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Comparing traffic state estimators for mixed human and automated traffic flows ☆

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ABSTRACT

This article addresses the problem of modeling and estimating traffic streams with mixed human operated and automated vehicles. A connection between the generalized Aw Rascle Zhang model and two class traffic flow motivates the choice to model mixed traffic streams with a second order traffic flow model. The traffic state is estimated via a fully nonlinear particle filtering approach, and results are compared to estimates obtained from a particle filter applied to a scalar conservation law. Numerical studies are conducted using the Aimsun micro simulation software to generate the true state to be estimated. The experiments indicate that when the penetration rate of automated vehicles in the traffic stream is variable, the second order model based estimator offers improved accuracy compared to a scalar modeling abstraction. When the variability of the penetration rate decreases, the first order model based filters offer similar performance.

1. Introduction

The recent viability of *vehicle automation and communication systems* (VACS) has motivated a growing interest to understand how modern transportation systems will evolve when the technologies are available at scale. Although the dream was first illustrated by General Motors as early as 1939 at the Highways & Horizons exhibit at the New York World's Fair, widespread commercial research and development of automated vehicles was brought to fruition following the DARPA Grand Challenges in the 2000s. An overview of other key historical developments in vehicle automation and communication systems (e.g., automated highways Fenton and Mayhan, 1991; Bender, 1991, automated vehicle control Shladover et al., 1991) leading to the state of practice today can be found in the reviews (Shladover, 1995; Ioannou, 2013; Van Arem et al., 2006; Buehler et al., 2009).

With the emergence of mixed traffic flows now eminent, the problems of modeling, estimating, and managing mixed traffic streams is now a pressing concern. Unlike human piloted vehicles, *automated vehicles* (AVs) have the capability to significantly reduce the headway between vehicles, potentially adding capacity without increasing the physical infrastructure. Because the AVs may have significantly different operating characteristics compared to the human operated vehicles, an open question is how to model and estimate traffic conditions when the flow is composed of a mix of VACS and non-VACS vehicles. Studies addressing various aspects of the modeling problem include (Bose and Ioannou, 2003; Li and Ioannou, 2004; Shladover et al., 2012; Diakaki et al., 2015; Ngoduy, 2012, 2013; Levin and Boyles, 2016). The articles

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(Ngoduy, 2012, 2013) propose a gas-kinetic macroscopic model to describe the operations of cooperative adaptive cruise control (CACC) traffic flow and adaptive cruise control traffic flow respectively. The work (Delis et al., 2015) contains a detailed review of the various approaches to model VACS in the traffic stream. Several studies also investigate the stability of traffic under various automation and connectivity considerations (Talebpour and Mahmassani, 2015; Van Arem et al., 2006; Davis, 2004; Bose and Ioannou, 2003).

In contrast, this article concerns the problem of combining real-time data streams with a (macroscopic) model of mixed AV and human piloted traffic to generate traffic state estimates. Classically, such problems for non-VACS traffic are posed as a sequential state estimation problem based on the state space form of the model and measurement system:

$$\begin{aligned} x^{n+1} &= f(x^n, \omega^n) \\ z^n &= h(x^n, v^n), \end{aligned} \tag{1}$$

where x^n denotes the traffic state at discrete time step n such as a vector of the density of traffic along the roadway, and f is a traffic flow model that evolves the traffic state from one time step to the next. The model noise ω^n is a random variable that represents the one time step prediction error of the model. The function h is known as the observation equation and defines how the vector of measurements z^n received at time n is related to the traffic state variable x^n, and v^n is a random variable describing the measurement error.

The problem of estimating the traffic state vector x^n using measurements $Z^n = \{z^1, \ldots, z^n\}$ and the system (1) was introduced with the early works of Gazis and Knapp (1971) and Szeto and Gazis (1972) in the 1970s through Kalman filtering and its extensions applied to data collected on the Lincoln Tunnel in New York City. Beginning in the early 1980s, a modified version of Payne's macroscopic model has been used for a variety of Kalman-based estimators (Cremer and Papageorgiou, 1981; Papageorgiou, 1983; Wang and Papageorgiou, 2005; Wang et al., 2009). Nonlinear variants of Kalman filtering (Blandin et al., 2012; Work et al., 2010; Sun et al., 2004; Sun and Work, 2014; Mihaylova et al., 2006; Jabari and Liu, 2013) and particle filtering (Mihaylova and Boel, 2004; Mihaylova et al., 2007; Sau et al., 2007; Polson and Sokolov, 2014; Chen et al., 2011; Wang et al., 2016) have also been applied to modifications of the *Lighthill Whitham Richards* (LWR) *partial differential equation* (PDE) and its discretization (Lighthill and Whitham, 1955; Richards, 1956; Daganzo, 1994, 1995).

Compared to human operated traffic without connectivity, filtering based approaches for traffic containing connected or automated vehicles is still relatively unexplored. The most closely related approaches are works of Bekiaris-Liberis et al. (2015, 2016) and Roncoli et al. (2016), which design a traffic state estimator under two key assumptions on mixed VACS and human operated vehicle flows. First, a scalar traffic flow model is used in the traffic evolution equation in which the velocity field along the roadway is treated as a known time-varying parameter, and is assumed to be provided by the connected vehicles in the traffic stream.

A second important assumption is that the velocity measurements from the automated vehicles are assumed to be representative of the velocity of all vehicle types. This assumption is motivated by the fact that in free flow, both vehicle types will have the same average speed (e.g., as established by the speed limit), and in congestion, the VACS are obstructed by other (human operated) vehicles and consequently adapt the same speed due to the difficulty of overtaking. This assumption is a critical one, and will be exploited in the present work to establish the connection of mixed automated and human operated traffic flow with a generalization of the *Aw Rascle Zhang* (ARZ) (Aw and Rascle, 2000; Zhang, 2002) model.

Under the two assumptions above, the state-space model and its observability is analyzed in Bekiaris-Liberis et al. (2015, 2016), and numerical experiments are performed using the macroscopic METANET model describing average density and speeds as the true state. Experiments validated on field data under various penetration rates are explored using the NGSIM dataset in Roncoli et al. (2016). Such a validation is appropriate if the mixed traffic stream is composed of VACS which drive at similar speeds and spacings as human operated vehicles, as is potentially the case for many connected vehicle systems. Other estimation approaches (Yuan et al., 2012; Seo et al., 2015) exploit additional sensor data available from some VACS to improve the traffic state estimates.

In the same general theme of Roncoli et al. (2016), Bekiaris-Liberis et al. (2015, 2016), in this work we compare two different models to predict the traffic state within an estimator when traffic is composed of human piloted and automated vehicles. One approach uses the classical LWR model, which specifies that vehicles are conserved and the speed of traffic is related to the total density of human and automated vehicles in the traffic stream. The second model uses a variant of the second order ARZ traffic flow model, known as the collapsed generalized ARZ model (Fan and Seibold, 2013). Note these models are more accurately referred to as 2×2 systems of conservation laws, but we adopt the common name "second order" in this article. Recently, a connection between second order models and two-class traffic flow models was established (Fan and Work, 2015), thereby motivating the use of the ARZ model for application for two-class traffic. Recognizing automated vehicles and human operated vehicles as two separate classes of traffic, the ARZ modeling framework is a natural modeling approach to predict the evolution of the traffic state. Other multi-class traffic flow models, such as Van Lint et al. (2008), Ngoduy and Liu (2007), Benzoni-Gavage and Colombo (2003) may be appropriate if overtaking is determined to be a critical feature of the mixed human and AV flow.

The main question addressed in this article is to what extent the additional modeling detail provided by two-class (equivalently ARZ) models can enhance the traffic estimates of mixed traffic flows. The estimation comparison is conducted in a micro simulation environment, where a subset of the vehicles are identified as automated, and consequently their properties are distinct from the vehicles simulated under typical human operated characteristics. Note in the present work we focus