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Three methods for estimating a range of vehicular interactions

Milan Krbálek [a,*], Jiří Apeltauer [a,b], Tomáš Apeltauer [b], Zuzana Szabová [a]

[a] Faculty of Nuclear Sciences and Physical Engineering, Czech Technical University in Prague, Prague, Czech Republic
[b] Faculty of Civil Engineering, Brno University Of Technology, Brno, Czech Republic

HIGHLIGHTS

- We present new approaches for estimating the number of cars influencing a decision-making procedure of drivers.
- Empirical data samples are subjected to advanced methods of statistical analysis.
- Consistency between the estimations used is surprisingly credible.
- We demonstrate that universally-accepted premise on short-ranged traffic interactions is not substantiated.
- All methods introduced have revealed that minimum number of actively-followed vehicles is two.

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ABSTRACT

We present three different approaches how to estimate the number of preceding cars influencing a decision-making procedure of a given driver moving in saturated traffic flows. The first method is based on correlation analysis, the second one evaluates (quantitatively) deviations from the main assumption in the convolution theorem for probability, and the third one operates with advanced instruments of the theory of counting processes (statistical rigidity).

We demonstrate that universally-accepted premise on short-ranged traffic interactions may not be correct. All methods introduced have revealed that minimum number of actively-followed vehicles is two. It supports an actual idea that vehicular interactions are, in fact, middle-ranged. Furthermore, consistency between the estimations used is surprisingly credible. In all cases we have found that the interaction range (the number of actively-followed vehicles) drops with traffic density. Whereas drivers moving in congested regimes with lower density (around 30 vehicles per kilometer) react on four or five neighbors, drivers moving in high-density flows respond to two predecessors only.

1. Motivation

Nowadays, a deeper understanding of the principles of vehicular dynamics is becoming increasingly important because of many reasons. It is essential that numerical/theoretical models are capable to reproduce a traffic reality more and more authentically since elaborated simulators can then more-responsibly predict impending traffic congestions, manage control systems in autonomous vehicles, or help with planning of inter-vehicular communication networks. For these reasons we now ask fundamental questions on a nature/intensity/range of inter-vehicle interactions.

* Corresponding author.
E-mail address: milan.krbalek@fjfi.cvut.cz (M. Krbálek).

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From a general viewpoint, any traffic system is an agent ensemble whose intelligent agents interact with a certain set of their neighbors. Although forces of such a kind are not directly measurable some recent works (see [1–9]) have revealed a way how to optimize a force-description to obtain a more realistic predictions of vehicular microstructure. In [2–5] authors have demonstrated that one-dimensional thermal gas, whose particles interact via a repulsion potential depending on reciprocal value of distance among succeeding cars, represents a suitable theoretical model that reproduces a microscopic structure of freeway traffic surprisingly good. However, this stochastic thermodynamic model as well as all the best-known microscopic traffic-models (follow-the-leader models, car-following models, intelligent driver model, optimal velocity model, Nagel–Schreckenberg model –see [10–12]) are based on the reductive premise that an "explicit force" exists between neighboring vehicles only. Such a property used to be referred to as a short-ranged interaction. To what extent does this premise correspond with traffic reality? Do there exist interactions among more neighbors as well? Is there any theoretically-substantiated methodology for estimating the number m of actively-followed vehicles (the so-called *interaction range*)? These are the issues that we will try to discuss in this paper.

Intuitively, one can expect (in contrast to basic principles of microscopic traffic modeling) that decision-making procedure of a driver (moving in congested traffic-regimes) is typically influenced by more circumjacent cars. This is referred to as a middle-ranged case. To conclude, the main objective of this paper is to estimate the interaction range in empirical traffic samples by means of several proven/innovative mathematical approaches. Furthermore, we plan to analyze how the interaction range evolves with changing values of basic macroscopic quantities like traffic flow or density.

2. Empirical data-sets and the segmentation procedure

Vehicle-by-vehicle data analyzed in this paper has been provided by the Road and Motorway Directorate of the Czech Republic (ŘSD ČR) and recorded at the Expressway R1 (also called the Prague Ring) in Prague, the Czech Republic. For intentions of this research we have used detectors located sufficiently far from any on/off-ramps where traffic flow is dense enough to generate congested traffic states. Here one can guarantee the conservation of the number of vehicles as well as a significant synchronization among moving vehicles. Only intensive inter-vehicular cooperation can hypothetically lead to a detection of an interaction range. Therefore, we have eliminated (by means of standard methods for statistical clustering) all the states associated to free traffic-phase where the intended detection loses its meaning. Above that, we analyze data from fast lanes only, because of a significant proportion of lorries, buses, tracks in main lanes. Such a reduction brings three important advantages. Firstly, in fast lanes there is an extremely low proportion of slow cars and no long vehicles. Secondly, fast-lane vehicles are coerced to more intensive interactions (due to higher speeds) and thirdly, fast-lane vehicles cannot be overtaken. These three factors strengthen target-ambitions of this paper.

The data records have been adapted into a set (or sets) having a form

$$\Omega = \left\{(\tau_k^{(\mathrm{in})}, \tau_k^{(\mathrm{out})}, v_k, \xi_k) \in T^{(\mathrm{in})} \times T^{(\mathrm{out})} \times V \times \Xi \,:\, k = 1, 2, \dots, N\right\}, \tag{1}$$

that is suitable for synoptical mathematical formulations. Here $T^{(\mathrm{in})}$ and $T^{(\mathrm{out})}$ are the sets of chronologically-ordered times when the kth vehicle entered/leaved the measuring device, respectively. V is the set of associated velocities and Ξ stands for the set of vehicular lengths. Denoting the sampling size by ℓ (which is here consistently considered equal to 50) and number of data-samples by K we acquire the data sub-samples

$$\Phi_j = \left\{(\tau_k^{(\mathrm{in})}, \tau_k^{(\mathrm{out})}, v_k, \xi_k) \in \Omega \,:\, k = (j-1)\ell + 1, (j-1)\ell + 2, \dots, j\ell\right\}. \tag{2}$$

For each sub-sample Φ_j ($j = 1, 2, \dots, K$) one can calculate the local flux

$$J_j = \frac{\ell}{\tau_{j\ell}^{(\mathrm{in})} - \tau_{(j-1)\ell+1}^{(\mathrm{out})}} \tag{3}$$

and local average velocity $\bar{v}_j = \ell^{-1}\sum_{k=(j-1)\ell+1}^{j\ell} v_k$. Besides, the expression

$$\varrho_j = \frac{J_j}{\bar{v}_j} \tag{4}$$

is accepted as a plausible approximation of the local vehicular density (according to [5,10]). Individual (re-scaled) time-clearances are then calculated using the standard definition (e.g. [5])

$$t_k = \frac{\ell\left(\tau_k^{(\mathrm{in})} - \tau_{(k-1)}^{(\mathrm{out})}\right)}{\sum_{i=(\lceil k/\ell\rceil-1)\ell+1}^{\lceil k/\ell\rceil\ell} \tau_i^{(\mathrm{in})} - \sum_{i=(\lceil k/\ell\rceil-1)\ell+1}^{\lceil k/\ell\rceil\ell} \tau_{i-1}^{(\mathrm{out})}}, \tag{5}$$

which ensures that for all sample-means it holds $\bar{x}_j := \ell^{-1}\sum_{k=(j-1)\ell+1}^{j\ell} t_k = 1$. As it is well known (from [13–18]), such a re-scaling procedure brings a considerable profit when revealing general relations in many economic/physical/biologic/socio-physical/purely mathematical systems. In analogy, we define (re-scaled) space-clearances by

$$x_k = \frac{v_{k-1}\ell\left(\tau_k^{(\mathrm{in})} - \tau_{(k-1)}^{(\mathrm{out})}\right)}{\sum_{i=(\lceil k/\ell\rceil-1)\ell+1}^{\lceil k/\ell\rceil\ell} v_{i-1}\tau_i^{(\mathrm{in})} - \sum_{i=(\lceil k/\ell\rceil-1)\ell+1}^{\lceil k/\ell\rceil\ell} v_{i-1}\tau_{i-1}^{(\mathrm{out})}}. \tag{6}$$