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Reinforcement Learning-Based Simulation of Semi-Active Suspension Systems in Quarter-Car Model

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Abstract
This study investigates the application of reinforcement learning (RL) techniques for simulating and managing semi-active suspension systems within a quarter-car model framework. Conventional controllers, such as PID and skyhook, typically depend on fixed parameters and simplified system assumptions, which can restrict their effectiveness when faced with nonlinear and variable road conditions. RL, on the other hand, provides a flexible, model-free control methodology that learns optimal strategies through continuous interaction with the vehicle's dynamic environment. In this work, three RL algorithms - Deep Q-Network (DQN), Proximal Policy Optimization (PPO), and Deep Deterministic Policy Gradient (DDPG) are utilized to reduce body acceleration and tire displacement, thereby enhancing both ride quality and handling performance. Simulation studies conducted on a range of road disturbances, including sinusoidal, step, and random profiles, reveal that RL-driven controllers outperform traditional approaches in terms of adaptability, robustness, and smooth control actions. The results highlight RL's capability to deliver efficient suspension control without requiring explicit system models or extensive manual tuning, demonstrating strong generalization to previously unseen conditions. These benefits underscore the potential of reinforcement learning as a powerful tool for developing intelligent, autonomous suspension systems in modern vehicles.

Keywords: *Adaptive control, Deep Q-network, Proximal policy optimization, Quarter-car model, Reinforcement learning.*

1. Introduction
Advancements in automotive systems demand improved ride comfort, vehicle stability, and adaptability to diverse road profiles. Suspension systems directly influence these factors by isolating passengers from road irregularities while maintaining tire contact with the ground [1], [2]. Conventional passive suspension systems are simple and reliable but cannot adapt to changing conditions. To overcome this limitation, active and semi-active suspensions were introduced, enabling real-time damping adjustments [3]. Machine learning (ML), and more specifically reinforcement learning (RL), has emerged as a powerful approach for such control problems. Unlike classical model-based methods, RL learns policies through interaction with the environment, making it well-suited for systems with nonlinear and uncertain dynamics such as suspension control [4], [5]. Recent deep RL advances enable efficient continuous control, offering strong adaptability to unseen conditions [10]– [14].

1.1. Semi-Active Suspension Systems
Suspension systems are broadly classified as follows [2], [3]:
- **Passive suspensions:** use fixed springs and dampers, low-cost but inflexible.
- **Active suspensions:** employ actuators to apply external forces, achieving optimal comfort but with high complexity and energy demands.
- **Semi-active suspensions:** utilize variable dampers (e.g., magnetorheological) to

modulate damping in real time. Semi-active designs balance performance and efficiency, making them attractive for modern vehicles. The main objective is to regulate damping for improved ride comfort, handling, and stability. RL enables autonomous optimization of damping without requiring explicit models or manual parameter tuning [4], [10].

2. Related Work

Classical controllers such as PID and skyhook remain popular for suspension systems [3]. While computationally efficient, they are limited in nonlinear and time-varying scenarios. Alternatives like sliding mode and fuzzy control provide more flexibility but require detailed modelling and are prone to stability issues. RL has achieved significant success in complex control domains. DQN demonstrated human-level decision-making [5], while PPO [6] and DDPG [7] advanced continuous control. In the automotive sector, RL has been applied to active suspension [8] and adaptive cruise control [9]. More recently, researchers have focused on semi-active suspensions, confirming RL's advantages in robustness and comfort improvements [10]– [14].

3. System Model and Problem Formulation

3.1. Quarter-Car Model

The quarter-car model represents vertical vehicle dynamics with two degrees of freedom: sprung mass (m_s) and unsprung mass (m_u). Parameters include suspension stiffness (k_s), tire stiffness (k_t), and variable damping coefficient (c).

3.2. Governing Equations

$$m_s\ddot{z}_s = -k_s(z_s - z_u) - c(t)(\dot{z}_s - \dot{z}_u)$$

$$m_u\ddot{z}_u = k_s(z_s - z_u) + c(t)(\dot{z}_s - \dot{z}_u) - k_t(z_u - z_r).$$

3.3. Control Objective

The damping coefficient is constrained as:

$$\boldsymbol{c_{\min} \le c(t) \le c_{\max}}$$

The damping force is:

$$\boldsymbol{F_d(t) = c(t)(\dot{z}_s - \dot{z}_u)}$$

The cost function combines ride comfort and handling:

$$\boldsymbol{J = \int_0^T \left[\alpha\, \ddot{z}_s(t)^2 + \beta\left(z_u(t) - z_r(t)\right)^2\right] dt,}$$

where α and β are weighting coefficients.

4. Simulation Environment

- **State space:** [z_s, $\dot{x}_s$, z_u, $\dot{x}_u$, z_r].
- **Action space:** damping coefficient bounded by [cmin, cmax].
- **Reward function:** negative weighted sum of body acceleration and tire deflection.
- **Road profiles:** sinusoidal, step, and random disturbances.

The environment is built in Python with numerical solvers (1–10 ms timestep).

5. Reinforcement Learning Algorithms

- **DQN:** Q-learning with neural network approximation for discretized actions [5].
- **PPO:** policy gradient with clipped objectives for stability and continuous actions [6].
- **DDPG:** actor-critic with deterministic policies for sample-efficient continuous control [7].

6. Simulation Setup

6.1. Vehicle Parameters

Table 1 Quarter-Car Model Parameters

Parameter	Symbol	Value	Unit
Sprung mass	m_s	290	kg
Unsprung mass	m_u	59	kg
Suspension stiffness	k_s	16,000	N/m
Tire stiffness	k_t	190,000	N/m
Damping range	cmin–cmax	100–1000	Ns/m

6.2. Road Inputs

- Sinusoidal with varying frequency.
- Step inputs (bumps).
- Random stochastic disturbances [2].

6.3. RL Training Parameters

Table 2 Reinforcement Learning Training Parameters

Parameter	DQN	PPO	DDPG
Learning rate	0.001	0.0003	0.001
Discount factor (γ)	0.99	0.99	0.99
Batch size	64	64	64
Replay buffer	100,000	–	100,000
Training episodes	1000	1000	1000

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7. Results and Discussion

7.1. Performance Metrics

Table 3 Performance Comparison of Suspension Controllers

Controller	RMS Acceleration (m/s^2)	RMS Tire Deflection (m)	Energy Proxy (J)
Passive	1.85	0.010	–
PID	1.30	0.007	15.2
Skyhook	1.12	0.006	13.8
DQN	1.05	0.0055	12.5
PPO	**0.95**	**0.0048**	**11.2**
DDPG	0.98	0.0050	11.7

7.2. Analysis

The RL-based controllers achieve lower acceleration and tire deflection compared to classical controllers. PPO demonstrates the best balance, while DDPG yields smoother damping profiles. Unlike DQN, which discretizes damping actions, PPO and DDPG exploit continuous spaces, improving efficiency.

Under random road inputs, RL controllers preserve performance, confirming robustness and generalization.

Conclusion

This study presented reinforcement learning-based semi-active suspension control using a quarter-car model. PPO and DDPG demonstrated superior performance relative to classical controllers, highlighting RL's ability to handle nonlinear and uncertain conditions. The model-free and adaptive nature of RL makes it a promising candidate for future suspension technologies. Future work includes hardware-in-the-loop validation and extension to full-vehicle dynamics.

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