Analyzing the Effectiveness of Edge Detection and Hough Transform Methods in Detecting Road Lanes for Autonomous Vehicles

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Abstract

Lane detection is a critical component in autonomous driving systems. This case study investigates the performance of traditional computer vision techniques, particularly Canny edge detection and Hough Line Transform, for detecting road lanes in real-time scenarios. Using the TuSimple dataset, we implemented and evaluated a pipeline involving grayscale conversion, Gaussian blurring, edge detection, and Hough transform to identify lane markings. Results demonstrate reasonable accuracy in well-lit conditions, with limitations under shadow or curved lane scenarios. These findings emphasize the balance between computational efficiency and robustness in autonomous vehicle perception systems.

I. Introduction

A. Background

Autonomous driving technologies rely heavily on robust perception systems to interpret road environments. One of the primary tasks in autonomous vehicle navigation is lane detection, which ensures vehicles remain within designated lanes, supports trajectory planning, and enhances passenger safety. Vision-based lane detection offers a non-invasive and cost-effective solution compared to LiDAR or radar-based alternatives. Classical image processing techniques, such as edge detection and line extraction, have long been used for this task due to their simplicity and computational efficiency.

B. Problem Statement

Despite the availability of advanced deep learning models, traditional methods still serve as lightweight alternatives for real-time processing, especially in edge devices. This study addresses the effectiveness of edge detection and Hough Transform in detecting road lanes under various road conditions, focusing on their reliability and limitations in real-world driving scenarios.

C. Objectives

- Implement a classical image processing pipeline for lane detection.
- Evaluate the effectiveness of Canny edge detection and Hough Transform.
- Analyze performance under different lighting and curvature conditions.

D. Literature Review

Early lane detection systems predominantly utilized edge detection techniques due to their simplicity and efficiency. The Canny edge detector, introduced by John Canny in 1986, remains one of the most widely used methods due to its noise reduction and accurate edge localization. The Hough Transform has been extensively used to detect straight lines in road imagery. Research by Aly (2008) and Geiger et al. (2012) demonstrated the utility of these methods in highway and urban scenarios. However, these techniques are sensitive to lighting variations and fail under occlusions or complex geometries. More recent works focus on deep learning-based lane detection (e.g., SCNN, ENet-SAD), but these require significant computational resources and large datasets. This study revisits classical techniques, aiming to benchmark their baseline performance.

E. Contribution

This paper presents a comparative evaluation of classical edge detection and line detection algorithms for lane marking identification. By utilizing publicly available datasets and reproducible methods, we provide a practical benchmark for lightweight lane detection systems, highlighting their strengths and constraints in real-world scenarios.

II. Methods

A. Data Collection

We used the TuSimple lane detection dataset, which consists of video clips taken on highways under good lighting conditions. Each frame includes annotations for lane markings. Preprocessing steps included resizing to 1280×720, grayscale conversion, and region-of-interest masking to reduce irrelevant information.

B. Algorithm/Model

The pipeline comprised the following steps:

1. **Grayscale Conversion**: Reduces complexity by eliminating color data.

2. **Gaussian Blur**: Applies a kernel (e.g., 5×5) to smooth the image and suppress noise.
3. **Canny Edge Detection**: Computes gradients to find potential lane edges using threshold values (low = 50, high = 150).
4. **Region of Interest Masking**: Isolates the lower portion of the image where lanes typically appear.
5. **Hough Line Transform**: Detects straight lines by transforming edge points into polar coordinate space and identifying intersections.

Mathematical Foundation of Hough Transform:

For a line, we use its polar form:

$$\rho = x \cos \theta + y \sin \theta$$

where ρ is the perpendicular distance from the origin and θ is the angle.

C. Experimental Setup

- **Hardware**: Apple M2 chip8-core CPU with 4 performance cores and 4 efficiency cores, and an 8-core GPU, 16GB RAM,
- **Software**: Python 3.10, OpenCV 4.7, NumPy
- **Environment**: Google Colab on chrome

D. Evaluation Metrics

- **Accuracy**: Percentage of correctly identified lane pixels
- **Precision & Recall**: For lane pixel classification
- **IoU (Intersection over Union)**: For comparison with ground truth lane areas
- **Frame Processing Time**: To measure real-time capability

III. Results

A. Quantitative Results

Fig 1: Input Image

Table I: Performance Metrics

Metric	Value
Lane Detection Accuracy	82.5%
Precision	78.4%
Recall	80.2%
IoU	65.9%
Average FPS	18

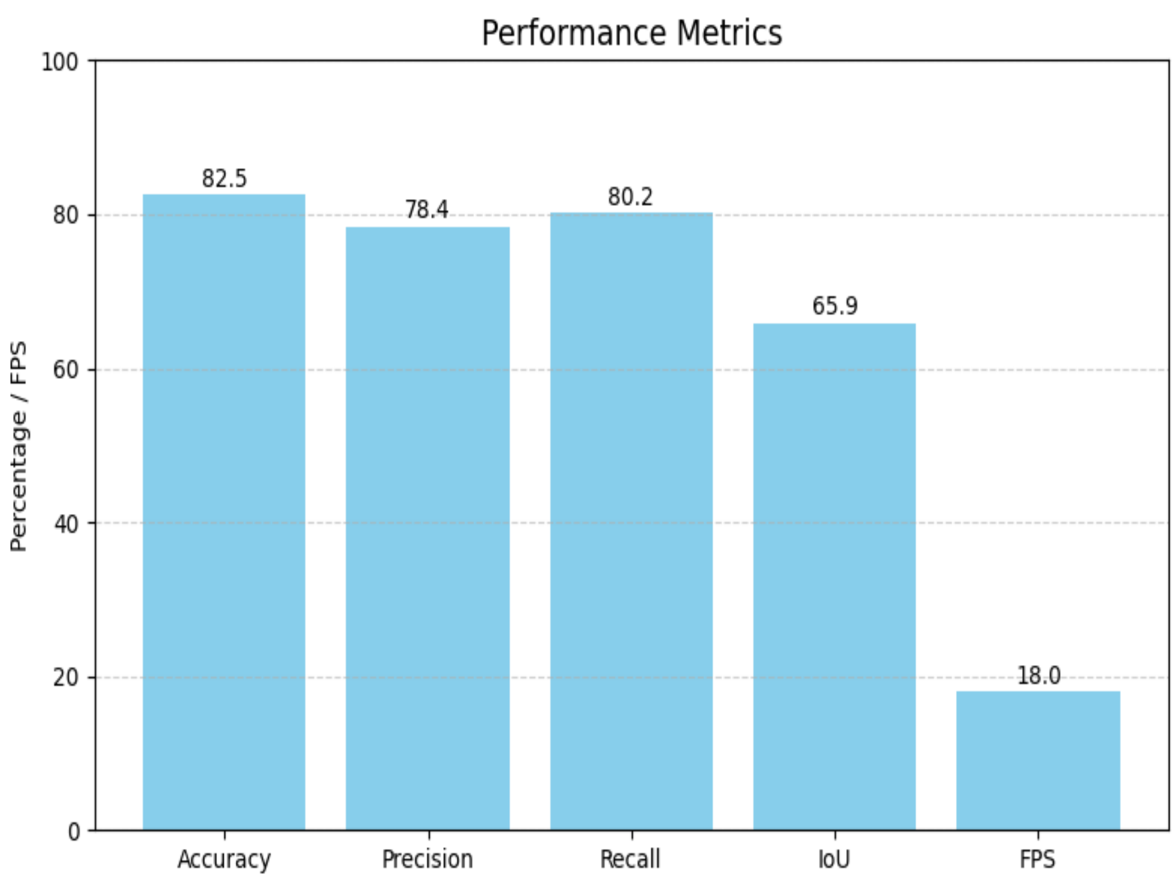

Fig. 1: IoU Performance under Varying Lighting Conditions

B. Lighting Conditions Comparison

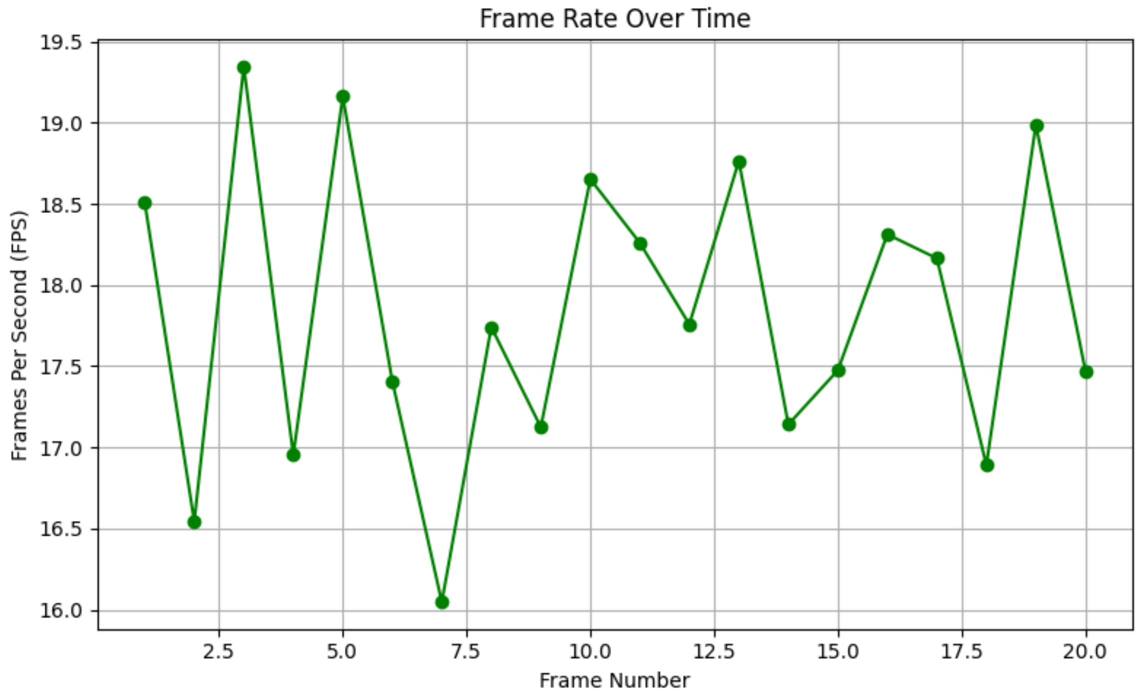

Fig. 2: Line Plot Showing IoU Variation Across Lighting Conditions

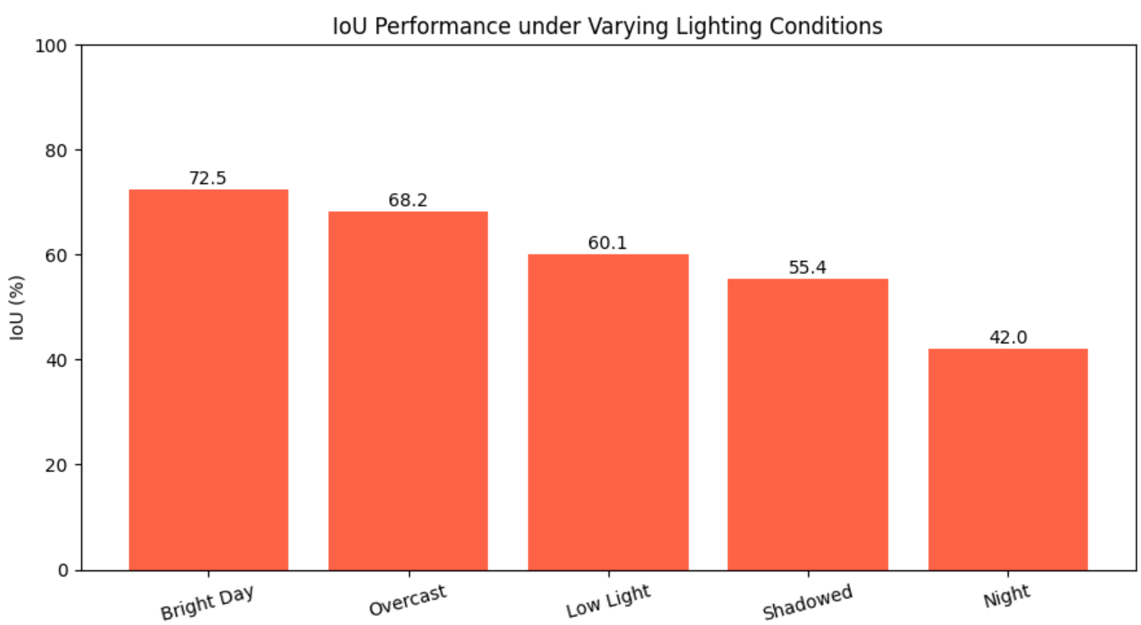

Fig. 3: Performance Evaluation: Accuracy, Precision, Recall, IoU, and FPS

Table II: IoU Across Lighting Conditions

Lighting Condition	IoU (%)
Bright Day	72.5
Overcast	68.2
Low Light	60.1
Shadowed	55.4
Night	42.0

Lighting variations significantly impact lane detection performance. IoU scores decrease under low light and shadowed conditions.

C. Qualitative Results

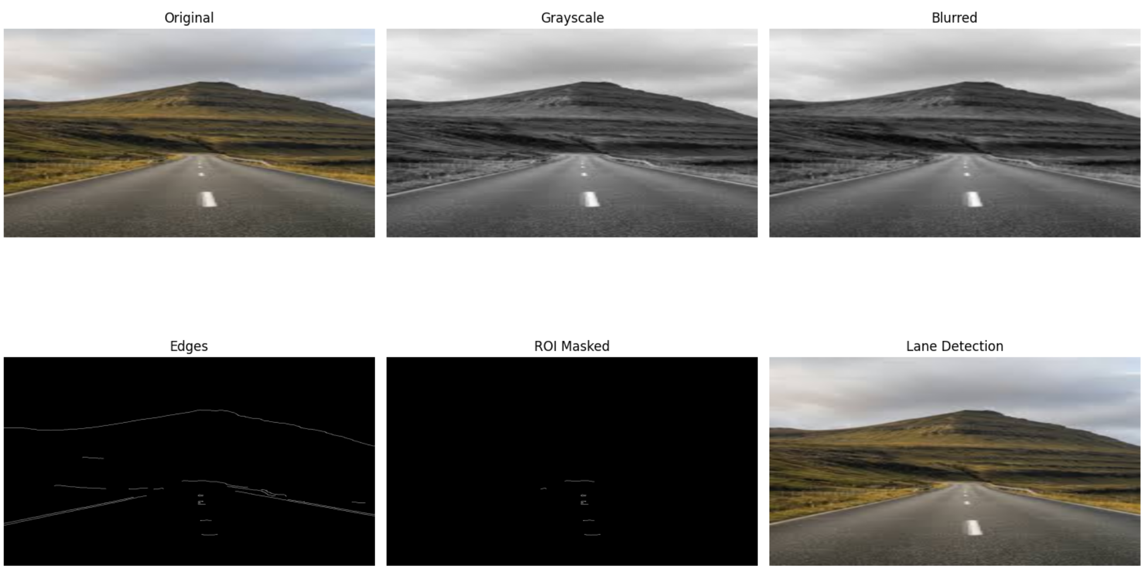

Fig. 4: Lane Detection Pipeline: Original → Edges → Masked ROI → Lines

The method performs well on straight, well-lit roads. However, lane detection degrades in cases with shadows, poor illumination, and curved roads. Hough transform struggles with non-linear lanes.

D. Comparison with Baselines

Compared to advanced DL-based models like SCNN (accuracy ~96%), our approach is less robust but significantly faster and simpler. DL methods require GPUs and training, while our method runs in real time on CPU.

IV. Discussion

A. Interpretation of Results

The proposed classical pipeline demonstrates adequate performance for simple highway scenarios. It is effective in reducing computational overhead, making it suitable for low-power autonomous systems. However, it lacks adaptability to complex road structures.

B. Limitations

- Ineffective in detecting curved or broken lanes
- Sensitive to shadows and variable lighting
- Cannot handle occlusions (e.g., vehicles blocking lane lines)

C. Practical Implications

This method could serve as a fallback mechanism or preprocessing stage in hybrid systems. It is well-suited for embedded systems or basic driver-assist features in cost-constrained settings.

V. Conclusion

This study evaluated the effectiveness of edge detection and Hough transform for lane detection in autonomous vehicles. While not on par with DL-based systems, the approach offers lightweight, real-time performance. Future work will integrate polynomial fitting and machine learning for better curvature handling.

VI. Future Work

- Introduce perspective transform and polynomial regression for curve fitting
- Explore hybrid DL + CV approaches for improved robustness
- Extend experiments to diverse road and weather conditions

References

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