothing by using 2D-FIR filter, Canny edge detection and image segmentation by Otsu' thresholding to improve the lane detection performance.

3.2.1. Gray-scale conversion

The initial stage of pre-processing is converting the RGB color image into grayscale image. After grayscale conversion, it only takes 8 bits to store a single pixel of the image instead of 24 bits RGB image. So, the processing time can be decreased by minimizing the amount of data to be processed. The colour image is converted to grayscale image by using Eq. (3).

$$GrayScale = [0.299 \quad 0.587 \quad 0.114]\begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (3)$$

where R means the intensity value of the red pixels, G means the intensity values of the green pixels and B represent the intensity values of blue pixels in the image.

3.2.2. Image smoothing

Two-Dimensional FIR filter is then applied to the grayscale image to enhance the image and improve the edge detection. It can be used to extract edge information and enhance the image in image-processing [28]. In this filter, the filtering operation is performed by applying the convolution operation on grayscale image with the filter kernel as shown in Eq. (4).

$$y(n,m) = \sum_{k=0}^{(I-1)} \sum_{l=0}^{(J-1)} C(k,l) * G(n-k, m-l) \quad (4)$$

$$C = [-1\ 0\ 1] \quad (5)$$

where $0 \leq n < I+M-1$ and $0 \leq m < J+N-1$, $y(n, m)$ represents the filtered image, $G(n, m)$ represents the grayscale image, C represents the filtered kernel, k and l are the coordinate values of the filter kernel, I and J are the dimension of the input image, M and N are the dimensions of the kernel, $*$ means the convolution operation. The filter kernel dimension is 1×3 as shown in Eq. (5). The pixel value of the filter kernel satisfies -1 to 1. So, Eq. (4) can be reduced to Eq. (6).

$$y(n,m) = \sum_{k=-1}^{k=1} C(k,l) * G(n-k, m) \quad (6)$$

3.2.3. Image segmentation

The next step is to apply the Otsu's thresholding to segment the binary image and remove the noise. The Otsu threshold method is a type of global thresholding methods and determine the optimal threshold for an image by doing the statistical analysis. The task of Otsu's thresholding is searching the optimal threshold value which minimize the within-class variance and generate a binary image and split into two classes: background (below threshold) and foreground (above threshold) respectively [29]. The within-class variance is calculated using Eq. (7).

$$\sigma_w^2 = w_b \sigma_b^2 + w_f \sigma_f^2 \quad (7)$$

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where σ_w^2 is the within-class variance, w_b and w_f are the weight factors, σ_b^2 and σ_f^2 are the variance of the background and foreground pixels. The intensity level with the minimum within-class variance is the optimal threshold. Image segmentation is performed according to the optimal threshold.

3.2.4. Edge detection

Edge detection is the process of finding the intensity changes or boundary of an object in an image. Due to discontinuities in brightness between the road background and the lane markings, edge detection can be very useful to highlight the edge features of the lane line. In this paper, Canny algorithm is used due to its robustness to noise. Canny edge detection is a multi-level edge extraction algorithm for extracting edge features from different visual objects. Five processing stages of Canny edge detection are as follows:

(1) Smoothing the image by using the Gaussian filter to remove noise. (Smoothing)
(2) Finding the intensity gradients with the Sobel operator. (Finding Gradients)
(3) Suppression the pixel values that is not at maximum. (non-maximum suppression)
(4) Determining the potential edges by using two threshold values. (double thresholding)
(5) Determining the final edges by eliminating all edges that are not connected to strong edge. (Edge tracking by hysteresis)

4.2 Feature extraction

In this research, the block-wise lane line features are extracted by using Hough Transform (HT). HT can be used to detect the instances of objects in an image. Most of the LD systems widely used HT as it is robust to noise and partial occlusion and can also detect both continuous and discontinuous lane lines. The principle of Hough Transform is that it draws a line joining the edge points if they lie on a straight line. HT detects all the straight lines passing through the feature point and stores the results in the accumulator matrix. Lane boundary lines positions are obtained by looking for the local maximum value in the accumulator matrix [30]. HT transforms the straight line model in Eq. (8) to the format in Eq. (9) and Eq. (10).

$$y = kx + b \tag{8}$$

$$\rho = x\cos\theta + y\sin\theta \tag{9}$$

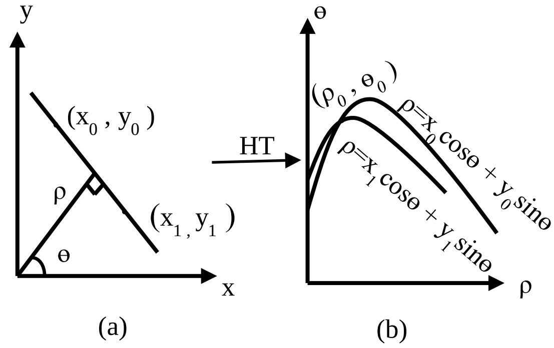

Figure. 3 Mapping from cartesian space to polar space: (a) and (b)

$$y = -\frac{\cos\theta}{\sin\theta}x + \frac{\rho}{\sin\theta} \tag{10}$$

where ρ represents the distance between the origin and the line, θ represents the line angle in polar space, x and y are coordinate values of the pixels in edge image, b and k represent the intercept and the slope values of the detected line. Fig. 3 illustrates the principle of Hough Transform algorithm. The point of the straight line passing the point (x_0, y_0) and the point (x_1, y_1) corresponds to the curve $\rho=x_0\cos_\theta+ y_0\sin_\theta$ and the curve $\rho=x_1\cos_\theta+y_1\sin_\theta$ on the (ρ, θ) parameter space after Hough Transformation.

The collinear point (x_0, y_0) and point (x_1, y_1) intersect at the same point (ρ_0, θ_0), where ρ_0 and θ_0 are the parameters of the line determined the points (x_0, y_0) and (x_1, y_1) respectively. Fig. 4 illustrates the flow diagram of the proposed feature extraction method. Based on the Hough Transform algorithm, seven lane line features (ratio, slope, distance, x_1, y_1, x_2, y_2) are extracted.

Ratio is the height to width ratio of the candidate line segments.

$$Ratio = \frac{h}{w} \tag{11}$$

where h is the height of the line segments and w is the width of the line segment.

The slope of a line is a number that describes both the direction and the steepness of the line. It can be calculated by using the following equations.

$$m = \frac{y_2-y_1}{x_2-x_1} \tag{12}$$

Distance is the length of the candidate line segments which is calculated as follow:

$$d = \sqrt{{(y_2-y_1)^2}/{(x_2-x_1)^2}} \tag{13}$$

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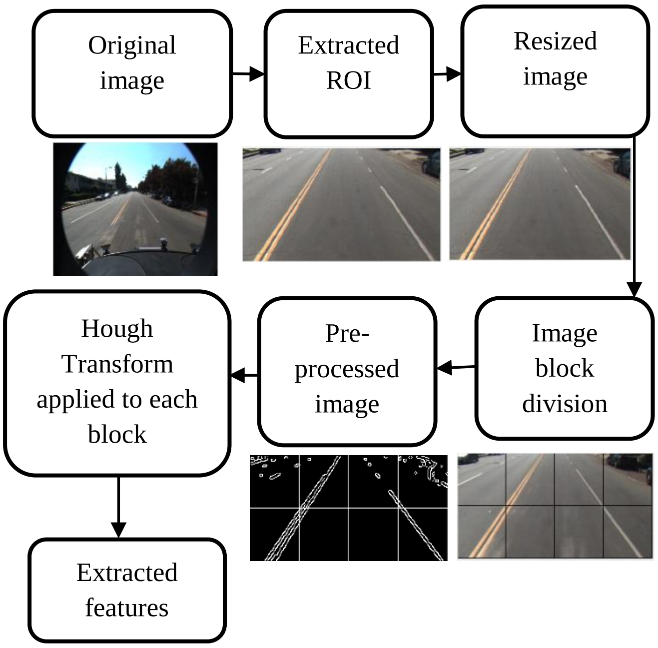

Figure. 4 Flow diagram of feature extraction

where x_1 and y_1 are the starting points of the candidate line segments. x_2 and y_2 are the ending points of the candidate line segments.

4.3 Lane detection

In this research, lane markings are detected by using Artificial Neural Network (ANN) due to its simplicity and less computation cost. The structure of the ANN to detect the lane markings is as shown in Fig. 5. This proposed system uses the Multi-Layer Neural Network which contains an input layer, two hidden layers and an output layer. The numbers of nodes for input, hidden and output layers are 8, 16, and 3 respectively. The inputs of the Neural Network are the extracted seven line features and the outputs are the left lane line, right lane line and non-lane line respectively. The number of neurons of hidden layer is determined to be twice the size of the input layer. Sigmoid (Logistic) function is used as the activation function of the artificial neurons. The error back-propagation algorithm based on gradient descent learning rule is used for training.

In the neural network architecture, the size of the weight matrix is calculated using the following equation.

$$W^1 = L_1 \times N \tag{14}$$

$$W^2 = L_2 \times L_1 \tag{15}$$

$$W^3 = M \times L_2 \tag{16}$$

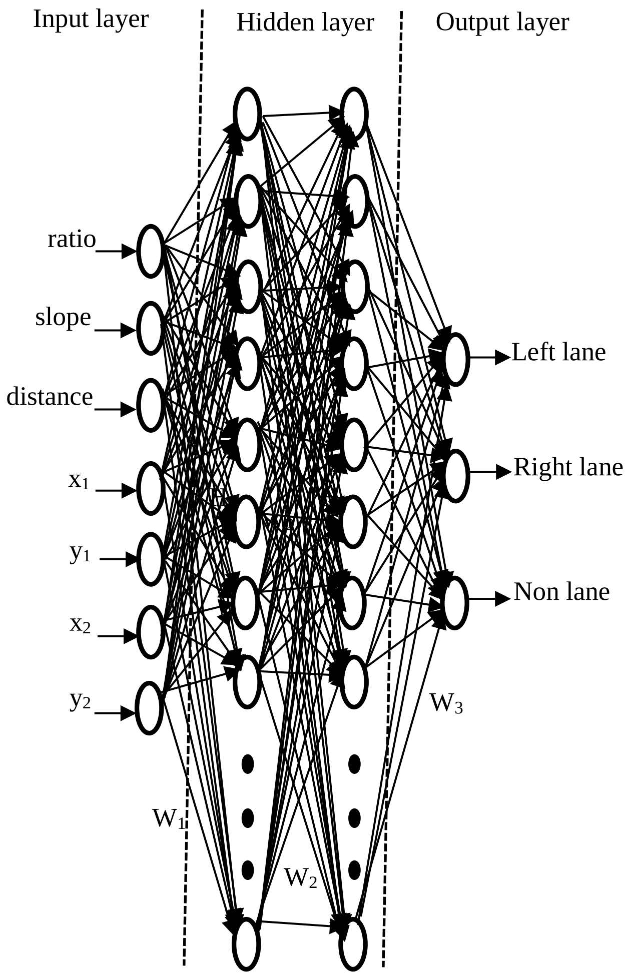

Figure. 5 The structure of Artificial Neural Network

Where W^1, W^2, W^3 are the weight matrices, L_1 is the number of neurons of first hidden layer, L_2 is the number of neurons of second hidden layer, N is the number of neurons of input layer and M is the number of neurons of output layer.

Furthermore, the output of each layer can be calculated using the following equations.

$$H_1 = f^1(W^1 X) \tag{17}$$

$$H_2 = f^2(W^2 H_1) \tag{18}$$

$$Y = f^3(W^3 H_2) \tag{19}$$

Where X is the values of input neurons, Y is the value of output neurons, H_1 and H_2 are the output values of the hidden layers, f^1, f^2 and f^3 are the activation functions, and W^1, W^2, W^3 are the weight matrices.

4. Experimental results

The performance of the proposed lane detection system is evaluated in Matlab environment using laptop and conducted the experiments on AMD

Ryzen 7 CPU @ 2.30 GHz and 8.00 GB RAM. We perform the experiment on the Caltech public lane dataset. The superior performance of the proposed framework will be evaluated using the quantitative evaluation methods: Accuracy, Precision, Recall and F-measure which are defined as the following.

$$Accuracy = \frac{TP+TN}{(TP+TN+FP+FN)} \tag{20}$$

$$Precisioin = \frac{TP}{TP+FP} \tag{21}$$

$$Recall = \frac{TP}{TP+FN} \tag{22}$$

$$F - measure = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{23}$$

Where TP means that the corresponding lane marking pixel is detected correctly, FP means that a background pixel is incorrectly detected as belonging to the lane marking, FN means that a true lane marking pixel is incorrectly detected as a background pixel.

4.1 Caltech lane dataset

The Caltech lane dataset contains four scenes that are taken on the roads of Pasadena, California. There are totally 1224 image frames with 640×480 size in continuous scenes from various types of environments: Cordova1, Cordova2, Washington1 and Washington2. Some scenes are shown in Table 1 .In this dataset, images are taken at day times and include a lot of shadow interferences. Since the direction of the line segment extracted in the shadow area is similar to the direction of the lane, it is difficult to accurately detect the lane. There are totally 4172 marked lanes in four clips. In cordova1, there are 919 marked lanes that have curvatures and some texts on the road. Cordova2 has 1048 marked lanes that have various pavement types and the sun is facing the vehicle. Washington1 has 1274 marked lanes that have shadows and passing vehicles.Washington2 has 931 marked lanes that have street writings and passing vehicles [18]. The dataset is divided into four clips as shown in the Table 1.

Table 1. Caltech lane dataset

Clips	**Name**	**Number of frames**	**Lane boundaries**
1	Cordova1	250	919
2	Cordova2	406	1048
3	Washington1	336	1274
4	Washington2	232	931
Total		1224	4172

4.2 Results and discussion

This section includes the experimental results of the proposed system and compares the result with the existing lane detection systems. We have evaluated the performance of our proposed method using the Caltech dataset. The image frames are given as input to the system. Firstly, region of interest extraction is performed on the input images and divide the sub-image blocks. And then, image pre-processing operation is applied on each image-blocks to enhance the images and improve performance. The seven line features are extracted on each block to detect the line that belongs to the lane. According to the extracted seven line features, we classify the line on each sub-image block as three class: class 1(left lane marking line), class 2 (right lane marking line), class 3 (non-lane line). We used 1749 training samples to classify the lines that belong to the left lane, right lane and non-lane markings. The average training time is 12.76 sec. Table 2 shows the confusion matrix of line classification using the extracted features and Table 3 shows the evaluation metrics (accuracy, precision, recall, F1 score) of the line classification by using the 300 image frames in the Caltech lane dataset. From the line classification results, we can see that the extracted features are effective and efficient for detecting the left and right lane marking. Fig. 6 illustrates the detection results on some image frames, where the green colour indicates the left lane marking and the blue colour indicates the right lane marking of the current driving lane.

Our proposed method can robustly detect the left and right markings of the current driving lane although the road conditions have some shadow occlusions, passing car, poor line paintings or some writings on the road. Total number of left and right markings of the current driving lane and detected lane markings by our method are shown in Table 4. In all clips, the accuracy of the left and right lane marking detection is 95.58 % and 93.67 % respectively. Furthermore, we compared our proposed method with the existing methods proposed in [6] that implemented the LD approach by using PPHT and Kalman filter, [16] that used the fusion of LSD and Kalman filter tested on Caltech lane dataset, [20] that

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Table 2. Confusion matrix of line classification

	Predicted Class			Total True Class
True Class	675	3	12	690
	3	828	33	864
	21	22	152	195
Total Predicted	699	853	197	

Table 4. The number of detected lanes marking in four clips

	Total		Detected lane	
	Left Lanes	Right Lanes	Detected Left Lane	Detected Right Lane
Cordova1	230	230	221	223
Cordova2	337	334	329	325
Washington1	319	321	302	287
Washington2	202	204	188	186
Total	1088	1089	1040	1021

Table 5. Comparison of the detection performance

Methods	Accuracy (%)	Time (ms/Frame)
M. Marzougui, (2020) [6]	93.82	21.54
S. Liu, (2018) [16]	94.52	22.96
T. Youjin, (2018) [20]	93.76	26.87
Y. Kortli, (2017) [25]	89.79	27.4
Proposed Method	94.67	17.64

Table 3. Line classification result

	Recall	Precision	F1 Score
left lane marking line	0.978	0.966	0.972
right lane marking line	0.958	0.971	0.964
non-lane line	0.779	0.772	0.776

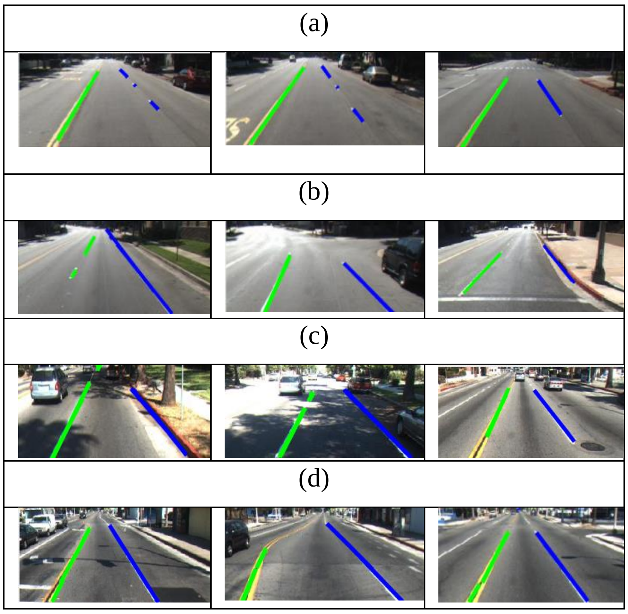

Figure. 6 results of lane detection by proposed method: (a) Cordova1, (b) Cordova2, (c) Washington1, and (d) Washington2

proposed the lane detection system based on vanishing point estimation in which line segment detector (LSD) was used to detect the candidate line segments and [25] which implemented the lane detection system by applying Sobel operator and Hough Transform method to detect the lane line. However, these methods still occur the false detection rate because of the repaired marks and shadow interferences and increase the computational complexity. In our proposed method, 2-D FIR filter is used to solve the lighting problems and false detection rate can be reduced by using the proposed block-wise line features. Since we divide the ROI into small image block, the proposed method can detect the curved road lane because the curves are appeared as the small straight lines in the block. In Fig. 6, by seeing the second image of the 3rd row and first and second images of the 4th row, we can see that

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our proposed system can accurately detect the lane marking although shadow interferences occlude on the road and can also detect the lane in curvy road condition. Comparison results are described in Table 5, in which the performance of the proposed method outperforms the state of the art LD methods in detection rate and computational time. The average processing time and the accuracy of the proposed method is 17.64 ms/frame and 94.67 %. As shown in Fig. 7 and Fig. 8, our method achieves better performance than the state of the art methods without tracking method to enhance the detection result.

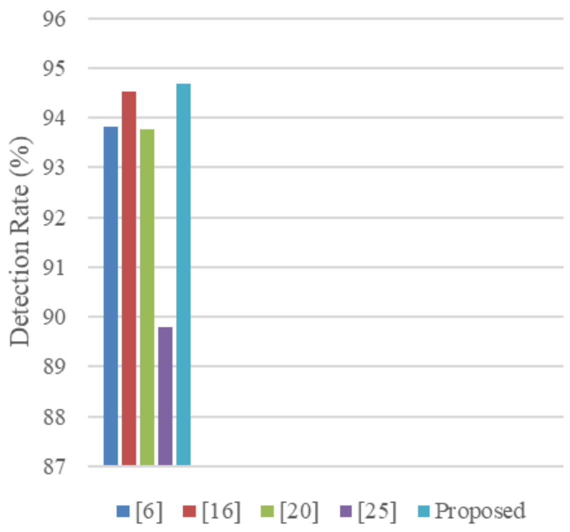

Figure. 7 Comparison results (detection rate) of lane detection performance

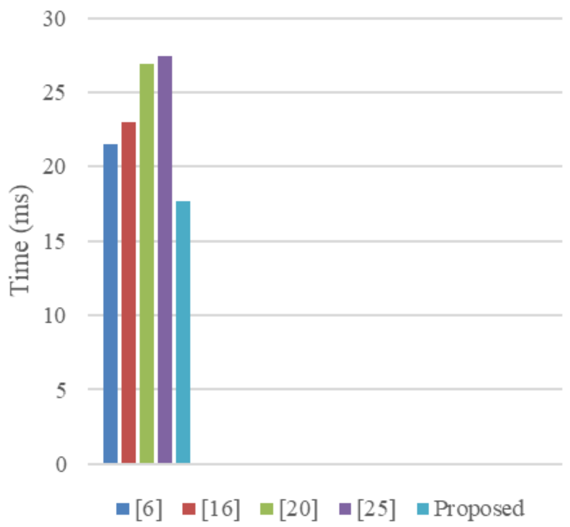

Figure. 8 Comparison results (processing time) of lane detection performance

5. Conclusion

In this research, the efficient and accurate lane detection method is proposed. The proposed system uses 2D FIR filter and Otsu's thresholding to get enhanced binary image and then Canny method is applied to extract the edge pixels. Block-wise Hough-transform based feature extraction techniques is proposed to extract the lane line features and ANN classify the left and right lane marking using the extracted block-wise features. The performance evaluation of the proposed system is conducted on Caltech public lane dataset. From the experiment, the proposed method can achieve promising results under the illumination and shadowy conditions, and also reduce the processing time. Furthermore, it can show that the proposed framework outperforms the other lane detection methods. The average detection rate is 94.67 % and the processing time is 17.64 ms/frame. Then, we will try to test the adaptive ROI extraction based on the YOLO algorithm for future work.

Conflicts of Interest

The authors declare that there is no conflict of interest with respect to the research, authorship, and/or publication of this article.

Author Contribution

Khin Hsu Wai contributed to the design and implementation of the research, the analysis of the results, and the writing of the manuscript. Dr. May The` Yu supervised this research.

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