Using Smartphones to Identify Ecological Driving Footprint

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Extended Abstract

The increased usage of private vehicles resulting from the modern reality of rapidly developing cities and the indications of the deterioration of the greenhouse effect make the investigation and the application of economically and environmentally sustainable solutions necessary. Towards this direction, many researchers have turned their attention to eco-driving. Recent findings indicate that eco-driving has a significant contribution in the reduction of fuel consumption and carbon dioxide emissions. Moreover, recent literature stresses variation in driving style leads to variation in fuel consumption and fuel efficiency. Eco-driving support system has been demonstrated to be effective in improving driving behaviour and reducing of fuel consumption (Magana and Munoz-Organero 2016). For example, five non-eco-driving behaviours (quick acceleration, rapid deceleration, high engine revolutions, too fast or unstable freeway speed and idling for a long time) can be detected through an eco-driving support system (Zhao et al. 2015). Information on the impact of hard acceleration and engine loading on fuel consumption can help to identify the difference between smooth and aggressive driving behaviours.

Most existing studies regarding emission or fuel consumption prediction only consider the averages of selected factors to predict fuel consumption over a travel distance (Alam and McNabola 2014). Limited research has been conducted on using real-time vehicle data and traffic conditions for emission or fuel consumption prediction. Most attempts to relate driving with fuel consumption are based on modeling and analytical approaches (Ahn et al. 2002, Zhou et al. 2016). Hsu et al. (2016) developed a framework to estimate the time a vehicle is in economy mode based on OBD-II extracted information such as the vehicle speed, engine speed (rpm), engine loading value and fuel consumption. Data about vehicle movement is also collected from a three-axis accelerometer (G-sensor). Magana and Munoz-Organero (2016) implemented machine-learning models to estimate fuel savings based on data coming from ODB-II devices.

The aim of this paper is to introduce a quantification metric of the ecological driving footprint (eDrive index) and to investigate its relationship with fuel consumption. eDrive is based on real-time data collected from smartphone sensors and is estimated using those data that describe the driving behavior of the user and the traffic conditions during the trip.

The development of the eDrive index of eco driving footprint is based on quantifying the eco driving duration as the remaining time after excluding idle time (#stops, acceleration from stop time), duration of driving in critical alignments (grades, sharp curves), duration of speeding, duration of harsh events (harsh braking, harsh acceleration) (Figure 1). Based on the estimation of eDrive indicator on the entire database of trip we can produce a scale for eDrive. This scale may alter in relation to setting (urban, highway etc). As this indicator quantifies the loss of driving efficiency due to roadway, traffic and driver specific factors, the criticality of each factor is not taken into consideration. For this, each one of the three components of eDrive (behavioral, roadway and traffic-travel) is further analyzed separately in relation to the per trip fuel consumption.

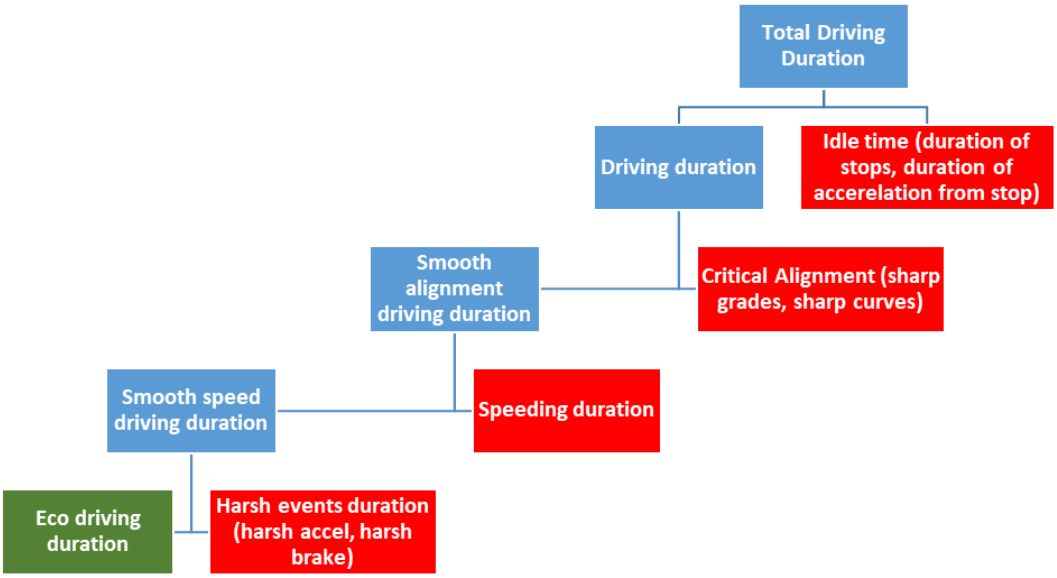

Figure 1: eDrive quantification scheme.

Further, to investigate the relationship between eDrive and fuel consumption, two experiments were conducted, one expanded, which examined the total trips of a specific user and one supervised, which examined the relationship on a specific route performed by a user.

Data was collected using the Oseven mobile application, developed for both iPhone and Android devices[1]. The application starts to collect raw data from smartphone using accelerometer, magnetometer, gyroscope and GPS data, without any user engagement. Also, the app can automatically identify when the user completed the trip and stop the recording. The data recorded by the mobile phone is transmitted to a central database where it is stored and processed. The database for the specific study consists of more than 20000 trips of 160

[1] https://www.oseven.io/

different drivers. To explore the relationship of eDrive with consumption, more than 500 per trip fuel consumption cases were taken into consideration from various types of vehicles and drivers.

Findings indicate that eDrive may vary between drivers considerably (Figure 2). There is a strong correlation of the eDrive index with fuel consumption when examining a specific route, as well as the importance of the influence of driving behavior (eDrive (behavior) indicator) to fuel consumption (Figure 3).

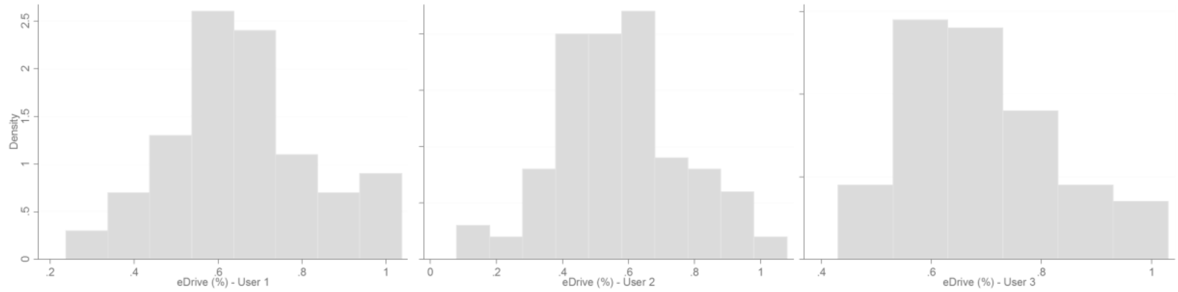

Figure 2: eDrive distribution for three drivers on their latest 100 trips.

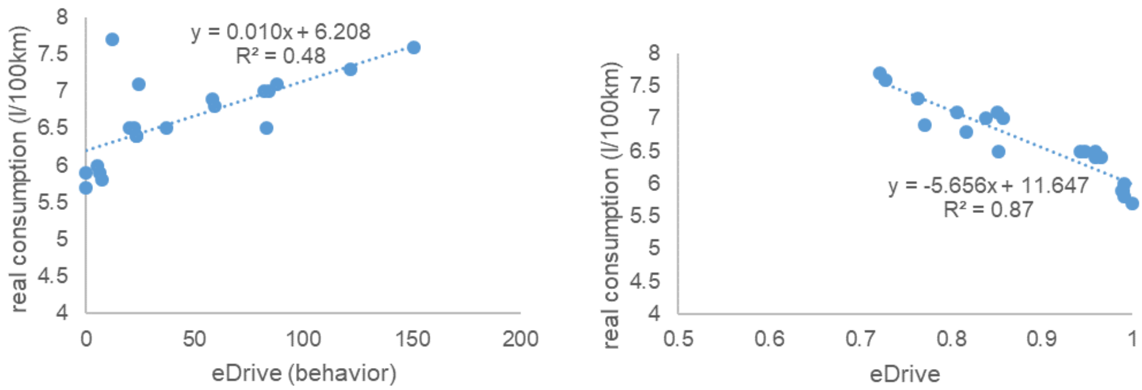

Figure 2: Scatter plot between and eDrive (behavior) (sec) and real per trip consumption (trips in same route) and eDrive (%) and real per trip consumption (trips in same route).

The above estimated relationships were also validated in a large scale dataset using the fuel VT-micro consumption model, a microscopic vehicle fuel consumption and emission modeling tool that allows users to estimate vehicle instantaneous fuel consumption and emission levels using a second-by-second vehicle speed profile (Ahn et al. 2002, Rakha et al. 2003, 2004).

The proposed modeling strategy enables the implicit quantified evaluation of the impact of behavior, geometry and traffic to the eco driving footprint, which in turn can be associated to fuel consumption. The exclusive use of smartphone data creates some limitations on the data that affect the ecological footprint. For example, there is no access to vehicle status data such as engine maintenance level or tire pressure. In addition, it is not possible to assess the use of the gearbox and its consequences on fuel consumption. Nevertheless, it is a low cost and massive manner to monitor the eco driving footprint with high network coverage.

Acknowledgements

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