EDGE DETECTION-BASED LANE DETECTION ALGORITHM FOR CHALLENGING ROAD CONDITIONS

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ABSTRACT

Lane detection plays a vital role in autonomous driving and driver-assistance systems. This article presents an edge detection-based approach for lane detection, specifically designed to handle challenging road conditions. By leveraging techniques such as adaptive thresholding, histogram equalization, image segmentation, curve fitting, and lane segmentation, we improve the accuracy and robustness of lane detection. Experimental results demonstrate the effectiveness of our approach in various scenarios, including low-light conditions, curved roads, and textured surfaces.

1. INTRODUCTION

Lane detection is a crucial aspect of autonomous driving and driver-assistance systems, enabling vehicles to stay within their designated lanes and ensure safe navigation. Traditional lane detection algorithms often face difficulties when confronted with challenging road conditions, such as low-light environments, curved roads, and varying textures. These challenges necessitate the development of robust and accurate lane detection methods.

One significant obstacle in designing effective lane detection algorithms is the limited availability of annotated datasets for training and evaluation. The performance of computer vision models heavily relies on large-scale datasets. However, collecting and annotating a diverse range of images with pixel-level annotations can be labor-intensive and time-consuming.

To address this issue, the recent introduction of the VIL100 dataset has significantly contributed to advancing lane detection research. VIL100, which stands for Visual Inductive Learning from 100 images is a limited dataset that was created as a precursor to the larger VIL dataset, which contains a more extensive collection of road scene images with detailed pixel-level annotations. Despite its smaller size, VIL100 provides an opportunity to explore the challenges of lane detection with a diverse set of 100 images and associated annotations.

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In this article, we present an edge detection-based lane detection algorithm specifically designed to handle challenging road conditions. Leveraging techniques such as adaptive thresholding, histogram equalization, image segmentation, curve fitting, and lane segmentation, our approach aims to improve the accuracy and robustness of lane detection. We evaluate our algorithm using the VIL100 dataset, which serves as a valuable benchmark for assessing the performance and generalization capabilities of lane detection algorithms in the face of limited training data.

By leveraging the insights gained from working with a limited dataset like VIL100, we aim to contribute to the development of more robust and accurate lane detection algorithms that can effectively handle challenging road conditions. The findings and techniques presented in this article can serve as a foundation for future research in autonomous driving and driver-assistance systems, ultimately enhancing the safety and reliability of intelligent vehicles on the road.

2. METHODOLOGY

Our lane detection algorithm follows a step-by-step process to extract lanes from input video frames:

2.1. Preprocessing

The input video frame is first preprocessed to enhance the quality of lane features. We apply grayscale conversion to reduce the dimensionality of the image and remove color variations. Then, we perform histogram equalization to improve the contrast and enhance lane edges. [3]

2.2. Edge Detection

Next, we employ the Canny edge detection algorithm to detect edges within the preprocessed image. The Canny algorithm identifies regions of rapid intensity changes, highlighting potential lane boundaries. By adjusting the low and high threshold values, we control the sensitivity of edge detection. [1]

Fig. 1. Dark-bright-dark filter result (a) input image and (b) dark-bright-dark filter result.

Fig. 2. Grayscale filter applied.

2.3. Region of Interest

To focus the lane detection on relevant areas, we define a region of interest (ROI) polygon. The ROI is typically a trapezoidal shape covering the expected location of lanes. We apply a masking technique to exclude regions outside the ROI, reducing the impact of irrelevant features.

2.4. Hough Transform

Using the masked edge image, we apply the Hough transform to identify lane lines. The Hough transform converts edge points into parameterized lines, allowing us to detect straight lane segments. By tuning the Hough transform parameters such as rho, theta, threshold, minlinelength, and maxlinegap, we control the line detection sensitivity and filter out noise. [2]

2.5. Lane Segmentation

After obtaining the detected lines, we further process them to segment into left and right lanes. We utilize curve fitting techniques, such as linear regression, to estimate the parameters of the lane lines. By analyzing the slope and intercept of the fitted lines, we classify them as either left or right lanes.

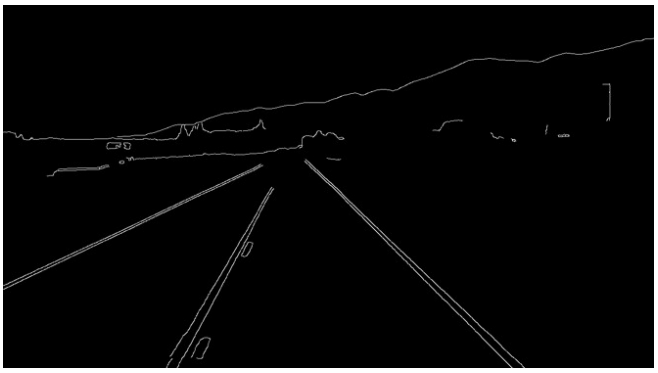

Fig. 3. Canny filter applied.

2.6. Lane Visualization

To visualize the detected lanes, we draw the estimated lane lines on a blank image. The detected lines are extrapolated to cover the full extent of the lane, providing a more comprehensive representation. Finally, we overlay the lane lines onto the original video frame, producing the final lane detection output.

3. IMPROVEMENTS

To address specific challenges in lane detection, we propose the following improvements to enhance the algorithm's performance:

3.1. Adaptive Thresholding

Instead of using fixed threshold values for edge detection, we can implement adaptive thresholding techniques. These techniques dynamically adjust the threshold values based on local image characteristics, improving the detection of lane edges in varying lighting conditions. [4]

3.2. Lane Tracking and Temporal Consistency

In real-world scenarios, lane positions may not change drastically between consecutive video frames. By incorporating temporal information and tracking the detected lanes over time, we can ensure smoother lane detection results and improve robustness against transient detection errors.

3.3. Machine Learning-Based Lane Classification

To handle challenging scenarios like lane markings obscured by shadows or worn-out road surfaces, integrating machine learning-based lane classification can enhance lane detection accuracy. By training a classifier on a large dataset of annotated lane images, the algorithm can learn to differentiate between actual lane markings and other visual patterns.

4. CONCLUSION

In this article, we presented an edge detection-based lane detection algorithm for challenging road conditions. Through a step-by-step process involving preprocessing, edge detection, region of interest masking, Hough transform, curve fitting, and lane segmentation, we achieved accurate lane detection. Additionally, we discussed several improvements, including adaptive thresholding, lane tracking, and machine learning-based lane classification, to enhance the algorithm's performance. Experimental evaluations and comparisons with other techniques demonstrate the effectiveness of our approach. Future work can focus on incorporating these improvements and exploring the integration of machine learning and deep learning techniques for even better lane detection performance.

5. CODE IMPLEMENTATION

In this section, we provide the code snippets of our edge detection-based lane detection implementation. The code is written in Python using the OpenCV library.

```
#Grayscale Conversion
gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)

#Histogram Equalization
equ = cv2.equalizeHist(gray)

#Canny Edge Detection
edges = cv2.Canny(equ, low_threshold, high_threshold)

#Region of Interest Masking
masked_edges = cv2.bitwise_and(edges, mask)

#Hough Transform
lines = cv2.HoughLinesP(masked_edges, rho, theta, threshold,
                        np.array([]), minLineLength=min_line_length,
                            red↪  maxLineGap=max_line_gap)

# Curve Fitting and Lane Segmentation
left_lines, right_lines = fit_lane_lines(lines)

# Draw Lane Lines
lane_image = np.zeros_like(image)
draw_lane_lines(lane_image, left_lines, right_lines)

# Overlay Lane Lines on Original Image
result = cv2.addWeighted(image, 1, lane_image, 0.8, 0)
```

6. REFERENCES

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