

Segmenting Lane for Car Automation and Detecting Vehicles Using Yolov3

Devakipriyadharshini V N¹, Praveensri T², Sreerenusankar V³, Dr Suguna R⁴

^{1,2,3,4}Computer Science & Engineering, Bannari Amman Institute of Technology, Erode, Tamilnadu, India.

How to cite this paper:

Devakipriyadharshini V N¹, Praveensri T²,
Sreerenusankar V³, Dr Suguna R⁴,
"Segmenting Lane For Car Automation and
Detecting Vehicles Using Yolov3",
IJIRE-V4I02-199-203.

Copyright © 2023 by author(s) and
5th Dimension Research Publication.
This work is licensed under the Creative
Commons Attribution International License
(CC BY 4.0).
<http://creativecommons.org/licenses/by/4.0/>

Abstract: Increasing safety, reducing traffic accidents, and saving lives are significant concerns in the automation of self-driving cars. To improve the safety precautions in self-driving automobiles, this project detects the lanes and vehicles in traffic. The fact that lane detection is essential in identifying which behaviours contribute to errors and accidents presents one of the challenges faced by self-driving car manufacturers that are now creating large numbers of autonomous vehicles for consumers. A more compelling case may be made for the development of intelligent vehicles by emphasising the improvement of safety conditions through full or partial automation of driving operations. Lane segmentation is a challenging topic because there are so many various sorts of road conditions that one could encounter when driving. We use the Yolov3 and CNN algorithms to segment the lane and detect the vehicles in the lane in order to ensure safe driving practises.

Key Word: YOLOv3, CNN, Open CV, Lane segmentation, Vehicle detection

1. INTRODUCTION

Smart transportation systems make use of smart infrastructure and intelligent cars to make roads safer and traffic flow better. A more convincing case for designing intelligent vehicles is that doing so will increase safety by totally or partially automating driving duties. Road detection was one of these duties, and it was crucial for driving assistance systems to know the lane design and the position of the vehicle in relation to the lane. Yet, the demand for safety is the most convincing case for adding autonomous capability to automobiles. In most nations, vehicle accidents continue to be the largest source of accident fatalities and injuries, resulting in tens of thousands of fatalities and millions of injuries each year. Highways in the nation's urban areas see a disproportionately high number of traffic fatalities and injuries compared to those in its rural parts. Hence, a device that can alert the driver of the danger has the potential to save a significant amount of lives. In this project, YOLOv3 architecture is being used for lane segmentation and vehicle detection using real-time data and live feed from OpenCV. To assure safety precautions, we use the YOLOv3 and CNN algorithms for segmentation lane and also detecting the vehicles on road.

2. LITERATURE REVIEW

Wael Farag, Zakaria Saleh [1] this research proposes a quick and accurate lane-lines recognition and tracking method. The suggested method is ideal for usage in self-driving automobiles or Advanced Driving Assistance Systems (ADAS). The proposed method places a strong emphasis on speed and simplicity so that it can be integrated into less expensive CPUs used by ADAS systems. The suggested method consists mostly of a pipeline of computer vision algorithms that build upon one another and consume raw RGB photos to generate the necessary lane-line segments that serve as the car's representation of the edge of the road.

Yong Tang, Congzhe Zhang, Renshu Gu, Peng Li, Bin Yang [2]. It is very practical and directly applicable for many operations in a traffic surveillance system to recognise and identify vehicles based on static photos. The processing of automatic vehicle detection and recognition will be covered in this paper. To find the car over the input image, Haar-like features and AdaBoost techniques are first utilised for feature extraction and classifier construction. Following that, multi-scale and multi-orientation vehicle characteristics are extracted using the Gabor wavelet transform and a local binary pattern operator in accordance with the outside interference on the image and the randomly positioned vehicle. In order to represent the vehicle features, the image is finally separated into small sections from which histogram sequences are retrieved and concentrated.

Abdulhakam.AM. Assidiq, Othman O. Khalifa, Md. Rafiqul Islam, Sheraz Khan [3]. In the context of advanced driver assistance systems, boosting safety and lowering traffic accidents, hence saving lives, are of major concern. It appears that future road vehicles will have to do complicated and difficult tasks including lane detection and road boundary detection. Its foundation is lane detection (which includes the localization of the road, the determination of the relative position between vehicle and road, and the analysis of the vehicle's heading direction). Using the vehicle's visual system is one of the main methods for detecting lane and border markings on the road. Due to the various driving situations that one may experience, lane recognition is a challenging topic. This research presents a vision-based lane recognition method that can operate in real time and is resistant to changes in illumination and shadows. The technology uses a camera that is mounted on the car to gather the front image before using a few different methods to identify the lanes. These lanes are retrieved using the Hough transform utilising two hyperbolas that are fitting to the lane's boundaries. Both painted and unpainted roads, as well as curving and straight roads, can use the proposed lane detection technology. Finally, a critical analysis of the methodologies

and their potential for future application were covered.

R.Roopa Chandrika, N.S.Gowri Ganesh, A. Mummoorthy, K.M.Karthick Raghunath [4]. Over the previous ten years, the number of automobiles has dramatically increased. In the world, there are more than 1 billion active automobiles, with 60 to 70 million of those in India. It's difficult to control such traffic jams and provide enough parking spaces. In order to control traffic as efficiently as possible, the authorities will be able to acquire statistics on traffic flow from vehicle counts and categorization on congested roadways. The method for detecting, counting, and classifying automobiles using image processing techniques is presented in the paper. Even though this topic has been the subject of a lot of research, there is always room for improvement. Vehicle detection and counting is divided into the following six steps: Image acquisition, analysis, object detection, counting, classification, and display of the results are the first five steps.

Ke Li,Rongchun Deng,Yongkang Cheng,Rongqun Hu,and Keyong Shen [5] Malignant traffic incidents like rear-end collisions can be easily avoided with the help of real-time detection and recognition of existing vehicles. This article focuses on the colour space preprocessing of the image and uses threshold segmentation approach and infrared image improvement to segment the front vehicle and backdrop because the infrared image has several drawbacks such weak contrast, noisy noise, and blurring edge. To put it another way, when analysing an infrared image obtained from an infrared CCD, noise is first removed using a median filter, and then the contrast of the image is increased using improved histogram equalisation. The image's vertical edge is enhanced using the vertical Sobel operator, and the image is segmented using the binary segmentation approach. Last but not least, vertical edge symmetry, aspect ratio, and gray-scale symmetry enable vehicle identification and recognition. The findings of the examination of experimental images and data demonstrate that the image processing technology examined in this work has fulfilled the desired objectives of the study.

Dr Narapareddy Ramarao B Vivek Bhat Kartik Kulkarni Ashley Raban Akbary [6]. Algorithms for path detection have been created and put into use to find and examine the drivable path in front of the autonomous vehicle. Some vehicles might solely employ cameras, while others might use cameras, LiDAR, GPS, and other technologies. One of the main strategies is to use the vehicle's vision-based technology to detect lane markings and road borders. However employing vision-based input to determine road centre parameters is one of this approach's trickiest challenges. The system gathers data using a variety of on-vehicle input sensors, then applies algorithms to provide path coordinates for autonomous vehicle navigation. This review report analyses and compares several solutions to the aforementioned problems that are suggested by research publications on path tracking methodologies.

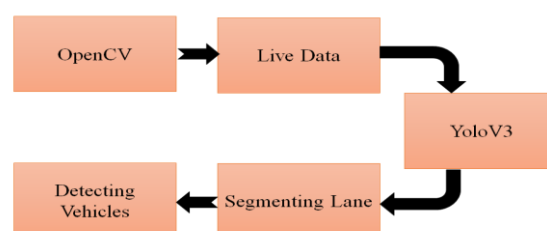
Jie Zhang, Yi Xu*, Bingbing Ni, and Zhenyu Duan [7] has been researched on lane segmentation. Two aspects of the proposed framework's primary contributions are highlighted: (1) To enhance overall performance, we propose a multiple-task learning architecture with mutually interrelated sub-structures between lane segmentation and lane border detection.(2) It is assumed that the lane border is anticipated as the outside contour of the lane area and that the lane area is forecasted as the result of area integration within the lane boundary lines. This results in the proposal of a novel loss function with two geometric restrictions taken into account. These changes significantly increase the resilience and accuracy of our technique on a number of criteria when combined with an end-to-end training process. For the KITTI dataset, CULane dataset, and RVD dataset, the suggested framework is assessed. A lane area and its limits really have a geometric relationship: lane areas always sit between lane boundaries, while a lane boundary is made up of the lane area's outer contour. Furthermore, when outliers seriously impede the first sub-process, extremely low performance may result.

Chaochao Meng , Hong Bao and Yan Ma [8] has done a review on vehicle detection. To solve the transportation problem with technology, society should investigate new transportation methods. The "vehicle-road" should be created in order to entice "people" out of the closed-loop system. The ultimate objectives are self-driving vehicles. Computer vision that is based on vehicle detection is a crucial component of perception in autonomous driving. More than 80% of how people see the world is based on visual perception, according to research on visual thinking. The development of visual perception is a crucial component of autonomous driving. It is challenging to create a visual intelligence system that can take the position of replacement perception.

III.PROBLEM IDENTIFICATION

This project recognises increasing safety, reducing traffic accidents and saving lives are significant concerns in the automation of self-driving cars. This project involves lane segmentation and vehicle detection for automated cars to assure safety and have additional features.. One of the challenges faced by self-driving car manufacturers who are currently producing a large number of autonomous vehicles for consumers is the fact that lane detection is crucial in recognising which behaviours contribute to errors and accidents.

IV.PROCESS PLAN



V.METHODOLOGY PROPOSED

The following phases make up the process for segmenting lanes and finding moving objects:

Preprocessing the raw image or video frame to improve contrast and lower noise is the first step. Histogram equalisation, colour space transformation, and Gaussian smoothing are typical preprocessing methods. The next step after preprocessing the input image is to separate the lane markings from the background. Many computer vision methods, including edge detection, colour thresholding, and Hough transforms, can be used to do this. The next stage is to track the lane markings over time in order to estimate the lane borders once they have been segmented. Several algorithms, like polynomial fitting or Kalman filters, can be used to do this. The next stage is to find automobiles inside the lane after the lane boundaries have been approximated. Template matching, Haar cascades, or machine learning techniques like deep neural networks can all be used to accomplish this. Following vehicle detection, in order to understand their movement and predict where they will travel in the future, it is necessary to follow them over time. Several object tracking algorithms, like the Kalman filter or the particle filter, can be used for this. The last stage is to post-process the results to eliminate any false detections or errors once the lanes and vehicles have been segregated and monitored. Many methods, including morphological procedures and region filtering, can be used to accomplish this.

Ultimately, the process of segmenting lanes and finding moving objects uses a combination of machine learning, computer vision, and image processing approaches. The precise techniques employed will be determined by the application and the resources at hand, but the general processes indicated above offer a sound framework for creating an efficient lane and vehicle detection system.

Dataset Preparation:

Assemble and annotate a dataset of pictures and videos with information about lanes and vehicles. The dataset needs to cover a diverse array of situations, such as various illumination, weather, and road kinds. Create training and validation sets from the dataset.

Model Training:

Train a model to recognise cars and lane segments in the images using the state-of-the-art object recognition technique YOLOv3. To improve the pre-trained model, use the annotated dataset. The steps that make up the training process are as follows: Make the annotations in YOLOv3 format. A text file must be created for each image with the class label and bounding box coordinates for each object. Download the pre-trained YOLOv3 model and make the necessary adjustments to recognise lane lines and cars. This requires changing the amount of output classes and the network configuration in order to improve performance. Train the upgraded YOLOv3 model with the annotated dataset using a deep learning framework like TensorFlow or PyTorch. To reduce the prediction error, the model's weights and biases are optimised during the training phase. To improve the effectiveness of the model, employ strategies including data augmentation, learning rate scheduling, and early stopping. Use multiple evaluation metrics, such as accuracy, recall, and F1 score, to assess the trained model on the validation set. To improve the model's performance, use the evaluation results to fine-tune its hyperparameters and, if necessary, repeat the training procedure.

Preprocessing for images and videos:

Upload the files and use fundamental preprocessing methods like scaling, colour conversion, and normalisation. By doing this, the photos are converted into a format that the YOLOv3 model can understand.



Figure 1.1

Lane Segmentation:

Use thresholding and edge detection algorithms to the preprocessed pictures to perform lane segmentation using OpenCV2. The route will be distinguished from the surrounding area by doing this. Grayscale-size the previously processed image. To decrease noise, apply a Gaussian blur to the image. Use a Canny edge detection technique to find edges in the blurred image. To concentrate on the road area, apply a region of interest mask to the edge-detected image. To find the lane lines, apply a Hough transform to the masked image. Create a lane mask by drawing the lane lines on a black image and filling in the spaces between them.

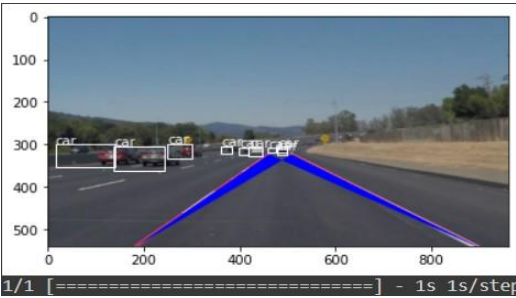


Figure 1.2

Vehicle Detection:

In order to find automobiles in the preprocessed photos, use the trained YOLOv3 model. Each vehicle that is detected will have bounding box coordinates provided by the model. To detect cars, run the preprocessed image through the YOLOv3 model. Use a non-maximum suppression and confidence threshold to remove the non-vehicle objects. Create bounding boxes around any cars that are detected.



Figure 1.3

Vehicle Tracking:

Use a tracking algorithm to keep track of the vehicles over a series of video frames. By contrasting the bounding boxes of identified cars in the current frame and those in the preceding frame, this can be accomplished. Give each vehicle that was found in the initial frame a special ID. Determine the separation between the bounding boxes of any identified vehicles in the current frame and the frame before. Assign the current frame bounding boxes to the previous frame bounding boxes based on the minimum distances. Update the tracked cars' bounding boxes and IDs. Together with overlaying the lane segmentation on the original image, draw bounding boxes around the detected vehicles. The findings of the vehicle and lane detection will then be visually represented. Make use of metrics for evaluation, such as accuracy.

VI.RESULT AND DISCUSSION

In this project, we have proposed a new lane segmentation and vehicle detection method in self-driving cars for improved autonomous vehicles. We analyzed several numbers of variables, including processing speed and precision to conclude the experiment. There are nearly as many methods for collecting the required data as there are potential data sources. In order to preprocess the input and train the YOLOv3 model, we obtained the necessary data and live feed from OpenCV. As a result of implementing the YOLOv3 architecture, we have come to the conclusion that automated vehicles will be safer and have lower accidents by segmenting lanes and detecting vehicles in self-driving cars.

We can achieve 80% accuracy by utilising Yolov3. Faster RCNN, SPP-net, and YOLOv3 are all efficient object identification models that have different strengths and disadvantages when compared to RCNN. Although Faster RCNN and RCNN are generally more accurate SPP-net and YOLOv3 are faster and more flexible but may be less accurate in some situations than slower and less flexible technologies. RCNN and Faster RCNN employ a two-stage approach and carry out more computations on each region suggestion, hence they require more training data and take longer to train than SPP-net and YOLOv3. The precise requirements of the application and the available computational resources determine which model should be used. YOLOv3 has a number of advantages over existing object identification models like RCNN, Faster RCNN, and SPP-net, including speed, flexibility, accuracy, and simplicity.

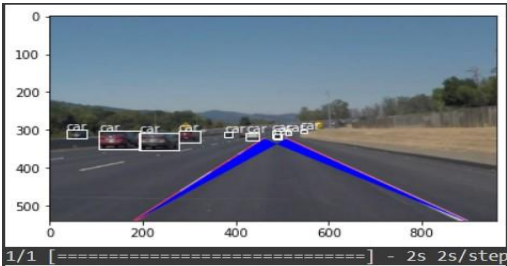


Figure 1.4

VII.REQUIREMENTS NEEDED FOR IMPLEMENTATION

Software Tool : Colab
Language : Python
Algorithms : YOLOv3, OpenCV

References

- [1]. Wael Farag, Zakaria Saleh “Road Lane-Lines Detection in Real-Time for Advanced Driving Assistance Systems”. Published in IEEE 2018 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT). DOI:10.1109/3ICT.2018.8855797.
- [2]. Sriashika Addala “Vehicle Detection and Recognition”. Published in 2020 Research paper on vehicle detection and recognition. DOI: 10.13140/RG.2.2.34908.82561.
- [3]. Abdulhakam.A.M. Assidiq, Othman O. Khalifa “Real Time Lane Detection for Autonomous Vehicles”. Published in IEEE 2008 International Conference on Computer and Communication Engineering Kuala Lumpur, Malaysia. DOI: 10.1109/ICCCE.2008.4580573.
- [4]. R.Roopa Chandrika, N.S.Gowri Ganesh “Vehicle Detection and Classification using Image Processing”. Published in IEEE 2019 International Conference on Emerging Trends in Science and Engineering (ICESE) Hyderabad, India. Page number 6. DOI: 10.1109/ICESE46178.2019.9194678.
- [5]. Ke Li, Rongchun Deng, Yongkang Cheng, Ronhgun Hu, Keyong Shen, “Research on Vehicle Detection and Recognition Based on Infrared Image and Feature Extraction”, Mobile Information Systems, vol. 2022, Article ID 6154614, 10 pages, 2022. <https://doi.org/10.1155/2022/6154614>.
- [6]. Narapareddy Ramarao B Vivek Bhat Kartik Kulkarni Ashley Raban Akbary “Lane Detection for Autonomous Vehicle”. March 2019 Journal of Engineering Research and Application, DOI: 10.9790/9622- 0903062835.
- [7]. Jie Zhang, Yi Xu*, Bingbing Ni, and Zhenyu Duan “Geometric Constrained Joint Lane Segmentation and Lane Boundary Detection”. 2018 Computer Vision Foundation, ECCV.
- [8]. Chaochao Meng , Hong Bao and Yan Ma “Vehicle Detection: A Review”. Journal of Physics: Conference Series, Volume 1634, The 2020 3rd International Conference on Computer Information Science and Application Technology (CISAT) 2020 17-19 July 2020, Dali, China. DOI 10.1088/1742-6596/1634/1/012107.