Comparing traffic state estimators for mixed human and automated traffic flows

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1 Introduction

With the emergence of mixed traffic flows now eminent, the problems of modelling, 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 *vehicle automation and communication systems* (VACS) and non-VACS vehicles.

A number of studies address various aspects of the modeling the mixed traffic [1–7]. In contrast, this work concerns the problem of combining real-time data stream with a (macroscopic) model of mixed AV and human piloted traffic to generate traffic state estimates.

Classically, both first order models [8, 9] and second order models [10, 11] have been developed for modeling the macroscopic traffic dynamics, where the second order model allows more flexibility in adjusting the behavior of the traffic flow depending on the composition of the traffic. The main question addressed in this work is to what extent the additional modeling detail provided by second order models can enhance the traffic estimates of mixed traffic flows.

2 Methods

This presentation summarizes our recent work [12], where two models are proposed for use within a model based estimator for mixed automated and human piloted traffic. The first and coarsest model is the seminal *Lighthill Whitham Richards* (LWR) model [8,9], which assumes that the total traffic density evolves according to a conservation law and a constitutive model of the traffic speed as a function of the traffic density. The effects of automated vehicles in the traffic stream are assumed to be entirely captured by the shape and parameters of the

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fundamental diagram. Consequently, the speed of traffic is determined by only the local density of all traffic regardless of vehicle types.

The second model uses a variant of the second order *Aw Rascle Zhang* (ARZ) [10,11] traffic flow model, known as the collapsed generalized ARZ model [13]. Recently, a connection between second order models and two-class traffic flow models was established [14], 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. In this work, the *generalized Aw Rascle Zhang* (GARZ) [15] is applied to model mixed traffic. The GARZ allows the fundamental diagram to be further adjusted based on the fraction of AVs in the traffic stream. In principle, AVs may operate with a much smaller spacing compared to regular traffic, due to the fact that the perception-interpretation-reaction time of an AV may be significantly reduced compared to humans. As a result, the velocity function (and therefore the fundamental diagram) depends not only on the density of traffic, but also the composition of the flow. The larger the fraction of AVs, the smaller the spacing between vehicles at a given speed, and consequently a larger flow can be maintained.

The second order model GARZ is compared to the classical first order LWR model within a traffic estimation framework using simulated real-time data streams. A particle filter [16, 17] is deployed with both models for traffic estimation. The particle filter is a fully nonlinear Bayesian estimator and is subject only to a Monte Carlo approximation error instead of Gaussianity or unimodal approximations exploited by minimal variance Kalman-based estimators.

The estimation comparison is conducted in a micro simulation environment, were a subset of the vehicles are identified as automated, and consequently their properties are distinct from the vehicles simulated under typical human operated characteristics.

3 Primary Results

A number of numerical experiments containing a mix of freeflow and congested traffic conditions with both AVs and human-piloted vehicles were conducted in a micro simulation environment. In each simulation, the inflow penetration rate of AVs is modeled as a random variable. The evaluation results show the second order model based estimator outperforms the first order model in terms of the traffic density accuracy when the variability of the penetration rate increases. At low penetration rate variability, the first order model-based estimator offers similar performance. This empirical finding is consistent with the fact that the second order model reduces to a first order model when the fraction of AVs is constant.

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