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ScienceDirect

Cognitive Systems Research

Cognitive Systems Research 50 (2018) 67–82

www.elsevier.com/locate/cogsys

A motivational driver steering model: Task difficulty homeostasis from control theory perspective

Action editor: Emilio Del-Moral-Hernandez

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Received 6 September 2017; received in revised form 9 January 2018; accepted 24 March 2018
Available online 7 April 2018

Abstract

A general and psychologically plausible collision avoidance driver model can improve transportation safety significantly. Most computational driver models found in the literature have used control theory methods only, and they are not established based on psychological theories. In this paper, a unified approach is presented based on concepts taken from psychology and control theory. The "task difficulty homeostasis theory", a prominent motivational theory, is combined with the "Lyapunov stability method" in control theory to present a general and psychologically plausible model. This approach is used to model driver steering behavior for collision avoidance. The performance of this model is measured by simulation of two collision avoidance scenarios at a wide range of speeds from 20 km/h to 170 km/h. The model is validated by experiments on a driving simulator. The results demonstrate that the model follows human behavior accurately with a mean error of 7%.

Keywords: Unified approach; Task difficulty homeostasis theory; Lyapunov stability method; Collision avoidance; Steering behavior

1. Introduction

Cognitive science, artificial intelligence (AI), and control engineering are the main fields of science for manufacturing new generation of intelligent machines, robots, and industrial systems. Cognitive scientists (psychologists, mathematicians, and computer science researchers) try to discover human brain operations to build brain computational models. AI researchers try to investigate cognitive models or other reasonable algorithms to make applicable intelligent systems. Control engineers try to develop mathematics of dynamic systems to grantee the stability and accuracy of the intelligent machines, robots, or other physical systems. They also consider the effect of sensor and actuator limitations in physical performance of the system. As complicated industrial intelligent systems demand all of the above abilities, today cognitive science, AI, and control engineering are getting closer so that no distinct boundary can be found between these fields of science.

Some intelligent systems, like intelligent drivers, need to represent complicate behaviors containing numerous factors, measurements, and uncertainties. Common traditional control engineering methods can not directly construct a controller to behave comprehensively, and cognitive or AI approaches should be joined to overcome the problems. Driving is an exact example of such applications especially when the intelligent system should interact with human drivers in advanced driver assistant systems (ADAS). In this study, a multidisciplinary approach is

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https://doi.org/10.1016/j.cogsys.2018.03.007
1389-0417/

devised for intelligent driver models that can be used also in other similar intelligent systems and AI applications.

Human-based driver models can be used for multitude of applications such as autonomous vehicles, advanced driver assistance systems (ADAS), traffic safety studies, and driver behavior analysis. The most challenging issue to improve intelligent transportation systems is the interaction with human drivers. Intelligent systems which are not human-based probably face more complexity to understand and predict human driver's behaviors. Accordingly, a psychological plausible driver model open a new way for psychologist, AI researchers, traffic engineers, and ADAS designers to explore the human driver's behavior and interact more effectively.

Despite the fact that many researchers in the fields of traffic psychology, ergonomics, cognitive science, control theory, and traffic engineering have created numerous models to describe driver's behavior, there is no generally-accepted model yet.

In the past decades, enormous variety of driver behavior models has been introduced. According to driver model classification stated in Winter and Happee (2012), driver models can be classified in two major groups: unspecific models and specific models.

The first group is built on psychological point of view like motivational models (Fuller, 2005; Wilde, 1994). Such models are unspecific, qualitative, and comprehensive. They do not present any mathematical formulation to be used as an input–output model. Also, there is no quantitative result to evaluate their performance (Winter & Happee, 2012). The second group is built on vehicle dynamics and control theories, which are specific, quantitative and deal with driving details. The specific models define distinct mathematical formulation to be used as an input–output model, while their paradigm is not consistent with driver psychological perspective (Winter & Happee, 2012). Consequently, there is a gap between motivational and control theory models.

This paper aims to unify unspecific and specific models. A suitable mathematical formulation for motivational models is devised by control theory methods. This model enjoys the generality of motivational models and also stability and exactness of control theory models.

The risk homeostasis theory (Wilde, 1994) and the task-difficulty homeostasis theory (Fuller, 2005) are the most well-known motivational models. The risk homeostasis theory demonstrates that the driver controls the perceived risk and keeps it close to the target level of risk. This theory was implemented to justify why introduction of antilock brake systems did not decrease the number of accidents as had been predicted before. The task difficulty homeostasis theory considers task difficulty as the main motivation similar to the risk homeostasis theory. It is used to define how drivers choose speed in different situations. The task-difficulty homeostasis theory is better suited to the control engineering techniques used in this paper. In this paper, task difficulty homeostasis theory is mathematically formulated by means of Lyapunov stability method (Lyapunov, 1992) of the control theory.

Task difficulty is estimated based on two major driving motivations for decision making as (a) task demand, and (b) driver capability. When demand is significantly less than driver capability, the task is easy. When demand equals driver capability, the task is achievable, but very difficult. If demand is more than capability, loss of vehicle control occurs. The driver tries to control the vehicle so that her/his capability exceeds task demand. This motivational model creates a platform for a general model devised in this paper.

The Lyapunov stability theory determines the stability of a dynamic system response such as a vehicle response in a collision avoidance maneuver. It defines a positive definite function and computes its time derivative. If the time derivative is negative, the positive definite function is bounded and the response is stable.

The task difficulty homeostasis theory can be formulated with the "Lyapunov stability theory" so that it can be considered as a unified multidisciplinary approach. The task demand can be used as a positive definite function. If the driver input is defined such that the time derivative of task demand becomes negative, the task demand will decrease and the loss of control will not occur.

This unified approach is applied to model driver steering behavior for collision avoidance in common traffic scenarios. Some research works have addressed driver steering models for collision avoidance using specific methods. They employ numerous methods such as fuzzy logic (Bauer, 2012; Grefe, 2005; Kovacs & Koczy, 1999; Llorca et al., 2011), neural network (Chonga, Montasir, Flintschc, & Higgsd, 2013), model predictive control (MPC) (Cao, Cao, Yu, & Luo, 2016; Erlien, Fujita, & Gerdes, 2016; Gray, Gao, Hedrick, & Borrelli, 2013; Kamal, JunImura, Hayakawa, Ohata, & Aiha, 2014), and optimal control (Gordon & Gao, 2014; Hayashi, Isogai, & Raksinchar, 2012; Phuc Le & Stiharu, 2013) to handle steering control. Moreover, some researchers try to consider cognitive limitations and human characteristics similar to human drivers on their models (Bi, Wang, Wang, & Liu, 2015; Fuller, Matthew, & Liu, 2010; Johns & Cole, 2012; Johns & Cole, 2015; Keen & Cole, 2006; Lio et al., 2015; Macadam, 2003; Odhams & Cole, 2009).

Most of the afore-mentioned models are designed to control steering wheel for specific applications. In addition, their mathematical formulation does not estimate human motivations or feelings so that they are not psychologically plausible.

Fuzzy logic driver models are usually developed for specific applications to limit the number of rules. In Llorca et al. (2011), an autonomous pedestrian collision avoidance system is presented, which processes lateral displacement and speed as input signals using fuzzy logic membership functions. Although this is a valid approach, it is not based on human driver perspective and is not psychologically plausible.