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Modeling the development of vehicle lateral control skills in a cognitive architecture

Shi Cao [a,b], Yulin Qin [a,c,d], Lei Zhao [a], Mowei Shen [a,e,*]

[a] Department of Psychology and Behavioral Sciences, Zhejiang University, Hangzhou 310028, China
[b] Department of Systems Design Engineering, University of Waterloo, Waterloo N2L 3G1, Canada
[c] Koguan Law School, Shanghai Jiao Tong University, 200030 Shanghai, China
[d] Department of Psychology, Carnegie Mellon University, Pittsburgh 15213, United States
[e] The National Key Laboratory of Human Factors, Hangzhou 310028, China

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ABSTRACT

The development of lateral control skills is crucial to driving safety. The current study examined a computational method using a cognitive architecture to model the learning process of vehicle lateral control. In a fixed-base driving simulator, an experiment compared the lateral control performance of non-drivers, novices, and experienced drivers. A cognitive model using Adaptive Control of Thought-Rational (ACT-R) was built to model the learning process of lateral control skills. The modeling results were compared with the human results. The drivers with more experience had better lateral control performance. The model produced similar results as the human results and modeled the progress of learning. The model provided a computational explanation for the mechanisms of lateral control skill learning. Implication and future studies were discussed.

1. Introduction

Computational modeling of driving performance has important theoretical and practical values to transportation research and safety, because computational models can help reveal the mechanisms underlying drivers' performance and support safety practices. Previous studies have proposed and examined driving performance models of both lateral control (Salvucci & Liu, 2002), longitudinal control (Eilers, Möbus, Tango, & Pietquin, 2013; Ranney, 1999; Sato & Akamatsu, 2008), and driving with concurrent tasks (Cao & Liu, 2014; Wu & Liu, 2007). However, few computational models have been developed to explain the learning of vehicle control skills. Adding the factor of driving experience, a recent study has built cognitive-architecture-based models that captured the difference in collision avoidance braking behavior between drivers with different levels of experience (Cao, Qin, Jin, Zhao, & Shen, 2014). Following the same line of research, the current study tested and examined a cognitive-architecture-based model that can simulate the learning progress of vehicle lateral control skills as the model cumulated experience in driving a simulated vehicle. We first compared the lateral control performance of three groups of drivers with different levels of experience in a simulated driving experiment and then developed a model in a cognitive architecture that can learn from a "non-driver" to an "experienced driver."

* Corresponding author at: Department of Psychology and Behavioral Sciences, Xixi Campus, Zhejiang University, Hangzhou 310028, China. Tel.: +86 571 88273820.

E-mail address: mwshen@zju.edu.cn (M. Shen).

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An important reason to model drivers' skill learning is to understand the mechanisms of drivers' skill acquisition and develop efficient and effective training methods (Huang & Ford, 2012; Weiss, Petzoldt, Bannert, & Krems, 2013). Novice drivers have been overrepresented in crashes (Cooper, Pinili, & Chen, 1995), partly due to their lack of driving skills (Groeger, 2000). Previous studies have identified novice drivers' skill deficiency, in the aspects of visual search (Mourant & Rockwell, 1972), hazard perception (Borowsky, Shinar, & Oron-Gilad, 2010), and vehicle control (Blaauw, 1982). To improve driving skills and safety, a wide range of countermeasures has been developed, including graduated licensing (Williams & Ferguson, 2002), hazard awareness training (Pollatsek, Narayanaan, Pradhan, & Fisher, 2006), and driving simulator training (Roenker, Cissell, Ball, Wadley, & Edwards, 2003). The development of effective training programs requires a substantial understanding of the mechanisms underlying driving skill learning.

Existing theories related to driving skill learning include the power law of practice (Fitts, 1964), the three stages of motor learning (Anderson, 1982; Fitts, 1964), closed-loop theory (Adams, 1971), and schema theory (Schmidt, 1975) (for a review, see Schmidt & Lee, 1999). These theories are mostly qualitative except the power law of practice, which is per se limited to modeling reaction time. There is still a lack of computational theories that can quantitatively model the learning of vehicle control skills. To fill in this research gap, the current study aims to develop a computational model that can simulate the learning of lateral control skills. A cognitive architecture called Adaptive Control of Thought-Rational (ACT-R), which has been used to model and explain cognitive skill learning (Anderson et al., 2004; Taatgen, Huss, Dickison, & Anderson, 2008), was extended and adopted to model the perceptual-motor learning of vehicle lateral control.

The following paragraphs introduce the bases of the modeling method used in this study, including the ACT-R cognitive architecture and a previous ACT-R driving model. Due to the limited space, we can only provide a concise review with the key points (for details, see Anderson & Lebiere, 1998; Anderson et al., 2004; Salvucci, 2006).

A cognitive architecture is both a computational theory of human cognition and a simulation program (Byrne & Pew, 2009). The current study used the ACT-R cognitive architecture, because (1) it has relatively well-developed learning mechanisms that can be extended and used to model driving skill learning, and (2) a previous study (Salvucci, 2006) has built an ACT-R driving model that provides the basic structure for the model in the current study.

In ACT-R, skills are represented as production rules, i.e., condition-action (IF-THEN) pairs. Each rule takes 50 ms (by default) to execute and has a utility that represents the relative desirability of use the rule. ACT-R assumes one rule per processing cycle, so multiple rules matched in the same cycle will compete. Rules with greater utilities have greater chances of being used. A production rule learning mechanism in ACT-R is the PG-C algorithm that updates a rule's utility based on its success rate P (Taatgen & Anderson, 2002; Taatgen et al., 2008). A rule's utility equals to P times G (goal value) minus C (cost). Among competing rules, the rules with higher success rates (superior rules) will get higher utilities than other rules with lower success rates (inferior rules), so the model can learn from both successes and failures. This algorithm is a computational implementation of trial-and-error learning, which has been studied for about a hundred years and applied in a wide range of fields including psychology (Hull, 1930), organizational behavior (Rerup & Feldman, 2011), artificial intelligence (Sutton & Barto, 1998), and autonomous vehicle control (Oh, Lee, & Choi, 2000). Compared with machine learning and artificial intelligence studies, this study (as well as other cognitive modeling studies) aims to accurately model human performance, including the limitation of human cognition, rather than to achieve general intelligence that may exceed human intelligence.

Salvucci (2006) built a driver model in ACT-R, utilizing a two-level control model that determines the change of the steering angle ($\Delta\varphi$) based on the near point visual angle (θ_{near}) and the far point visual angle (θ_{far}) as in Eq. (1),

$$\Delta\varphi = k_{far}\Delta\theta_{far} + k_{near}\Delta\theta_{near} + k_I \min(\theta_{near}, \theta_{n\max})\Delta t, \tag{1}$$

where $\theta_{n\max}$ (set to 0.07) controlled the maximum of θ_{near}. The duration of a control cycle is represented by Δt; min represents the function of minimum; k_{far}, k_{near}, and k_I are three parameters, controlling the weights of the three components in the equation, that is, a stable far point angle, a stable near point angle, and a near point at the center of the lane (Salvucci & Gray, 2004). The near point is set as the middle point of the lane 10 m ahead, and the far point is one of (a) the vanishing point of a straight road, or (b) the inner tangent point of an upcoming curve, or (c) the lead vehicle when there is one. In a typical control cycle, three production rules fire consecutively in 150 ms, perceive visual information and issue a motor control action turning the steering wheel to maintain lateral position in the center of the lane.

The previous ACT-R driving model was designed to model generally experienced drivers and therefore has no learning mechanism. The current study focuses on modeling the learning of lateral control skills, comparing the modeling results to the human data collected from a simulated driving experiment.

2. Method

2.1. Participants

Forty-five adults, non-drivers, novices, and experienced drivers each 15 persons, participated in the experiment. For the three groups, the recruiting criteria were no driving experience for non-drivers, holding a valid driver's license but with a total mileage no more than 1000 km for novices, and holding a valid driver's license and with a total mileage no less than 200,000 km for experienced drivers respectively.