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Managing partially automated network traffic flow: Efficiency vs. stability

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ABSTRACT

This paper analyzes how a central agent may bring a mixed traffic system including both human-driven and autonomous vehicles to an equilibrium that both maximizes the efficiency and is stable under the control. The evolution of the human drivers' route choices, as well as the agent's control measures, is described using a joint day-to-day (DTD) dynamical model based on probability route choice. Within this setting, we show that (1) the fixed point of the proposed dynamical system coincides with the unique mixed equilibrium, and (2) the system is asymptotically stable *in continuous time*, namely it always converges to the mixed equilibrium from a given initial state. We then examine how alternative control policies may affect the transition trajectory leading to the mixed equilibrium. Two alternative control schemes are proposed and analyzed. The first, referred to as the stability-first control, aims to stabilize a given disequilibrium as soon as possible. The second seeks to minimize the total system cost accumulated over the transition period, hence called the efficiency-first control. We propose a continuous time optimal control formulation for both schemes and discuss how the formulation can be discretized and solved to local optimality using existing algorithms. Numerical experiments conducted on two illustrative examples highlight the differences among the three control schemes and how the share of autonomous vehicles affects the tradeoff between the efficiency and stability of the mixed traffic system.

1. Introduction

Since Google Inc. launched its self-driving car project in 2009, autonomous vehicle technology has been advancing at a breathtaking pace, rapidly moving from science fiction movies into the planning books of car manufacturers, mobility service providers, city managers, and transportation engineers alike. Bertoncello and Wee (2015), after interviewing more than 30 experts around the world, predicted that autonomous vehicles could begin to enter consumer market as early as 2020 and become the mainstream transport mode by 2050. Various studies estimate that AVs could significantly reduce traffic-related accidents (Bertoncello and Wee, 2015), increase road capacity (Ackerman, 2012), lower the overall travel cost, and cut the carbon footprint of travel (Greenblatt and Saxena, 2015). Perhaps more important, AVs are poised to undermine the foundation of the present car ownership structure—Tuttle (2015) estimates the car ownership could plunge by almost

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50%—and thereby reshape all industries built on top of it: car manufacturing, car insurance, transportation, to just name a few.

While experts are still debating when and how the world will be ready for AVs, most agree that the society must be prepared to not only embrace the impacts, but also take advantage of these robots. Among other things, AVs bestow traffic engineers the ability to fully control a large fraction of vehicular traffic, which they have dreamed about for years. A critical issue, however, is how to deal with a traffic mix that consists of both AVs and those driven by humans (referred to hereafter as human-driven vehicles, or HVs). Realizing that this problem will persist for years to come (perhaps until HVs are outlawed), much of the current research efforts focus on addressing the various challenges inherent in such a mixed traffic system. Levin and Boyles (2016b) propose a cell-based dynamic traffic assignment model that allows human and autonomous vehicles to share the roads. Levin and Boyles (2016a) then apply the above model to optimize dynamic lane reversal decisions, which change lane directions at high temporal and spatial resolutions in order to fully utilize the controllability of autonomous traffic. Some researchers suggest that operating autonomous and human vehicles on separated infrastructure may be more efficient (Godsmark and Kakkar, 2014). For example, AVs can form platoons much more easily in a dedicated area/lane free of HVs' interference. Chen et al. (2016, 2017) examine the issue of optimally dedicating part of the infrastructure to AVs. In the former, the allocation of lanes is considered; whereas in the latter, an entire area in the network is designated as an AV-only zone, within which the route choice of AVs is fully controlled to maximize operational efficiency.

Unlike Chen et al. (2017), this study assumes that the route choice of all AVs can be controlled by a central agent regardless of where they are in the network. Therefore, the challenge for the agent is not to make an optimal zoning decision, but rather to anticipate the interactions between human and autonomous vehicles, and to choose a proper route for each AV in order to achieve a desirable system objective. A similar setting is adopted in Zhang and Nie (2018), which aims at exploring the tradeoff between efficiency (i.e., the travel time savings) and control intensity (i.e., the number of AVs from each OD pair that must surrender their own route choice to the agent). This paper will examine and compare, for any given market penetration rate of AVs, various control strategies that the central agent may choose to bring the mixed traffic system to a stable equilibrium, where the system both admits the maximum efficiency and is stable under control.

We shall start with a simple and myopic control policy, which guides the AVs to maximize the system efficiency on day t according to the observations made on day $t-1$. Hence, the evolution of human drivers' route choices, as well as the agent's adaptive control measures, is described using a joint day-to-day dynamical model based on probability route choice (Cantarella, 2013; Cantarella and Cascetta, 1995; Cascetta and Cantarella, 1993; Horowitz, 1984; Watling, 1999). Within this setting, we first show that the fixed point of the proposed dynamical system coincides with the unique mixed equilibrium. We then prove the asymptotic stability of the system, which asserts that the proposed dynamical system always converges to the mixed equilibrium *in continuous time*. To the best of our knowledge, the proof of the asymptotic stability in the given setting—mixed equilibrium, probabilistic path choice, and continuous time—is new.

Another focus of the present paper is on the transition trajectory leading to the mixed equilibrium from an initial state, or a disequilibrium. As Friesz et al. (1994) noted, in reality, the underlying transportation network rarely stays at a stationary state due to the changes in infrastructure (e.g. topology, capacity, and mode), transport/land use policies and demand patterns. In the context of the present paper, the market penetration rate of AVs is expected to increase robustly in a long transition period (Litman, 2014), which would render the stable equilibrium a constant moving target. It is thus essential to understand how the transition to the equilibrium may be guided by controlling an AV fleet.

In this paper, the agent is assumed to have the choice between minimizing (1) the length of the transition period and (2) the cumulative cost that the system incurs for a given transition period. The first objective concerns the system's ability to return to the equilibrium as soon as possible (i.e., stability), while the second focuses on the "lifecycle" system cost associated with the transition (i.e., efficiency). Which objective is more appropriate depends on the underlying application and needs not concern us for now. Instead, the focus is to formulate and solve the control problems corresponding to these objectives, and to explore their differences and similarities through numerical results.

The rest of this paper is organized as follows. Section 2 briefly reviews the literature and explains how the existing studies differ from and are related to the present paper. Section 3 presents notations and theoretical results about the mixed traffic equilibrium. Section 4 describes the day-to-day dynamical model embedded with a simple control scheme and discusses its properties. Section 5 proposes two alternative optimal control strategies and formulates the resulting optimization problems using the optimal control theory. Section 6 presents and discusses the results of numerical experiments and the last section concludes the study with a summary of findings and remarks on directions for future research.

2. Related studies

2.1. Mixed traffic equilibrium

Mixed traffic equilibrium problems have been studied for decades in various forms. Haurie and Marcotte (1985) assume that traffic from each OD pair is controlled by an independent agent, who competes with other agents non-cooperatively – following the user equilibrium, or UE, principle – while attempting to minimize the total travel cost for the traffic under her control – following the system optimum, or SO, principle. Harker (1988) not only proves the existence and uniqueness of such a mixed equilibrium in a more general setting (i.e., each agent is allowed to control more than one OD pair) but