Applying deep reinforcement learning for magnetorheological damper on the active suspension control system

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Abstract: *This article introduces an innovative method for designing a controller for vehicle suspension systems featuring magnetorheological (MR) dampers. The approach revolves around the idea that an optimal control strategy can be achieved by applying a reinforcement learning algorithm with continuous states and actions, utilizing data from real-world or simulated experiments. The Twin Delayed Deep Deterministic Policy Gradient (TD3) algorithm is used to process sensor data and determine the appropriate actuation voltage for the MR damper. To assess the system's effectiveness, a quarter vehicle model is employed, incorporating the modified Bouc-Wen MR damper model. This model enables the calculation of key suspension metrics, including displacement, sprung mass acceleration, and dynamic tire load within the suspension workspace. The reward function in the deep reinforcement learning algorithm is based on the sprung mass acceleration. Results from numerous simulated experiments demonstrate that this approach outperforms traditional suspension control methods in terms of both ride comfort and stability.*

Keywords: *Magnetorheological-damped Suspension, Deep Reinforcement Learning, MR Damper, Suspension System Control.*

1. Introduction

As one of the most essential components of a vehicle, the suspension system plays a crucial role in enhancing ride comfort and road handling, while also preventing damage and minimizing passenger fatigue. Suspension systems are generally categorized as passive, active, or semi-active. Due to the fixed and unalterable nature of passive suspension parameters, passive systems are unable to ensure both ride comfort and stability when external conditions or suspension parameters change. To address these limitations, active and semi-active suspension systems, which feature adjustable parameters, have been developed. However, real-world applications inevitably involve uncertainties, such as road roughness and varying suspension parameters.

Magnetorheological (MR) fluid dampers are adaptive and controllable devices that have garnered significant attention due to their appealing characteristics, including simplicity, low power consumption, and high force capacity. Their versatility has led to widespread use across various industries, such as automotive [1][2], civil engineering [3][4], and railway transportation [5]. MR dampers are classified as semi-active devices because they generate damping force by applying voltage to their coils, eliminating the need for a mechanical mechanism. As a result, two types of controllers are required to manage semi-active suspensions. First, the system controller calculates the necessary damping force to simultaneously achieve both ride comfort and road handling, using inputs from the suspension system's state feedback. Second, the damper controller determines the appropriate voltage to apply to the MR damper, ensuring the actual damping force aligns with the force specified by the system controller.

With the emergence of Deep Learning (DL) techniques that address many of the key limitations found in traditional machine learning algorithms, some researchers have explored the application of DL to suspension control. In [3], the authors present a DDPG-based algorithm designed for a specific type of suspension system. However, a major limitation of this algorithm is its inability to find a globally optimal solution to the problem.

This paper introduces an enhanced DRL controller that integrates both a system controller and a damper controller to optimize ride comfort and stability. It is important to note that MR-based suspension systems function in two modes: in open-loop mode (without a controller), the system operates with a constant damping coefficient, similar to passive suspension systems. In closed-loop mode, both the system and damper controllers work together to adjust the damping force in response to varying road conditions by fine-tuning the voltage input to the damper.

2. MR-damped suspension model

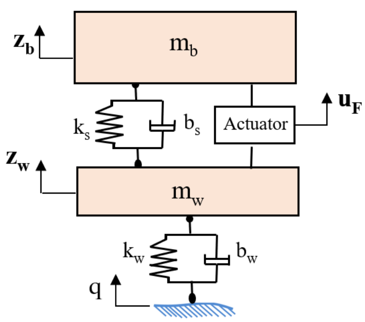

Fig 2.1. A quarter-car model with two operational modes for a semi-active suspension system.

Based on the above definition, the dynamics model of the active suspension system can be described approximately linearly by the following equation:

$$\begin{cases} m_b\ddot{z}_b + b_s\left(\dot{z}_b - \dot{z}_w\right) + k_s\left(z_b - z_w\right) = u_a \\ m_w\ddot{z}_w - b_s\left(\dot{z}_b - \dot{z}_w\right) - k_s\left(z_b - z_w\right) + k_t\left(z_w - q\right) + b_t\left(\dot{z}_w - \dot{q}\right) = -u_a \end{cases}$$

(1)

Where, m_b is the sprung mass, which represents the mass of the vehicle body and is supported by the suspension; z_b is the displacement of the sprung mass; b_s is the damping coefficient of the suspension for the sprung mass; k_s is the spring constant of the suspension for the sprung mass; m_w is the unsprung mass, which represents the mass of the wheel and tire that are not supported by the suspension; z_w is the displacement of the unsprung mass; k_t is the spring constant of the suspension for the unsprung mass.

3. TD3 application in closed-loop vibration control for a semi-active suspension system

The main inputs for vehicle dynamics are road disturbance profile and damping force produced by the MR device. The outputs are body (sprung mass) acceleration and suspension working space (SWS). The RL-Agent inputs for implementing a controller for a one-quarter suspension system are body acceleration, denoted by q, and a reward function, which is as follows:

$$r = \begin{cases} 0 & \text{if } q = q_{goal} = 0 \\ -kq^2 & \text{if } q \neq 0 \end{cases} \quad (2)$$

Where k is a hyperparameter that specifies the intensity coefficient for agent punishment, the agent punishments experienced in the replay buffer are also exerted in the RL-agent. The damper's input voltage must be applied to the coil via the RL-agent output (action). TD3 analyzes its performance by measuring body acceleration and fine-tuning its action to road profile disturbances. The surrounding environment consists of a vehicle suspension system equipped with an MR-damper and a road profile. The agent is a neural network that constructs the controller part. The hyperparameters listed in Table 2.1 pertain to TD3 agents used in closed-loop suspension control. Fig 2.2 detail the block diagram of closed-loop semi-active suspension system with DRL Agent.

The hidden size is 400 and 300 neurons in each layer for the actor and critic network, respectively. The optimization method is Adam for both actor and critic networks. The discount factor γ is 0.8. The input voltage varies from 0 to 3 V, and the damping force varies from -1.5 to 1.5 KN. 0.002 Adam 2

Table 2.1. The parameters for the MR-damper

Network	Learning Rate	Optimizer	Delay for update
Actor	0.002	Adam	2
Critic	0.002	Adam	1
Actor Target	0.006	--	2
Critic Target	0.006	--	2

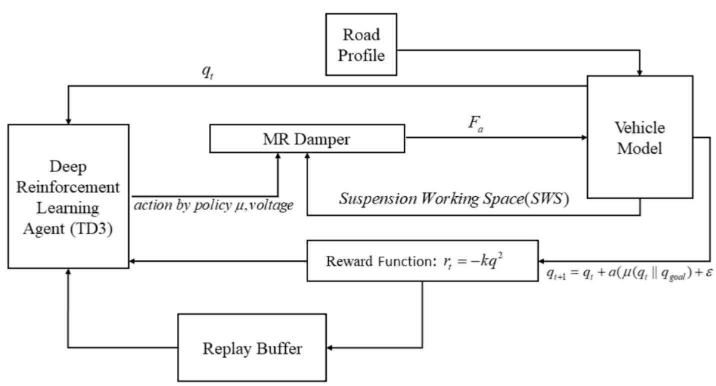

Fig 2.2. Closed-loop semi-active suspension system block diagram with DRL Agent

4. Results and Discussion

Vertical Body Acceleration (BA), Dynamic Tire Load (DTL), and Suspension Working Space (SWS) are the three key performance metrics used in vehicle suspension design to enhance ride comfort and road handling, while also preventing excessive bottoming out of the suspension system. To achieve these goals, minimizing BA or SWS improves ride comfort, while reducing DTL enhances road handling and limits suspension displacement. In this study, BA is selected as the objective function. Two types of controllers for semi-active suspension are evaluated in this section: the RL-based TD3 controller and a PID controller, with the latter's gains optimized using the Particle Swarm Optimization (PSO) algorithm from [4]. Additionally, a passive MR system (MR-Passive) with no voltage applied to the damper's coil is examined as a baseline.

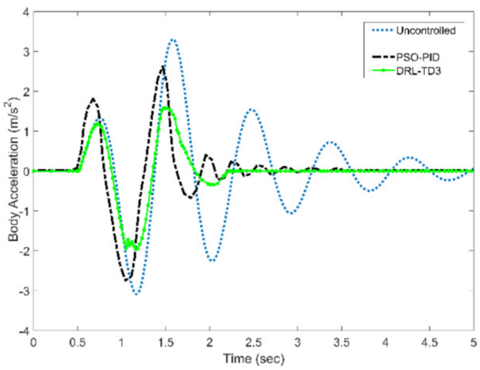

Fig 2.3. Body Acceleration (BA)

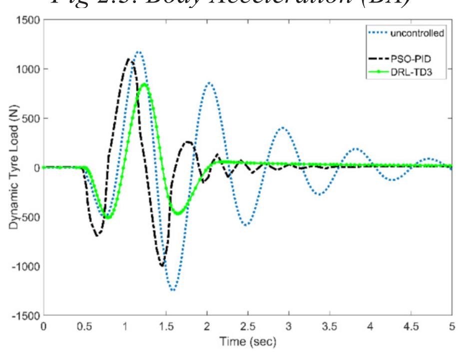

Fig 2.4. Dynamic Tire Load (DTL)

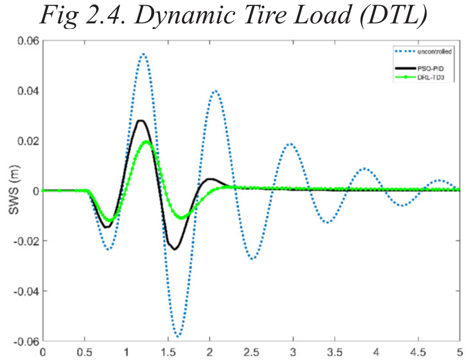

Fig 2.5. Suspension Working Space (SWS)

The results demonstrate unequivocally that the DRL-based controller (TD3) algorithm outperforms PSO-tuned PID. TD3 is excellent at dissipating vibrations caused by bump excitation. Additionally, it reduces settling time and enhances road holding and ride comfort.

DRL TD3 significantly decreases body acceleration, suspension displacement, and dynamic tire load in comparison to an uncontrolled suspension system by 35.8%, 68.5%, and 33.6%, respectively. Simultaneously, PSO-PID reduces those criteria by 32.2%, 50%, and 12.4%, respectively, compared to MR passive (uncontrolled suspension).

5. Conclusion

Our study highlights the effectiveness of the DRL-based TD3 algorithm in reducing vibrations in semi-active suspension systems with MR dampers. We hope these findings will advance the development of more sophisticated control strategies for semi-active suspensions and encourage further research in this domain. The potential application of DRL algorithms across various fields, along with the integration of transformers and computer vision in future research, could pave the way for significant breakthroughs in control and optimization.

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