Image Processing-Based Lane Recognition Algorithms for Autonomous Driving

24510133 Jeon Hyunsik[#1]

[#1] *General Graduate School Department of Automotive Engineering*

[1] engineer0104@seoultech.ac.kr

YouTube: https://youtu.be/c-ezdtfenlI?si=Yr0NVZOljKqaSRgZ

Abstract**—** **In this paper, we propose a lane recognition algorithm for autonomous driving. Unlike recent lane recognition methods using deep learning, this algorithm does not require pre-trained data and can be applied to various platforms other than vehicles. It is designed to recognize orange and white lanes separately, assuming obstacle avoidance scenarios, allowing for driving within the lane area even if only one of the two lanes is recognized. Additionally, it includes a control algorithm, making immediate application possible with the proposed algorithm alone. The algorithm was tested in scenarios assuming obstacle avoidance and varying weather conditions, specifically during transitions through tunnels where the illumination changes. Experimental results confirmed that the proposed method allows for stable lane recognition under these conditions.**

I. Introduction

Autonomous driving technology has become a crucial component of modern transportation systems. For autonomous driving, it is essential for vehicles to accurately recognize lanes and adjust their driving path accordingly. While existing deep learning-based lane recognition methods boast high accuracy, they require large amounts of training data and significant computational resources. Therefore, there is a need for an efficient lane recognition method that can be applied not only to vehicles but also to various other platforms. In this paper, we propose a lane recognition algorithm based on image processing technology to meet these requirements.

II. MIAN BODY

A. Overview of Image Processing-Based Lane Recognition

The image processing-based lane recognition algorithm is divided into eight main stages: preprocessing, lane color detection, edge detection, region of interest (ROI) setting, straight line detection through Hough transform, optimal line derivation through linear regression, center point calculation, and driving direction determination. This process enables stable real-time lane recognition. Additionally, it is designed to detect and distinguish between the center line and the white lane, and it can operate in scenarios with two cameras.

B. Algorithm Design

The proposed algorithm consists of the following steps: 1. Preprocessing: Reduce image noise using Gaussian blur. 2. Lane Color Detection: Detect orange and white lanes using HSV color space filters. 3. Edge Detection: Detect edges in the image using Canny edge detection. 4. Region of Interest (ROI) Setting: Define the lower part of the image as the region of interest to detect lanes. 5. Hough Transform: Detect straight lines using the Hough transform and recognize them as lanes. 6. Linear Regression: Apply linear regression to the detected lines to derive the optimal lane. 7. Center Point Calculation and Driving Direction Determination: Calculate the center point of the frame and compare it with the lane's slope to determine the driving direction.

Through these steps, the proposed algorithm enables real-time and stable lane recognition and driving path setting. Future research will focus on improving the performance of the proposed algorithm by introducing various optimization techniques. Additionally, plans include the use of LiDAR sensors to enhance obstacle avoidance capabilities. Sensor fusion technology will enable more precise environmental perception, which is expected to further improve the safety and reliability of autonomous vehicles.

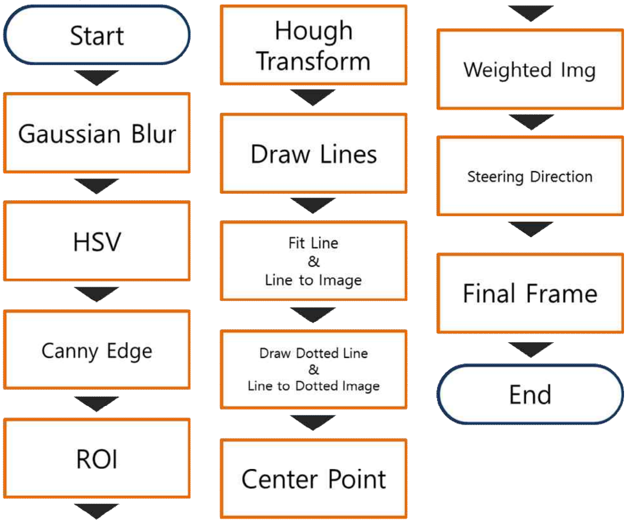

Figure 1. Algorithmic Diagram

C. *Preprocessing and Lane Color Detection*

In the preprocessing stage, Gaussian Blur is applied to the input image to reduce noise. Then, the image is converted to the HSV color space to detect orange and white lanes. This is an algorithm that filters the component values of Hue, Saturation, and Value. HSV filtering is more versatile than RGB filtering because it allows setting not only the color but also the saturation and brightness values to specify a particular color, making it suitable for traffic light signal classification [1]. Through this preprocessing process, the accuracy of lane recognition can be improved, and computational efficiency can be increased.

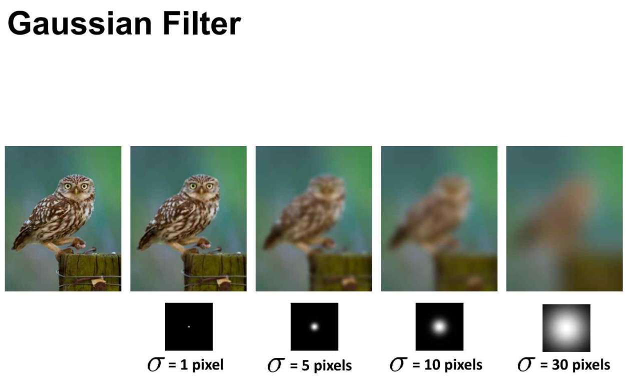

Figure 2. Gaussian Filter[2]

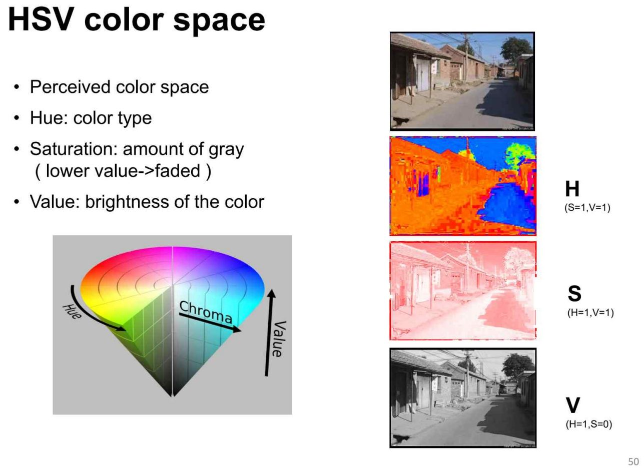

Figure 3. HSV Filter[3]

Figure 4. Original photo

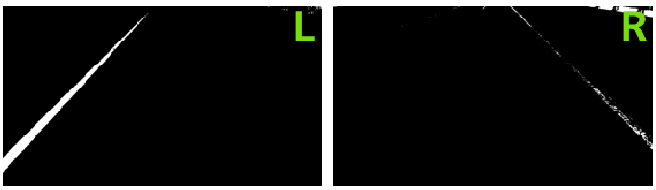

Figure 5. Apply a light Gaussian filter for noise removal & Apply an HSV filter

D. *Edge Detection and Region of Interest Setting*

Edges in the image are detected using the Canny edge detection method. Subsequently, the Region of Interest (ROI) technique is employed to detect lanes only within the designated area. This approach reduces computational load and increases accuracy by analyzing only the parts necessary for vehicle driving. By setting the region of interest, unnecessary information is excluded, allowing the extraction of essential information required for lane recognition.

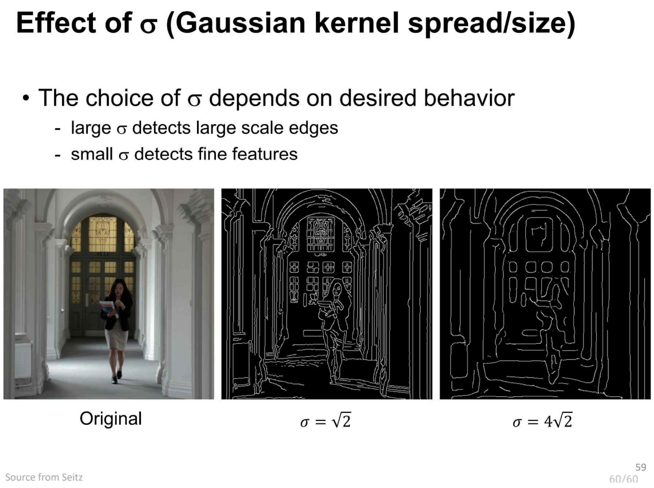

Figure 6. Canny Edge[4]

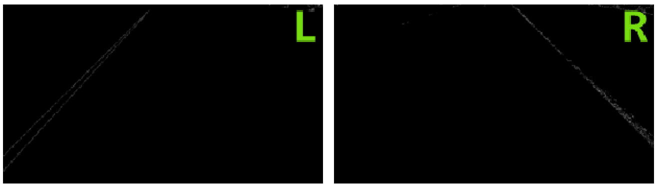

Figure 7. Canny Edge filter applied.

Figure 8. Region of interest (ROI) filter applied. The left lane, which detects the center line, designates a wide area assuming a situation of center line invasion.

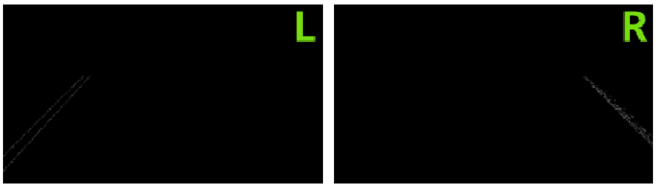

Figure 9. Filter results (line detection from the above image).

E. Detecting Lines Using Hough Transform

The Hough Transform is a widely used method for detecting geometric shapes such as lines and circles in images. This technique transforms every point in an image into the parameter space and detects shapes based on the accumulation of these parameters. The Hough Transform is a feature detection method that converts the technical space domain into the parameter domain to effectively detect geometric components such as lines, circles, ellipses, and curves. The traditional Hough Transform method maps all possible lines passing through a point into space and uses voting to find the maximum value, thereby extracting lines. Specifically, it gathers points lying on the line of the desired slope and transforms them into a line.[5] The Hough Transform has the advantage of being robust to noise and outliers, providing stable results, and is particularly effective in detecting multiple lines simultaneously, making it suitable for complex images. This allows for accurate detection of lane positions.

On the other hand, RANSAC (Random Sample Consensus) is an algorithm that fits models through random sampling and iteratively finds the optimal model. RANSAC is relatively sensitive to noise and may be less stable since it considers only a subset of the data rather than the entire dataset. While RANSAC requires separate processing to detect multiple line segments and optimize the algorithm, the Hough Transform utilizes the entire dataset, making it robust to noise and capable of detecting multiple shapes simultaneously. Therefore, we employ the Hough Transform algorithm for lane detection due to its robustness and efficiency in handling complex images.

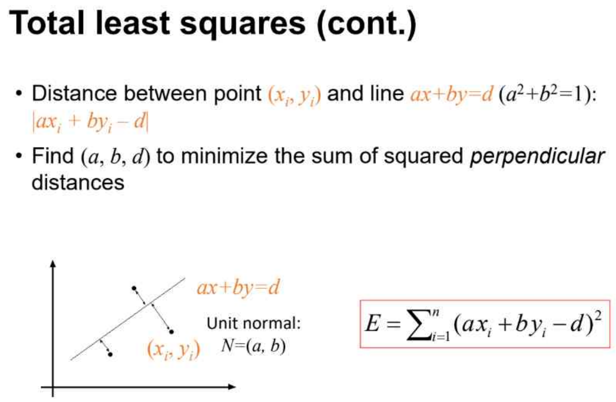

Figure 10. Hough Transform.[6]

F. Deriving the Optimal Line through Linear Regression

Linear regression is applied to the multiple detected line points to derive the optimal line. This enables accurate lane recognition even when the detected lane is distorted or incomplete. The lane extracted through linear regression plays a crucial role in setting the driving path, ensuring the stable driving of the vehicle.

$$\text{slope} = \frac{vy[0]}{vx[0]}$$

$$\text{intercept} = y[0] - \text{slope} \cdot x[0]$$

Figure 11. Calculation of Slope and Intercept

$$y1 = \text{img\_shape}[0]$$

$$x1 = \left\lfloor \frac{y1 - \text{intercept}}{\text{slope}} \right\rfloor$$

$$y2 = \lfloor \text{img\_shape}[0] \cdot 0.6 \rfloor$$

$$x2 = \left\lfloor \frac{y2 - \text{intercept}}{\text{slope}} \right\rfloor$$

Figure 12. Calculation of Line Coordinates at the Bottom and 60% Height of the Image

$$\text{width\_ratio} = \frac{\text{img\_shape}[1]}{\text{BASE\_WIDTH}}$$

$$\text{height\_ratio} = \frac{\text{img\_shape}[0]}{\text{BASE\_HEIGHT}}$$

$$\text{red\_x} = \lfloor x2 + 750 \cdot \text{width\_ratio} \rfloor$$

Figure 13. Calculation of Width and Height Ratios

G. *Center Point Calculation and Driving Direction Determination*

The distance from the frame's center point to the detected lane is calculated, and the detected lane's slope is compared to determine the driving direction. This plays a crucial role in controlling the vehicle to ensure it does not deviate from the lane. Driving direction determination is an essential element for enhancing the driving safety of the vehicle and must be performed in real-time. To confirm real-time processing, the final steering angle value and FPS value are displayed in the upper left corner of the final output screen.

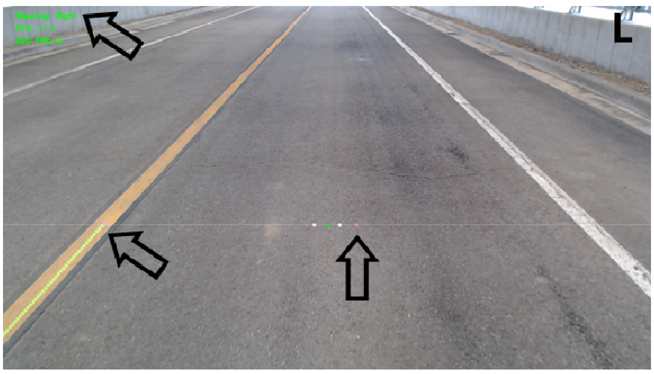

Figure 14. Final image output after line detection and optimization, combined with the original photo (left).

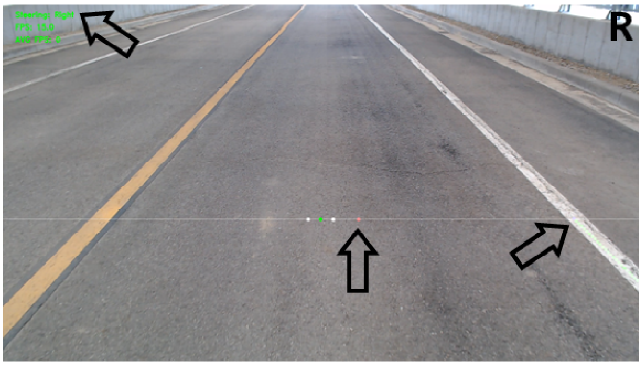

Figure 15. Final image output after line detection and optimization, combined with the original photo (right).

It was confirmed that lanes were successfully detected using the above algorithm.

H. *Related Work*

Lane recognition is one of the basic functions of autonomous vehicles and is crucial for stable driving. Related research includes sliding window techniques and deep learning-based lane recognition. The sliding window technique uses Bird's Eye View transformation to move a specific area of the image to find lanes, and while the proposed algorithm differs in approach, the performance is similar [7]. Deep learning-based methods guarantee high accuracy but require large amounts of training data and significant computational resources. To address these issues, this study proposes an efficient image processing-based lane recognition algorithm.

III. Implement and Experiment

A. *Experimental Environment*

This study was implemented in an Ubuntu Python 3.8.19 environment using an AMD Ryzen 5 5600X 6-Core Processor and Titan X GPU. The camera was fixed at the center of a mobile platform, and it was confirmed that results could be processed up to 70 FPS.

The experiment was conducted using images and recorded videos inside the tunnel of K-City, an autonomous driving test city located in Hwaseong, Gyeonggi Province, South Korea. The tunnel's environment, characterized by limited illumination changes and diverse experimental possibilities due to the nature of the autonomous driving test city, provided suitable conditions for evaluating the performance of the proposed algorithm. Figure 8 shows the results of applying the proposed algorithm to a video assuming a static obstacle avoidance scenario. By detecting the center-line, the system recognizes that the vehicle has crossed the center-line and outputs a steering value to keep the center-line on the left side of the vehicle.

Figure 16. Application of the proposed algorithm in an obstacle avoidance scenario. Even though the white line is not detected, it can be confirmed that the steering value is output by detecting only the orange line.

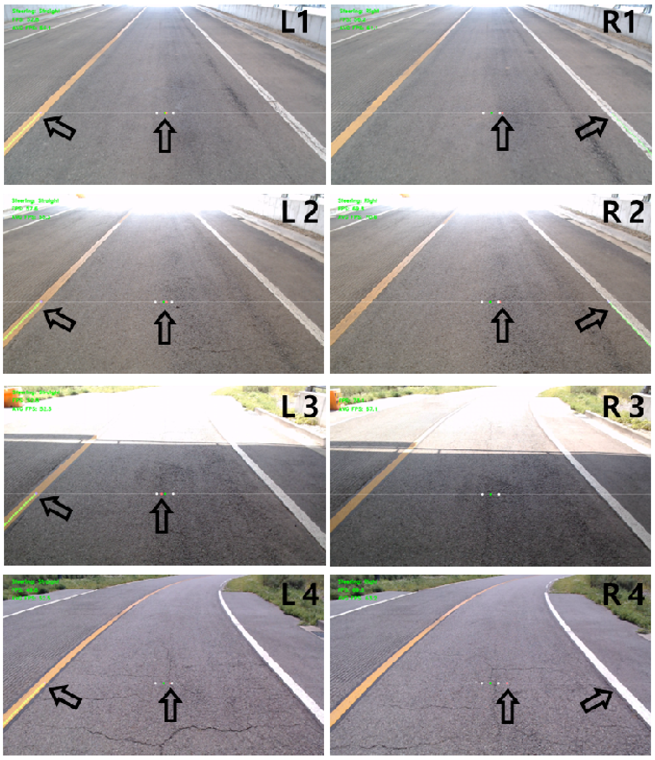

Figure 17. Application of the proposed algorithm in a scenario where the illumination changes as the vehicle exits a tunnel. In R3, the white line was temporarily not detected, but the orange line continued to be detected, confirming that the steering value was being output.

B. *Results Analysis*

The experimental results demonstrated that the proposed algorithm could reliably recognize lanes even under significant illumination changes occurring when exiting a tunnel. The image processing surpassed 30 FPS, reaching up to 70 FPS, proving the feasibility of real-time processing. This indicates that the combination of camera sensor-based image processing enabled smooth driving path configuration. It suggests that if LiDAR sensors are additionally utilized, more comprehensive autonomous driving, including obstacle avoidance, can be achieved.

IV. Conclusions and Future Research Directions

In this paper, we proposed an image processing-based lane recognition algorithm for autonomous driving. The proposed algorithm can be applied to various platforms that require lane recognition without pre-trained data and can be easily extended to obstacle avoidance algorithms as well. Experimental results confirmed that the algorithm can recognize lanes with high accuracy even in situations with significant changes in illumination. This demonstrates that the proposed algorithm can maintain stable performance under various lighting conditions.

However, during the experiments, there were instances where performance varied depending on hardware capabilities. This can affect the real-time processing capability of the algorithm, and future research should focus on optimization to address this issue. Specifically, image calibration adjustments such as the averaging of HSV values should be introduced to ensure consistent performance across different lighting conditions.

Additionally, the algorithm proposed in this paper was implemented based on a two-lane road with a center-line on the left side of the vehicle. In situations where the center-line is not detected, it is possible to drive based on the white line, but the presence of a white line on the left side of the vehicle can lead to recognition errors.

Refining the proposed algorithm could make it applicable to real-time autonomous driving systems. This will require further testing and validation in various real road environments, along with the introduction of various optimization techniques to maximize the efficiency of the algorithm. For example, a hybrid approach with deep learning-based lane recognition algorithms could further enhance performance.

Lastly, while the proposed algorithm currently uses only a camera sensor, future research could incorporate additional sensors such as LiDAR to improve obstacle avoidance capabilities. Sensor fusion technology would enable more precise environmental recognition, thereby further enhancing the safety and reliability of autonomous vehicles.

This study presents a fundamental algorithmic direction for solving the lane recognition problem of autonomous vehicles and suggests various possibilities for future research directions. Based on this research, it is expected to contribute to the advancement of autonomous driving technology.

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