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A machine learning approach for detecting and tracking road boundary lanes

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Abstract

Road boundary lanes are one of the serious causes of road accidents and it affects the driver and people's safety. Detecting road boundary lanes is a challenging task for both computer vision and machine learning approaches. In recent years many machine learning algorithms have been deploying but they failed to produce high efficiency and accuracy. This paper presents a novel approach to alert the driver when the car leaps beyond the Road boundary lanes by employing machine learning techniques to avoid road mishaps and ensuring driving safety. Performance is assessed through the generation of experimental results on the dataset. When compared with state-of-the-art lane detection techniques, the proposed technique produced high precision and high efficiency.

Keywords: Real time transportation; Road boundary lane detection; Convolutional neural networks; Machine learning

1. Introduction

Research on road lane detection using image processing and machine learning techniques was an important research field both in developed countries and in developing countries [1]. As the number of vehicles grew, numerous intelligent systems were built to help drivers drive safely. Lane detection is an essential aspect of any driver assistance program. There are currently several major challenges facing researchers working on lane detection, such as attaining reliability to variations in the lighting and background clutter. Fig. 1 presents some challenging road lane samples. In recent years, the advancement of image processing techniques and the availability of low-cost visual sensing equipment have paved the way for various methods of automatic road lane detection [2]. The feasibility of automatic road lane detection approaches stems from the fact that the textures of lanes are recognizably different from the background of the pavement surface [3]. In recent days applying image processing technique and artificial intelligence (AI) method for enhancing the accuracy and productivity of the task of interest is increased. Moreover, irregular background illumination and complex pavement texture/color are still major challenges that computer vision-based methods have to overcome. Hence, other advanced approaches of image processing and AI should be investigated to construct automatic road boundary lane detection models. The current study is dedicated to establish a new AI based model for automatically recognizing boundary lanes in asphalt pavement images.

Rest of the paper is structured as follows: Section 2 presents related work. Section 3 contains information about the data-set and the methods suggested.

Section 4 starts with Results and Discussion and continued with Conclusion and future work in Section 5.

2. Literature survey

This section presents review of the existing literature. For analyses of road boundary lane detection, significant literature from multiple sources is referenced. The authors took the most common approaches to road lane detection involving Hough Transform, Canny edge detection with Hough, HSV-ROI, and CNN based. In this section these strategies are presented. Dubey et al. [4] proposed a new model to detect the lanes at diverse environmental conditions by using Gaussian filter and Hough transform. Mammeri et al. [5] presented a novel method to detect the road lanes by merging MSER with Hough and achieved good performance. Mingfa et al. [6] developed

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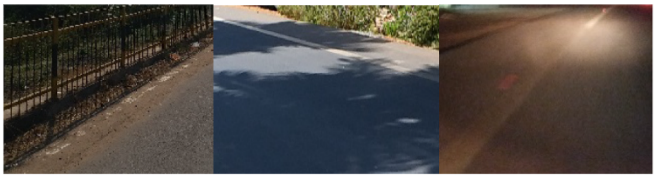

a) Soil hid b) Tree shadow c) Street Light

Fig. 1. Examples of challenging road lane images.

Table 1
Performance analysis of existing lane detection approaches.

Methodology	Accuracy
Guassianfilter+Hough transform [4]	89%
MSER+Hough [5]	92%
HSV-ROI+Hough [6]	95%
CNN Based [7]	96%
Improved LD+Hough [10]	96%
LaneNet [11]	97%

Table 2
Summary of data collection.

Image type	Total images	Training (80%)	Testing (20%)
Day time images	1400	1120	280
Low light images	1200	960	240
Night time images	1400	1120	280

an efficient and accurate lane detection technique through extracting white features from image. Kim et al. [7] suggested a lane detection model based on convolutional neural network and random sample consensus. Zou et al. [8] suggested a CNN and RNN based approach to detect the road boundary lanes. Péter et al. [9] presented an automated lane changing approach for vehicles by employing environment detection with LIDAR. Zhang et al. [10] introduced a novel approach to detect the lanes based on improved lane line detection algorithm. Wang et al. [11] suggested a two stage strategy called LaneNet to propose edges, lines and localize the road lanes.

2.1. Limitations in existing approaches

The existing approaches are failed to detect the lanes which are degraded with sand hid, tree shadows and high illumination conditions (Fig. 1). The proposed method is implemented to resolve the aforementioned drawbacks encountered in existing approaches.

3. Methodology

The current techniques listed in Table 1 show less accuracy and efficiency in road lane detection. Therefore a novel approach is proposed to detect the road lanes with high precision and accuracy by combining convolution neural networks with line detection (CNN-LD). The authors suggest a novel algorithm or pseudo code along with mathematical equations to test the efficacy and accuracy. The pipeline for proposed approach is depicted in Fig. 2

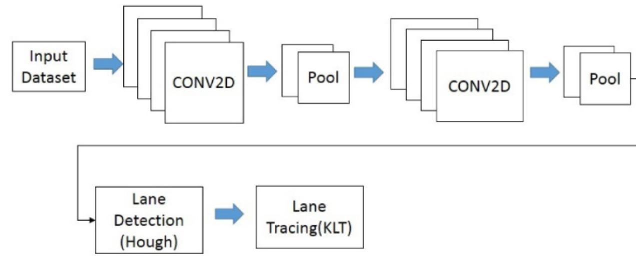

Fig. 2. Proposed methodology pipeline.

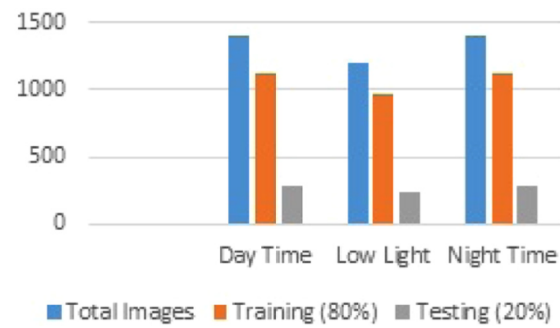

Fig. 3. Graph showing number of samples taken for training and testing.

3.1. Dataset

A well-annotated road lane dataset is an essential prerequisite for yielding accurate results. Therefore, new road lane dataset is accumulated at various lighting conditions, such as daytime, night time as well as low light circumstances, due to the absence of a publicly accessible dataset. The image sequences were often acquired in rural, urban, and highway environments in Rajahmundry, Andhra Pradesh's surroundings through the use of Samsung C7 Pro mobile phone fastened to bike. The dataset consists of 4000 image samples of road boundary lanes with divergent environmental factors. Table 2 provides a summary of the data collection.

The graph shown in Fig. 3 represents the total number of images considered to train and evaluate the proposed model from each class (day, night, low light).

The foremost objective of the proposed CNN-LD model is to increase accuracy and efficiency of lane detection. The CNN-LD approach adopted is going through four segments. The input images are fed to two CONV2D layers in the first segment, and then Sobel filters are preserved to discern the edge features. Region of Interest is obtained in the second segment. Then, Enhanced Line detection algorithm (Hough) is used in the third stage to draw clear lines on the first step image output. Kanade–Lucas–Tomasi (KLT) tracker feature is considered in the fourth segment. It is a faster tracking method to locate the lines that uses information about spatial intensity to direct the search for a position that gives the best match.

3.2. Edge detection

Convolutional Neural Network-based approach merged with Sobel filters is used to detect the edges from the ground

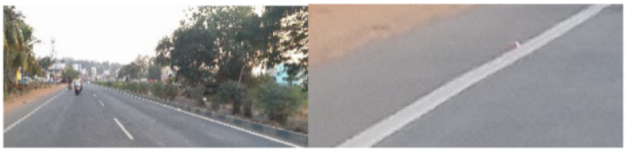

Fig. 4. Region of interest.

truth sample image. The Sobel operator uses two 3 × 3 kernels to detect the horizontal and vertical lines on the input image. Let I is the image, A_x and A_y are vertical and horizontal line detection masks. Now apply masks on the image I to perform convolution operation. The input image I is convolved with a vertical mask A_x as shown in Eq. (1).

$$A_x = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} * I \tag{1}$$

Then apply horizontal mask A_y on the input image I for convolution as shown in Eq. (2).

$$A_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * I \tag{2}$$

where * denotes 2- Dimensional convolution operation. Further A_x and A_y are expanded to compute gradient smoothing as shown in Eqs. (3) and (4).

$$A_x = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} * \left(\begin{bmatrix} 1 & 0 & -1 \end{bmatrix} * I\right) \tag{3}$$

$$A_y = \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} * \left(\begin{bmatrix} 1 & 2 & 1 \end{bmatrix} * I\right) \tag{4}$$

From Eqs. (3) and (4), the gradient magnitude A_m is computed as shown in Eq. (5).

$$A_m = \sqrt{A_x^2 + A_y^2} \tag{5}$$

Using Eq. (5), compute the gradient direction Δ as shown in Eq. (6). For vertical edge Δ is zero.

$$\Delta = \operatorname{atan}\left(\frac{A_y}{A_x}\right) \tag{6}$$

3.3. Region of Interest (ROI)

Instead of representing the lines on the complete image the non-road features are cropped out from the obtained image by employing ROI as depicted in Fig. 4 and then apply a line detection algorithm on the extracted region.

3.4. Line detection

Hough transform [12] is applied to the output obtained from the edge detection module. Hough transform is used to recognize lines that appeared on the image in the Hough space. Often the form in Eq. (7) is used to represent all straight lines L_{all} presented on the obtained ROI image.

$$L_{all} = -\frac{\cos\beta}{\sin\beta}.x + \frac{q}{\sin\beta} \tag{7}$$

Here β is a line angle and q is the distance from the line to origin.

3.5. Line tracking

Authors have illustrated the way lines are represented on an image in Section 3.3. Now this section describes the method to identify the line features and track them using Kanade–Lucas–Tomasi features tracking methodology [13]. Let 'p_x' be a point on image I_m. The main motive is to find the location of q_y on image I_n corresponding to p_x on I_m. Apply Eq. (8) to detect p_x on I_m.

$$\overline{V}_{opt} = G^{-1}\overline{b} \tag{8}$$

Here, G and $\bar{b}$ given as Eqs. (9) and (10)

$$G = \sum_{x=M_x-N_x}^{M_x+N_x} \sum_{y=M_y-N_y}^{M_y+N_y} \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \tag{9}$$

And

$$\overline{b} = \sum_{x=M_x-N_x}^{M_x+N_x} \sum_{y=M_y-N_y}^{M_y+N_y} \begin{bmatrix} \delta I & I_x \\ \delta I & I_y \end{bmatrix} \tag{10}$$

Proposed CNN-LD Pseudocode:

Input: Well annotated Road Lane image dataset (Pn).

Output: Detecting and tracking lanes with high accuracy and efficiency.

1. **Begin:**
2. Pre-process the road lane dataset (P_n).
3. Fed the image samples to CNN for feature extraction
4. For i=1 to P_n do // Extracting features
5. For layers (K): 1 —> K-1 do //here K is 3
6. Obtain the edge feature map F_m
7. End For
8. End For
9. Apply equation5 on F_m to isolate gradient edges
10. Cropping out the Region of Interest from step 9
11. Apply equation7 on detached ROI to represent all lines.
12. Apply Line tracking method illustrated in section 3.4
13. **End**

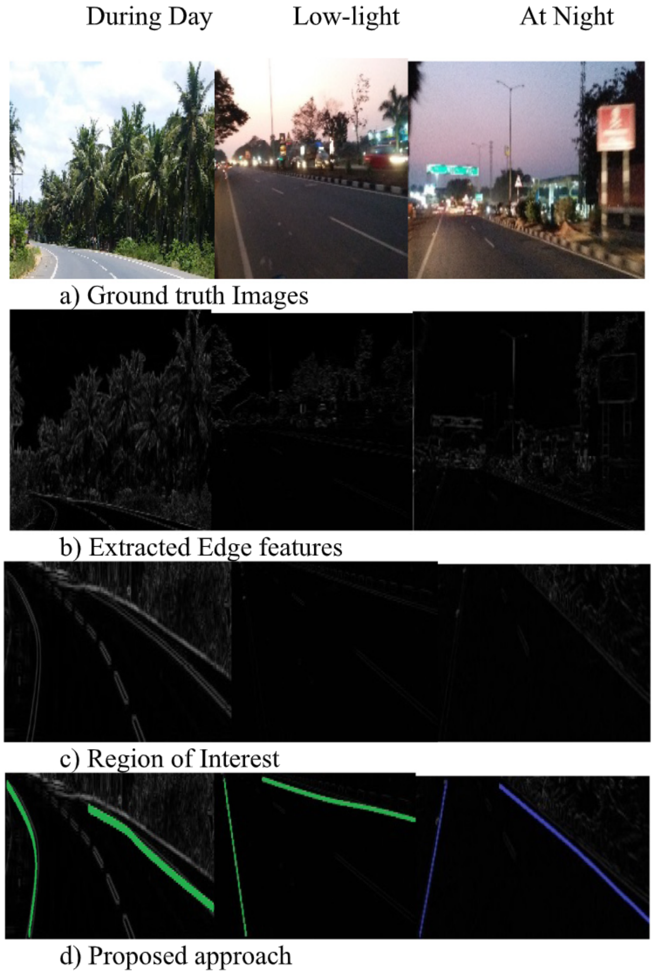

Fig. 5. Experimental results.

4. Results and discussion

This proposed CNN-LD method has been implemented using MATLAB. The scientific values legitimize for the proposed CNN-LD approach and the comparisons of road boundary lane detection with the established methods [4–7,10,11] are explored in this section. The proposed CNN-LD method is performed with and without performing data augmentation operation on dataset. It shows outstanding results with performing data augmentation operation. The results of the same with improved accuracy are shown in Table 3. The experimental outcomes are presented in Fig. 5.

Fig. 5(a) shows the sample ground truth images considered for boundary lane detection. Fig. 5(b) depicts edge detected images. Fig. 5(c) portrays the Region of Interest. Fig. 5(d) Illustrates the detected boundary lane images of the proposed approach and Fig. 6 showing the sample real-time road boundary lane detection output.

Evaluation metrics such as accuracy, precision, recall, and F-measure are computed under the road boundary lane detection process and made a comparison with the current state-of-the-art methods. The comparative analysis of the proposed approach with the existing methods is illustrated in Table 4.

Table 3
Proposed approach accuracy with and without data augmentation.

CNN-LD	Without data augmentation	Data augmentation
Day time images	97.52	98.68
Low light images	95.81	96.93
Night time images	95.43	96.27

Table 4
Comparative analysis of proposed CNN-LD method with existing methodologies.

Methodology	Accuracy	Precision	Recall	F1-scores
Guassianfilter+Hough transform [4]	89.79	91.65	88.32	89.96
MSER+Hough [5]	92.09	93.35	91.75	92.54
HSV-ROI+Hough [6]	95.72	97.93	94.89	96.41
CNN Based [7]	96.59	98.09	95.73	96.91
Improved LD+Hough [10]	96.62	97.21	96.17	96.69
LaneNet [11]	97.37	98.19	97.06	97.62
Proposed CNN-LD	**98.68**	**98.92**	**98.87**	**98.89**

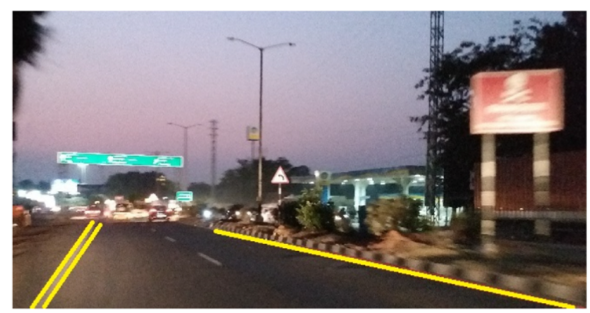

Fig. 6. Real time sample output.

5. Conclusion

The authors have presented a new approach CNN-LD for detecting and tracking the road boundary lanes. Unlike other methods, the proposed approach is based on the convolutional neural network to extract the edge features. A normalization process has been employed to achieve the best results. Research findings have shown that the proposed CNN-LD is significantly better than the state-of-the-art methods. The suggested solution is assured to be beneficial in terms of both accuracy and performance.

CRediT authorship contribution statement

Satish Kumar Satti: Conception and design of study, Acquisition of data, Analysis and/or interpretation of data, Writing - original draft. **K. Suganya Devi:** Conception and design of study, Analysis and/or interpretation of data, Writing - review & editing. **Prasenjit Dhar:** Acquisition of data, Writing - original draft. **P. Srinivasan:** Conception and design of study, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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All authors approved the version of the manuscript to be published.

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