

RC Car Project

Lane Keeping Control in Autonomous Driving by Computer Vision Approach

SEP 742 - Group 1

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01 Introduction

02 Computer Vision

03 Hardware and Control

04 Summary and Future Work

Project Background

Why Lane-Keeping?

- Core task in autonomous driving
- Improves safety, comfort, and traffic flow
- Critical in highway scenarios

Our Approach

- Use a vision-based system on an RC car
- Focus on detecting lanes and adjusting steering



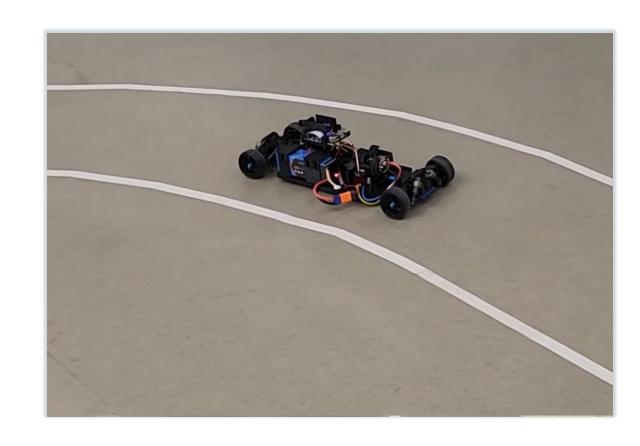
Problem Definition

Main Tasks

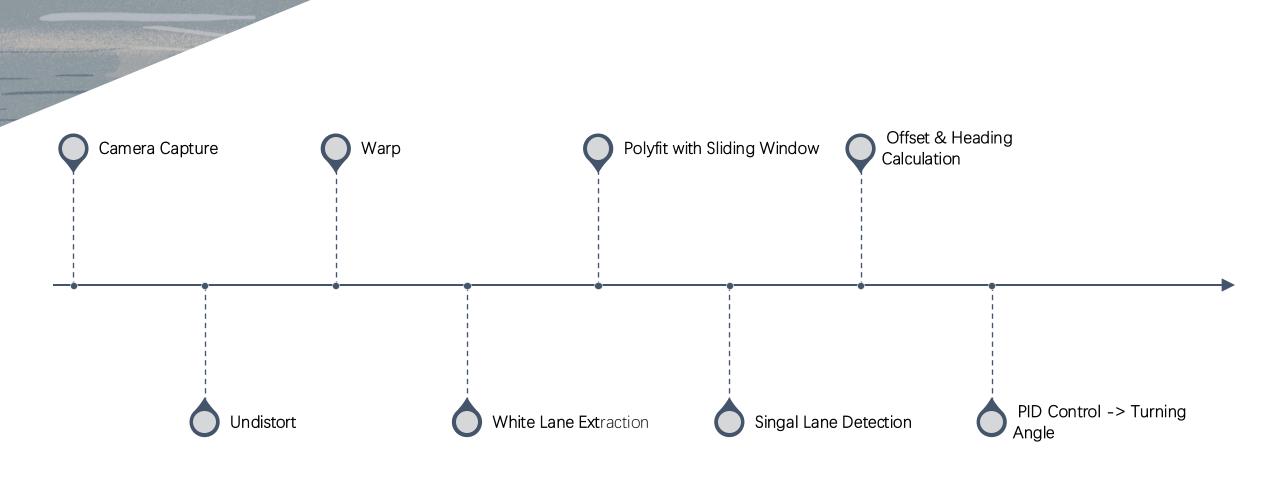
- Detect lane boundaries
- Estimate curvature & position
- Control steering in real-time

In our setup

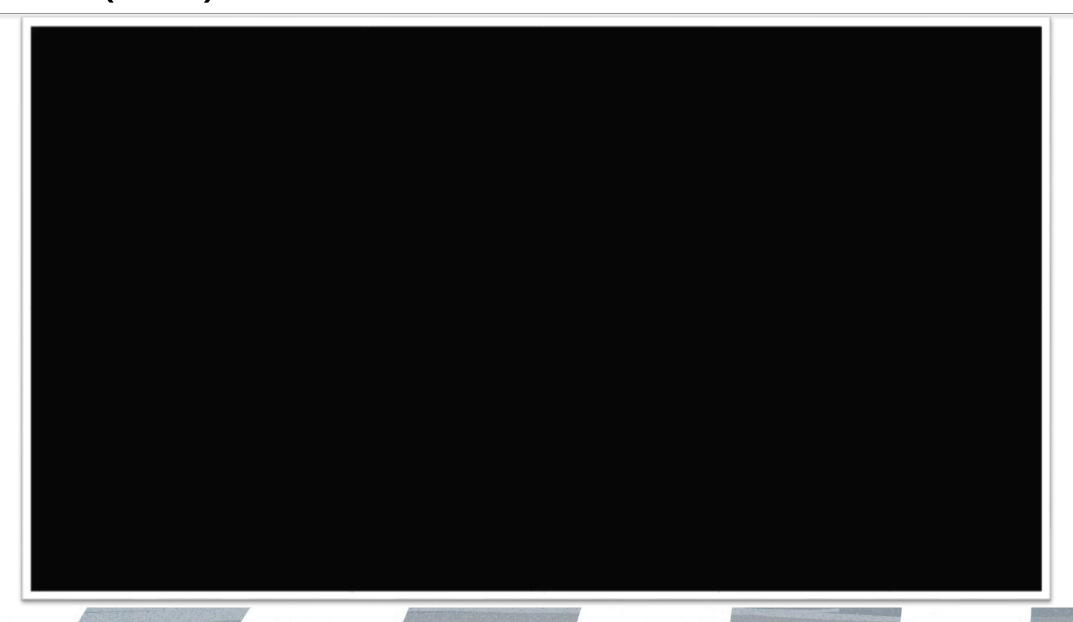
- Maintain constant forward speed
- Adapt to different curve geometries
- Focus on lateral control (not lane change or obstacle avoidance)



System Flowchart



01 Demo (video)







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Scene Preparation

Computer vision-based lane detection systems require precise scene preparation to create a standardized view of the road environment.









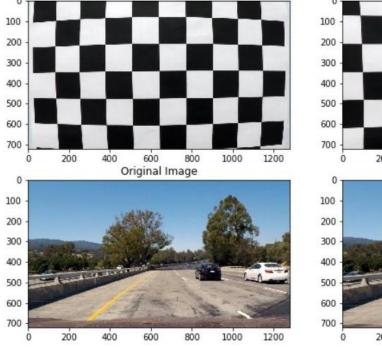
Scene Preparation

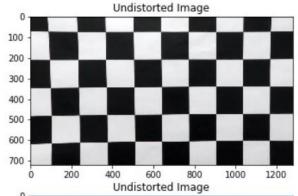
Correct lens distortion by establishing the relationship between 3D world coordinates and 2D image coordinates through parameters such as length, point, and distortion coefficients.



Camera Calibration

Original Image









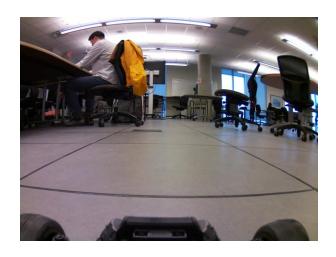


Scene Preparation

Correct lens distortion by establishing the relationship between 3D world coordinates and 2D image coordinates through parameters such as length, point, and distortion coefficients.



Camera Calibration



Original Image



Undistorted

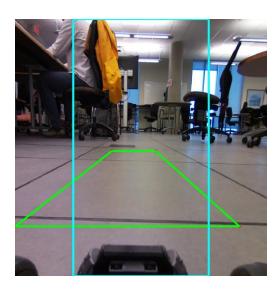


Scene Preparation

A perspective transformation is applied to obtain a bird's-eye view of the road, converting the frontal camera perspective into a top-down view where lane lines appear parallel rather than converging at the horizon.



Aerial View Transformed



a) Original Image



b) Aerial View Transformed

Image Transformation - HSV

HSV converts the input BGR image to HSV space and applies specific thresholds to identify lane markings.

- Color Information (Hue)
- Color Saturation (Saturation)
- Brightness (Value)

(Abbas & Kadhim, 2024; Hillel et al., 2012)

With carefully tuned thresholds, we can detect both white and yellow lane markings on roads and have higher resistance on interferences compared with RGB image.







a) Original Image

b) Image Extracted
White-Yellow in RGB

c) Image Applied White-Yellow HSV

Edge Detection - Canny

Lane lines possess a distinct characteristic: they typically form long, continuous borders!

Noise Reduction

Apply Gaussian filter to smooth image and reduce noise

Gradient Calculation

Use Sobel operator to find intensity gradients

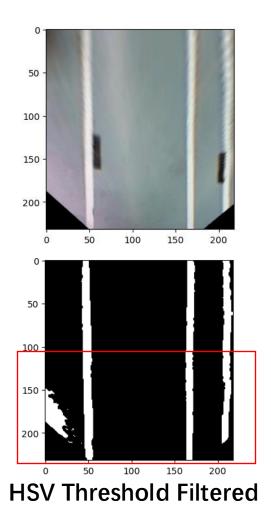
Double Thresholding on Classified Pixels

- o Strong: above high threshold
- o Weak: between low & high
- Non-edge: below low threshold
 Link weak edges to strong ones if connected.

(Malche, 2024; Educative, 2025; Scikit, 2013)



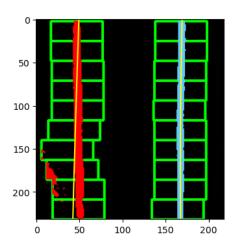
Lane Detection using Sliding Window



30000 -25000 -15000 -10000 -5000 -0 - 50 100 150 200 Peak Peak

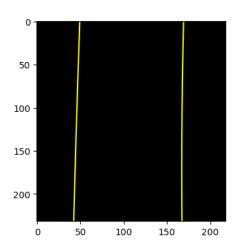


- Build histogram from bottomhalf of the image
- Split left and right by mid point
- Select peak points as initial left lane and right lane starting location





- Building blocks vertically
- Whole image split into n windows
- Filtering points calculate average x – reposition next window



Polynomial Fitting

- 2-degree polynomial
- $y=ax^2+bx+c$
- Next sliding window location base on fitting

Lane Geometry – Offset, Heading

Offset

When y=height, solve $y_{left} \rightarrow (x0, y0)$

When y=height, solve $y_{right} \longrightarrow (xl, yl)$

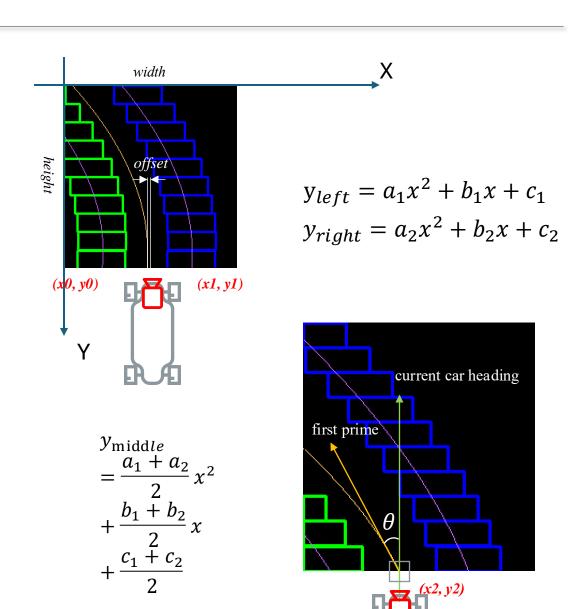
y0=y1=height

offset =
$$\frac{width}{2} - \frac{x_0 + x_1}{2}$$
 The camera always point at the mid point of the image!

Heading

$$y'(x_n) = (a_1 + a_2)x_n + \frac{b_1 + b_2}{2}$$
, at given point x_n

$$\theta = \arctan(a_1 + a_2)$$





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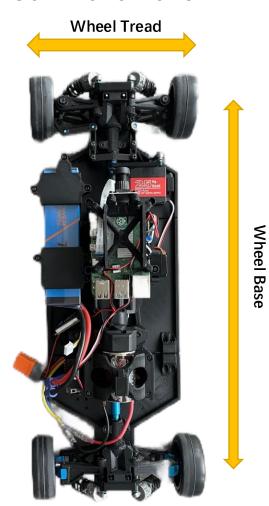
C O N T

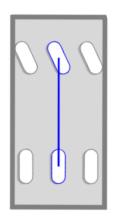
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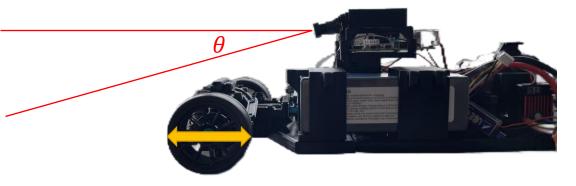
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RC Car Hardware





Two-Wheel Bicycle Model



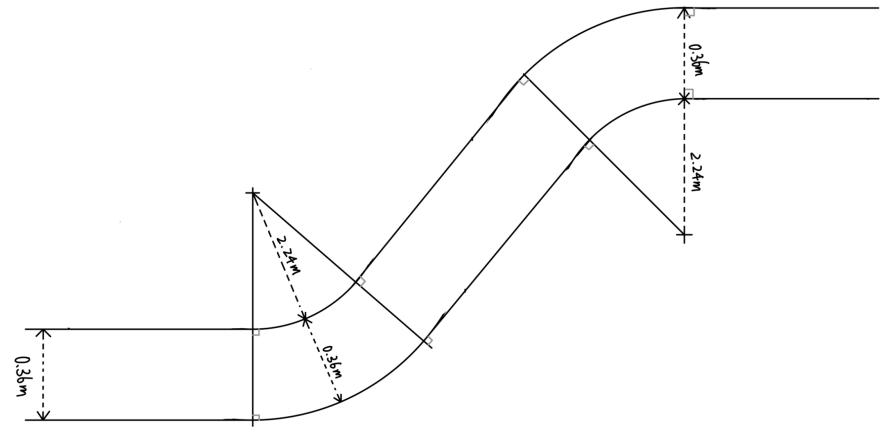
Wheel Diameter

Specification	Value
Wheel Base	0.4 m
Minimum Turning Radius	~2.8 m
Maximum Steering Angle	~8°
Camera Incline Angle	10°
Camera Resolution	Up to 2592x1944

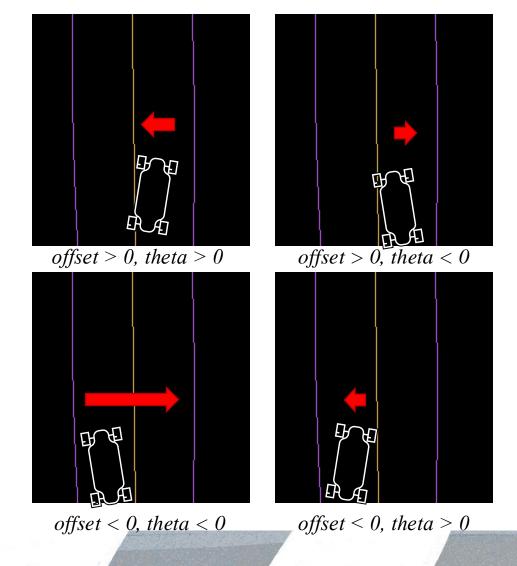
Track Design



- 2. Left Turn
- 3. Straight Line
- 4. Right Turn
- 5. Straight Line



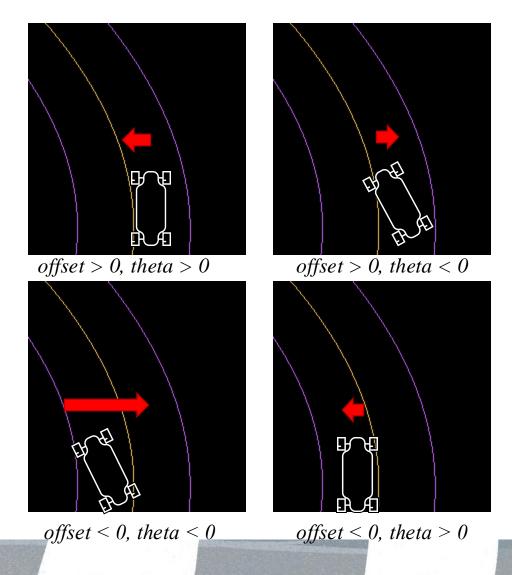
PID Control



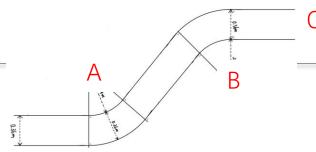
offset $\rightarrow 0$, theta $\rightarrow 0$

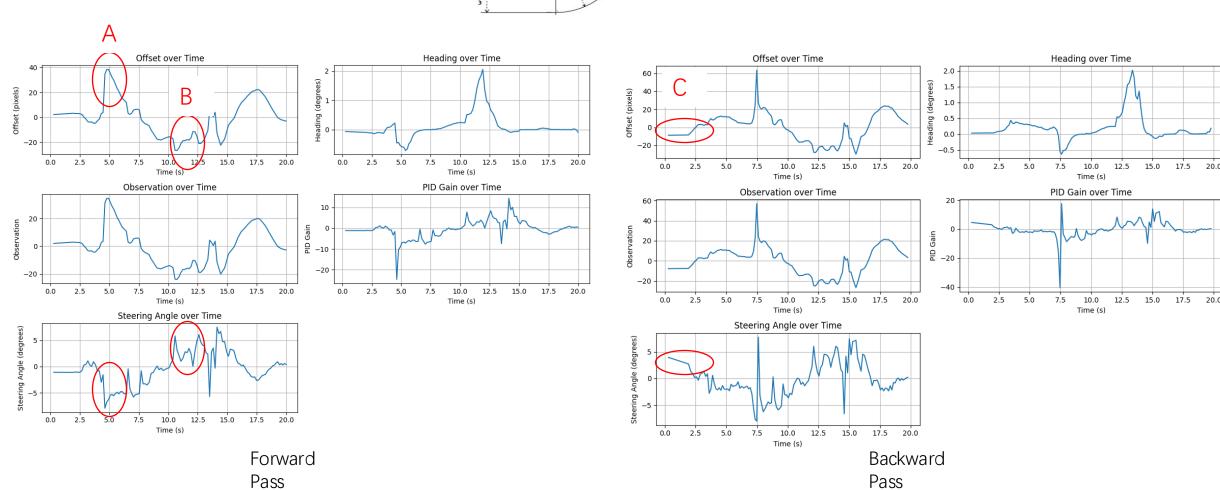
Observation =
$$k * Offset (1 - k) * Heading \theta = tanh(\lambda * Gain) * \omega_{max}$$

PID Gain = PID(SetPoint, Observation)



System Control Analysis







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Overview

- Successfully ran the entire pipeline
- Very fast, achieving 10 fps, allowing steering adjustments 10 times per second
- Strong results from PID parameter tuning
- Accelerated parameter tuning driven by data plots

Hardware Limitations

- Camera: Narrow FOV (Field of View) causes loss of one lane during turns
- Vehicle does not go perfectly straight forward, though PID control compensates

Software Pipeline

- HSV thresholding is not robust; strong illumination (e.g., sunlight or reflections) causes poor filtering
- Hard-coded corner cases lack flexibility



https://github.com/YeChen-coder/RCCarRelated

Motivation for CNN-Based Steering

Limitations of Traditional Computer Vision Manual Feature Engineering:

Reliance on edge detection, thresholding, and geometric heuristics.

Environmental Sensitivity:

Fails under dynamic lighting (shadows/glare) and structural ambiguities (faded/blocked lane markings).

Scalability Challenges:

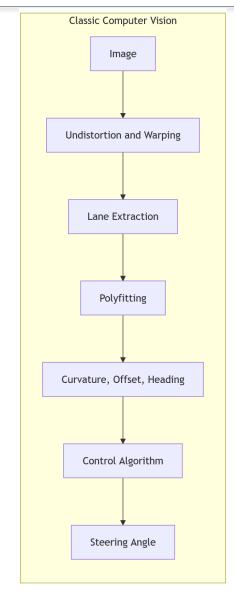
Requires frequent recalibration (HSV thresholds) for new environments.

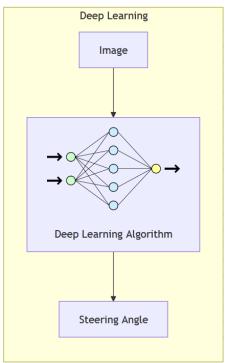
Advantages of Deep Learning Solutions End-to-End Learning:

Direct pixel-to-steering mapping without manual feature engineering.

Robustness:

Learns latent patterns from numerous examples.





Software-based Experiment Setup

Simulation Environment

Udacity's Self Driving Car Simulator

Dataset

https://github.com/rslim087a/track/
Collected from 3 cameras (center, left, right)
Includes steering angles, throttle, reverse, and speed

Data Processing

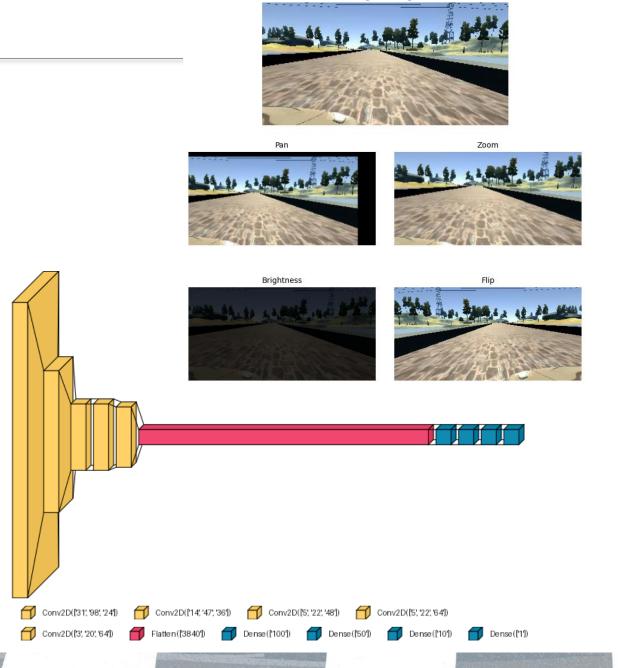
Bin Balancing Random Affine Transformation Side Cams with steering angle correction (±0.15)

Model

NVIDIA PilotNet 5 convolutional layers (ELU activation, dropout) 4 fully connected layers (ELU activation)

Evaluation

Validation Loss (MSE) Human Observation (lane adherence, recovery from deviation)



Original Image

Key Challenge in Porting CNN Based Steering to RC Car

Missing Side Cameras

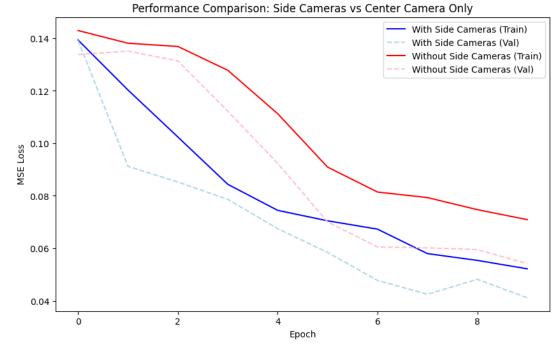
RC car has only a front-facing camera. No data regarding lateral displacement.

Comparative Experiment: 3-Camera vs. Center-Camera Training

Replicated center cam images as side cam images for center-cam only data to ensure data balance
Trained with same arch (batch=100, Ir=1e-3, epochs=10)

Used the same validation set for comparison

Val Loss: 3-Cam (0.041) vs. Center-Cam (0.054) Observation: 3-Cam recovered more drastically from drifting while the Center-Cam in some circumstances failed to keep in the lane



Conclusion and Porting Suggestions

Prioritize sensor diversity, add more cameras, add sensors like IMU to gain spatial information Adjust the CNN layout based on specific tasks/environments (input image dimensions, output dimensions, depths) Pair CNN predictions with rule-based corrections for fail-safe maneuvers

RC Car Platform Exploration





Robot Operating System (ROS)

https://www.diyrobocars.com/



Thank you! Feel free to reach out!

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