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Travel time estimation by urgent-gentle class traffic flow model

Yongliang Zhang[a], M.N. Smirnova[b,*], A.I. Bogdanova[b], Zuojin Zhu[a,b,*], N.N. Smirnov[b,c]

[a] Faculty of Engineering Science, USTC, Hefei, 230026, China
[b] Faculty of Mechanics and Mathematics, LMSU, Moscow, Russia
[c] Scientific Research Institute for System Analysis, Russian Academy of Sciences, Moscow, Russia

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ABSTRACT

To estimate travel time through a ring road, an urgent-gentle class traffic flow model (UGM) with viscoelastic and ramp effects is developed. Vehicles in traffic flow are divided into urgent and gentle categories, and the urgent class has the demand of arriving at destination in time, while the gentle class hasn't. It is assumed that the urgent and gentle classes have the same instantaneous speed to simply the mathematical modeling. To validate the proposed traffic model, a Navier–Stokes like model (Zhang, 2003) is further extended just for validating the present model. Numerical simulations based on the present model are carried out to calculate the travel time on a ring road with total length of 80 km and four initially assumed jams. It was found that similar to the effect of initially assumed jams, the on/off ramp flows play significant roles in the formation and evolution of traffic flow patterns. Urgent density fraction propagates at local traffic speed, its temporal evolution and spatial distribution curves have different shapes as compared with that of traffic density and speed. The average travel time increases monotonically with the increase of ring road initial density. Rational management of road operation is necessary.

1. Introduction

Traffic flows have been widely studied due to the significant impacts on travel time and economic activities. Therefore, to explore characteristics and properties of traffic flows, many macroscopic traffic models have been developed, among which is the well-known model LWR (Lighthill and Whitham, 1955; Richards, 1956), the Euler model (Payne, 1971), the gas-kinetic-based model (Helbing and Treiber, 1998; Hoogendoorn and Bovy, 2000), the Navier–Stokes like model (Kerner and Konhäuser, 1993), and the generic model (Lebacque et al., 2007; Lebacque and Khoshyaran, 2013).

A conserved higher-order anisotropic traffic flow model was developed by introducing a pseudo-density transformed from the velocity, with traffic pressure taken as a function of the pseudo-density and the relaxation of velocity to equilibrium (Zhang et al., 2009). The model has certainly provided a fresh point of view for traffic flow modeling, however its potential of application needs further studies. For instance, how to assign the value of the so-called pseudo-density, and how to choose the density-velocity relationship as well as its corresponding effects.

* Corresponding authors.
E-mail addresses: wonrims@inbox.ru (M.N. Smirnova), zuojin@ustc.edu.cn (Z. Zhu).

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Traffic flow pattern formation phenomena in traffic systems have a spectrum surprisingly rich. These phenomena can be described by the car-following models, the cellular automaton models (Nagel and Schreckenberg, 1992; Helbing and Huberman, 1998; Chowdhury et al., 2000), the gas-kinetic models or the fluid-dynamical models (Nagatani, 2002). Some traffic flow questions have been answered (Helbing, 2001).

Using the gas-kinetic based approach (Ngoduy, 2012), a macroscopic model was developed (Ngoduy, 2013) to describe the traffic flow where intelligent vehicles are moving closer to each other than manual vehicles and operating in a form of many platoons each of which contains several vehicles. A stochastic conservative model in continuous time over discrete space, following a misanthrope Markovian process was studied (Tordeux et al., 2014). Generic second order modeling (GSOM) family can be expressed as a system of conservation laws; for models of the GSOM family, an adequate framework for effective numerical methods was obtained (Costeseque and Lebacque, 2014).

A new formula of non-equilibrium traffic flow models based on their isomorphic relation with optimal control problems was given (Li and Zhang, 2013). With the formula, generic initial-boundary conditions can be easily handled and a simplified numerical solution scheme for non-equilibrium traffic flow models can be devised.

In recent years, in analogy to non-Newtonian fluid flow, viscoelastic traffic modeling has been carried out to develop macroscopic continuum models (Zhu and Yang, 2013; Bogdanova et al., 2015), for which the sensitivity of traffic flow to viscoelasticity has been explored recently (Smirnova et al., 2016; Smirnova et al., 2017).

For travel time prediction, Chang and Mahmassani (1988) examined two heuristic rules, which are proposed for describing urban commuters' predictions of travel time as well as the adjustments of departure time in response to unacceptable arrivals in their daily commute under limited information. Based on the notion, they found the magnitude of the predicted travel time depends on each commuter's own experience, including recallable travel time, schedule delay, and difficulties in searching for a satisfactory departure time. To estimate travel time, Dailey (1993) demonstrated the viability of using cross-correlation techniques with inductance loop data to measure the propagation time of traffic. An improved algorithm for estimating travel time with dual loop detectors was reported by Lint and der Zijpp (2003). The travel time prediction results and accuracy generated by different prediction models were discussed by Chien and Kuchipudi (2003).

For travel-time prediction, support vector regression (SVR) was applied (Wu et al., 2004). In comparison its results to other baseline travel-time prediction methods using real freeway traffic data, it was found that the SVR predictor can significantly reduce both relative mean errors and root-mean-squared errors of predicted travel times.

A freeway travel time prediction framework was reported (van Lint et al., 2005), it exploits a recurrent neural network topology, the so-called state space neural network (SSNN) has preprocessing strategies based on imputation. The SSNN model is based on the lay-out of the freeway stretch of interest, can yield good accurate and robust travel time predictions on both synthetic and real data.

To predict arterial traffic conditions using streaming GPS (global positioning system) probe data, a hybrid modeling framework was proposed (Hofleitner et al., 2012). The model is based on a well-established theory of traffic flow through signalized intersections and is combined with a machine learning framework to both learn static parameters of the roadways (such as free flow velocity or traffic signal parameters) as well as to estimate and predict travel times through the arterial network. It was indicated that this approach is a significant step forward in estimating traffic states throughout the arterial network using a relatively small amount of real-time data.

To estimate arterial route travel time distribution, a Markov chain technique was presented (Ramezani and Geroliminis, 2012). Given probe vehicles travel times of the traversing links, in the technique a two-dimensional (2D) diagram was established with data points representing travel times of a probe vehicle crossing two consecutive links. To cluster each 2D diagram to rectangular sub spaces (states) with regard to travel time homogeneity, a heuristic grid clustering method was developed. It was found that the results are very close to the Markov chain procedure and more accurate once compared to the convolution of links travel time distributions for different levels of congestion, even for small penetration rates of probe vehicles.

For urban road network travel time estimation, Jenelius and Koutsopoulos (2013) presented a model using vehicle trajectories obtained from low frequency GPS probes as observations, where the vehicles typically cover multiple network links between reports. The network model separates trip travel times into link travel times and intersection delays, allows correlation between travel times on different network links based on a spatial moving average (SMA) structure. The potential of using sparse probe vehicle data for monitoring the performance of the urban transport system was highlighted by case study.

To predict experienced travel time for congested freeways, a methodological framework was developed (Yildirimoglu and Geroliminis, 2013). The method sequentially includes a bottleneck identification algorithm, clustering of traffic data in traffic regimes with similar characteristics, development of stochastic congestion maps for clustered data and an online congestion search algorithm, which combines historical data analysis and real-time data to predict experienced travel times at the starting time of the trip. It was found that the proposed method provides promising travel time predictions under varying traffic conditions.

For travel time estimation on urban arterials, variational theory was applied (Hans et al., 2015). It was reported that the LWR model can be expressed as a least cost path problem, which can be simply applied on a graph with a minimal number of nodes and edges when the fundamental diagram is triangular (sufficient variational graph– SVG); described how to obtain a tight estimation of the arterial capacity by properly identifying the most constraining part of the SVG, found