

## Lane Line Detection for Autonomous Vehicles using Computer Vision

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### Abstract:

Lane line detection is a crucial component of modernized driver assistance technologies and it enhances the overall safeness of the vehicle when it is moving. Real time vision-based system that detects lane lines for autonomous vehicles using a front-facing camera on a vehicle, is introduced. By leveraging computer vision-based technologies, the suggested system can identify lane boundaries. Utilizing a live video stream, we were able to identify lane borders, curve radii, and lane orientation. Utilizing this information, the system can manage the steering wheel automatically to perform smooth bends on highways without the need for user input, improving safety and comfort while ensuring that the car stays centered within the lane lines. The camera used to film this video was perched above the car. After importing this video, we fixed the distortion introduced by the camera. To extract the road markings from the raw picture, color and gradient threshold strategies are applied to the unobstructed picture. A perspective transform is then used to produce an aerial viewpoint of the picture. Sliding window search is used to locate the relevant lane line pixels, and second-degree polynomials are then fitted to locate the road markings on the left and right. Reverse-twisting the original picture into the recognised lane borders computes and displays the radius of lane curvature as well as the current location of the vehicle relative to the lane centre. The testing findings demonstrate that our suggested approach reliably finds the lane on the road's surface under various lightning situations.

**Keywords:** Lane Line Detection, Camera Calibration, Color and Gradient Thresholding, Bird's Eye View, Computer vision

### Introduction:

Advanced Driver Assistance Systems (ADAS) were evolved for the purpose of improving the safety and comfort of passengers by providing assistance to the driver in various driving tasks. The creation of a lane-detecting and lane-keeping capacity, which is essential for self-driving automobiles, is one of the major hurdles in creating ADAS. Systems for lane detection and maintenance must be extremely precise, dependable, and able to function in a range of lighting and weather scenarios.

For autonomous vehicles and their occupants to be safe, lane line detection is essential. Without precise lane line identification and tracking, the vehicle might veer off the road or even into another lane, endangering both it and other cars. Autonomous cars can keep their position inside their lane and accurately navigate highways by sensing lane lines,

lowering the likelihood of accidents brought on by human mistake. The vehicle may also modify its speed and trajectory in accordance with the state of the road due to lane line detection. The car can employ lane detection, for instance, to follow a bend in the road and alter its speed accordingly. This increases the comfort and safety of passengers and guarantees that the vehicle stays on track. Moreover, lane line detection is not only important for highway driving but also for urban environments where there are multiple lanes and complex road configurations. In these situations, accurate lane detection is essential for navigating through traffic and avoiding collisions with other vehicles. Lane line detection is a critical component of autonomous vehicle technology that ensures the safety and precision of driving. It is one of the key challenges that must be addressed for the development of fully autonomous self-driving cars. The lane lines are accurately detected using computer vision methods in this suggested system under multiple lightning circumstances.

**Existing System:**

A crucial role is played by lane line finding in advanced driver aid technologies. There are several existing systems for lane line detection. Conventional detection techniques still require human parameter adjustments, have several issues, and are very vulnerable to impact from interfering objects, lighting changes, and pavement degradation.

Deep learning techniques, like convolutional neural networks (CNNs), may acquire high accuracy in lane line detection by learning from a large amount of annotated data. However, deep learning approaches can require significant computational resources, which can be a limitation in some applications. Additionally, deep learning models may be more challenging to interpret, which can make it difficult to diagnose and fix errors or improve system performance. Deep learning-based systems require large amounts of training data and may not be able to handle all driving conditions.

Lane detection using the Hough Transform and Support Vector Machine can be sensitive to changes in lighting conditions, which can cause false detections or missed lane markings. The Hough Transform is limited to detecting straight lines, which can be a limitation for detecting curved road markings, which are more frequent in actual driving scenarios

**Proposed System:**

We suggested a new approach for lane line detection and tracking to fix the flaws in the current ones. In this proposed lane line detection system, computer vision methods are used to detect lane lines with a camera positioned on the front of a vehicle. The benefit of using computer vision is that we can easily assess each stage.

In this proposed system, the footage was captured with a camera that was mounted above the vehicle. We corrected the camera-induced distortion after importing this video. To extract the lane lines from the binary picture, colour and gradient threshold approaches are subjected to the unobstructed picture. The image is then given a bird's-eye view via a perspective adjustment. The required lane line pixels are located using a sliding window search, and the left and right road markings are then fitted using second-order polynomials. The radius of lane curvature and the present location of the vehicle in relation to the lane centre are computed and shown by reverse-twisting the original image into the recognised lane borders.

The flowchart below illustrates the steps involved in the suggested method.

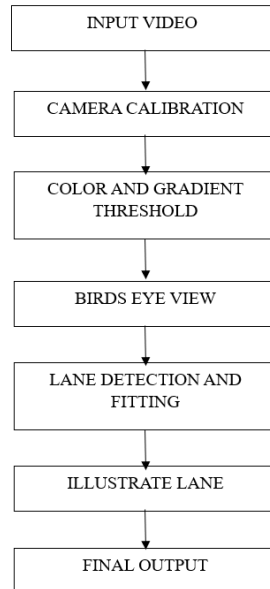


Figure 1. Methodology of the proposed system

**Camera Calibration**

The project's first step is to calibrate the camera. It is essential because, the input video taken by a digital camera may be distorted in a few ways due to the nature of the medium itself. Lenses optical designs, as well as the camera's position in relation to the object or the object's position inside the frame, both contribute to these distortions. The accuracy of lane detection may be impacted by these distortions. In order to successfully recognise the lane line in the image, we had to encounter these distortions. This distortion is fixed by the calibration. There are various ways to calibrate a camera, but the checkerboard calibration method is the most used. Using the matching spots in the photographs, one may estimate the camera's parameters by taking numerous pictures of a planar checkerboard pattern from various angles. The discrepancy between the actual and predicted sizes of the picture's inside corners was computed. To rectify the distorted calibration picture, a distortion matrix and distortion coefficients are computed using this data. We can use the opencv method cv2.calibrateCamera() to determine the arrays that characterize the distortion of the lenses if we have at least 20 photos of chessboards taken from various perspectives and then the cv2.undistort() function can then be used to remove the distortion.

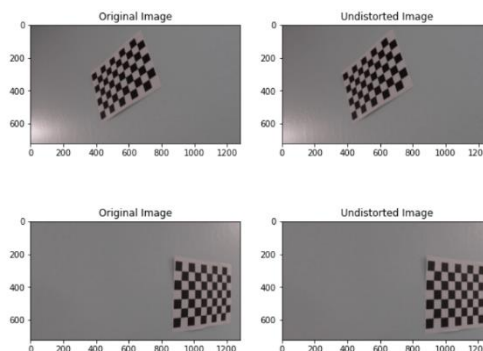


Figure 2. Chessboard photos of the distortion before and after correction.

Here are some test-image examples.

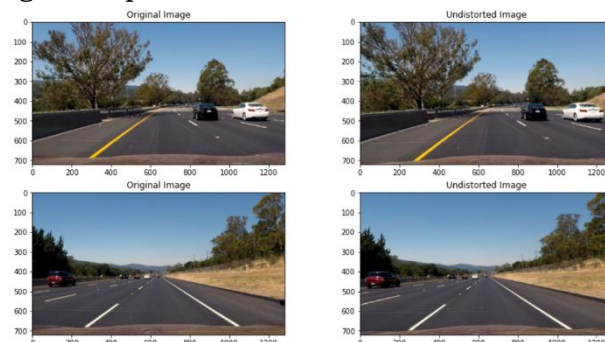


Figure 3. Photos of the distortion before and after correction.

**Color and gradient threshold**

The thresholding technique is used to divide a picture into tiny pieces to demarcate bounds. It's a method for transforming a grayscale or shaded picture into a binary one. The binary image simplifies the process of establishing the credibility of the lane line from the image. Pictures with a lot of contrast worked better than those with less.

The road's lanes need to be found. To eliminate what we don't want, we apply color and gradient thresholds. The lanes have certain characteristics, such as being either white or yellow. Lanes and the road stand out sharply from one another. Also, they create an angle because they aren't completely vertical or horizontal in the image. Using opencv to convert color to HSV space, we perform a color threshold filter to select only yellow and white parts (Hue, Saturation and Value). This can be accomplished using the HSV dimension since it separates color (hue), color intensity (saturation), and brightness (value). The images after the color thresholding can be shown in the below figures.

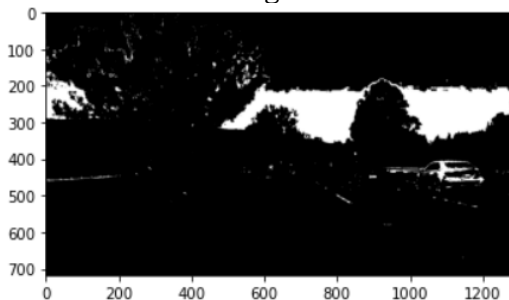


Figure 4. White color threshold filter

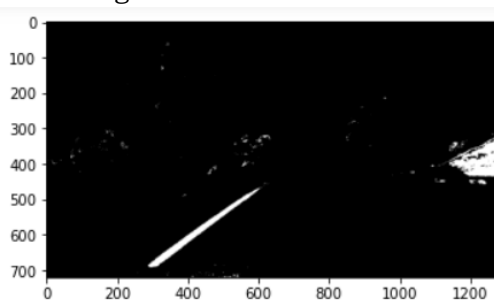


Figure 5. Yellow color threshold filter

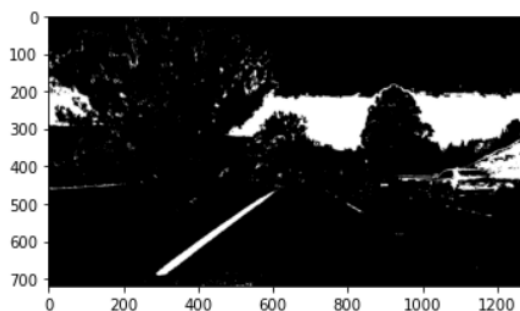


Figure 6. Combination of Yellow and white color threshold filters

Next, we used Sobel filters to identify possible lines and edges. If there are no additional yellow or white markers on the road, you may use the color masks above to choose lanes. The white and yellow markings on certain roadways make this difficult. Thus, we further

used Sobel filters for edge detection to ensure there was no room for misunderstanding. By conducting a 2-dimensional convolution on the original picture and the Sobel operator, Sobel filters are used in image processing to extract edges from an image (or filters). A mathematical expression for this process is,

$$G_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} \circ A \quad \text{and} \quad G_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \circ A$$

Sobel filter, circle denotes convolution operation

Intensity gradients or changes may be seen in the x and y directions of a picture using a Sobel filter. After thresholding by magnitude and direction, we get an image where 1s only appear at the picture's edges. For the S and L channels of the HLS picture, we will use Sobel filters and set thresholds based on the strength of the gradients in the x and y directions. We settled on the HLS channel since prior research had shown that the HLS colorspace was the most reliable when it came to identifying edges.

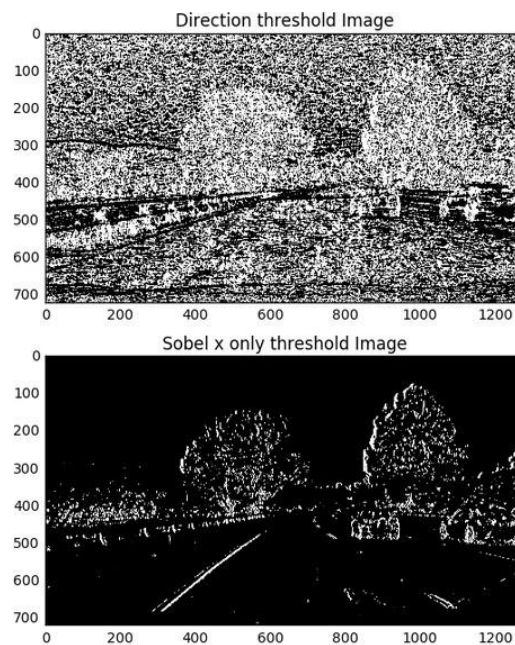


Figure 7. Sobel thresholding

Then, we merged Sobel filter binary masks with color masks to provide a more accurate lane indication.

### Bird's Eye View

Bird's Eye View (BEV) is a concept in computer vision that is commonly used in lane line detection for autonomous vehicles. The basic idea behind BEV is to obtain a top-down view of the scene being captured by the vehicle's camera(s), and then process the image to detect and track lane markings. By providing a top-down view of the scene, BEV can help to improve the accuracy and reliability of these tasks, which are critical for the safe operation of autonomous vehicles. Bird's eye view is accomplished through a combination of perspective transformation and image warping.

Camera-captured images might be distorted due to lens or sensor shortcomings. The term "perspective distortion" describes how things seem bigger and smaller, respectively, when they are closer to and distant from the camera. Although it may seem like the lanes in the input picture converge after a certain distance, they fact run in parallel with one another. The solution is to use a perspective transform, which flattens a three-dimensional view of the environment into a two-dimensional aerial viewpoint in which lanes are constantly



parallel to one another. As a result, we can use this technique to pinpoint the precise position of the lane line inside the picture.

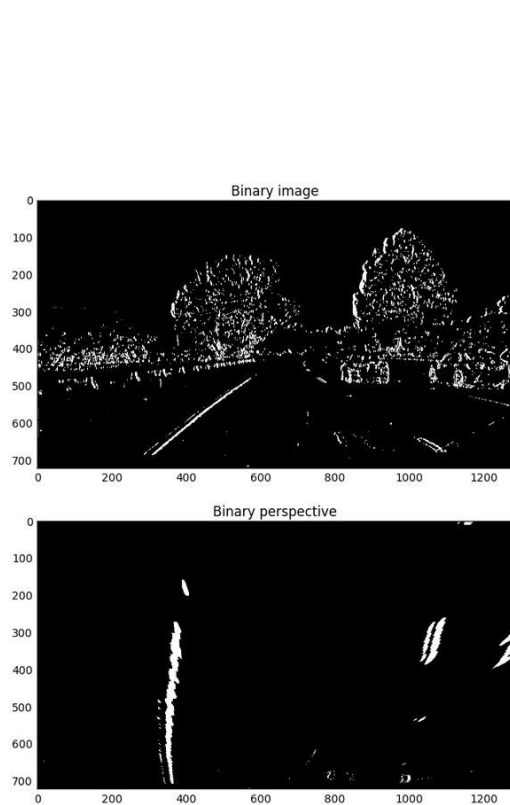


Figure 8. Bird's-eye view of binary image

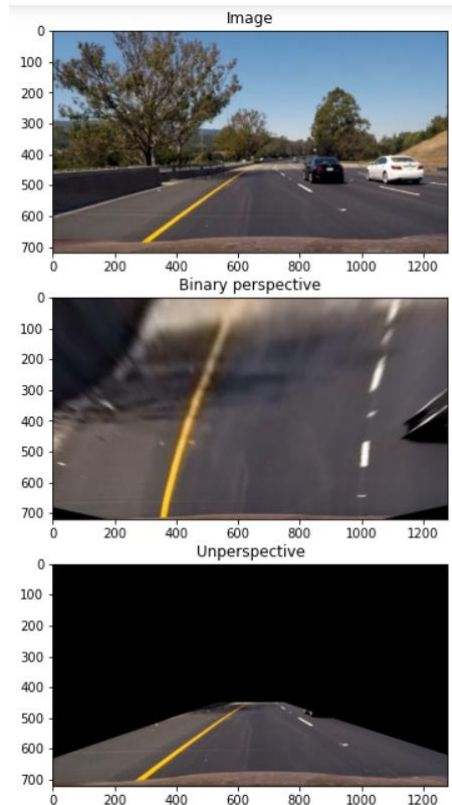


Figure 9. Bird's-eye view of binary test-images

**Lane detection and fitting**

We fit the lane with a polynomial of second order,  $x = ay^{**2} + by + c$ . Using a histogram on the image's lower half allows us to make more accurate lane location estimates.

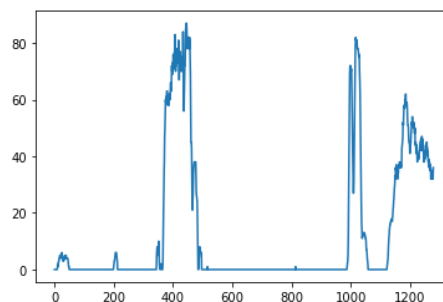


Figure 10

The notion is that the more vertical points there are, the more likely it is that the lane will be there. By doing so, we can locate the starting position. After that, we centre each window by determining the mean of its left and right halves, returning the picture to its original proportions. The data is saved as points within the windows. After that, we use the numpy polyfit function to get the most accurate second-order polynomial representation of the lanes, as seen in the graphic below. Green trash cans represent the windows, while blue and yellow traces represents the lanes.

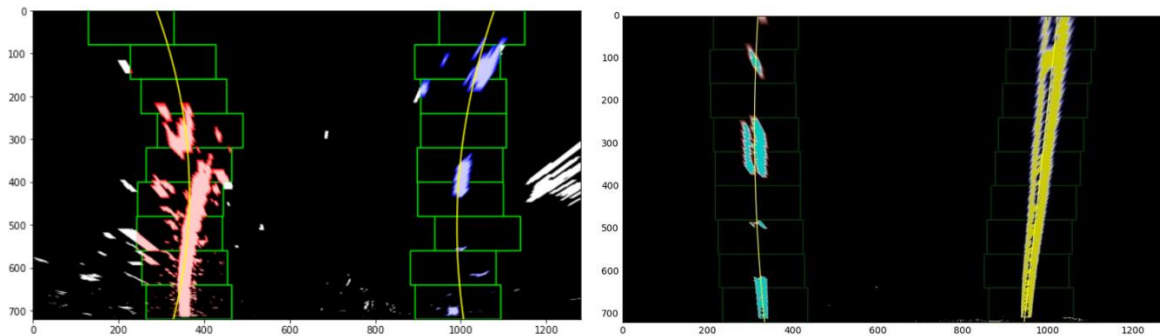


Figure 11. Example of fitting of lane lines

**Curvature of lanes and vehicle position with respect to center**

Every point on a given curve has a radius of curvature equal to the radius of the circle that encircles it, having the same tangent and curvature there. It was shown with the below example figure

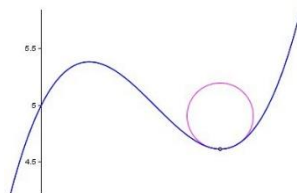


Figure 12. Image of curvature

Calculating the radius of the tiniest circle that is perpendicular to the lane line allowed us to arrive at an accurate value for curve of the lane. For direct lanes, the radius value would be very high. By correctly specifying the pixel height and width in relation to the lane length and width, respectively, metric units were allocated to the pixel space. We averaged the bottom coordinates of the left and right lane markers, subtracted the offset we established in the centre, then multiplied the result by the pixel-to-real-world lane width ratio to calculate how far a car was from the centre of the lane. Following is a formula for calculating the radius of curvature.

$$\text{Radius of curvature} = \frac{\left[1 + \left(\frac{dy}{dx}\right)^2\right]^{3/2}}{\left|\frac{d^2y}{dx^2}\right|}$$

The selected point is the vehicle's foundation (at the very bottom of the picture) from which we may measure the radii of the two lines (one left, one right).

**Warp back to the camera view and display information**

The distorted check picture has been warped back onto the corrected shot so that roadblocks may be more easily identified. That's the process of transforming the exclusive, distortion-free bird's-eye view image format. Body by body, the procedure is carried out. The lane markers have been correctly detected, and the distorted check picture has been restored to its original form.

**Results Analysis and Discussion:**

The following image depicts the results of an experiment for lane identification. Lanes are properly detected and shown by this lane detection method under typical lightning conditions. The distance of the lane from the car, its curvature, and its direction are all estimated and displayed. This method is effective under various lightning situations. Some of the images of the final output video are shown in the below Figure 12,13,14.



Figure 13

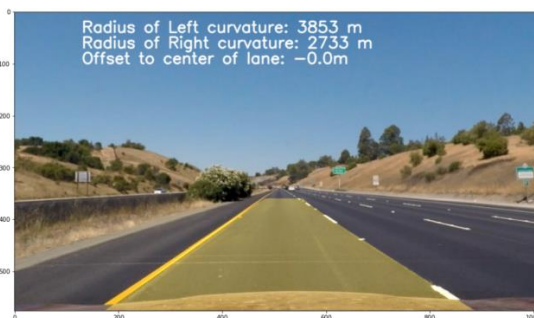


Figure 14



Figure 15

### Conclusion

The suggested lane line detection system for autonomous vehicles use computer vision technologies to reliably identify road lanes and curves, providing drivers with advanced notice of potential hazards. In order to reduce the number of collisions caused by drivers racing around corners too quickly. Without requiring user input, the system can control the steering wheel to make gentle turns on roads, increasing safety and comfort while ensuring that the car stays in its lane. Lane line detection for autonomous vehicles using computer vision techniques helps to achieve high accuracy and real-time performance.

### References

1. A. R. Qureshi et al., "Robust Lane Detection and Tracking in Challenging Scenarios using Deep Learning," IEEE Transactions on Intelligent Transportation Systems, 2020.
2. X. Pan et al., "LaneNet: Real-Time Lane Detection Networks for Autonomous Driving," IEEE Intelligent Vehicles Symposium (IV), 2018.
3. A. Kamble, S. Potadar, June. Lane Departure Warning System for Advanced Drivers Assistance. In 2018 Second International Conference on Intelligent Computing and Control Systems (ICICCS) (pp. 1775-1778). 2018, IEEE
4. Song, J., Wu, X., & Sun, Z. (2017). A robust lane detection algorithm based on multiple image features. Journal of Advanced Transportation, 2017, Article ID 9784682
5. Li, X., Han, C., & Zhou, J. (2017). A lane detection algorithm based on binary morphology for autonomous vehicles. Proceedings of the 2017 IEEE International Conference on Cybernetics and Intelligent Systems (CIS) and IEEE Conference on Robotics, Automation and Mechatronics (RAM), pp. 236-241
6. Zhang, H., Yang, X., & Lu, J. (2020). A novel lane detection method based on convolutional neural network and clustering. Proceedings of the 2020 IEEE 3rd



- International Conference on Intelligent Transportation Engineering (ICITE), pp. 222-227.
7. Luo, X., Cheng, B., & Xiong, Z. (2019). A robust lane detection algorithm based on adaptive morphology and Kalman filter. Proceedings of the 2019 IEEE 2nd International Conference on Intelligent Transportation, Big Data and Smart City (ICITBS), pp. 138-142.
  8. Zhang, R., Wang, C., & Zhang, Y. (2018). A robust lane detection algorithm based on Canny and Hough transform. Proceedings of the 2018 International Conference on Information Science and System (ICISS), pp. 277-281.
  9. J. Kim, M. Lee. November. Robust lane detection based on convolutional neural network and random sample consensus. In International conference on neural information processing (pp. 454-461). 2014, Springer, Cham.
  10. W. Li, X. Gong, Y. Wang, P. Liu. 2014, October. A lane marking detection and tracking algorithm based on sub-regions. In Proceedings International Conference on Informative and Cybernetics for Computational Social Systems (ICCSS) (pp. 68-73). 2014 IEEE.