Transportation Research Part B 86 (2016) 1–18

Contents lists available at ScienceDirect

Transportation Research Part B

journal homepage: www.elsevier.com/locate/trb

Information metrics for improved traffic model fidelity through sensitivity analysis and data assimilation

A. Sopasakis[a,*], M.A. Katsoulakis[b]

[a] *Mathematical Sciences, Lund University, Box 118 Lund SE-22100, Sweden*
[b] *Department of Mathematics and Statistics, University of Massachusetts, Amherst, MA 01003, United States*

ARTICLE INFO

Article history:
Received 17 March 2015
Revised 30 December 2015
Accepted 7 January 2016
Available online 4 February 2016

Keywords:
Traffic model parametrization
Inverse dynamic Monte Carlo
Stochastic microscopic dynamics
Information theoretic tools
Relative entropy rate
Fisher information matrix
Controlled fidelity

ABSTRACT

We develop theoretical and computational tools which can appraise traffic flow models and optimize their performance against current time-series traffic data and prevailing conditions. The proposed methodology perturbs the parameter space and undertakes pathwise analysis of the resulting time series. Most importantly the approach is valid even under non-equilibrium conditions and is based on procuring path-space (time-series) information. More generally we propose a mathematical methodology which *quantifies traffic information loss*.

In particular the method undertakes sensitivity analysis on available traffic data and optimizes the traffic flow model based on two information theoretic tools which we develop. One of them, the relative entropy rate, can adjust and optimize model parameter values in order to reduce the information loss. More precisely, we use the relative entropy rate as an information metric between time-series data and parameterized stochastic dynamics describing a microscopic traffic model. On the other hand, the path-space Fisher Information Matrix, (pFIM) reduces model complexity and can even be used to control fidelity. This is achieved by eliminating unimportant model parameters or their combinations. This results in easier regression of parametric models with a smaller number of parameters.

The method reconstructs the Markov Chain and emulates the traffic dynamics through Monte Carlo simulations. We use the microscopic interaction model from Sopasakis and Katsoulakis (2006) as a representative traffic flow model to illustrate this parameterization methodology. During the comparisons we use both synthetic and real, rush-hour, traffic data from highway US-101 in Los Angeles, California.

1. Introduction

Unlocking the hidden mechanisms behind a number of observed and still not well-understood traffic phenomena is one of the fundamental tasks in traffic science. In that respect modeling and simulation is paramount in resolving and understanding complex traffic dynamics. Testing and comparing results from simulations against reality is essential.

Traffic modeling and parameterization approaches have recently intensified due to the demand for faster and sometimes automatic parameter evaluation. The increasing deployment and testing of Vehicle Automation and Communication Systems

---

* Corresponding author. Tel.: +46 462224440.
E-mail address: sopasak@maths.lth.se (A. Sopasakis).

http://dx.doi.org/10.1016/j.trb.2016.01.003

(VACS) which is currently occurring promises to revolutionize the field and reshape the landscape of what is possible and what can be achieved (Bishop, 2005). With the advent of GPS enabled devises and a flood of incoming unordered traffic related data new methodologies must be developed which can quickly appraise and accordingly adjust the traffic model in order to best emulate the changing traffic conditions (Fan and Work, 2015).

Producing a successful such traffic model on the other hand involves, among other things, fitting the model to actual data and testing its performance under observed roadway conditions. Anyone who has tried to fit models to real data in order to emulate actual traffic conditions however knows well that this is a cumbersome task with non-unique solutions and can involve ad-hoc procedures. “Solving is often more of an art than a science”, Emery and Nenarokomov (1998). Not surprisingly methods which work well for obtaining parameters of linear systems may lead to substantial errors (Leontaridis and Billings, 1987) when applied to linearized or nonlinear systems such as those typically comprising current traffic flow models.

Significant recent progress has been made in developing sensitivity analysis tools in areas such as chemical reactions, biological networks, mathematical finance, operations research etc. The reason for this wide spread appeal of sensitivity analysis is that it allows us to test model robustness as well as increase understanding of the relationship between input and output parameters. Sensitivity analysis furthermore simplifies regression. This is achieved by identifying and removing redundant model parameters or fixing parameters that have minor effect. A primary sensitivity test can ease the calibration stage by identifying and focusing on the sensitive parameters.

One of the many challenges within model parameterization is that the process depends strongly on the traffic situation as well as the data. If for instance the data involves congested traffic then parameters related to setting the free flow velocity would be unimportant. If instead we are looking at a junction with several entrances and exits lane changing parameters would suddenly become more important. This dependence on the data is discussed in detail in Treiber and Kerstin (2013). In general the traffic context is of great importance when parameterizing a traffic model and is one of the main reasons that dynamic parameterization is a very important and emerging area within traffic modeling.

Some of the most common approaches of parameter estimation include maximum likelihood, least squares, Bayesian cost method or Maximum-A-Posterior (MAP) to name a few. Typical mechanisms include log-likelihood methods and Girsanov transformations, Glynn (1990); Nakayama et al. (1994); Plyasunov and Arkin (2007) or pathwise sensitivity methods, Sheppard et al. (2012). Many of the existing sensitivity analysis mechanisms however are usually associated with an overwhelming computational cost as the parameter space increases. Finite difference sensitivity analysis methods, Anderson (2012); Rathinam et al. (2010), for instance usually involve gradients and incur great computational costs as the number of parameters increases. The gradient-free information theoretic methods in Pantazis and Katsoulakis (2013) on the other hand can avoid these costs and in that respect the methodology we propose here stems from such an approach. Some related data fitting methods were also recently proposed in the context of coarse-graining of molecular simulations in Katsoulakis and Plecháč (2013).

Applying statistical mechanics in order to reconstruct the most likely parameter space for the traffic flow model is not an entirely new idea. Most of the proposed methodologies depend on knowing or assuming an equilibrium distribution of the system dynamics. Tossavainen and Work (2013) for instance use Markov chain Monte Carlo methods to sufficiently sample the parameter space and from that estimate the essential parameters for the traffic flow model. Their method is applicable to traffic flow models based on the discrete velocity equation. The approach focuses on reconstructing the values of the parameters comprising the flow-density relationship for that traffic flow model. In order to achieve this objective the authors built posterior distributions of the traffic flow model parameters related to the flow-density relationship. Subsequently an optimization problem needs to be solved in order to obtain the values of the parameters which reduce model sensitivity attributed to errors within the data. Success of this method therefore relies on assuming the correct form for the inverse crime (Kaipioa and Somersalob, 2007) relationship as well as obtaining a solution to the optimization problem.

A slightly different, although common approach for statistical mechanics, is proposed in the traffic model by Morimura et al. (2013). The authors put forth a method which estimates the state transition probability matrix of the Markov chain representing the dynamics of the traffic model. In order for this transition matrix to be constructed the authors must assume that the equilibrium distribution of the traffic dynamics is known in advance. The methodology can be applied even under limited information conditions such as partial traffic observations. This is therefore a very interesting approach due to the direct possible applicability under actual traffic conditions. The authors in Wang et al. (2006) follow a similar approach for a stochastic macroscopic freeway network traffic model. Due to its macroscopic nature the model has the obvious advantage that a much larger network can be considered and quickly analyzed. This method can also be applied under sparse traffic data. Currently this method is based on a particular underlying stochastic model. Instead of making assumptions about the underlying equilibrium behind the traffic dynamics the authors assume knowledge of some of the important model parameters. This limitation however can be eased by implementing some of the methods proposed in Yildirimoglu and Gerolimitis (2014).

A similar approach is followed by Roncoli et al. (2015) where a new multi-lane macroscopic traffic model for highways is derived. Each lane is modeled individually with a first-order macroscopic traffic flow model and divided into segments. The model originates from the conservation equation and applies the cell transmission paradigm in order to properly transmit flow information between each segment within the same lane. This model is furthermore extended to account for lane changes by incorporating information about lateral and longitudinal interactions. Assumptions behind the model are reasonable and feasible throughout. Features such as the capacity drop or limited capacity off-ramps are incorporated. This model