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Speed profile estimation using license plate recognition data

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ABSTRACT

Vehicle speed profile is a fundamental data support for calculating vehicular emission using the micro-emission model. However, achieving accuracy and breadth for the speed profile estimation is difficult. This study proposes a new vehicle speed profile estimation model using license plate recognition (LPR) data. This model allows speed profile estimation of every individual vehicle between two consecutive intersections. A systematic LPR data-mending method is developed to infer the information of unmatched vehicles. Using the complete arrival and departure information as boundary conditions, a customized car-following model combined with dummy-overtaking hypothesis and boundary constraints is then applied to estimate the speed profile of vehicles. The proposed model is validated using ground truth speed information from a field experiment conducted in Langfang City in China. Results show that the model can fully capture the pattern of ground truth speed profile. A complementary model validation using the Next Generation Simulation dataset and a model application for calculating emissions are also conducted. The numerical results indicate the effectiveness of the proposed model in estimating vehicle speed profile and emissions.

1. Introduction

Motor vehicle exhaust emissions are important contributors to air pollution. Vehicular emission is heavily affected by vehicle driving conditions, particularly the speed profile. The speed profile means the curve of speed change versus time. Over the past few decades, well-established macroscopic/mesoscopic emission estimation methods have been widely used on freeways or highways with uninterrupted flow using the aggregated traffic characteristics (e.g., average speed, traffic volume, and distance traveled) (Evans and Herman, 1978; Barth et al., 1999; Barth and Boriboonsomsin, 2008; Zegeye et al., 2013; Shang et al., 2014). However, for roadways with interrupted flow (e.g., arterial roads with traffic signals), emission estimation is difficult and cannot use average traffic speed alone (Yang et al., 2011; Sun et al., 2015); the reason is that vehicles with the same average speed present significantly different speed profiles in arterial roads from those on freeway segments (Nesamani et al., 2007). As a result, microscopic approaches that can reasonably estimate speed profile in the individual vehicle level are necessary to estimate the emissions of arterial roads accurately.

Abbreviations: LPR, license plate recognition; MRE, mean relative error; NGSIM, Next Generation Simulation; CMEM, comprehensive modal emissions model; FVD, full velocity difference; GA, genetic algorithm; RMSE, root-mean-square error; MAE, mean absolute error.

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Recently, several microscopic models with reconstructed vehicle speed profiles are proposed. Yang et al. (2011) estimated vehicle trajectories by explicitly modeling driving modes, such as steady-state cruise, acceleration, deceleration, and idle modes. Then, the estimated vehicle trajectories are used to calculate emissions. This method obtains improved emission estimation results compared with macroscopic/mesoscopic methods but is limited by its incapability to capture detailed behavior of individual vehicles, such as the acceleration and deceleration processes (Sun et al., 2015). Following Yang et al.'s (2011) study, Sun et al. (2015) extended the vehicle trajectory estimation method proposed by Sun and Ban (2013) to a modal decomposition speed profile estimation method for emission estimation using mobile sensing data. Uniform deceleration, state-dependent acceleration, and random-noise-added cruise process are considered to provide a realistic speed profile. Sun et al.'s (2015) method overcomes the limitations of Yang et al.'s (2011) method and obtains reasonable emission estimation results. However, the estimated speed profiles in Sun et al.'s (2015) study are still different from the ground truth speed profiles because of the rigidly modal decomposition of the traveling process. In addition, the estimated number of vehicles may not match the ground truth data because of the limitation of mobile sensing data, thereby leading to emission estimation errors. Therefore, a microscopic method that can model the fine vehicle speed profiles of the entire traffic flow must be developed. License plate recognition (LPR) data provide an alternative solution to this end.

LPR is an emerging technology that is widely used in urban and highway transportation systems. In recent years, large-scale LPR systems have been rapidly deployed in many countries. For example, Beijing has an LPR system with 1958 LPR cameras covering the entire metropolitan area (Beijing Traffic Management Bureau, 2017); this number is expected to increase in the next few years (Beijing Municipal Committee, 2016). The data obtained from the LPR system can provide information about the departing timestamps of vehicles at the stop line as well as their license plate number. LPR systems have been employed in many different transport applications involving enforcement, vehicle monitoring, and access control (Nakanishi and Western, 2005; Rossetti and Baker, 2001). With the unique identification of vehicle license plate, LPR data are used for detailed traffic information estimation, such as link travel time estimation (Bertini et al., 2005; Yasin et al., 2009) and queue length estimation (Zhan et al., 2015). Compared with other decentralized data (e.g., mobile sensing data and GPS data), LPR data do not suffer from the issue of low penetration rate because LPR cameras can record the information of nearly all vehicles departing from an intersection. Therefore, LPR data can be used to model the entire traffic flow and overcome the aforementioned limitations of Sun et al.'s (2015) method. However, LPR data are seldom available to the research community due to privacy issues, and research efforts to develop data analytics for complex transportation applications, including vehicle speed profile estimation, are limited. Despite the increasing recognition accuracy of the LPR system, LPR data still suffer from a low matching rate of license plate number between upstream and downstream intersections (Section 2). Some LPR data-mending methods have been proposed but are flawed. Oliveira-Neto et al. (2012) proposed license plate-matching procedures based on the probability model; these procedures improve the matching rate of LPR data but fail to recover the complete information of LPR data. Zhan et al. (2015) used an interpolation model based on the Gaussian process to infer unobserved and erroneously recognized data; however, this model filters out a large amount of prior information and thus results in low accuracy.

In this study, we propose a hybrid framework for speed profile estimation that fully utilizes the information provided in LPR data. This framework allows the detailed estimation of the speed profile of every individual vehicle between two consecutive intersections. An LPR data-mending model combining the advantages of Oliveira-Neto et al.'s (2012) method and Zhan et al.'s (2015) method is first developed to infer the information of all unmatched vehicles. This data-mending model overcomes the drawbacks of Oliveira-Neto et al.'s (2012) method and Zhan et al.'s (2015) method and fully utilizes valid data information. Next, we use a highly customized car-following model to estimate the speed profile of vehicles. This model can reconstruct vehicle trajectories under the boundary constraints provided in LPR data. A field experiment is conducted in Langfang, Hebei Province, China to collect ground truth data for validation. The ground truth vehicle speed profile data are collected using two probe vehicles equipped with GPS devices. The results show that the model can fully capture the pattern of the ground truth speed profile. The mean relative error (MRE) of speed profile estimation is 12.98%. A complementary validation is conducted using the Next Generation Simulation (NGSIM) Peachtree Street dataset (US Department of Transportation—FHWA, 2008) and shows that the proposed model is robust. Then, the estimated speed profile is applied to estimate emissions with comprehensive modal emissions model (CMEM; Barth et al., 2001). The estimation relative errors of fuel consumption, CO emissions, and NO_x emissions are approximately 16% in the individual vehicle level.

The contributions of this work are summarized as follows:

1. A systematic LPR data-mending method is proposed to infer the complete information of unmatched vehicles, thereby overcoming the drawbacks of previous research and maximizing the use of valid data information.
2. A customized car-following model fully corresponding to LPR data characteristics is proposed. The model can be extended to other micro-traffic information estimation methods using similar data (e.g., RFID data).
3. The speed profile of vehicles on road segments is estimated using LPR data.

The rest of the paper is organized as follows. Section 2 presents the proposed data-mending method. Section 3 presents the speed profile estimation using the proposed customized car-following model. Section 4 presents the field experiment design, and Section 5 shows the numerical results. Section 6 elaborates the conclusions of the study.