Lane Detection of the Road in the Autonomous Driving Vehicle

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Abstract—In this project we leverage an application to lane detection of the road in the urban streets based on the some image processing techniques, we will evaluate the performance of method in different type of the datasets such as straight and curve road in different weather condition. we proposed the results of this application for most of the image datasets in the experiment and result setction.

$Note$ **:** The link of the project and demo video uploaded in the GitHub [1] and YouTube[2] respectively(because i can not upload the video datasets through the Ninova due to limitation of upload size).

Index Terms—Segmentation, Lane finder,computer vision, Image Processing, Udacity, Autonomous drivers

1 INTRODUCTION

THE autonomous vehicles [1] [2]have been dreams about and even attempted almost since the advent of the automobile, they have really began to pick up steam in the past couple of years, with both the incumbent players making moves as well as many technology companies. Self-driving cars use a blend of machine learning, computer vision and various other areas in order to take over the actions of a human driver, providing for safer and more reliable travel. There are many other important benefits, including potential easing of traffic congestion and potential to lower pollution if concepts like ride- sharing continue to increase in use. Our motivation is to forces the image processing techniques approaches for building a method with ability to direct the automobile in true direction in the roads. Steering the automobile in the safe direction is the important part of the autonomous vehicles.

Actually learning the road based on the lane seems ridiculous and unbelievable, but for following the roads that have standard lane can be good facility. If we are skipping straight lane to a fully autonomous vehicle with , this may not be logical. However, for many consumers, they will likely see more step-by-step changes, and showing them that the car can always sense the lanes will go a long way in getting them comfortable with a computer doing the driving for them. Even short of this, enhanced lane detection could alert an inattentive driver when they are not careful on the road.

1. https://youtu.be/J5fz2avho7s
2. https://github.com/Ayanzadeh93/Lane-detection-of-the-road

Fig. 1. image datasets that provide by udacity NanoDegree courses, This images contain two types of road such as straight and curved road.

1.1 Literature Review

Due to importance and sensitivity of the autonomous driving fields, most of the methods that have used in this field is based on the deep learning algorithm. Bojarskiet al. [1][2][3] propose the good performance with convolutional neural networks (CNNs) from a front-view camera to steering

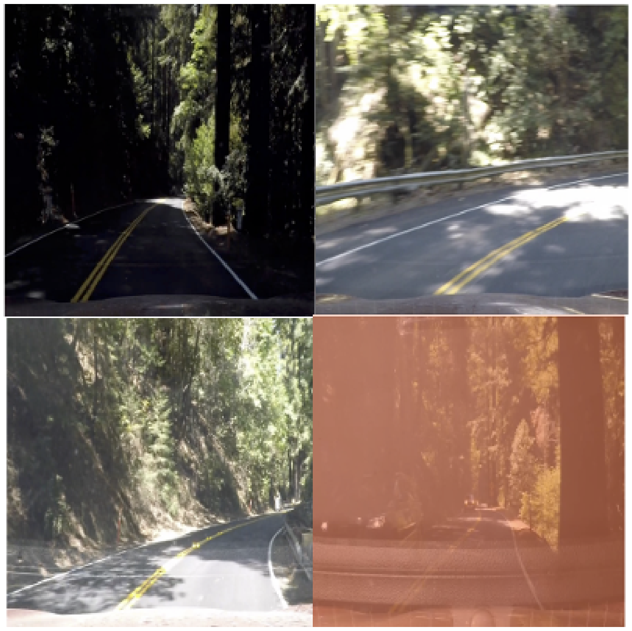

Fig. 2. Thhis images has captured from challenging video, they are some challenges such as motion, dark area and other related problem in the image

controls, Xu Et al. [4] proposed a prediction approach that takes pixel of the raw image and base on the prior signal state of the vehicle predicts the sequence of discretized actions. There are other approaches that based one the classical methods of image processing systems; the randomized Hough transform [11][12] is the good examples, which is a quickerand a more efficient in memory and counterpart of the classical Hough transform that have good performance for line finding of the roads that are mostly straight.

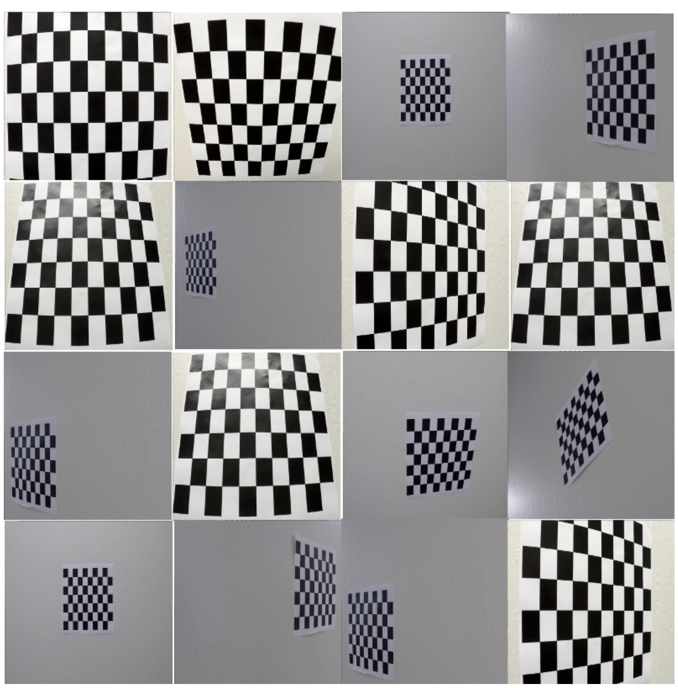

Fig. 3. Chessboard images data set for camera calibration.

Fig. 4. (left image is the edges of the image.)

1.2 Goals of the project

The main properties that the lane marking (or boundary) detection techniques should possess are: 1. The quality of lane detection should not be affected by shadows, which can be cast by trees, buildings, etc. 2. It should be capable of processing the painted and unpainted roads. It should handle curved roads rather than assuming that the roads are straight. 3. It should use the parallel constraint as a guidance to improve the detection of both sides of lane markings (or boundaries) in the face of noises in the images.

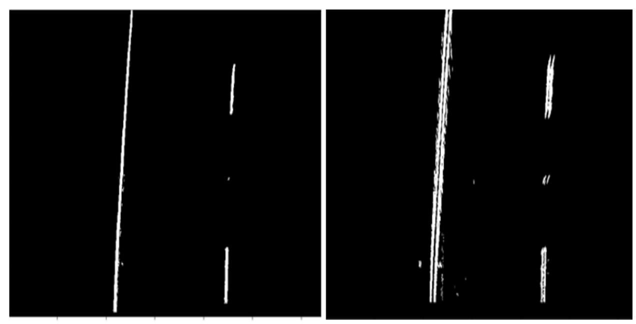

Fig. 5. masking of the image for righ and left lane.

2 Used Methods

2.1 Camera Calibration

Image distoration occures when cameras look image at objects that have 3D feature in the real-world and want to transform them into 2D plane in the image. Actually this transform can not be efficient and bring a lot of distoration in the image, this distoration changes the shape and size of the object in this transformation. So, the fisrst steps in analyzing the images distoration level as pre-processing step. actually this step has significant effect on the performance of lane detection, because distorted images show the lane of the image in some parts curvy and keep it out the the detection application from reality and also makes an image look tilted so that some objects appear farther away or closer than they actually are in reality. Camera Calibration maps 3D points 2D points one. This can be done with the images that has grid pattern such as a chessboard. This process uses multiple images of chessboards from different distance and angle, the images are putted as input and return the camera calibration values and we use this value matrix withe the original images of datasets to make them unsorted image.

Fig. 6. above image is the orginial image and the below one the undis-orted image based on the matrix coefficient.

2.2 Perspective Transform

The next step in the process is perspective transform. In this project, we have the camera at the car that has the front-view perspective. This perspective has provides a lot of problem during the lane detection, First lane detection with front-view perspective bring the lots of error to our vision and we see the all lanes in the images the converge to one point at the end of the roads; this is cause of our vision system that try to transform a 3D space into a 2D space so this error of view decrease our performance in the detection of the lane and cause of of error in our detection. Therefore, with implementing the perspective transform, lanes of the image will be seen parallel and we do not have any convergence of the road in any parts of the lane. Furthermore, perspective transform help us to concentrate on the region of interest instead of whole the image. In transform perspective we immigrate our vision from front view to the eye-bird view, so this perspective helps us to delete unnecessary part of the image and focus on the lane region. Hence, perspective transform reduce our error and reprocess step for preparing the image for analyzing.for implementing this technique, we need to choose the 4 point in the output of the transform region. by doing this our input point will be warped to the new coordination at the output, For instance, in straight line we choose two points on each lane as input of image and the output will be imagine where image would be parallel; At the end with inverse perspective transform we draw the lane on the original image or video frames. After perspective transform we should binarize our image and masking the interested region to extract the both yellow and white lane, for reaching this purpose we convert our color space from RGB to the HSL to have better performance in distinguishing the lanes from other regions. Afterward, we are masking the images for yellow color(Fig5) and combine it with the masking of white lane and combine both of this with these with our extractors of edges to have robust lane(Fig8). At the end we will find our lanes based on the peaks of the histogram.

Fig. 7. The results of image after implementing the perspective trans-form.

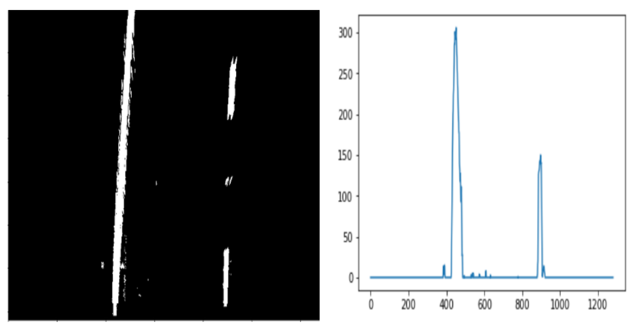

Fig. 8. (right) after combining the mask image for yellow in HSL channel and image edge detect ions results. (left) histogram of the Right image.

2.3 Polynomial fitting

The next step in lane detection after perspective transform is the polynomial fitting, actually we should fit second order polynomial for both sides of the roads and for reaching this purpose we should follow these steps. The first and important thing is calculating the bottom half of the image and partitioning the image into several horizontal slices, actually this slices has the performance like the searching method around their given scopes. For finding the interested object in the images we start from the bottom slice and find the pixels that is has similar feature to the lane of the road, specially we are finding the region has the most white pixel in horizontal coordination. Afterwards we iterate this step vertically to segments of the image in vertical sides, after this traverses, in both x and y direction for whole of the slice windows, we are fitting these points with the polynomial functions. For implementing this scenario to the

Fig. 9. our application detection in the challenging video

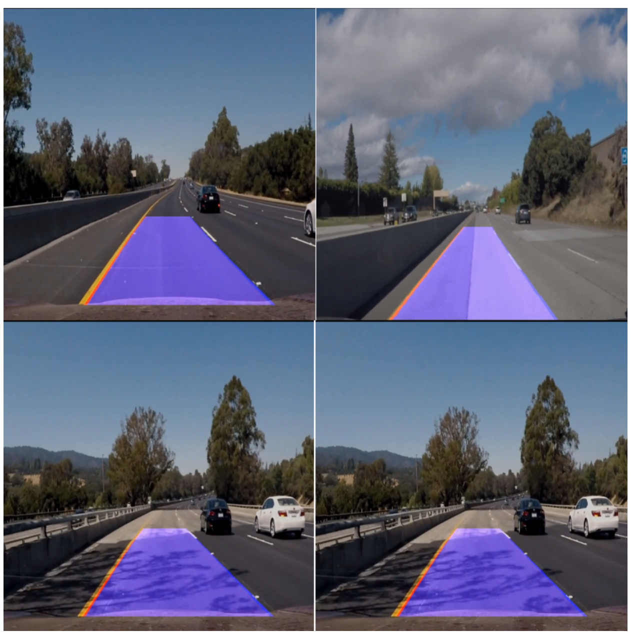

Fig. 10. our lane detection application for straight roads.

video, we have the temporal correlation between video, so in this condition if our proposed algorithm can not find the lane features in specific frame in the video, it easily skip that frames and postpone it to the next frames; Therefore, this techniques can improve the computation time of the process. hence, to have algorithmic perspective from the method we explain it as follow, Calculate a histogram of the bottom half of the image(Fig8), Partition the image into 9 horizontal slices Starting from the bottom slice in the image, this slice size is 200 pixel wide window around the left peak and right peak of the histogram we repeat this way up to the horizontal window slices to find pixels that are similar to be part of the left and right lanes.

Fig. 11. wrong detection of application in some parts of challenging video

3 Experiment Results

According the previous section, we analyze our methods for different types of roads and extend our implementation to the video, the results of this project has shown in Fig9,11. we have robust performance on the images of straight road and this is because of the specializing the mask for each left and right lane in the roads, converting the color space to the HSL and also using the additional erosion mask help us to have acceptable performance in the curved roads too. In the Fig11, we put the wrong detection of the lane in some parts of the video, Actually, low lighting , rapid curve change , higher reflections of the windshield and motion in some parts of the video decrease our detection in the challenging video. however, we have good performance in first 500 frames of the challenging video and it can be acceptable results for our project. Maybe implementing the method that based on the deep learning models can help us to increase the accuracy of detection in lane recognition applications.

4 Discussion

The biggest issue by far for me were sudden changes of condition(going from bright to dark or dark condition to bright environment). so, in this case, the lane of the road completely lost, Although,we implementing the erosion mask and equalization in the image they still can cause major problems, which is evident from harder challenge video. bad quality of the lines, Shadows of the tree from the sun, sharper curves in the road have impact on the detection of the lane. Moreover, The averaging of polynomial coefficients over the last couple of iterations maybe is not efficient .Maybe employing the Some robust filters for denoising the and employing the adaptive threshold for different weather condition for prediction of the robust threshold can increase our performance in the curved road videos.

5 Conclusion and Furture Work

One of the key opportunities for improvement would be to apply a adaptive threshold for lane detection when building my polynomial. For instance, durin the processing of image where the left lane has very little white pixels at all, we can calculate adapively and just reuse the lane polynomial from the previous frame. One possible improvement for future implementation would be a Color Windowing search process. This function could scan each color space in small blocks while searching for the region that yields the best pixel for lane finding. The Harder Challenge video has images where even Histogram Equalization is not helpful. These images are either very dark shadows of trees in the forest or extra bright and motion in the image and overexposure, we think that Color Windowing function would be very useful for this condition.

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