Autonomous Lane Detection

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Motivation

Reliable lane detection is crucial for autonomous driving and advanced driver assistance systems (ADAS). This project implements a lightweight classical computer vision pipeline to detect lane markings, focusing on efficiency, interpretability, and robustness under typical driving conditions without relying on deep learning.

Scientific & Technical Context

Classical lane detection identifies road lanes using color and edge information. By avoiding complex deep learning models, these methods provide a clear baseline and insight into algorithmic performance.

Classical Lane Detection Pipeline

Pipeline Stages:

- **Color filtering:** Isolates white and yellow lanes
- **Grayscale conversion and Gaussian smoothing:** Reduces noise and simplifies images.
- **Canny edge detection:** Highlights lane boundaries.
- **Region of interest masking:** Focuses on road area.
- **Probabilistic Hough Transform:** Detects line segments in the edge image.
- **Lane averaging and extrapolation:** Combines line segments into smooth lane boundaries.

Input Data

Raw RGB frames captured from a forward-facing vehicle camera under varying illumination.
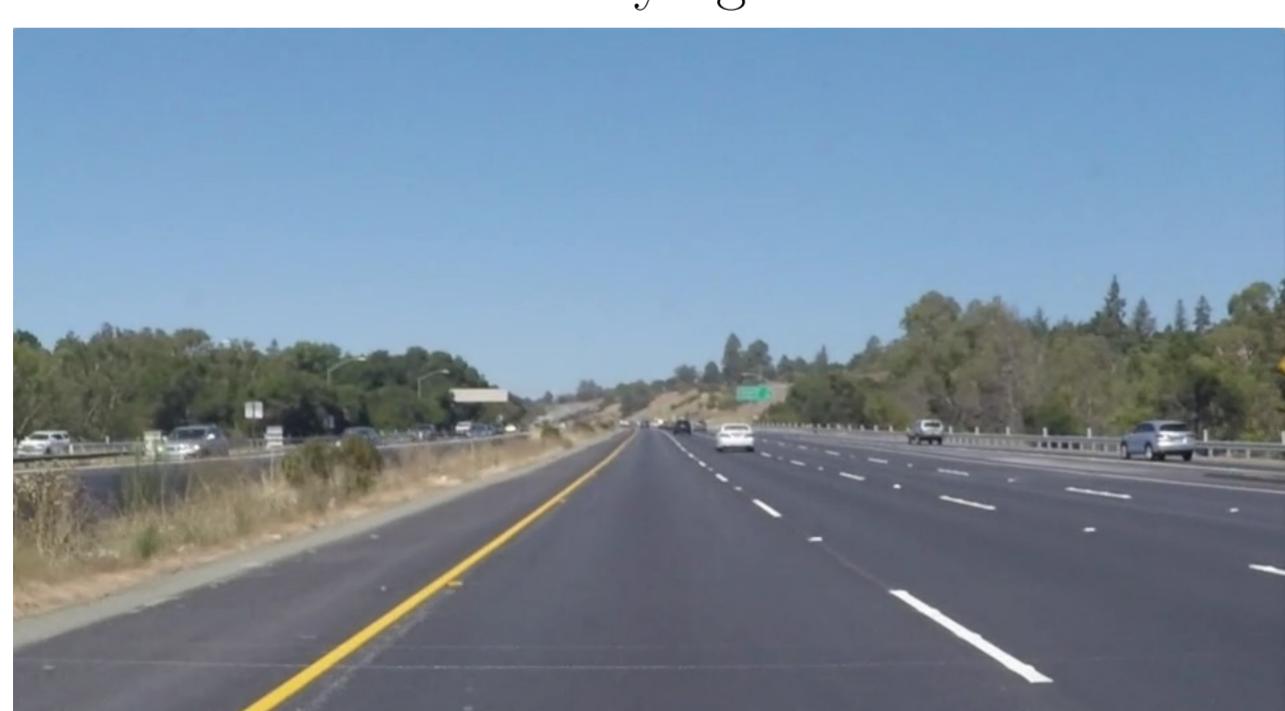
Figure 1: Original input image

Preprocessing & Feature Extraction

- **Color filtering:** Extracts white and yellow lane markings
- **Grayscale + Gaussian blur:** Suppresses noise
- **Canny edges:** Highlights lane boundaries
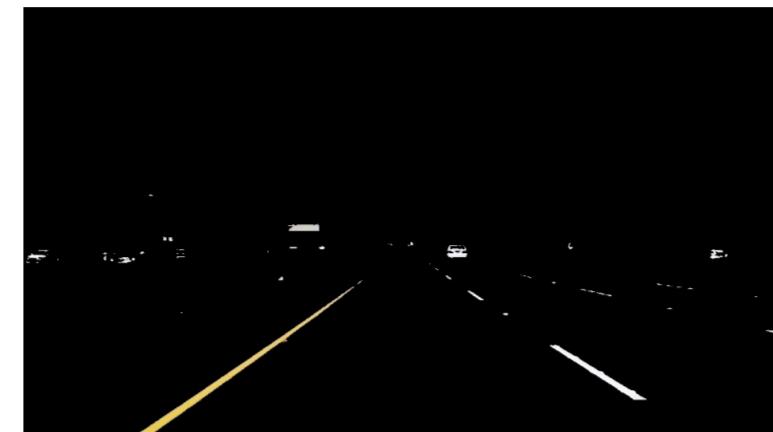
Figure 2: Color filtering isolates lane markings

**Figure 3:** Grayscale conversion and Gaussian smoothing
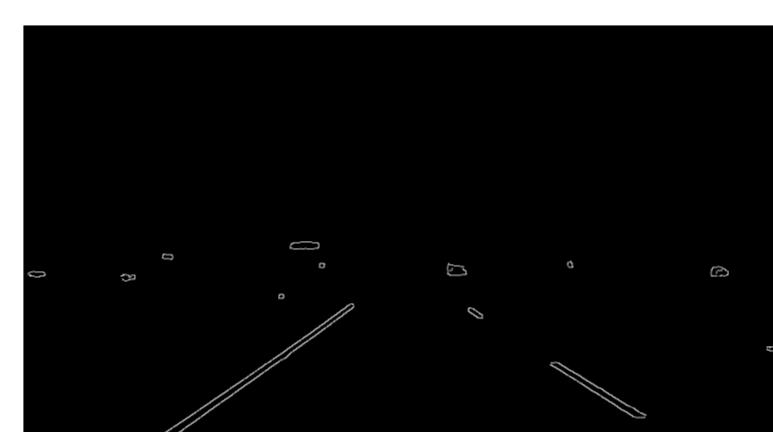
Figure 4: Canny edge detection highlights lane boundaries

Region of Interest

A polygonal mask restricts processing to the road area, removing sky and vehicles.
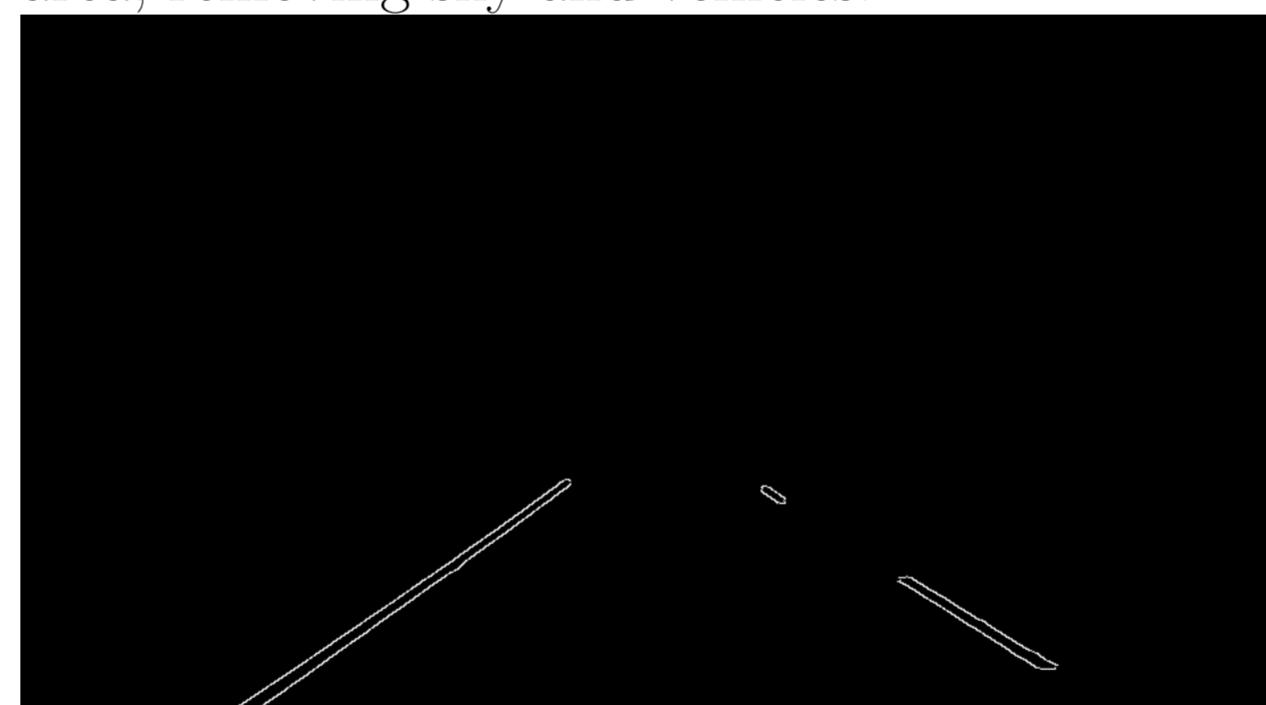
Figure 5: ROI masking reduces false detections

Hough Line Detection

The probabilistic Hough Transform detects straight line segments. Segments are filtered by slope and position.

Figure 6: Hough-detected line segments

Lane Averaging & Final Output

Detected segments are averaged and extrapolated to form stable lane boundaries.

Figure 7: Final averaged lane overlay

Parameter Tuning & Evaluation

The lane detection pipeline was tuned to maximize accuracy and real-time performance. The following parameters were used based on empirical testing:

- **Canny edge thresholds:** 50 / 150
- **Region of Interest (ROI):** lower 60% of the frame
- **Slope filter:** $|m| > 0.5$ (filters nearly horizontal lines)
- **Hough Transform minimum line length:** 40 px

Evaluation on AMD Ryzen 7 5700U (16 GB RAM, 64-bit OS):

- **Successful lane detections:** 87%
- **Processing speed:** 38 FPS
- **Frames tested:** 500+

Limitations

- Heavy shadows
- Worn lane markings
- Strong illumination changes

Conclusions & Future Work

Conclusions

- Classical vision reliably detects lane markings
- Interpretable and computationally efficient

Forthcoming Research

- Enhancing robustness under varying lighting and weather conditions
- Extending the approach to curved and multi-lane roads
- Temporal smoothing and lane tracking for video sequences
- Performance comparison with deep learning-based lane detection methods