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Connected cruise control among human-driven vehicles: Experiment-based parameter estimation and optimal control design

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ABSTRACT

In this paper, we consider connected cruise control design in mixed traffic flow where most vehicles are human-driven. We first propose a sweeping least square method to estimate in real time feedback gains and driver reaction time of human-driven vehicles around the connected automated vehicle. Then we propose an optimal connected cruise controller based on the mean dynamics of human driving behavior. We test the performance of both the estimation algorithm and the connected cruise control algorithm using experimental data. We demonstrate that by combining the proposed estimation algorithm and the optimal controller, the connected automated vehicle has significantly improved performance compared to a human-driven vehicle.

1. Introduction

Over the past few decades, passenger vehicles are equipped with more and more automation features during the efforts to improve active safety, passenger comfort, and traffic efficiency of the road transportation system. In particular, adaptive cruise control (ACC) was invented to alleviate human drivers from the constant burden of speed control (Labuhn and Chundrlik, 1995). While the influence of ACC is yet to be observed in real traffic due to its low penetration rate, theoretical studies have found that ACC-equipped vehicles may only have limited benefits on traffic flow (Vander Werf et al., 2002; van Arem et al., 2006; Shladover et al., 2012). In particular, ACC vehicles may not be able to effectively suppress the speed fluctuations propagating through the vehicle string, as each ACC vehicle only responds to its immediate predecessor (Barber et al., 2009).

In order to overcome such limitations in an ACC-equipped vehicle platoon, cooperative adaptive cruise control (CACC) has been proposed using vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication (Milanes et al., 2011; Wang et al., 2014; Ploeg et al., 2014b; Ploeg et al., 2014a; Milanes and Shladover, 2014; di Bernardo et al., 2015; Wang, 2018). CACC has been shown to improve fuel economy and traffic efficiency both in theory and in experiments (Li et al., 2015; Zhou et al., 2017; Lioris et al., 2017; Li et al., 2017a; Li et al., 2017b; Li et al., 2017c). However, the application of CACC in the early stages of driving automation may be significantly limited by the requirement that all vehicles in a CACC platoon be equipped with ACC aside from V2X communication devices (van Nunen et al., 2012; Englund et al., 2016). In particular, (Shladover et al., 2015) commented that "at low market penetrations, ⋯ the probability of consecutive vehicles being equipped is negligible". Since V2X devices have relatively low cost compared with ACC and other driving automation systems, it is desirable to exploit the benefits of V2X without being restricted by the penetration rate of ACC. Thus, we need to consider a connected automated vehicle design that is able to utilize V2X information in partially connected and automated environment (Jiang et al., 2017; Zhao et al., 2018; Fountoulakis et al., 2017).

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For the longitudinal control of such a connected automated vehicle, we proposed a class of connected cruise controllers (CCC) that exploit ad hoc V2V communication with multiple human-driven vehicles ahead (Orosz, 2016; Ge et al., 2018). Indeed, connected cruise control can be viewed as an "advanced CACC implementation that adds information from vehicles that are beyond the direct line of sight" (Shladover et al., 2015). By utilizing motion information from multiple vehicles ahead, connected cruise control is able to gain "phase lead" as it responds to speed fluctuations propagating through the vehicles (Orosz et al., 2017). Several theoretical studies have shown that connected cruise control is able to significantly improve active safety, fuel economy, and traffic efficiency of the connected automated vehicle, especially by providing head-to-tail string stability (Zhang and Orosz, 2016; Ge and Orosz, 2014; Avedisov and Orosz, 2017; Orosz, 2016; Ge et al., 2016).

However, previous studies generally assumed that the connected automated vehicle has a priori knowledge on the dynamics of its predecessors (Zhang and Orosz, 2016; Ge and Orosz, 2014; Qin and Orosz, 2017). While such an assumption may hold for a platoon of pre-assigned automated vehicles (Ploeg et al., 2014b; van Nunen et al., 2012; Englund et al., 2016), it will not hold for a system where a connected automated vehicle drives behind several human-driven vehicles. Therefore, to create "comprehensive preview" about incoming traffic perturbations based on motion information farther ahead (Shladover et al., 2015), the driving parameters of preceding human-driven vehicles need to be estimated. Once the human car-following behavior can be described quantitatively, connected automated vehicle designs can be implemented among human-driven vehicles in real traffic, and the benefits of V2V can be harvested beyond platoons of automated vehicles.

While the steady-state driving behavior of individual cars can be deduced from aggregated traffic data, driving parameters such as the feedback gains and driver reaction time delay need to be estimated based on the trajectories of individual cars. While feedback gains can be estimated in delay-free systems using Lyapunov-type methods (Diop et al., 2001; Gomez et al., 2007) and data-driven methods (Monteil and Bouroche, 2016; Lin et al., 2018), it is still challenging to estimate the delay time and feedback gains simultaneously (Orlov et al., 2003; Drakunov et al., 2006; Ge and Orosz, 2016). Moreover, stringent convergence conditions often make Lyapunov-type methods unrealistic for human parameter estimation in real-world traffic. Thus, in this paper we propose a sweeping least square method to simultaneously estimate human feedback gains and reaction time delay using motion information received through V2V, in particular the dedicated short range communication (DSRC). By testing the sweeping least squares algorithm with experimental data, we obtain the distributions and variations of human feedback gains and driver reaction time. Then, using the optimal connected cruise control framework established in Ge and Orosz (2017), we design a connected cruise controller and demonstrate the performance improvements of the connected automated vehicle following human-driven vehicles. While stochastic perturbations and gains in human-driven vehicles have been considered (Moser et al., 2018; Chen et al., 2018), this CCC design is among the first efforts to consider stochastic reaction time delay in human-driven vehicles.

The rest of this paper is organized as follows: in Section 2 we describe a theoretical car-following model for human-driven vehicles; in Section 3 we propose a sweeping least square method to estimate driving parameters for human drivers; in Section 4 we validate the estimation algorithm in a four-car experiment and discuss the variation and distribution of human parameters; in Section 5 we design an optimal connected cruise controller based on the average human car-following behavior and demonstrate the performance improvement; and finally in Section 6 we conclude the results and discuss future research directions.

2. Theoretical car-following model

In this section, we consider the longitudinal motion of vehicles in a single lane; see Fig. 1(a), and introduce the theoretical car-following model in non-emergency situations (Helbing, 2001; Treiber et al., 2006; Orosz et al., 2010). The dynamics of a conventional vehicle i is

$$\begin{aligned}\dot{h}_i(t) &= v_{i+1}(t) - v_i(t),\\ \dot{v}_i(t) &= \alpha_i(V_i(h_i(t-\tau_i)) - v_i(t-\tau_i)) + \beta_i(v_{i+1}(t-\tau_i) - v_i(t-\tau_i)).\end{aligned} \tag{1}$$

Here the dot stands for differentiation with respect to time t, h_i denotes the spacing, (i.e., the bumper-to-bumper distance between the vehicle i and its predecessor), and v_i denotes the velocity of vehicle i; see Fig. 1(a). According to (1) the acceleration is determined

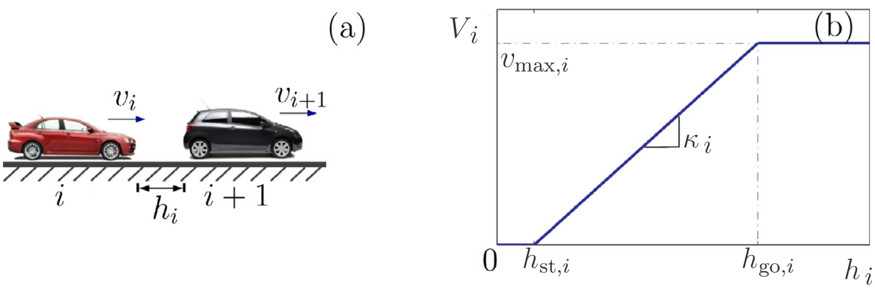

Fig. 1. (a): Single-lane car-following of human-driven vehicles showing the spacing and the velocities. (b): The range policy (2) where $v_{\max,i}$ is the maximum velocity, $h_{\mathrm{st},i}$ is the smallest spacing before the vehicle intends to stop, and $h_{\mathrm{go},i}$ is the largest spacing after which the vehicle intends to maintain $v_{\max,i}$.