# A Vison Based Lane Detection Approach Using Vertical Lane Finder Method

2022 International Conference on Distributed Computing, VLSI, Electrical Circuits and Robotics (DISCOVER) | 978-1-6654-8716-0/22/$31.00 ©2022 IEEE | DOI: 10.1109/DISCOVER55800.2022.9974938

Vidya Sagar S. D.
*Department of PG Studies & Research in Computer Science*
*Kuvempu University*
Shivamogga, Karnataka, India
vidyasagarsd@gmail.com

Prabhakar C. J.
*Department of PG Studies & Research in Computer Science*
*Kuvempu University*
Shivamogga, Karnataka, India
psajjan@yahoo.com

***Abstract*— This paper presents a novel approach for detection of lane using Kirsch operator and VLF method. The problem of detecting lane using vision sensors poses many problems such as atmosphere of the road, traffic intensity on the road, pollution, shadow of a tree, and other objects on the road. Normally, in any roads, the lanes are colored with yellow and white with different purpose. To highlight yellow and white lanes in a given RGB image, conversion from RGB to HSL and RGB to HSV is performed. The Gaussian filter is employed to smooth the image and to remove the noise, followed by edge detection using Kirsch operator. After edge detection, to retain only candidate lane lines in edge map, we compute the orientation of gradient and select the pixels which are representing candidate lanes. Finally, a VLF method is used to detect lanes in the image. The experiments are conducted using KITTI benchmark dataset and results are evaluated using popular metrics. Through experiments we demonstrate that detection of lane using proposed method yields promising accuracy.**

***Keywords*— Lane detection, ADAS**

## I. Introduction

The departure warning is given to the driver when vehicle is departing from existing lane is called as LDW, which is one of prominent components assist drivers to avoid collision and follows two important phases i.e., lane detection and tracking of lane. During vehicle moving on highways, there may be chance of crossing lanes without knowledge of the driver then the LDW system which is installed in new generation vehicles alerts the driver to avoid collision. Once the driver gets LDW alert, then the driver controls the vehicle by diverting back into the existing path. The LDW is advanced technology for semi-autonomous vehicles, which is helpful for reducing accidents. The detection of lane is very important phase in LDW and methods have been proposed by many researchers based on machine vision and image processing [1]. Other applications of detection of lane in addition to LDW are road identification, obstacle detection, and other driving safety measures [2]. Furthermore, a number of intelligent transportation applications, including road navigation, lane positioning, and lane-level mapping, can be enhanced on the foundation of accurate detection of lane. Duxx et al. [3] [4] have proposed a method for detection of lane and done significant work. In the vision based methods, lane detection accuracy is depend upon the how accurately extract lane features such as color, texture, or edge information.

In the LDW literature, the many methods have been proposed by researchers and still the problem is not completely solved due to many challenges and issues with LDW systems. These challenges are fog, snow, rainy conditions, complex background, image variation due to curves, and lane appearance types [5]. Because different countries use different lane markers, it is difficult for detection of lane.

The existing techniques for lane detection can be broadly classified into three groups such as: learning-based approaches [6] [7], features-based approaches [8], and model-based approaches [9]. In the learning-based approach, training the system using sample images of lane markings and classification of road image as lane marked image or not are the two stages of the learning-based approaches. Edges, gradient, color, brightness, texture are used in the feature-based approaches, which is relatively insensitive to road shapes. In the methods where Models are fitted on lanes use low features. As we know that lane geometry is in the form straight lines, regular curves, or snake-like curves. Hence, the model-based lane detection fits the geometric model depend upon the types of lane geometry. As per geometry of lane, the lane models are widely used such as linear, parabolic and the hyperbola model. In this paper, we proposed feature-based approach for lane detection which overcomes the limitations of the model-based and learning-based approaches.

Generally, feature-based lane detection approaches consist three steps: they are pre-processing, edge detection and road line detection. In the pre-processing step, Gaussian filtering and other techniques are employed to smooth the image or to remove noise from the image, which is further cropped to select area of interest i.e. road region. In the second step, Sobel operator and Canny edge operator are the promising and effective methods for detecting the lane edges. In the third step, after edge detection, it is important to detect lines prior to lane detections because lane lines are straight in nature. Hence, the straight lines are detected from edge map either using lane features or lane geometry model. In feature-based methods for lines detection, normally, Hough transformation is applied. Many traditional feature-based lane detection algorithms apply some combinations of these techniques aiming to overcome many challenges involved in lane detection.

A. Dubey et al. [10] have proposed a new method to detect the curvy lanes and blind turns. Using Gaussian filter, Hough transform and inverse perspective projection. Mammeri et al. [11] present a novel lane detection and tracking system using a fusion of Maximally Stable Extremal Regions (MSER) and Progressive Probabilistic Hough Transform (PPHT). First, MSER is applied to obtain a set of blobs including noisy pixels (e.g., trees, cars and traffic signs) and the candidate lane markings. After that, to detect lines the PPHT is applied. Fang Zheng et al. [5] proposed an algorithm directly identifying lane line in Hough space without using edge detection. The image is transformed into Hough space using Hough transform, and in the Hough space, the lines are selected based on parallel physical characteristics such as length, geometrical angle characteristics, and in the intercept characteristics of the lane line (Fang Zheng et al., 2018) [15].

For lane detection, there are substantial number of methods has been proposed using deep learning models. The deep learning strategies have achieved overall performance for detection of lanes by extracting discriminative capabilities in a data-driven manner. Mamidala et al. (2019) [12] proposed an encoder-decoder convolution neural network primarily based totally on the structure of SegNet. Tabelini et al. (2020) [13] has presented a PolyLaneNet to detect lane which are used in real-time ADAS applications. Zou et al. [14] proposed CNN and RNN primarily based totally method to detect the street boundary lanes. Wang et al. [15] has proposed LaneNet to detect edges, traces and localize the street lanes. The drawback of deep learning models for lane detection is that it requires thousands of images to train the deep learning model

Contributions of our proposed method are as follows. (1) The lanes are detected by using VLF method which is light weight processing technique for lane detection (2) Our model can efficiently work to detect lane lines in scenarios which are present in KITTI benchmark dataset such as shadows, road discoloration, degraded lane marks, shadow of traffic pole and can provide more accurate results of lane detection are compared with previous state of art methods.

## II. METHODOLOGY

This section introduces a lane detection approach for the detection of low-level features such as edges and lines. There are three steps involved such as pre-processing, edge detection and lane detection. A detailed description of each step is given in the next subsection.

### A. Pre-Processing

The road environment involves a lot of challenges as shown in the Fig. 1, which includes interference of color with road environment and light intensity noise. These makes it hard to distinguish the difference in white lines, yellow lines, and vehicles from the background. The RGB color space used in the video stream is extremely sensitive to light intensity, and the effect of processing light at different times is not guaranteed. The main purpose of pre-processing is able to detect both the yellow and white lane lines.

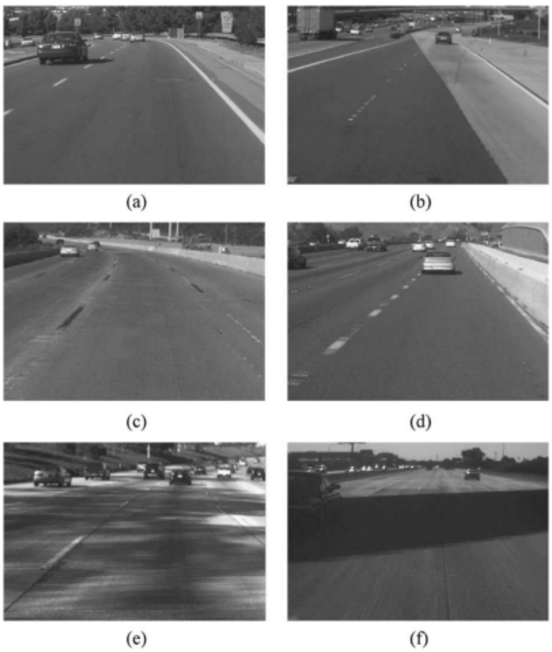



Fig. 1. Images representing different challenges of Lane detection such as (a) Vehicle shadow on solid lane (b) Road discoloration (c) Degraded Lanes (d) Blur Lane lines images due to pollution (e) Shadows on the road (f) Dark Shadow on the road due to underpass roads.

In order to detect both white and yellow lane lines, we are using color-space transformations such as RBG to HSL and RGB to HSV. The resultant image after applying color transformation is combined using Bitwise OR operation. In order to handle the discolored patches on the road surface, we convert the original image into grayscale and darken the image. This step helps to handle discoloration patches on the road. The resultant darkened image and the bitwise OR image of HSL output and HSV output are combined using Bitwise AND operation. In order to reduce noise and to smooth the image, we use Gaussian smoothing. The resultant frames are shown in the Fig. 2.

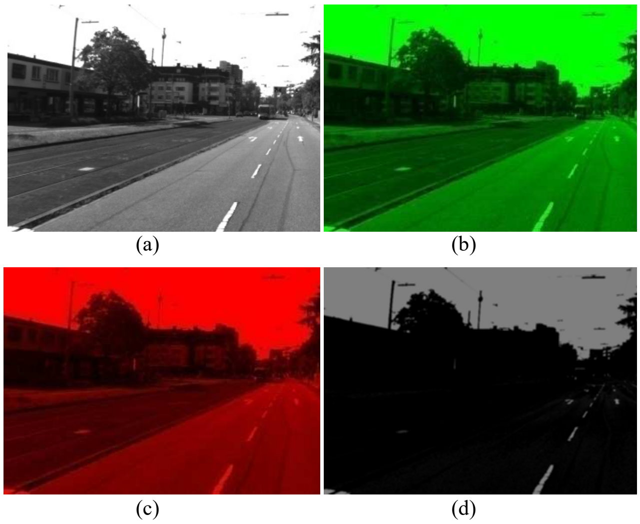



Fig. 2. Preprocessing results (a) original frame (b) Results of RGB to HSL (c) Results of RGB to HSV (d) Results of Gaussian Filter.

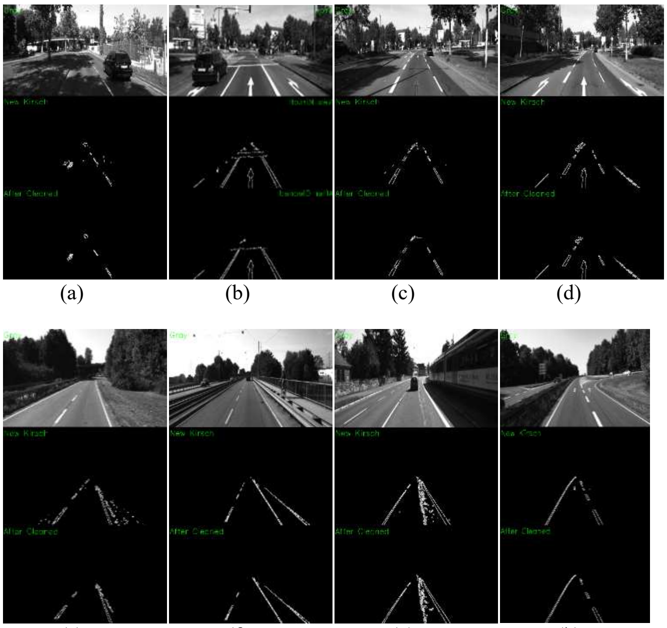
### B. Edge Detection Using Kirsch Operator

Edges in an image plays a vital role in image processing as they can be used to locate and identify various objects present in the image also it can help in calculation of various properties like perimeters and areas of the objects. In the process of edge detection, there is a great need in enhancing the image contrast between the edges and the road background to makes the edges more visible. The benefits of Kirsch operator motivated us to employ for edge detection from pre-processed image obtained from the previous step. Kirsch method detects edges on eight compass directions using eight filters. In all resultant eight edge maps obtained from all eight different direction filters, we retain only two direction edge maps such as north edge map and south edge map. The Binarization is applied for both north kirsch edge and south kirsch edge. The binarized north kirsch edge and south kirsch edge are combined further which yields final edge map. The Fig. 3. shows the Kirsch eight filters for all eight directions. The Fig. 4. Illustrates the results of combined Kirsch edge maps of south and north edge maps.

$$E = \begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix} NE = \begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix} N = \begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} NW = \begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$$

$$W = \begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix} SW = \begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix} S = \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix} SE = \begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}$$

Fig. 3. Kirsch filters for all eight directions (E=East, NE=North East, N=North, NW=North West, W=West, SW=SouthWest, S=south, SE=South East)



(a) (b) (c) (d)

(e) (f) (g) (h)

Fig. 4. Krisch edge map on sample images of KITTI dataset. The first row and fourth row show original images. The second row and fifth row shows combined krisch edge map. The third and sixth row shows the cleaned images using morphological operators.

In the combined edge map, all edge segment pixels are not representing lanes. The only pixels with an angle range from 40 to 45 degree are representing lanes. Hence, a condition is set based on gradient orientation in order to retain pixels based on angle range from 40 to 45 degree and to discard other angle pixels. The gradient orientation angle of every pixel is calculated using following equations.

$$\nabla_i = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} \tag{1}$$

$$G_x = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} \tag{2}$$

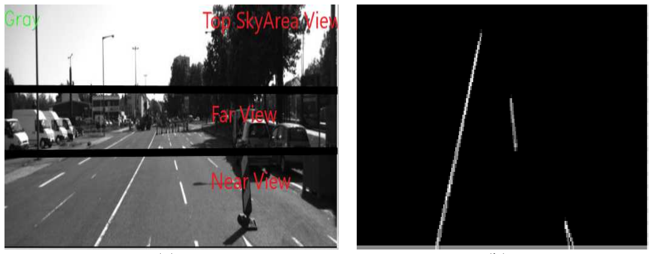
$$G_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \tag{3}$$

$$\nabla_i = mag(\nabla) = \left[G_x^2 + G_y^2\right]^{1/2} = \left[\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2\right]^{1/2} \tag{4}$$

$$\theta = \tan^{-1}\left(\frac{G_x}{G_y}\right) \tag{5}$$

It is not necessary to detect the entire image when detecting some of the significant objects. As a result, we must consider calculating the ROI. ROI refers to the area of an image that only contains the objects that need to be detected. For lane detection context, image with lane lines in front of the car is significant region (ROI). The sky, buildings, trees, and other natural elements objects contained in an image have no effect on lane detection but may cause less-than-ideal detection. Extraction of ROI can reduce the irrelevant portion of an image while retaining the relevant portion, which saves time and improves detection accuracy. For calculating ROI, dynamic ROI extraction is employed. Dynamic ROI is defined as the area obtained using the dynamic ROI extraction method based on the position of lane lines. The quadrilateral formed by the four starting and also in ending points of the lane lines in front of the driver. Only near view is taken for processing rest of the two views are ignored to reduce processing time and to increase robustness of the model.

We employ morphological techniques on a binarized edge map. The opening procedure removes smaller pixels compared to structure parts, yet smooths the image's contours, creating discontinuous image edges. While the closing operation process eliminates tiny dark pixels, it maintains the continuity of the image borders and can fill in any gaps between image edges.




(a) (b)

Fig. 5. ROI extraction result. (a) Represents road image contains three views such as Top Sky View, Far View and Near View. (b) ROI extraction using Dynamic ROI method.

*C. Lane Detection using VLF Method*

Let $P_c \in \mathbb{R}^{i \times j}$ be the photo captured from camera, where $i$ and $j$ represent the number of rows and columns, respectively.The rough ROI $P_c \in \mathbb{R}^{i_r \times j}$ is identified by some priors, where $i_r$denote the number of rows of $P$.The rough ROI $P$ is further divided into two blocks: $A \in \mathbb{R}^{i_r \times j_m}$ and $B \in \mathbb{R}^{i_r \times j_n}$, where $j_m$denote the number of columns of $A$ and $j_n$ denote the number of columns of B.The block $A$ is further divided in to two blocks: $A_1 \in \mathbb{R}^{i_r \times j_a}$ and $A_2 \in \mathbb{R}^{i_r \times j_b}$, where$j_a, j_b$ denote the number of columns of blocks $A_1$and $A_2$, respectively. Similarly, the block $B$ is again divided into two blocks: $B_1 \in \mathbb{R}^{i_r \times j_c}$ and $B_2 \in \mathbb{R}^{i_r \times j_d}$ , where $j_c$ and $j_d$ denote the number of columns of blocks $B_1$ and $B_2$ , respectively. Next, for each block $A_1, A_2, B_1, B_2$ of rough ROI $P$, we compute the mean value $\bar{P}_v$ of each column as follows:

$$\bar{P}_v = \sum_{u=1}^{i_r} \frac{P_{uv}}{i_r}, \quad v = 1, 2, \dots, j. \tag{6}$$

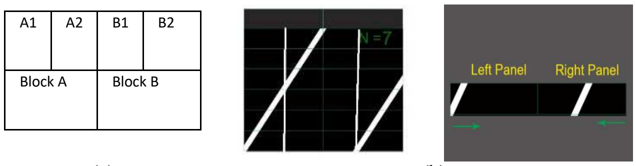
In the block A, we calculate the mean value $\bar{P}_v$ $(v = 1, 2, \dots, j_m)$ of each column in the left to right fashion and in the block $B$, we calculate the mean value $\bar{P}_v(v = j_{m+1}, j_{m+2}, \dots, j)$ of each column in the right to left fashion. Next, we calculate the column value $d$ with minimal mean value for each block $A_1, A_2, B_1, B_2$ using the formula given below:

$$d = E(\min(\bar{P}_v)), \quad v = 1, 2, \dots j. \tag{7}$$

OR

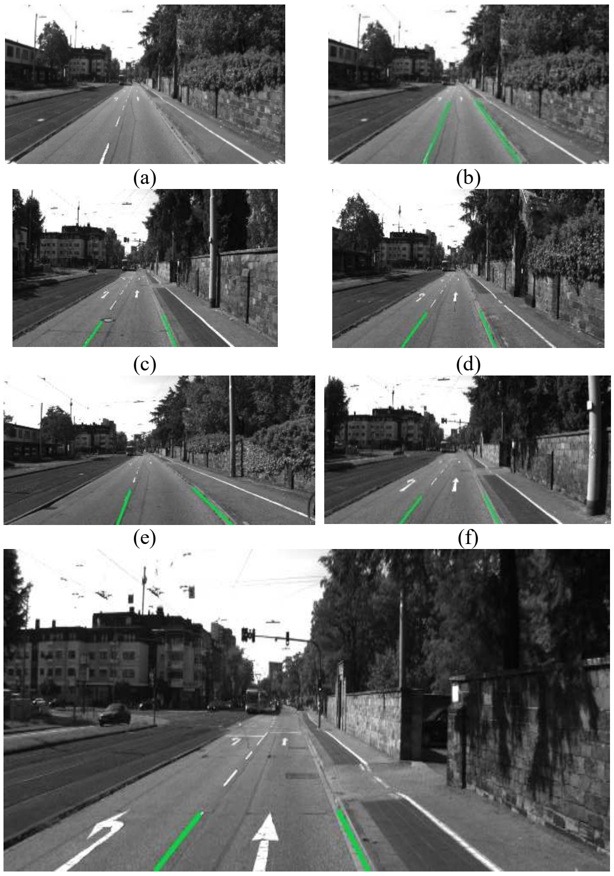
$$d_1 = E(\min(\bar{P}_v)), \quad v = 1, 2, \dots, j_a \quad \text{(for block } A_1\text{)}$$
$$d_2 = E(\min(\bar{P}_v)), \quad v = j_{a+1}, \dots, j_m \quad \text{(for block } A_2\text{)}$$
$$d_3 = E(\min(\bar{P}_v)), \quad v = j_{m+1}, \dots, j_c \quad \text{(for block } B_1\text{)}$$
$$d_4 = E(\min(\bar{P}_v)), \quad v = j_{c+1}, \dots, j \quad \text{(for block } B_2\text{)}$$

$E \rightarrow$ Operator used to extract the column value with minimal mean value. With reference to block $A$, if intensity value exists for block $A_1$, then we do not move onto block $A_2$ for further computation. Similarly, with reference to block $B$, if intensity value exists for block $B_2$, then we do not move onto block $B_1$ for the next computation. We remark that the existence of intensity value implies the existence of lane in the corresponding block.




(a) (b)

Fig. 6. (a) Structure of VLF (Vertical Lane Finder) which shows the Block A and Block B, (b) VLF Method applied on Image



(a) (b) (c) (d) (e) (f) (g)

Fig. 7. Results of lanes detection on sample frames of KITTI dataset. (a) Original sample frames of KITTI benchmark dataset (b) Result of lane detection using our approach from b-g which contains results lanes detection scenarios such as (c) Results of the lane detected on the degraded Lanes on the road (d) Results of lanes detected which contains shadows of poles and electric cables on the road (e-g) Results of lanes detected which contains road patches, Road sign marking and discoloration of road.

## III. Experimental Results and Discussion

The lane detection method was tested using data from the Karlsruhe Institute of Technology and the Toyo ta Technological Institute (KITTI)[16].The KITTI dataset is one of the most popular datasets for mobile robots and autonomous driving. High-resolution RGB cameras, grayscale stereo cameras, and a 3D laser scanner have recorded hours of traffic conditions. Lane markings of various kinds are captured, including single-sided (SS) lane markings that are either clear or unclear, totally shadow-covered (FSC) lane markings, and partially shadow-covered (PSC) lane markings (TMI). In the middle of the TMI lane markers is a traffic sign. Instead of using whole KITTI dataset, we selected 600 frames with lane boundaries comprises different environmental problems, such as pole shadow, tree shadow, deteriorating lane lines, and decolorization of road and traffic sign signs.

In order to evaluate the lane detection performance of the method, the ground truth of every frame is obtained based on manually count the number of lanes per frame, the number of detected lanes per frame, the number of correctly detected lanes per frame and the number of false positive lanes per frame.

$$N_T = N_D + N_F \tag{8}$$

$$\text{Lane detection rate frame}=\left(\frac{N_D}{N_T}\right) * 100 \tag{9}$$

$$\text{False positive rate in lane detection} =\left(\frac{N_F}{N_T}\right) * 100 \tag{10}$$

where $N_T$- Total number of detected lane, $N_D$ - Total number of correctly detected lane and $N_F$ - Total number of false positive lane.

The proposed lane detection method is evaluated based on lane detection rate using 600 frames of KITTI dataset. The proposed method for lane detection has achieved detection rate of 95.66%. In the proposed method, more emphasis is given for preprocessing in order to retain only vertical lane line, and to overcome challenges such as pole shadow, tree shadow, road discoloration and horizontal line marks in order to increase the robustness of the method. The Table I shows the lane detection rate and false detection rate of the proposed method using KITTI dataset.

TABLE I. The evaluation results of the proposed method on 600 frames of KITTI dataset

| | |
|---|---|
| Total frames($N_T$) | 600 |
| Correctly detected lane($N_D$) | 574 |
| False positive lane($N_F$) | 26 |
| Lane Detection Rate in % | 95.66 |
| False Positive Rate in % | 4.33 |

## IV. Comparison with Existing Method

The experimental results of the proposed method is compared with existing lane detection methods proposed by the Haloi et al. [17] and Guotian et al. [18]. Haloi et al. [17] has proposed a method for robust lane detection system using steerable edge features and RANSAC polynomial fitting. The models developed by Haloi et al. [17] and Guotian et al. [18] for lane detection are implemented and tested for 600 frames of KITTI benchmark dataset. Guotian et al. [18] have proposed a method for lane detection where top-hat transform is used to enhance the contrast and filter out the interference of some non-lane objects. Binarization and edge detection are used to extract feature points. Then, Hough transform algorithm with polar angle and distance constraint is used for lane fitting. Haloi et al. [17] for lane detection, the system relies on a singular camera component. For this purpose, it employs a tweaked version of Inverse Perspective Mapping that relies on illuminant Invariant approaches and a small number of extrinsic camera parameters to detect lanes. The lanes are represented by steerable filters of the second and fourth orders that are resistant to shadowing. Lab color space and illuminant invariant representation are used to eliminate the effects of shading and glare. Using a strong RANSAC fitting algorithm, it assumes that lanes are cubic curves. Detection of Road lanes are boundary are identified in this model.

The comparison results of both the proposed method with state-of-the-art lane detection methods for 600 frames of KITTI dataset is presented in Table II.

TABLE II. COMPARISON ON KITTI DATASET WITH THE STATE OF ART MODELS.

| Method | Total Frames used | Lane detected Frames | Lane detection Rate(%) |
| --- | --- | --- | --- |
| Haloi et al. [17] | 600 | 565 | 94.26 |
| Guotian et al. [18] | 600 | 568 | 94.83 |
| **Our method** | **600** | **574** | **95.66** |

The investigational results of the proposed lane detection method is compared with other existing road lane detection methods proposed by the Haloi et al. [17] and Guotian et al. [18]. In both the model it has false detection rate in lane mark identification and pole shadow which has been mainly focused in the proposed model to increase the accuracy of lane detection. We performed experimentation using KITTI dataset. The highest accuracy of the proposed method for lane detection is mainly due to the combination of feature based and mathematical model based approach. Which can able to handle the detection of lane line in challenging situation such as pole shadow, electric cable shadow, degraded lane and lastly lane marks on the road. The VLF model will identify only left and right lane and reduces the processing of each row by 50 percent. Because once it encounter lane in Block A it skips second part of Block A. Likewise in Block B it follows the same fashion. The model is self-sufficient to handle dynamic situation which has made to increase its accuracy to 95.66% compared to the state of art method. The limitation of the model is it reduces lane detection accuracy during heavy fog and rainy condition on the road.

## V. CONCLUSION

In this paper, we presented a lane detection method, which uses the Kirsch Edge maps and VLF method to detect lanes in complex background on the structured roads. The Proposed method can handle challenges such as pole shadow, shadows of tree, degraded lane marks, decolorization of road and traffic sign marks which are present in structured roads. The proposed Lane detection model is evaluated using 600 frames of KITTI dataset and achieved with an accuracy of 95.66%. The proposed lane detection method is compared with two state-of-the-art lane detection methods using 600 frames of KITTI dataset based on detection accuracy. The comparison results shows that the proposed method exhibit highest accuracy compared to its competitors. Some of the limitations of our method is that it works only for day conditions and does not support for night scenarios, rainy weather conditions and also for zebra crossing lane markings.

## REFERENCES


[1] Jung S., Youn J. and Sull S., " Efficient lane detection based on spatiotemporal im- ages," IEEE transactions on intelligent transportation systems, vol. 17(1), 2016, pp. 289-295.

[2] Chen H Z and Jin Z L., "Research on real-time lane line detection techonogy based on machine vision," International Symposium on Intelligence Information Processing and Trusted Computing. Huanggang, China, 2010: 528–531.

[3] Duxx, Tan K. K. and Htet K.K., "Vision-based lane line detection for autonomous vehicle navigation and guidance," 10th Asian Control Conference (ASCC), Kota Kinabalu, Malaysia, 2015.

[4] Duxx and Tan K. K. , "Comprehensive and practical vision system for self Driving vehicle lane-level localization," IEEE transactions on image processing, 2016, vol. 25(5), pp. 2075-2088.

[5] Y. Xing et al., "Advances in vision based lane detection: Algorithms, integration, assessment, and perspectives on ACP based parallel vision," IEEE/CAA J. Autom. Sinica, vol. 5(3), 2018, pp. 645–661.

[6] R. S. Mamidala, U. Uthkota, M. B. Shankar, A. J. Antony, and A. V. Narasimhadhan, "Dynamic Approach for Lane Detection using Google Street View and CNN," IEEE Reg. 10 Annu. Int. Conf. Proceedings/TENCON, 2019, pp. 2454-2459.

[7] Ze Wang, Weiqiang Ren, Qiang Qiu, "LaneNet: Real-time lane detection networks for autonomous driving," 2018.

[8] Ying Z., Li, G., Zang X., Wang R., and Wang W., "A Novel Shadow free Feature Extractor for RealTime Road Detection," In Proceedings of the 24th ACM International Conference on Multimedia, Amsterdam, The Netherlands, 2016, pp. 15–19.

[9] Zhou S., Jiang Y., Xi J., Gong J., Xiong G., Chen H.A., "A Novel lane detection based on geometrical model and Gabor filter," In Proceedings of the 2010 IEEE Intelligent Vehicles Symposium, La Jolla, CA, USA, 2010, pp. 59–64.

[10] Dubey, A., and Bhurchandi K. M."Robust and real time detection of curvy lanes (curves) with desired slopes for driving assistance and autonomous vehicles," 2015.

[11] Abdelhamid Mammeri, Azzedine Boukerche and Guangqian Lu, "Lanedetection and tracking system based on the MSER algorithm, hough transform and kalman filter," In Proceedings of the 17th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems, 2014.

[12] R. S. Mamidala, U. Uthkota, M. B. Shankar, A. J. Antony, and A. V. Narasimhadhan, "Dynamic Approach for Lane Detection using Google Street View and CNN," IEEE Reg. 10 Annu. Int. Conf. Proceedings/TENCON, 2019, pp. 2454-2459.

[13] Tabelini L., Berriel R., Paixao T. M., Badue C., De Souza, A. F., & Oliveira Santos, T., "Polylanenet: Lane estimation via deep polynomial regression," In 2020 25th International Conference on Pattern Recognition *(ICPR)*,2020 , pp. 6150-6156.

[14] Qin Zou, et al., "Robust lane detection from continuous driving scenes using deep neural networks," IEEE Trans. Veh. Technol., 2019.

[15] Ze Wang, Weiqiang Ren, Qiang Qiu, "LaneNet: Real-time lane detection networks for autonomous driving", 2018.

[16] Geiger P. Lenz C. Stiller, and Raquel Urtasun, "Vision Meets Robotics: The KITTI Dataset," Int. J. Robot. Res., vol. 32(11), 2013, ,pp. 1231-1237.

[17] Haloi M, Jayagopi D B.,, "A robust lane detection and departure warning system," IEEE Intelligent Vehicles Symposium (IV). *Seoul, South Korea: IEEE*, 2015, pp. 126–131.

[18] FAN Guotian, G., Li, B., Han, Q., Jiao, R., & Qu G., "Robust Lane detection and tracking based on machine vision," ZTE Communications, vol *18*(4), 2021, pp. 69-77.