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A Speed Limiter System Base Hybrid Deep Reinforcement Learning and Disturbance Observer

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Abstract

Over speeding is the paramount among causes of accidents which also keep an increase in the risks of injuries and crashes. These reports prompted the inspiration of proposing speed limiter system to eliminate human negligence. The proposed controller achieved superior performance: the settling time to stabilize the vehicle speed became shorter and the overshoot was reduced even under critical disturbance. Many approaches to vehicle speed control (VSC) have been proposed to meet these objectives. However, the still suffer from numerous overshoot due to noise such as offset, lag, and communication delay between the display speed and wheel speed. in recent years, the reinforcement learning (RL) approaches have attracted significant attention as a possible solution to address the limitations associated with the real time optimization and the feedback controllers. This paper focuses on the design and experimental validation of a vehicle speed limiter algorithm using a hybrid RL base DOB and a speed observer for speed limit control. The primary objective of this study was to incorporate the RL in VSL control strategies to reduce overshoot when modeling speed limiters with errors and other disturbance. The proposed controller can be an effective solution for the development of automated driving systems and for mass production, since it is simple to implement as well as robust to disturbance.

1. Introduction

Over speeding is the paramount among causes of accidents which also keep an increase in the risks of injuries and crashes [1]. According to Global status report on road safety 2018, Low-income countries possess 1% of the world's vehicles but recorded 13% of road traffic deaths while high-income countries poise 40% of the world's vehicles but records 7% of road traffic deaths. Human errors account for more than 90% of vehicle accidents. In contrast, mechanical failures are accountable for 2% only [2]. These reports prompted the inspiration of proposing speed limiter system to eliminate human negligence. Embedded speed limiters are now becoming a safe assistance for over speeding drivers, which can save the lives of so many people every year. So many researches had been carried out aimed at developing and reliably monitor and limit over speeding with the aid of speed limiter system [3].

Many approaches to vehicle speed control have been proposed to meet these objectives. In the automotive industry the classic method is a proportional integral derivative (PID) controller, since it is simple, robust, and reliable. Many studies have been conducted based on the PID[4, 5]. The performance of the PID controller can be affected by the model uncertainty and external disturbance. Therefore, the PID gain can be conservatively chosen to guarantee its robustness. To improve the performance of the PID, a gain scheduling scheme is used [6], but this requires too many calibration parameters considering driving conditions.

There are also studies based on optimal control theory, such as linear quadratic control [6] and model predictive control[7], to develop longitudinal vehicle control. However, these approaches require an accurate vehicle model. To cope with the problems identified in previous research, many studies have been performed on topics such as PID-based learning algorithms[8], sliding mode control [9], and artificial intelligence [10]. However, most of these methodologies need to be validated in vehicle experiments under various driving conditions. Moreover, the algorithms need to be implemented in a real-time controller. However, in recent years, the reinforcement learning (RL) approaches have attracted significant attention as a possible solution to address the limitations associated with the online optimization and the feedback controllers [11-13].

RL is a type of Machine Learning, and thereby also a branch of Artificial Intelligence. RL allows machines and agents to automatically determine the ideal behavior within a specific context to maximize its performance [14, 15]. The RL learns directly from the interactions between states and actions through trial and error. The RL agent takes optimal actions under various states according to the long-term accumulation of rewards. As a result, a well-trained RL agent can, theoretically, make predictions on system evolution and achieve a proactive control scheme.

Thus, this study proposed a hybrid approach base on RL and DOB for speed limit control. With the contribution of the DOB, the proposed controller can reduce overshoot and minimize steady-state error without feedforward and integrator control. In addition, the speed observer is also designed to reduce the overshoot due to noise such as offset, lag, and communication delay between the display speed and wheel speed, because the proposed controller operates according to the display speed.

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The article is organised as follows: Section 2 elaborates the review of related work; section 3 states the mathematical modelling and the description of the proposed model, while section 5 & 6 presents the experimental results and conclusion are drawn respectively.

2. Related Work

Speed limiter system is classified into four major groups: Speed limiter frameworks which are also referred to as techniques or algorithms, speed limiter simulators, speed limiter sensors and speed limiter experimental setup that are derived from the literatures that applied speed limiter systems of vehicles. However, in this research, we focus on the development and implementation of novel artificial intelligence base speed limiter frameworks and algorithms. Numerous frameworks base on AI have been proposed recently in the context of autonomous and smart driving assistance. For example, [16] presented control scheme for permanent magnet synchronous motors (PMSM). compared to conventional method the result was reliable and effective it was limited when driving in bad weather. Moreso, [17] presented a practical approach for developing speed limiter with the aid of a proportional error gain (P), disturbance observer (DOB) and a speed observer. The proposed approach reduce overshoot and minimized steady-state error compared with conventional controllers.

When there are modeling errors due to control delays, disturbances, and/or testing with a High-Fidelity Model (HFM) of the vehicle, the DRL-trained policy performs better with large modeling errors while having similar performance [18]. Thus, reinforcement learning (RL) addresses the problem of a decision maker faced with a sequential decision problem [19]. However, there are only a limited number of papers in the literature that utilized reinforcement learning in the development of speed limiter system. For example, [20] proposed in RL in controlling a team of unmanned aerial vehicles to maximize wild fire coverage. The results show that DRL outperformed receding-horizon control by a moderate margin. [21] proposed RL in controlling non-linear electrical power oscillation damping where RL is 10 times faster than other method.

In summary, there is a few literatures on DRL in modeling speed limiter with errors and disturbance. Our motive originates from solving a traditional optimal control problem that can be represented by state-space equations.

3. Methodology

In this section, the design of the DOB-based vehicle speed controller is presented. In order to realize the first-order closed-loop system, a proportional controller is applied considering the nominal model. Moreover, the speed observer is designed to minimize the overshoot due to the noise of the display speed.

3.1 Proposed Framework

The primary objective of this study was to incorporate the RL in VSL control strategies to reduce traffic congestion at recurrent merge bottlenecks on freeways. The plant uncertainty and external disturbance are lumped into a disturbance term and compensated for by the DOB. With the contribution of the DOB, the proposed controller can reduce overshoot and minimize steady-state error without feedforward and integrator control. In addition, the speed observer is also designed to reduce the overshoot due to noise such as offset, lag, and communication delay between the display speed and wheel speed, because the proposed controller operates according to the display speed.

RL is inspired by behaviorist psychology considering how agents ought to take actions in an environment in order to maximize the cumulative reward. A RL agent interacts in discrete time steps with its environment which is typically formulated as a Markov decision process (MDP). Optimization of VSL control requires the determination of optimal speed limits. The action of an agent is to activate different speed limits at the decision interval. The transition time from one sate to another state after activating VSL control is unity. Each time the agent takes an action that affects the current state, the state changes. Thus, the VSL control problem can be formulated as a MDP problem and can be processed by RL technique

For this research, A QL-based VSL control strategy was integrated into the speed limit system. The most critical issue was to determine the optimal speed limit given the traffic flow states at the bottleneck area. If the speed limit was too low, the VSL control would transfer delay from the target bottleneck to the upstream area. If the speed limit was too high, the VSL control would not be able to fully prevent the capacity drop. In the proposed control strategy, the optimal speed limit for a particular traffic state was determined using the QL agent as shown in Fig. 1.

The crucial elements in the QL agent included: (a) State (b) Action (c) Reward. The objective of the QL-based VSL strategy was to reduce the system travel time. With the vehicle speed control, the sending and receiving functions were determined by the minimum value between the speed limit of the vehicle speed controller and the free flow speed *Vf:*

$$\sigma_i(k) = \min\{\{v_{sl}(k), v_f\} \cdot d_i\ (k) \cdot n_i, Q_{vsl}\} \tag{1}$$

$$\sigma_i(k) = \min\{w_i \cdot\ (d_{i,jam} - d_i(k)) \cdot n_i, Q_{vsl}\} \tag{2}$$

where $d_i\ (k)$ was the density at cell i at time k, n_i was the number of lanes, Q_{vsl} was the maximum flow under current speed limit, w_i was the kinematic wave speed, and $d_{i,jam}$ was the jam density.

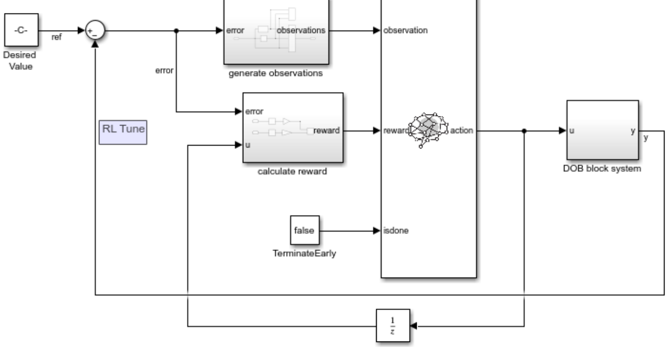

Figure 1: Proposed RL-DOB Observer Tune Model

4. Experimental Results

The performance of the proposed controller was compared to conventional controller such as a PI controller and the DOB-based proportional controller. The parameters of each controller were tuned to have equivalent nominal performance and shown in Table 1 respectively.

Table 1: RL Episode Parameters

Maximum Episode	500
Episode reward	2
Episode Steps	4
Episode Q0	3.885
Average Reward	1.2
Average steps	4
Windows length for averaging	10
Learn rate for actor	0.001
Learn rate for Critic	0.001
Maximum number of episodes	500
Maximum number of Steps per Episode	4

4.2. NCAP test

Overall, the proposed controller consisting of RL, DOB and speed observer are shown schematically in Fig. 2

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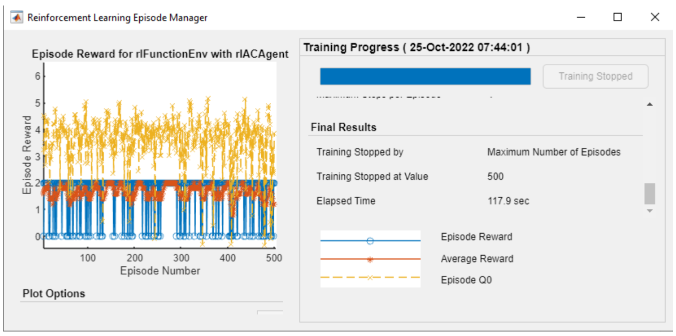

Figure 2: RL episode manager

In order to evaluate the control performance, the vehicle experiments were conducted under NCAP test procedures, which are performed at three representative set speeds. Figures 3 show the results of acceleration tests between the PID, DOB-based controllers and the proposed RL-DOB controller from 0 to 50 km/h, respectively.

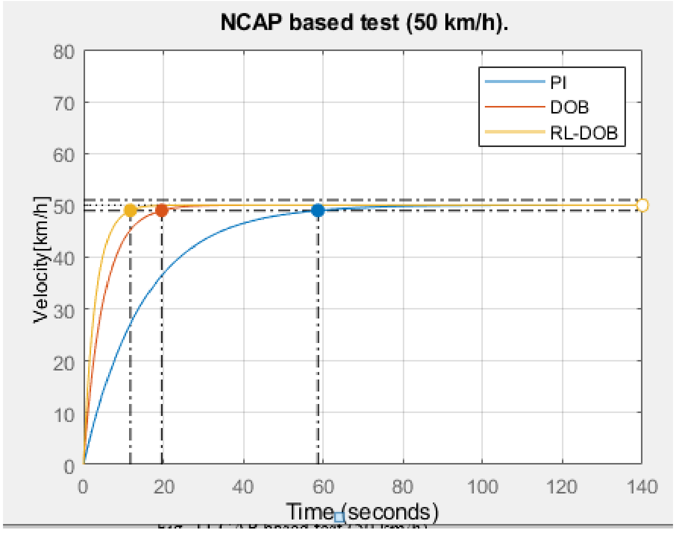

Figure 3: CAP based test (50 km/h).

5. Conclusion

This paper focuses on the design and experimental validation of a vehicle speed limiter algorithm using a hybrid RL base DOB and a speed observer for speed limit control. The primary objective of this study was to incorporate the RL in VSL control strategies to reduce overshoot when modeling speed limiters with errors and other disturbance. Thus, the speed observer is also designed to reduce the overshoot due to noise such as offset, lag, and communication delay between the display speed and wheel speed, because the proposed controller operates according to the display speed and freeway traffic. The proposed controller achieved superior performance: the settling time to stabilize the vehicle speed became shorter and the overshoot was reduced even under critical disturbance. The proposed controller can be an effective solution for the development of automated driving systems and for mass production, since it is simple to implement as well as robust to disturbance.

Declaration of Competing Interest

The authors have declared no conflicting interest.

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