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Macroscopic traffic state estimation using relative flows from stationary and moving observers

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ABSTRACT

This article presents a procedure to estimate the macroscopic traffic state in a pre-defined space-time mesh using relative flow data collected by stationary and moving observers. The procedure consist of two consecutive and independent processes: (1) estimate point observations of the cumulative vehicle number in space-time, i.e., $N(x, t)$, based on relative flow data from the observers and (2) estimate flow and density in a pre-define space-time mesh based on the point observations of N. In this paper, the principles behind the first process are explained and a methodology (the Point-Observations N (PON) estimation methodology) is introduced for the second process. This methodology does not incorporate information in the form of a traffic flow model or historical data. To evaluate this performance and improve our understanding of the methodology, a microscopic simulation study is conducted. The estimation performance is effected by the homogeneity and stationarity of traffic in estimation area and in the sample area. In case of large changes in traffic conditions, e.g., from free-flow to congestion or stop-and-go waves, a better sampling resolution will improve localizing these changes in space and time and hence improve the estimation performance. In the simulation study, the proposed methodology is also compared with estimates based on loop-detector data. This indicates that the combination of the proposed methodology and data yields an alternative for existing combinations of methodology and data. Especially, in terms of density estimation the introduced methodology shows promising results.

1. Introduction

This paper addresses macroscopic traffic state estimation. Estimates of the macroscopic traffic flow variables, i.e., flow q, density k and speed u, can be used as input for control decisions within dynamic traffic management applications (Papageorgiou et al., 1991; Smaragdis et al., 2004).

The estimation procedure introduced in this paper allows us to estimate the macroscopic traffic flow variables within a pre-defined space-time mesh using stationary and moving observers. This procedure consists of two main (independent and consecutive) processes. These are: (1) estimate the cumulative vehicle number N for points along the observed paths in

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space-time (we will call these point-observations) using traffic sensing data from stationary and moving observers and (2) estimate q and k in a pre-defined mesh based on point-observations of N.

This paper has two important contributions. The first and more generic contribution is the full estimation procedure. We propose to use equipped and/or automated vehicles that observe the relative flow with respect to their trajectory in combination with stationary observers. The traffic sensing data from these observers can be fused on the cumulative vehicle number level (first process) and can be used to estimate the macroscopic traffic conditions (second process). Both processes are explained in this paper. The second and more specific contribution is the methodology designed for the second process. This methodology is called the Point-Observation N (PON) estimation methodology. The two processes require independent methodologies and should in our view not be discussed in detail in a single paper. Therefore, in this paper, we explain the second process in detail, while we solely explain the principles behind the first process.

This paper is organized as follows. Section 2 provides the existing methodological basis for our work and positions this work within the research field. Next, we explain the two processes in Sections 3 and 4. The PON estimation methodology (explained in Section 4) is evaluated using a simulation study in Sections 5 and 6. We conclude with the conclusions and discussion in Section 7.

2. Background on macroscopic traffic state estimation

In this section, we discuss the topic of macroscopic traffic state estimation and explain how the proposed methodology differs from existing work. First, Edie's generalized definitions of the macroscopic traffic flow variables and the three-dimensional representation of traffic flow are provided. Second, the categorization discussed by Seo et al. (2017) is used to categorize the proposed estimation approach. Third, we elaborate on different types of traffic sensing data used for macroscopic traffic state estimation and which data are used in the proposed estimation procedure. And finally, we discuss our estimation output and how this relates to existing work.

The generalized definitions of flow q, density k and speed u, for an area $\mathcal{D}$ in space-time are provided by Edie (1965):

$$q_{\mathcal{D}} = \frac{\sum_i d_i}{A_{\mathcal{D}}} \tag{1}$$

$$k_{\mathcal{D}} = \frac{\sum_i r_i}{A_{\mathcal{D}}} \tag{2}$$

$$u_{\mathcal{D}} = \frac{q_{\mathcal{D}}}{k_{\mathcal{D}}} \tag{3}$$

where d_i and r_i respectively denote the distance traveled and time spent by vehicle i within the area $\mathcal{D}$ and $A_{\mathcal{D}}$ denotes the surface of $\mathcal{D}$. $\Sigma_i d_i$ and $\Sigma_i r_i$ respectively denote the Total Travel Distance (TTD) and Total Time Spent (TTS) in $\mathcal{D}$.

Makigami et al. (1971) proposed the three-dimensional representation of traffic flow. The three dimensions are space, time and the cumulative vehicle number, where $N(x, t)$ denotes the cumulative vehicle number at location x and time instant t. As vehicles are discrete, N can be represented as a discrete variable. Here, $N(x, t)$ increases instantly by one vehicle at the time instant t when a vehicle passes location x.

We want to describe traffic flow on a macroscopic level. For this purpose, the discrete N can be smoothed (Makigami et al., 1971). For the smoothed and continuously differentiable N, the macroscopic traffic flow variables can be described based on the three dimensions. The macroscopic variables for a point in space-time, i.e., (x, t), are given by the time and space derivatives of $N(x, t)$:

$$q(x,t) = \frac{\partial N(x,t)}{\partial t} \tag{4}$$

$$k(x,t) = -\frac{\partial N(x,t)}{\partial x} \tag{5}$$

$$u(x,t) = \frac{q(x,t)}{k(x,t)} \tag{6}$$

Seo et al. (2017) categorizes the estimation approach into three categories (i.e., model-driven, data-driven and streaming-data-driven) based on information input. Following this categorization, the methodology presented in this study can be categorized as a streaming-data-driven traffic state estimation methodology. Examples of other streaming-data-driven methodologies are Wardrop and Charlesworth (1954), Seo and Kusakabe (2015) and Florin and Olariu (2017). A streaming-data-driven methodology does not depend on information in the form of a traffic flow model, fundamental diagram or historical data, but solely relies on real-time data and 'weak' assumptions such as the conservation-of-vehicles. Therefore, 'it is robust against uncertain phenomena and unpredictable incidents' (Seo et al., 2017). At the same time, Seo et al. (2017) denotes two limitations of streaming-data-driven methodologies: (1) additional information (e.g., a traffic flow model) is needed to