Modeling Multi-Level Choices of Control Transitions In Full-Range Adaptive Cruise Control

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Extended abstract (992 words)

Introduction

Driving assistance systems such as Adaptive Cruise Control (ACC) and automated vehicles can contribute to mitigate traffic congestion, accidents, and levels of emissions. Automated vehicles may increase roadway capacity, improve traffic flow stability, and speed up the outflow from a queue [1]. The functionalities of automated systems have been gradually introduced into the market, such as in the case of Adaptive Cruise Control (ACC). The ACC assists drivers in maintaining a desired speed and time headway, therefore influencing substantially the performance of the driving task. In certain traffic situations, drivers may prefer to disengage ACC and resume manual control [2]. These transitions between automation and manual driving are called *control transition* [3] and may influence considerably traffic flow efficiency [4] and safety [5]. Recently, *full-range* ACC systems that can operate in dense traffic have been introduced into the market. These ACC systems are more likely to be active in dense traffic conditions and have a positive impact on traffic flow efficiency [6]. Despite the influence of control transitions on driving behavior, most car-following and lane-changing models currently used to evaluate the impact of ACC do not describe this process and therefore could result in misleading predictions. A few microscopic traffic flow models [7-9] have proposed deterministic decision rules for transferring control, which do not account for variability between and within drivers in the decision-making process. Recently, Varotto et al. [10] have identified the main factors influencing drivers' choice to resume manual control in full-range ACC. Drivers are likely to deactivate the system when approaching a slower leader and to overrule it by pressing the gas pedal a few seconds after it has been activated. However, this study did not quantify explicitly the range in which the ACC system operation is acceptable for drivers and ignored the possibility of adapting the ACC target speed to regulate the longitudinal control task. For this purpose, a comprehensive model framework explaining the underlying decision-making process of drivers in control transitions and speed regulations is needed.

Research objectives

This research aims to develop such a novel modelling framework and test the following research hypotheses based on empirical data:

H_1: Control transition and speed regulation choices with full-range ACC are related to the driver behavior characteristics (speed, acceleration, distance headway and relative speed) which inform risk feeling and task difficulty evaluations in driver control theories [11];

H_2: The range in which ACC system operation is considered acceptable differs significantly between drivers and is influenced significantly by driver characteristics.

Research Methods

Based on previous studies [10-12], we propose two levels of decision-making (Figure 1): risk feeling and task difficulty evaluation, and system state and speed regulation choice. At the highest level, the driver evaluates whether the *actual level* of risk feeling and task difficulty (RFTD) falls within the range which is considered *acceptable* to maintain the ACC active and the current target speed. The

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unobservable RFTD is modelled as a latent variable with a mean value which is a function of the driver behavior characteristics. The RFTD evaluation is formulated as an ordered probit model in which two parameters linked to the driver characteristics define the lowest and the highest feeling of risk acceptable. Drivers who feel a risk higher than the maximum value acceptable choose to deactivate the ACC (transition to *Inactive*) or to maintain the system active and decrease the target speed. If the actual RFTD level falls within the acceptable range, the ACC remains active and the target speed is not regulated. Drivers who feel a risk lower than the minimum value acceptable choose to overrule the system by pressing the gas pedal (transition to *Active and accelerate*) or to maintain the system active and increase the target speed. These decisions are formulated as logit models in which the choices are influenced by the functionalities of the ACC system and environmental conditions. An individual specific error term is introduced to capture the effect of unobserved drivers' characteristics on the choices repeated over time. The probability of deactivating the ACC is given by the product of the probability of the actual level of RFTD being above the maximum acceptable value and the conditional probability of transferring to *Inactive*. The probability of overruling the system by pressing the gas pedal is given by the product of the probability of the actual level of RFTD being below the minimum acceptable value and the conditional probability of transferring to *Active and accelerate*.

Results

The model is estimated using the software PythonBiogeme [13]. The dataset was collected in an on-road experiment in which twenty-three participants drove a research vehicle equipped with full-range ACC on a 35.5-km freeway in Munich during peak hours. Estimation results showed that the risk feeling and task difficulty are considered high when driving at high speeds and short headways, and when approaching a considerably slower vehicle. Interestingly, experience with the ACC system, driving styles, self-reported workload and perceived usefulness of the system influence significantly the acceptable range of risk feeling. When the risk feeling is above the maximum value acceptable, drivers are more likely to deactivate the system in proximity to on-ramps and before exiting the freeway. When the risk feeling is below the minimum value acceptable, drivers are more likely to overrule the system by pressing the gas pedal a few seconds after the system has been activated.

Conclusion and future research

These findings shed light on the decision-making of drivers when transferring control and regulating the desired speed and have important implications for developing driving assistance systems which can adapt their settings based on different traffic situations and driver characteristics. The key implication of this study is that, to describe driver interaction with ACC, we need a conceptual framework that connects driver behavior characteristics, driver characteristics, ACC system settings, and environmental factors. Current research efforts focus on the model development and estimation. The final model can be implemented into a microscopic simulation to assess the impact of control transitions on traffic flow efficiency and safety.

Keywords: Control transitions, Adaptive Cruise Control, on-road experiment, driver behavior, choice model.

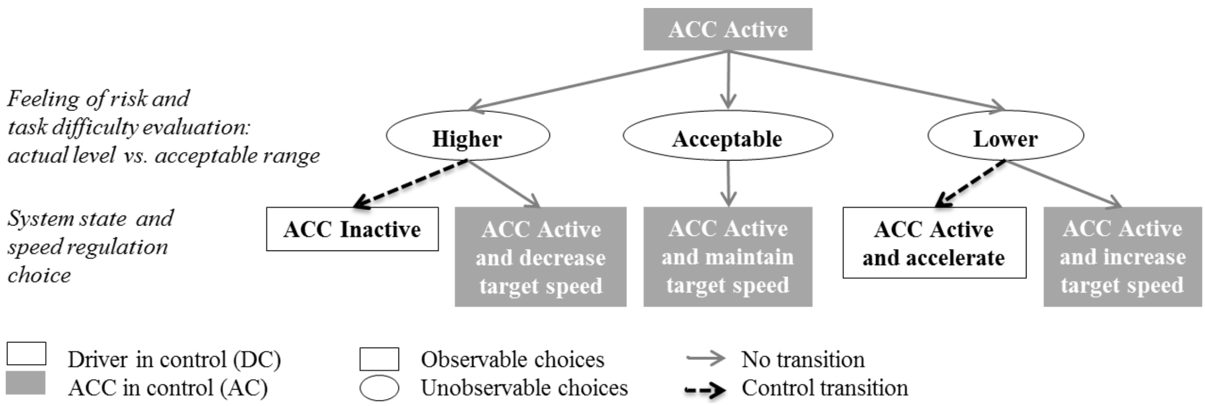

Figure 1: Model framework for driver behavior in control transitions between ACC and manual driving.

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