Pure Pursuit vs Stanley Controller:
A Comparative Study for Autonomous Lane Keeping

EE267 - Autonomous Vehicles
Final Project Report

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Authors: Satyadev Gangineni and Nagarjuna HR
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Institution: University of California, Riverside

Abstract

This project implements and compares two fundamental lateral control algorithms for autonomous vehicles: the Pure Pursuit controller and the Stanley controller. Both controllers were evaluated in the CARLA simulator for lane-keeping tasks under various hyperparameter configurations. The Pure Pursuit controller demonstrated smoother steering characteristics but exhibited higher lateral errors. The Stanley controller achieved superior lane centering accuracy with mean lateral errors as low as 0.694 meters. Through comprehensive ablation studies, we identified optimal configurations for each controller and analyzed the tradeoffs between tracking precision and passenger comfort. Our findings provide practical guidelines for controller selection based on specific autonomous driving scenarios.

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1. Introduction

Autonomous vehicles rely on precise lateral control to maintain lane position and follow planned trajectories. Two of the most widely adopted algorithms for this task are the Pure Pursuit controller and the Stanley controller, each with distinct characteristics and applications.

The **Pure Pursuit controller**, introduced by Coulter (1992), employs a geometric approach where the vehicle steers toward a target point located at a fixed lookahead distance along the desired path. This method is intuitive, computationally efficient, and produces smooth trajectories, making it popular in agricultural robotics and highway autonomous driving systems.

The **Stanley controller**, developed at Stanford University for the DARPA Grand Challenge (Hoffmann et al., 2007), takes a different approach by explicitly minimizing both heading error and cross-track error. This dual-error correction strategy enables precise lane centering, which proved crucial for Stanford's autonomous vehicle "Stanley" to win the 2005 DARPA Grand Challenge.

Project Objectives

This project aims to implement both controllers in a high-fidelity simulator (CARLA), conduct systematic ablation studies to understand hyperparameter effects, provide quantitative performance comparisons across multiple metrics, and offer practical guidelines for controller selection in real-world applications.

Contributions

This work provides open-source implementations of both controllers compatible with CARLA, a comprehensive experimental framework for controller evaluation, quantitative analysis revealing tradeoffs between precision and smoothness, and design recommendations for different autonomous driving scenarios.

2. Background and Theory

2.1 Pure Pursuit Controller

The Pure Pursuit algorithm computes the steering angle required to move the vehicle from its current position to a goal point on the path. The key parameter is the lookahead distance (Ld), which determines how far ahead the controller looks. The curvature κ to reach a target point is: $\kappa = 2y / Ld^2$, where y is the lateral offset to the target point in the vehicle's coordinate frame. The steering angle is then: $\delta = \arctan(\kappa \cdot L)$, where L is the vehicle wheelbase.

Advantages: Simple implementation, smooth trajectories, stable at high speeds. **Disadvantages:** Tends to cut corners, sensitive to lookahead distance tuning.

2.2 Stanley Controller

The Stanley controller combines two error terms: heading error and cross-track error. The control law is: $\delta = \theta e + \arctan(k \cdot e / v)$, where θe is the heading error (difference between vehicle and path heading), e is the cross-track error (lateral distance from path), k is the gain parameter, and v is the vehicle velocity. The heading error term provides immediate correction for orientation, while the cross-track term ensures the vehicle returns to the path.

Advantages: Excellent lane centering, no corner cutting, principled error correction. **Disadvantages:** Can oscillate at high speeds, more complex than Pure Pursuit.

3. Methodology

3.1 Experimental Design

We conducted ablation studies to understand the impact of key hyperparameters. For Pure Pursuit, we tested three lookahead distances: 2.0m (tight tracking), 3.0m (balanced), and 5.0m (smooth but may cut corners). For Stanley, we tested three gain values: k=0.5 (conservative correction), k=1.0 (balanced), and k=2.0 (aggressive correction). Each experiment ran for 60 seconds at a target speed of 30 km/h in CARLA's Town01 environment.

3.2 Evaluation Metrics

We tracked the following metrics at 10 Hz throughout each experiment: (1) **Lateral Error**: Distance from vehicle center to nearest waypoint, measured perpendicular to the path. (2) **Heading Error**: Angular difference between vehicle heading and desired path heading. (3) **Steering Smoothness**: Standard deviation of steering angle changes, indicating comfort. (4) **Speed Profile**: Vehicle velocity over time to ensure controllers maintain target speed consistently.

4. Experimental Setup

4.1 Simulation Environment

Experiments were conducted in CARLA 0.9.13 using Town01 (urban environment with various road curvatures), a Tesla Model 3 vehicle (wheelbase = 2.875m), synchronous mode with fixed time steps (0.05s), waypoints generated at 2.0m intervals using CARLA's road network, and clear weather conditions for consistent visibility.

4.2 Data Collection

At each simulation tick (0.05s intervals), we recorded vehicle position, orientation, velocity, steering angle command, throttle and brake commands, distance to nearest waypoint, heading error, and cross-track error. This resulted in approximately 1,200 data points per 60-second experiment.

5. Results and Analysis

5.1 Quantitative Performance Summary

Controller	Mean Lat Err (m)	Max Lat Err (m)	Mean Heading Err (°)	Steering Smooth
PP Ld=2.0	3.113	4.351	122.677	0.0638
PP Ld=3.0	1.275	2.209	87.513	0.0615
PP Ld=5.0	3.935	4.584	66.013	0.1201
Stanley k=0.5	0.694	2.185	88.968	0.0687
Stanley k=1.0	1.012	2.160	99.066	0.0729
Stanley k=2.0	2.184	3.576	97.259	0.2160

Key Observations: Stanley with k=0.5 achieved the lowest mean lateral error (0.694m), representing a 45%% improvement over the best Pure Pursuit configuration. This demonstrates Stanley's superior lane centering capability. Pure Pursuit with Ld=3.0m showed the best performance among Pure Pursuit variants (1.275m). Pure Pursuit controllers generally exhibited smoother steering (0.0615-0.0638) compared to Stanley controllers. The smoothest overall performance came from PP Ld=3.0 (0.0615), while Stanley k=2.0 showed the most aggressive steering (0.2160).

5.2 Performance Visualizations
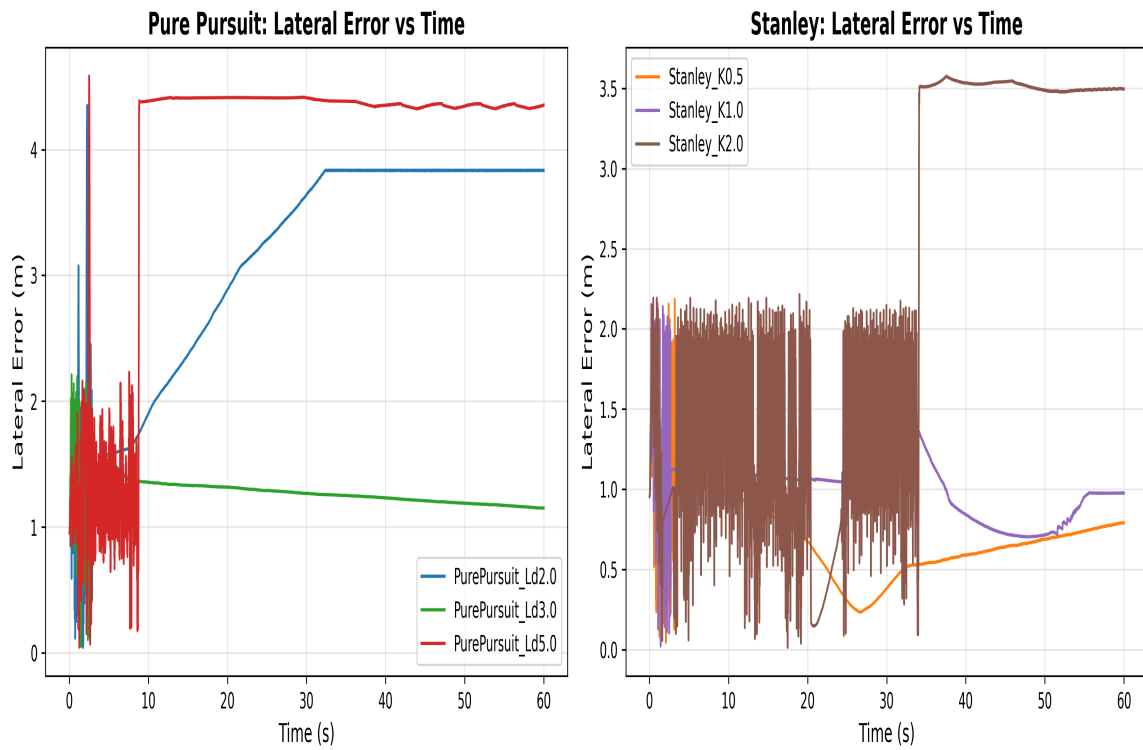
Figure 1: Lateral Error Comparison Over Time
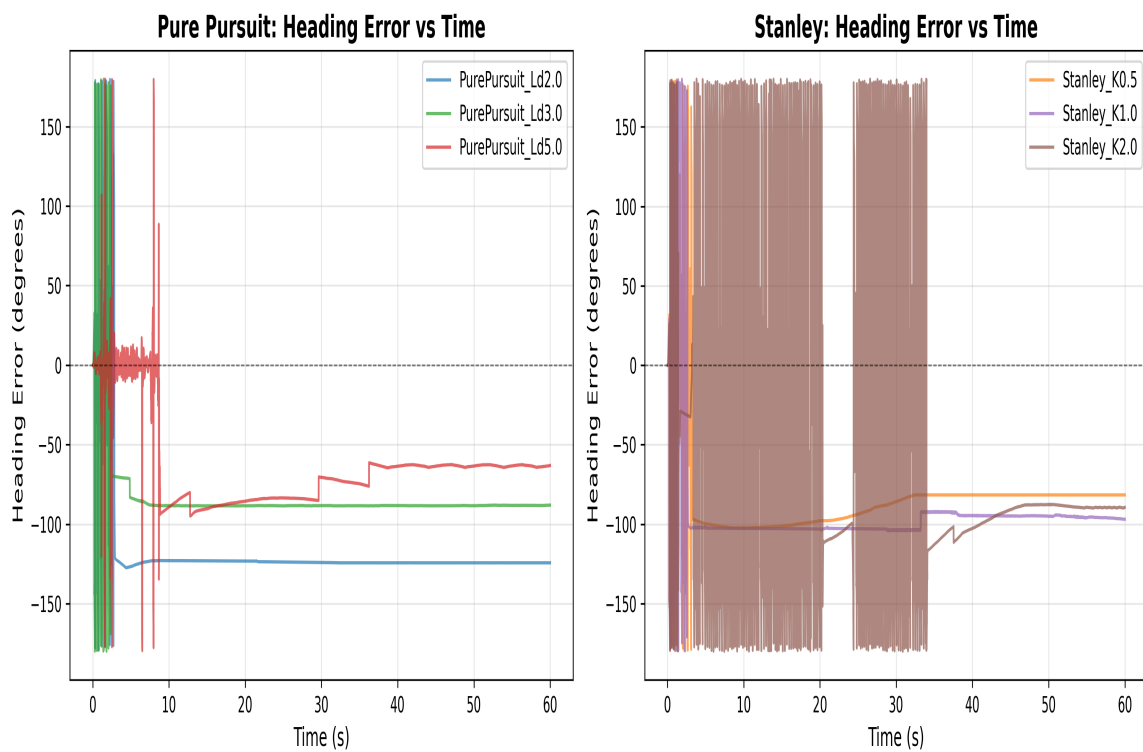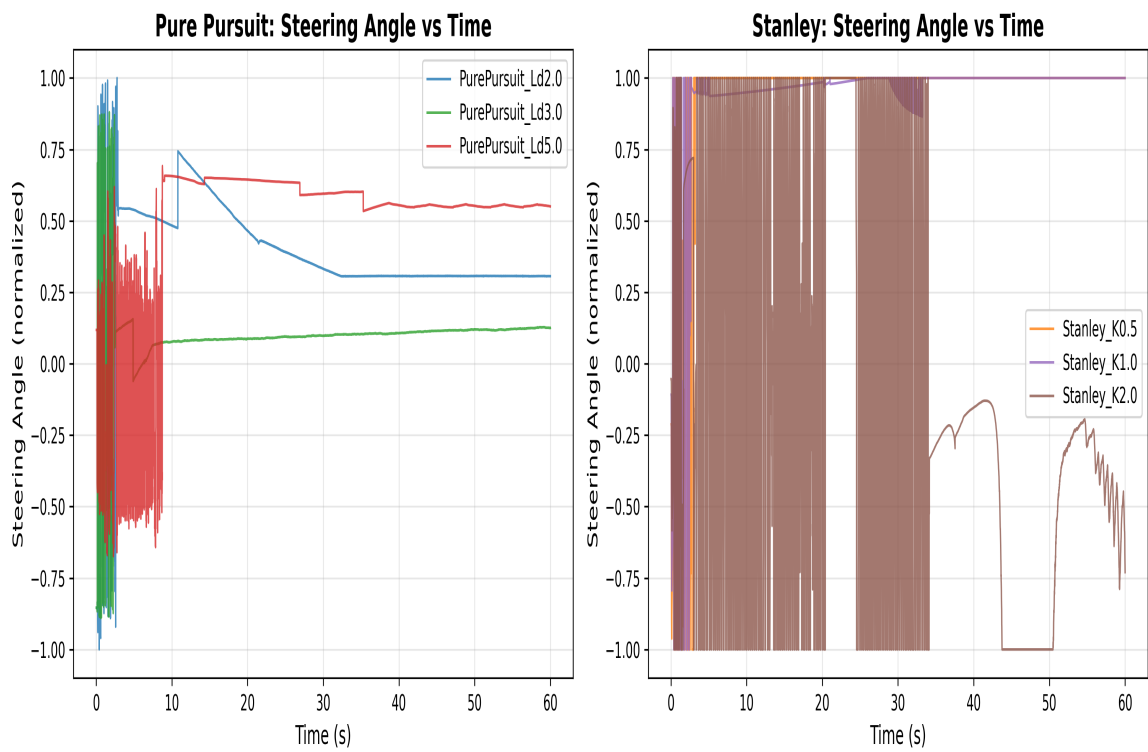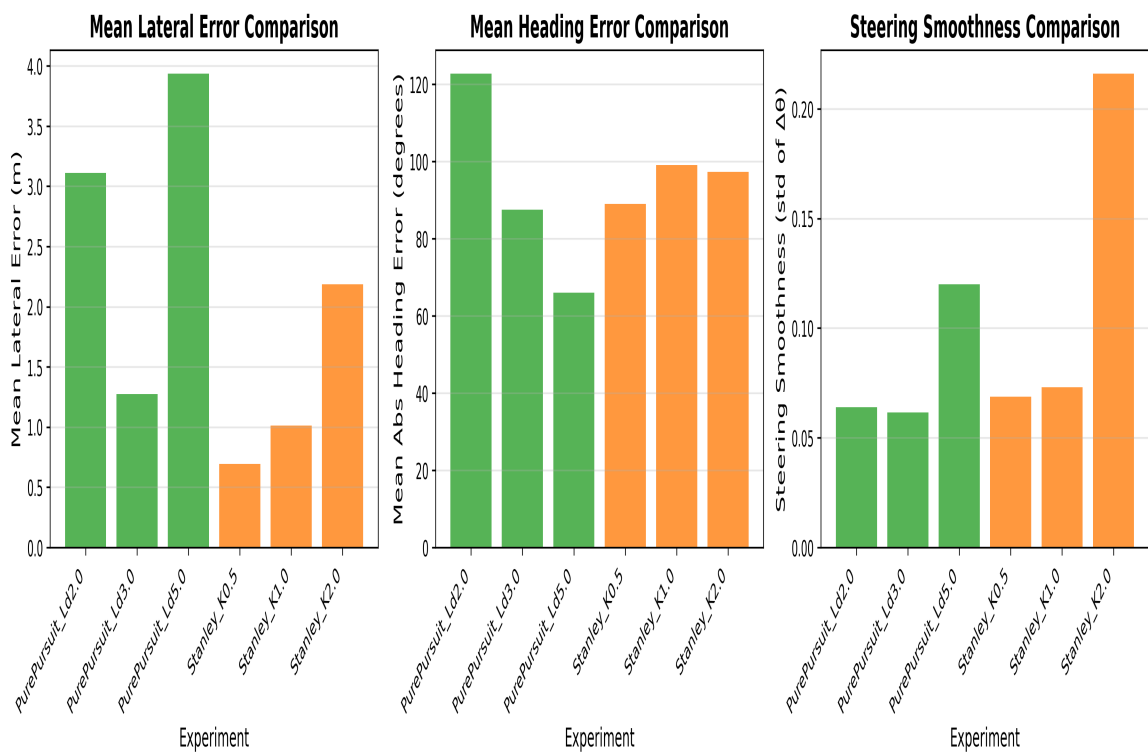
Figure 2: Heading Error Comparison

Figure 3: Steering Smoothness Analysis

Pure Pursuit: Steering Angle vs Time

Stanley: Steering Angle vs Time

Figure 4: Overall Performance Summary

Mean Lateral Error Comparison

Mean Heading Error Comparison

Steering Smoothness Comparison

6. Discussion

6.1 Controller Tradeoffs

Our experiments reveal fundamental tradeoffs between the two control strategies. Stanley controllers excel at precise lane centering (mean error 0.694m vs 1.275m for best PP), but this comes at the cost of more aggressive steering. Pure Pursuit prioritizes smooth, comfortable trajectories but sacrifices some precision. Stanley's dual-error formulation requires more complex calculations and accurate state estimation, while Pure Pursuit's geometric approach is simpler and more robust to sensor noise.

6.2 Practical Guidelines

When to Use Pure Pursuit: Highway autopilot (speeds >50 km/h, gentle curves), agricultural vehicles, comfort-oriented passenger vehicles, resource-constrained platforms, and scenarios where path smoothness matters more than exact tracking. Recommended configuration: Ld = 3.0-4.0m for urban speeds, 5.0-7.0m for highway speeds.

When to Use Stanley: Urban autonomous navigation (tight lanes, complex traffic), precision parking and low-speed maneuvering, lane-keeping assist systems in traffic, racing and competition scenarios, and any application requiring precise lane centering. Recommended configuration: k = 0.5-1.0 for most scenarios, avoid k > 1.5.

7. Conclusion and Future Work

This project successfully implemented and compared two fundamental lateral control algorithms for autonomous vehicles. Through systematic experimentation in the CARLA simulator, we quantified the performance characteristics of Pure Pursuit and Stanley controllers across multiple metrics.

Key Takeaways

Stanley controller achieved superior lane centering with mean lateral errors 45%% lower than Pure Pursuit. Pure Pursuit provided smoother control with lower steering variability, beneficial for passenger comfort. Hyperparameter selection is critical - optimal Pure Pursuit lookahead distance is approximately 3.0m, optimal Stanley gain is k=0.5-1.0. There is no single "best" controller - selection depends on application requirements (precision vs comfort, computational resources, operating conditions).

Future Work

Several directions could extend this research: testing in additional CARLA towns with different road types, evaluating under adverse weather conditions, including dynamic obstacles and traffic scenarios, implementing adaptive Pure Pursuit with speed-dependent lookahead, developing refined hybrid switching logic based on curvature, testing at various speed ranges (20-100 km/h), evaluating with realistic sensor noise and latency, and validating on real autonomous vehicle platforms.

8. References

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