Linking automobile trajectories and fuel consumption

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1. Introduction

Petrol powered traffic has replaced domestic heating and industry as the main causes for urban air pollution (Colvile, Hutchinson, Mindell, & Warren, 2001). Automobile combustion engines are responsible for the better part of a city’s CO₂ and NOₓ pollutants. The amount of pollutants emitted by a vehicle largely depends on fuel consumption: the more fuel the vehicle consumes, the higher its emissions. Consequently, reducing automobile fuel consumption has become an important interdisciplinary field of research. However, until recently, efforts in this field have focussed predominantly on the vehicle. In our research we want to address petrol-fuelled road traffic and its energy consumption from a different perspective, the perspective of movement and the road infrastructure:

In automobile traffic, which movement patterns cause high fuel consumption and where in a city’s road network do these occur?

In this paper we compare movement against fuel consumption derived from a car’s on-board diagnostic device (OBD). First, we split trajectories into segments. For the segments we calculate curves for speed, acceleration and slope and derive statistics. We compare these against fuel consumption and identify correlations. In a later stage we build on the correlations to estimate the energy efficiency of large numbers of automobile trajectories (without OBD fuel measures) in an urban road network.

The remainder of this paper is organized as follows. In section 2 we present related work. In section 3 we introduce our methodology. In section 4 we present preliminary results. In section 5 we give an outlook on future research.

2. Related work

The relationship between movement, work and energy can be used to estimate fuel consumption of petrol-powered vehicles. The Virginia Tech Comprehensive Power-Based Fuel Consumption Model (VT-CPFM) derives the instantaneous power of a vehicle from the instantaneous movement (Rakha, Ahn, Moran, Saerens, & Bulck, 2011); and models the vehicle’s instantaneous fuel intake. VT-CPFM has been verified in empirical analyses (Minett, Salomons, Daamen, Van Arem, & Kuijpers, 2011).

VT-CPFM allows for very accurate estimations of fuel intake. However, it requires an in-depth understanding of both the vehicle’s characteristics and the geographical
context. In contrast to this, Ribeiro, Rodrigues, and Aguiar (2013) derive instantaneous fuel consumption from GPS speed and acceleration data using statistical relationships only. Moreover, Jakobsen, Mouritsen, and Torp (2013) compare GPS speed and acceleration to OBD fuel consumption to evaluate eco-driving advice.

3. Pre-processing, segmentation and deriving statistics

Our data comprise around 7000 km GPS trajectories of one vehicle (VW Caddy), recorded in and around the city of Salzburg, Austria. The data are recorded at 1 Hz. In an experiment we found this a suitable sampling rate to derive speed measurements from GPS car trajectories. The results of this experiment are summarized in a separate journal paper, which is currently under review. As GPS elevation measures are prone to error (Hofmann-Wellenhof, Legat, & Wieser, 2003), we merge the trajectory data with a digital terrain model of 1m spatial resolution. Moreover, we synchronize the data with instantaneous fuel consumption from the vehicle’s OBD. Thus, each trajectory point consists of a spatial position – in Universal Transversal Mercator (UTM), a timestamp, an elevation and a fuel value. In a first step, we pre-process the data and calculate speed, acceleration, slope and fuel intake along the trajectory.

![Figure 1. A segment along a trajectory and its speed, acceleration and slope.](image)

After pre-processing we split the trajectories into segments of 100 meters. We choose segments over single point measurements as a basis for comparison for two reasons: firstly, due to the systems limitation we cannot guarantee a full temporal synchronisation of GPS and OBD measurements. In segments this error will be averaged out. Secondly, we plan to map the trajectories and observed energy consumption to a road network in a later stage. (This also implies that data-driven segmentation is not an aim of this study.) In a road network, the segmentation length...
will be defined by the network’s edges, i.e. the distance between two crossings. We argue that 100 meter is a good first approximation for a street edge. However, we also performed tests for 50 and 200 meter segments leading to similar result. For reasons of brevity, these are omitted.

During segmentation we remove incorrect data points, i.e. points where speed exceeds 160 km/h, acceleration $5m/s^2$ or slope $\mp 20\%$. Moreover, we require all points in a segment to be sampled at a constant sampling rate of one second. Segments that don’t meet this criterion are excluded.

For each of the segments we calculate three principal curves for speed, acceleration and slope. From these curves we derive further statistics:

- average speed, acceleration and slope (along the segment)
- standard deviation of speed acceleration and slope (along the segment)

In a next step we relate these statistical variables to fuel consumption. Figure 1 shows one example for a segment and its curves for the three principal parameters.

4. Preliminary results

By and large, the relationship between movement and fuel consumption depends on two parameters (see also Ribeiro et al. (2013) and Joumard, Jost, Hickman, and Hassel (1995)):

- the instantaneous power of the vehicle (for definition, see Rakha et al. (2011))
- varying efficiency of the combustion engine at different speed

Figure 2a shows the relationship between average speed along a segment and fuel consumption. It provides a good impression of the efficiency of the engine at different speed:

- for speed $< \sim 40$ km/h: the engine is very inefficient, fuel consumption is very high, but decreases as speed increases
- for $\sim 40$ km/h $<$ speed $< \sim 90$ km/h: the engine is efficient, fuel consumption is (mostly) low
- for speed $> \sim 90$ km/h: the engine is inefficient, fuel consumption rises as speed increases

However, the values for a certain speed occur across a wide range forming a dispersed band rather than a crisp functional relationship. Ideally, instantaneous power should now define where on this band the fuel consumption comes to lie. On the one hand, the most power-saving movement should cluster on the lower edge of the band, (turquoise dots in Figure 2b). These segments include movement with very low acceleration along downhill roads. On the other hand, power-intensive movement should occur on the upper edge of the band (red dots in Figure 2b). These segments comprise movement with very high acceleration along uphill roads.
Unfortunately, from Figure 2b follows that the relation between fuel consumption and most power-saving/intensive movement does not always hold. Fuel consumption may result from parameters not related to motion, such as the driving behaviour, weather conditions, the use of heating, or the loading of the car.

Figure 3a shows the relationship between average acceleration and fuel consumption for segments between 60 – 70 km/h and an average slope between ±1%. Similarly, Figure 3b shows the relationship between average slope and fuel consumption for average acceleration between ±0.4 m/s². For similar movement, both average acceleration and slope have a clear linear correlation to fuel consumption; Pearson’s correlation coefficient (PCC) is well above 80%. We observe the same linear relationship throughout all other types of similar movement, i.e. average speed between 70 and 80 km/h and an average acceleration of 2 – 4 %.
As a first conclusion, the data allow to link speed, acceleration and slope to fuel consumption. However, this relationship cannot be explained globally by a simple linear model. Moreover, it does not hold for all observations due to the influence of parameters not related to movement.

5. Outlook and future work

The future work on this paper divides into three parts. Firstly, we continue the systematic statistical analysis of all derived movement parameters and their relationships to fuel consumption. Secondly, we define classes of energy consumption and create a model to estimate these from the movement data. We verify this model with additional trajectory data from different cars. Third, we apply the model to large numbers of map-matched GPS trajectories without OBD fuel measurements and estimate their energy consumption along the road network of the city of Salzburg.

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References


