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CONNECTED AUTOMATED VEHICLES AND ITS

# A Comprehensive Driving Decision-Making Methodology Based on Deep Reinforcement Learning for Automated Commercial Vehicles

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## Abstract

Effective driving decision-making significantly enhances the safety of automated commercial vehicles. Different from small passenger vehicles mainly focusing on anti-collision, the inducements of collision and rollover for commercial vehicles are coupled with each other. However, these factors are not considered together which results in a limitation in the safety performance. This paper proposes a novel comprehensive driving decision-making methodology based on deep reinforcement learning (CDDM-DRL) for automated commercial vehicles in expressway scenarios. The CDDM-DRL consists of two parts. First, a feature encoding network is designed to encode hierarchical features from traffic situations and driving conditions, which can provide more useful feature information. Then an actor–critic network incorporating ensemble methods is developed to learn and provide effective driving actions, such as whether to turn and when to turn. Finally, extensive simulations in common and challenging scenarios with different traffic densities were performed. Experimental results show that our proposed method is better than some classical DRL methods in terms of time headway, backward clearance, lateral acceleration, etc. Moreover, it can prevent collision and rollover simultaneously, and realize safe driving decision-making for automated commercial vehicles.

**Keywords** Automated commercial vehicle · Safe decision-making · Anti-collision · Anti-rollover · Deep reinforcement learning

### Abbreviations

| | |
|---|---|
| $p_{\mathrm{lon}}$, $p_{\mathrm{lat}}$ | Longitudinal position and lateral position of the ego vehicle, respectively |
| $v_{\mathrm{lon}}$, $v_{\mathrm{lat}}$ | Longitudinal velocity and lateral velocity of the ego vehicle, respectively |
| $a_{\mathrm{lon}}$, $a_{\mathrm{lat}}$ | Longitudinal acceleration and lateral acceleration of the ego vehicle, respectively |
| $a^*_{\mathrm{lat}}(t)$ | Lateral acceleration threshold of the ego vehicle |
| $\theta_{\mathrm{h}}$ | Heading angle of the ego vehicle |
| $j$ | ID number of the surrounding vehicle |
| $Y_{\mathrm{rel}\_j}$, $X_{\mathrm{rel}\_j}$ | Relative longitudinal position and lateral position with the surrounding vehicle $j$, respectively |
| $v_{\mathrm{rel}\_j}$, $a_{\mathrm{rel}\_j}$ | Relative velocity and relative acceleration with the surrounding vehicle $j$, respectively. |
| $\pi^*$ | Optimal driving action |
| $\pi$ | The output driving action |
| $S_t$ | State at time $t$, which is the input of our proposal |
| $A_t$ | Action at time $t$, which is the output (driving action) of our proposal |
| $A_{\mathrm{lon}}$, $A_{\mathrm{lat}}$ | Longitudinal and lateral action, respectively |
| $R_t$ | Reward at time $t$ |
| $\omega_1, \omega_2, \omega_3$ | Weight factor of the anti-collision reward function, anti-rollover reward function, and yaw stability reward function, respectively |
| $\gamma$ | Discount factor |
| $A^{\pi}(S_t, A_t)$ | Dvantage function |

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