

Lane and Object Detection for Autonomous Vehicle using Advanced Computer Vision

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ABSTRACT

The vision of this project is to develop lane and object detection in Autonomous Vehicle system to run efficiently in normal road condition and to eliminate the use of high cost Light based LiDAR system to implement high resolution cameras with advanced computer vision and deep learning technology to provide an Advanced Driver Assistance System (ADAS). Detecting lane lines could be a crucial task for any self-driving autonomous vehicle. Hence, this project was focused to identify lane lines on the road using OpenCV. The OpenCV tools such as colour selection, the region of interest selection, grey scaling, canny edge detection and perspective transformation are being employed. This project is modelled as an integration of two systems to solve the real-time implementation problem in autonomous vehicles. The first part of the system is lane detection by advanced computer vision techniques to detect the lane lines to command the vehicle to stay inside the lane marking. The second part of the system is object detection and tracking is to detect and track the vehicle and pedestrians on the road to get a clear understanding of the environment to plan and generate a trajectory to navigate the autonomous vehicle safely to its destination without any crashes, this is done by a special deep learning method called transfer learning with Single Shot multibox Detection (SSD) algorithm and Mobile Net architecture.

KEYWORDS: *opencv; edge detection; transfer learning; ssd-mobilenet architecture*

INTRODUCTION

An autonomous vehicle is one that can drive itself from a starting point to a predetermined destination in “autopilot” mode using various in-vehicle technologies and sensors, including adaptive cruise control, active steering (steer by wire), anti-lock braking systems (brake by wire), GPS navigation technology, lasers and radar. It utilises a fully automated driving system in order to allow the vehicle to respond to external conditions that a human driver would manage. It transform transportation into a utility available to anyone, anytime. This requires advances in many aspects of vehicle autonomy, ranging from vehicle design to control, perception, planning, coordination, and human interaction. Computer Vision gives vision to the AV and make the vehicle to perceive through the world by understanding the objects in the environment to make live critical intelligent decision by the use of advanced Computer Vision techniques, Machine Learning and Deep Learning [2].

A. LANE DETECTION

An increasing safety and reducing road accidents, thereby saving lives are one of great interest in the context of Advanced Driver Assistance Systems (ADAS). Apparently, among the complex and challenging tasks of future road vehicles is road lane detection or road boundaries detection. It is based on 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). One of the principal approaches to detect road boundaries and lanes using vision system on the vehicle. However, lane detection is a difficult problem because of the varying road conditions that one can encounter while driving. In this paper, a vision-based lane detection approach capable of reaching real time operation with robustness to lighting change and shadows is presented. The system acquires the front view using a camera mounted on the vehicle then applying few processes in order to detect the lanes [6].

B. OBJECT DETECTION USING TRANSFER LEARNING

Transfer learning generally refers to a process where a model trained on one problem is used in some way on a second related problem.

In deep learning, transfer learning is a technique whereby a neural network model is first trained on a problem similar to the problem that is being solved. One or more layers from the trained model are then used in a new model trained on the problem of interest.

We used Transfer Learning method to implement this convolutional neural network evaluated on the PASCAL VOC detection dataset. This network has 24 convolutional layers followed by 2 fully connected layers. Instead of the inception modules used by SSD- MobileNet architecture simply use 1*1 reduction layers followed by 3*3 convolutional layers, Single Shot object Detection (SSD) can achieve a single crop top-5

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accuracy of 88% on the ImageNet. ssd final layer predicts both class probabilities and bounding box coordinates. This model is called the MobileNet [1]. The Architecture of MobileNet is shown in the figure 1.

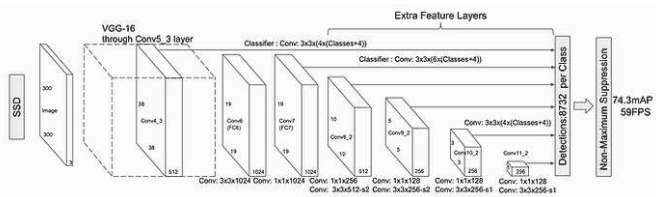


Figure 1: SSD-MobileNet architecture (source: SSD: Single Shot MultiBox Detector, unified real-time object detection)

I. ALGORITHM

The block diagram of the proposed lane detection system is shown in figure 2.

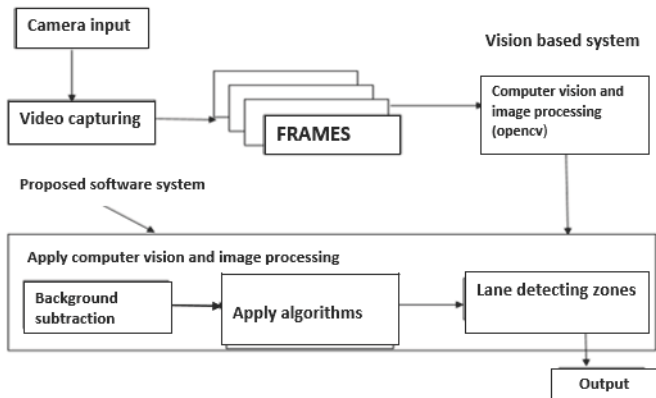


Figure 2: block diagram of lane detection system

The description of each block is explained below:

1. Camera input: the HD cameras that are placed in the front of the autonomous vehicle is used as the input source for finding the lane and object detection process.
2. Video capturing: the real time video is captured by the camera and is taken as the input.
3. Frames: the captured video is split into frames for further processing.
4. Computer vision and image processing: this process is to perform functions like enhancing the picture quality and smoothing the images.
5. Background subtraction: to get the undistorted images we use techniques like Gaussian blur, smoothing, and edge detection to the input images.
6. Apply algorithms :the algorithms Namely canny edge detector, perspective transformation and sliding window techniques are used to get the clear detection of lanes.
7. Lane detecting zones: after applying the algorithms the ROI is found and the Hough transform is applied to the cropped image to detect the lines in the image.
8. Output: here the lane lines are programmed to detect lanes even without the lane markings along with the road map for advanced driver assistance system (ADAS).

The advanced techniques used are canny edge detection, perspective transformation, sliding windows.

II. DESIGN

The step by step lane detection pipeline is shown in the figure 3, it outputs the stacked images of lane line in each process from distortion correction to perspective transform.

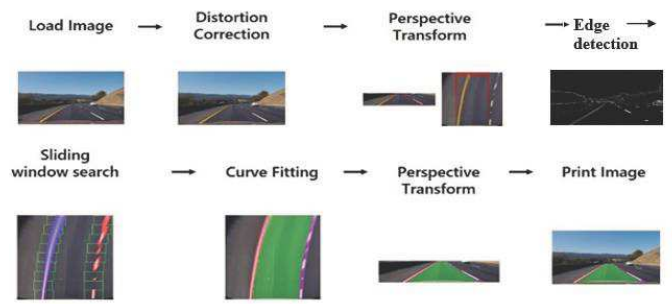


Figure 3: lane detection pipeline

A. DISTORTION CORRECTION

By calibrating a camera, we can enable a self-driving car to know the location of pedestrians, dogs, and other objects relative to the car [4].

Calibrating the camera is the process of using a known real-world pattern (e.g. a chessboard) to estimate the extrinsic parameters (rotation and translation vectors) and intrinsic parameters (e.g. focal length, optical centre, etc.) of a camera’s lens and image sensor to reduce distortion error caused by the camera’s imperfections as shown in figure 4.

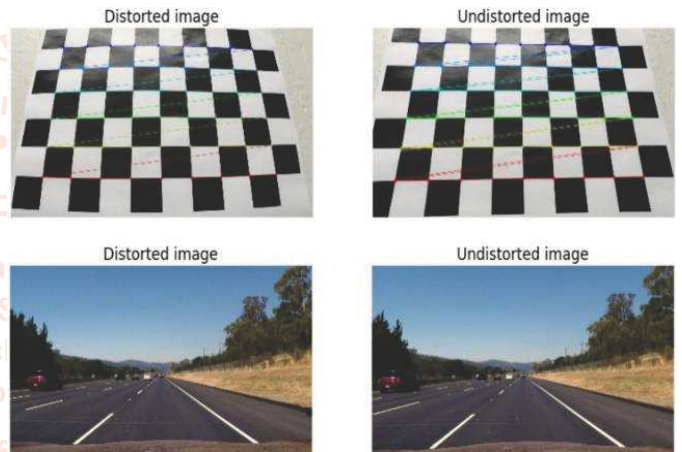


Figure 4: effect of calibration on the distorted image

B. EDGE DETECTION

The first step in detecting this marking is converting the colour-segmented image grayscale and then using edge detection [3]. In this we have used canny edge detector to produce the best edge image as shown in figure 5.

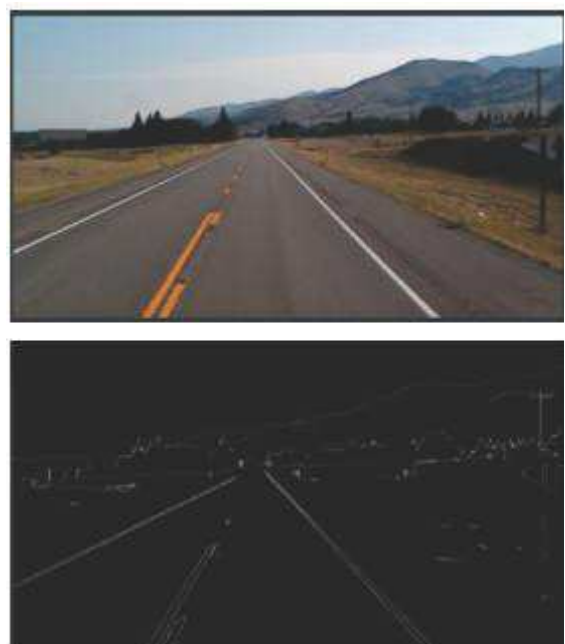


Figure 5 result of canny edge detection

C. PERSPECTIVE TRANSFORMATION

Certain features like the curvature of the road lane markings is found using a technique called perspective transformation that transforms the

undistorted image to a "birds-eye view" of the road as shown in the figure 6 , this focuses only on the lane lines and displays them in such a way that they appear to be relatively parallel to each other.



Fig 6 perspective transformation of the original image

D. SLIDING WINDOW SEARCH

Now the lanes can be identified by using the sliding window search approach to identify the regions of the frame with the highest density of non-zero pixels as shown in the figure 7. we have used 9 sliding windows for better results [13].

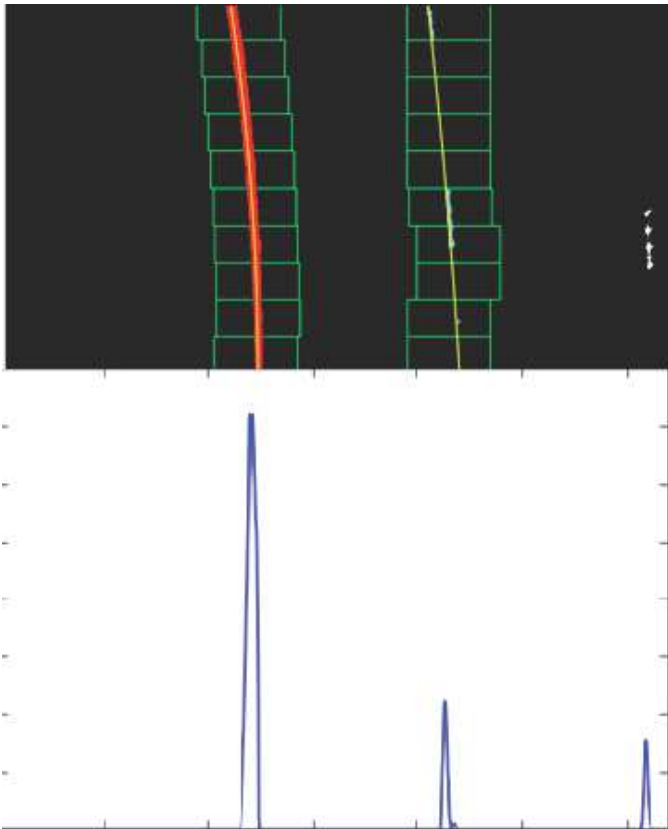


Fig 7 sliding window search

III. RESULTS

A. LANE DETECTION

The final result of the lane detection is shown in the figure 8, figure 9 and figure 10, it outputs the area inside the detected lane marking in green colour to generate the driveable trajectory to send the control commands to the actuator. Our project output has been tested on three real time captured input videos which also describes the information that contains the lane info along with road curvature, deviation and the road map.



Fig 8 lane detected on the input video

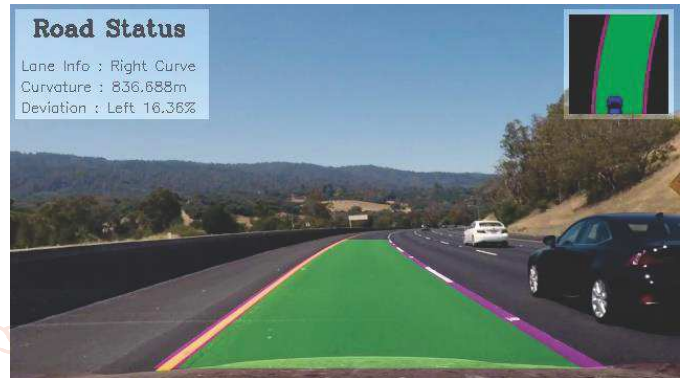


Fig 9 Detected lane on the challenge video

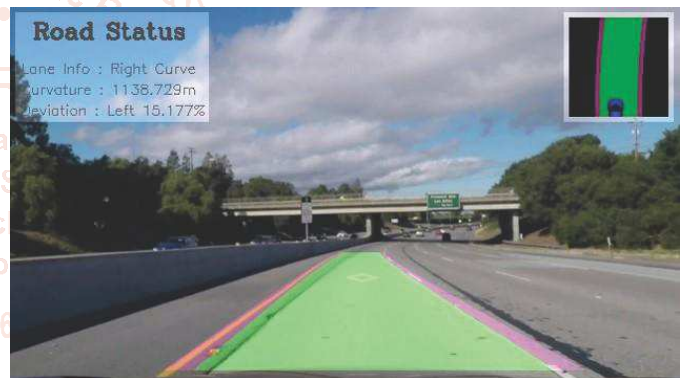


Fig 10 detected lane on the harder challenge video

B. OBJECT DETECTION AND TRACKING

The output from the object detection and tracking is shown in the figure 11, it detect and tracks the object in the road with bounding box with the accuracy of 85%. The use of SSD and Mobile Net gives faster detection and tracking with better accuracy of the model as shown in figure 12.



Fig 11 Detected and Tracked vehicle

This model shows 98% accuracy in training and 83% in validation as shown in figure 12.

The reason for the drop of accuracy in validation set is that the model over fitted with the training data. In real-time dropout layers can be added to the model to prevent this overfitting [1].

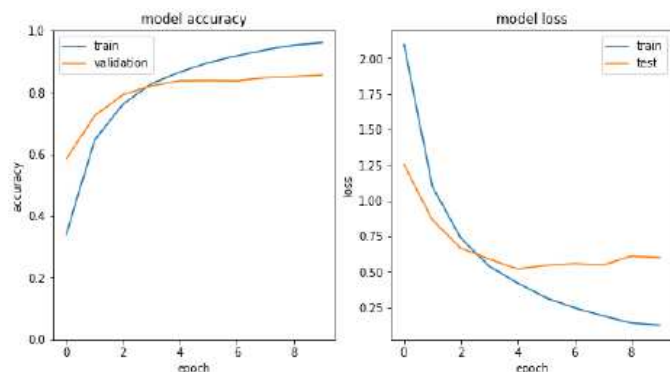


Fig 12 Accuracy and Loss of Transfer Learning Model

CONCLUSIONS

The autonomous vehicle system is developed to run the Vehicle precisely with advanced computer vision and deep learning techniques. The output from the lane detection system is used to generate reference trajectory to keep the autonomous vehicle inside the lane to avoid accidents by advanced computer vision. The object detection and tracking with the help of Single Shot object Detection (SSD) algorithm gives very fast and accurate results to detect and track the objects in the road at high frame rate. The accuracy and performance of this network are greater than that human in making optimized and rapid decisions, this results in reduced accidents causing random human error. In lane detection, previous research has been focusing on complex algorithms and expensive sensing devices to process input data. These kinds of methods usually involve heavy computing and high cost experiments. This project pursues an alternative way in lane detection. This project was mainly focused on reducing the cost of sensors and to use simple and efficient algorithm to detect moving objects and lane from just the camera input. This method will be efficient in identifying the lane lines and remove interfering noises in lane detection.

REFERENCES

- [1] Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C. Y., & Berg, A. C. (2016, October). Ssd: Single shot multibox detector. In European conference on computer vision (pp. 21-37).
- [2] Lex Fridman(2018) "Human-Centered Autonomous Vehicle Systems: Principles of Effective Shared Autonomy" arXiv:1810.01835v1.
- [3] G. Stevica, Goma, Ahmed (2012), "Detection of road borders based on texture classification," International

Journal of Advanced Robotic System, pp. 2548-55.

- [4] Zhang, Zhengyou. "A flexible new technique for camera calibration." IEEE Transactions on pattern analysis and machine intelligence 22.11 (2000).
- [5] C. B. Wu, L. H. Wang and K. C. Wang, "Ultra- low Complexity Block-based Lane Detection and Departure Warning System," in IEEE Transactions on Circuits and Systems for Video Technology, vol. PP, no. 99, pp. 1-1.
- [6] V. Q. Nguyen, C. Seo, H. Kim and K. Boo, "A study on detection method of vehicle based on lane detection for a driver assistance system using a camera on highway," 2017 11th Asian Control Conference (ASCC), Gold Coast, Australia, 2017, pp. 424-429.
- [7] Ren, S., He, K., Girshick, R., Sun, J.: Faster R- CNN: Towards real-time object detection with region proposal networks. In: NIPS. (2015)
- [8] Szegedy, C., Reed, S., Erhan, D., Anguelov, D.: Scalable, high-quality object detection. arXiv preprint arXiv:1412.1441 v3 (2015)
- [9] Tan, T. Hong, T. Chang, and M. Shneier (2006), "Color model-based real-time learning for road following," Proc. IEEE Intell. Transp. Syst. Conf, pp. 1639-45. New York: IEEE.
- [10] Rotaru, T. Graf, and J. Zhang (2008), "Color image segmentation in HIS space for automotive applications." J. Real-time Image Process, pp. 1928-35. New York: IEEE.
- [11] .M. A. Alvarez, A. M. Lopez (2011), "Road detection based on Illuminant Invariance," Intelligent Transportation System, IEEE Transactions on, pp. 2165-74. New York:IEEE.
- [12] S. D. Buluswar, B. A. Draper (1998), "Color Machine Vision for Autonomous Vehicles," Int. J. Eng. Applications of Artificial Intelligence, pp. 392-99. New York: IEEE.
- [13] Wei, Yichen, and Litian Tao. "Efficient histogram-based sliding window." 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. IEEE, 2010.
- [14] L. Fletcher, L. Petersson, and A. Zelinsky (2003), "Driver Assistance Systems based on Vision In and Out of Vehicles", Intelligent Vehicles Symposium,, Volume 5, pp.51-57.
- [15] K.-Y. Chiu and S.-F. Lin, "Lane detection using color-based segmentation," in Proc. IEEE Intelligent Vehicles Symp., 2005, pp. 706-711.