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A model to estimate and interpret the energy-efficiency of movement patterns in urban road traffic

Peter Ranacher [a,*], Richard Brunauer [b], Stefan Christiaan Van der Spek [c], Siegfried Reich [b]

[a] Department of Geoinformatics - Z_GIS, University of Salzburg, Schillerstraße 30, 5020 Salzburg, Austria
[b] Salzburg Research Forschungsgesellschaft mbH, Jakob-Haringer-Straße 5, 5020 Salzburg, Austria
[c] Delft University of Technology, Faculty of Architecture, Department of Urbanism, Julianalaan 134, 2628 BL Delft, The Netherlands

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ABSTRACT

Urban road traffic is highly dynamic. Traffic conditions vary in time and with location and so do the movement patterns of individual road users. In this article, a movement pattern is the behaviour of a car when traversing a road link in an urban road network. A movement pattern can be recorded with a global navigation satellite system (GNSS), such as the Global Positioning System (GPS). A movement pattern has a specific energy-efficiency, which is a measure of how fuel-intensively the car is moving. For example, a car driving uniformly at medium speed consumes little fuel and, therefore, is energy-efficient, whereas stop-and-go driving consumes much fuel and is energy-inefficient. In this article we introduce a model to estimate the energy-efficiency of movement patterns in urban road traffic from GNSS data. First, we derived statistical features about the car's movement along the road. Then, we compared these to fuel consumption data from the car's controller area network (CAN) bus, normalized to the car's overall range of fuel consumption. We identified the optimal feature set for prediction. With the optimal feature set we trained, tested and verified a model to estimate energy-efficiency, with the fuel consumption serving as ground truth. Existing fuel consumption models usually view movement as a snapshot. Thus, the behaviour of the car remains unknown that causes a movement pattern to be energy-efficient or energy-inefficient. Our model views movement as a process and allows to interpret this process. A movement pattern can, for example, be energy-inefficient because the car is driving in stop-and-go traffic, because it is travelling at high speed, or because it is accelerating. Our model allows to distinguish between these different types of behaviours. Thus, it can provide new insights into the dynamics of urban road traffic and its energy-efficiency.

1. Introduction

Global navigation satellite systems (GNSS) provide a new means to collect traffic probe data and to study traffic phenomena in urban areas. Cars equipped with GNSS loggers record so-called trajectories, discrete snapshots of movement in space and time [see, for example,] Zheng, Zhang, Xie, and Ma (2009). Such traffic probe data are commonly referred to as floating car data (FCD) Shekhar and Xiong (2008), Zheng, Capra, Wolfson, and Yang (2014). In addition to trajectories, FCD sometimes also contain on-board sensory data, such as fuel consumption data derived from the car's controller area network (CAN) bus.

FCD provide a network-wide view on the dynamics of traffic in urban areas. FCD help to analyse traffic conditions Shekhar and Xiong (2008), allow to identify congestions Andrienko, Andrienko, Hurter, Rinzivillo, and Wrobel (2011) and reveal delay patterns (Brunauer and Rehrl (2014). Moreover, FCD are used to find critical locations in urban road networks Zhou, Fang, Thill, Li, and Li (2015), to estimate travel times Simroth and Zahle (2011), Wang, Zheng, and Xue (2014) and to predict fuel consumption along routes Guo, Yang, Andersen, Jensen, and Torp (2014). Thus, FCD are a basis for fuel-saving routing (Andersen, Jensen, Torp, and Yang (2013), Boriboonsomsin, Barth, Zhu, and Vu (2012)), for optimizing urban logistics Ehmke, Meisel, and Mattfeld (2012) and for improving urban traffic planning Zheng, Liu, Yuan, and Xie (2011).

In this article we introduce a model to estimate from FCD how energy-efficiently cars move in an urban road network. In a purely data-driven approach, we compared movement patterns recorded with the Global Positioning System (GPS) to fuel consumption data recorded with a car's CAN bus. We trained, tested and verified a regression model to estimate the energy-efficiency of a movement pattern, with the fuel consumption data serving as ground truth. A movement pattern is defined as the behaviour of a car when traversing a road link in a road network. Hence, it is a process captured with the GPS. The energy-efficiency of a movement pattern is a measure of the fuel-efficiency of this process. A car traversing a road link at uniform speed, for instance, consumes less fuel and therefore is more energy-efficient than a car traversing the road link in stop-and-go traffic Jakobsen, Mouritsen, and

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[*] Corresponding author.
E-mail address: peter.ranacher@gmail.com (P. Ranacher).

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Torp (2013). In contrast to exiting models, our approach allows to interpret and to classify different types of movement patterns. One pattern might be energy-inefficient because of stop-and-go traffic, another because of a constant sharp acceleration or travelling at high speed. Our model is able to distinguish between these and to reveal the behaviour of the car.

Estimating energy-efficiency is closely related to estimating fuel consumption from GNSS movement data. The published literature distinguishes between two types of models to address this problem (Guo et al. (2014): Instantaneous models predict a car's fuel consumption at a specific point in time from the car's instantaneous movement. Aggregate models predict a car's fuel consumption along a road link (or a succession of road links) from its average movement. Neither of both models are suitable for estimating and interpreting the energy-efficiency of a movement pattern. Instantaneous models, on the one hand, make predictions for a snapshot rather than a process. Aggregate models, on the other hand, deliberately reduce the complexity of movement for the sake of aggregation. They estimate the fuel consumption of a process with a single value. This value does not allow to interpret the movement pattern (was the car driving at high speed or accelerating?). Moreover, the existing aggregate models are usually based on only a few, simple input parameters, such as average speed and the travelled distance [see] Guo et al. (2014). To the best of our knowledge, there are no aggregate models that specifically address the dynamics of movement (speed and acceleration) and the gradient along the road. This is surprising, since these parameters strongly influence fuel consumption and almost all instantaneous models use them for prediction.

For our model, a movement pattern is the behaviour of a car when traversing a road link. We described this behaviour with sixteen features, which were derived from the car's speed, acceleration and the gradient along the road. Then we designed a regression model and tested which combination of features was best suited to estimate energy-efficiency. Finally, we used this optimal feature set to interpret the movement pattern. In short, the model.

(1.) estimates the energy-efficiency of a movement pattern (how energy-efficient is it?)

(2.) and allows to interpret the movement pattern (why is it energy-efficient or inefficient?).

For (1), we found that the performance of the regression model strongly depended on the number and combination of features used for prediction. The optimal feature set included very detailed information on the dynamics of the movement (i.e. the variability of speed and acceleration) and the gradient along the road link. Since GPS elevation estimates are affected by large errors (Hofmann-Wellenhof, Legat, and Wieser (2003) this may require to combine GPS trajectories with additional elevation data in order to achieve reliable results, such as elevation data from a digital surface model.

For, (2) we demonstrated that parallel coordinate plots (PCP) can both verify the plausibility of the regression model and help to interpret different types of movement patterns. For example, the PCP of a sharp acceleration considerably differs from the PCP of stop-and-go driving and, thus, allows to distinguish between these two.

Section 2 presents the related work. Section 3 introduces the regression model and specifies its requirements, Section 4 presents the results. Section 5 discusses the plausibility of our results and explains how the model can be used to interpret movement patterns and their energy-efficiency.

2. Background and related work

In this section, we provide a brief introduction to the related work. We discuss existing models to estimate the fuel consumption of cars from movement data, henceforth referred to as a fuel consumption models (FCM). Guo et al. (2014) distinguish between two types of FCM: instantaneous (1) and aggregate FCM (2).

(1.) Instantaneous FCM, on the one hand, rely on the instantaneous movement of a car and estimate fuel consumption at a particular instant in time. Some instantaneous models are strongly oriented on the physics behind the car's movement, such as the VT-CPFM model by (Rakha, Ahn, Moran, Saerens, and Bulck (2011)), the EMIT model by (Cappiello, Chabini, Nam, Lue, and Abou Zeid (2002) or the SIDRA-Inst by Bowyer, Akcelik, and Biggs (1985), whereas others are purely statistical models. These include the VT-Micro model by Rakha, Ahn, and Trani (2004), the MEF model by (Lei, Chen, and Lu (2010), and the model by Ribeiro, Rodrigues, and Aguiar (2013).

The FCM listed above are very heterogeneous in terms of their input features used for prediction. The VT-CPFM, for example relies on detailed vehicle-related information (e.g., the mass of the vehicle and its air resistance), location-related information (e.g. the rolling resistance of the road) and movement related information (e.g. the instantaneous speed and acceleration). On the contrary, the VT-Micro uses only two features (instantaneous speed and acceleration). These two features are also used in all other models with the only exception being the SIDRA-Inst model, which does not consider acceleration. Moreover, four of the models rely on the gradient along the road to estimate fuel consumption (the VT-CPFM, SIDRA-Inst and the model by Ribeiro et al.).

The vehicle specific power (VSP) model Jimenez-Palacios (1999) estimates a car's instantaneous power per unit mass. VSP can be used as a proxy for fuel consumption. The VSP model can easily be calculated and interpreted Song, Yu, and Tu (2011), which is why it has gained increasing popularity for modelling emissions and fuel consumption [see, for example,] Chang et al. (2013), Davis, Lents, Osses, Nikkila, and Barth (2005), Song and Yu (2009)).

(2.) Aggregate FCM, on the other hand, use the average movement of the car to estimate fuel consumption for a particular level of aggregation, e.g. the fuel consumption along a road link or a succession of several road links Guo, Ma, Yang, Jensen, and Kaul (2012). The SIDRA framework by Bowyer et al. (1985) provides three aggregate models (SIDRA-4Mode, SIDRA-Running, SIDRA-Avg) to estimate aggregate fuel consumption. The SIDRA4-Mode, for example, takes as input features average speed, the road gradient and distance. Depending on the car's mode (cruising, accelerating, decelerating, idling) the model calculates a fuel consumption value. The values of all modes are then summed up and yield the car's aggregate fuel consumption along a road. The SIDRA-Running and SIDRA-Avg are simpler versions of the SIDRA4-Mode model. SIDRA-Avg for example, uses only the average speed for prediction. In general, all SIDRA models rely on average speed as the main input features; acceleration, on the contrary, is not specifically addressed.

The aggregate model by Song, Yu, and Wang (2009) is based on VSP. It results in a unit-less indicator for fuel consumption along a road link, rather than an estimate for fuel consumption. Moreover, the model does not consider the gradient along the road as an input feature.

Finally, the aggregate model by Tavares, Zsigraiova, Semiao, and Carvalho (2009) calculates an estimate for fuel consumption based on the average speed and the weight of the vehicle. The model does not address acceleration or the gradient along the road. Moreover, it is mainly applicable for heavy vehicles, i.e. for trucks. For a detailed summary of the existing FCM, including a performance evaluation, we refer to Guo et al. (2012, 2014).