Towards a Reality-Enhanced Serious Game to Promote Eco-Driving in the Wild

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Abstract. Reality-enhanced serious games (RESGs) incorporate data from the real world to enact training in the wild. This – with the proper cautions due to safety - can be done also for daily activities, such as driving. We have developed two modules that may be integrated as field user performance evaluators in third-party RESGs, aimed at improving driver's fuel efficiency. They exploit vehicular signals (throttle position, engine revolutions per minute and car speed), which are easily accessible through the common On-Board Diagnostics-II (OBD-II) interface. The first module detects inefficient and risky driving manoeuvres while driving, in order to suggest improvement actions based upon fuzzy rules, derived from analyzing naturalistic driving data. The second module provides an eco-driving categorization for a drive via two indicators, fuel efficiency and throttle position values. The estimation of fuel efficiency for the whole trip relies on the mentioned signals, plus the OBD-II calculated engine load. Data from 'enviroCar' project's, a naturalistic driving archive, was used in a simulation. The results are promising in terms of accuracy and encourage further steps towards more effective modules to support a better driving performance, for RESGs.

Keywords: Eco-driving · Gamification · Serious game (SG) · Reality-enhanced serious game (RESG) · Driving pattern · Fuel consumption (FC) · Fuel efficiency

1 Introduction

In addition to smarter vehicles and roads, improving driver behavior still has a significant potential to increase road safety, fuel efficiency and reduce emissions [1, 2]. It has been estimated that vehicle drivers can save up to 25% of fuel by adopting efficient driving patterns [3], with variations depending on the type of a vehicle [4].

Studies have demonstrated that eco-driving (economic or ecologic driving) advice supports fuel-saving [5]. This can decrease fuel consumption (FC) from 5 to 25% [3]. Thus, there is a need to continuously motivate the drivers towards eco-driving. However, advice might also be misinterpreted, which may lead to a worse performance [4]. Hence there is a need to provide drivers with proper and understandable advice.

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Encouraging eco-driving could be promoted using serious games (SGs) and gamification, which applies game-style mechanics and experience designs in non-game contexts and activities [7–9]. These techniques have been trialled in the automotive and transportation sector because of their motivating and inspiring potential [10, 11]. Given the frequently critical operation context, user experience must be carefully designed [12]. Furthermore, users' privacy should be taken into account [13, 14].

A SG can improve the user experience by combining training and entertainment. In the emerging genre of reality-enhanced serious games (RESGs), in-game progress is due not only to the digital gaming ability of the player, but also it depends on sensing a user's performance in the actual target field [1, 11, 15]. This is an evolution of pervasive gaming [16], where the game's fictive world blends with the physical world connecting a digital game environment with reality, and allows opening and exploiting a direct, possibly real-time (RT), link between a game and a training objective. Therefore, field users' performance becomes a key factor [11] and should be easily understandable to supply effective coaching feedback to players.

This paper contributes to the field by proposing two driving profiling algorithms (for RT feedback and for trip-level categorization), usable as pluggable modules in RESGs towards reducing FC. Given the effectiveness of monitoring a driver's behavior [17], the outcome of the former module can be used to provide direct feedback via voice prompts and/or other means suited to the driving environment. Both algorithms analyse the changes of throttle position (TPS), revolutions per minute (RPM) and car speed. Those vehicular signals are easily understandable to any driver. They are accessible through the On-Board Diagnostics-II (OBD-II) interface [18]. We also considered the OBD-II calculated engine load in the FC estimation for the second algorithm.

Significant changes in TPS, RPM and speed are detected as FC-relevant events, e.g., signaling overtaking. We developed our algorithms exploiting open data extracted from the enviroCar project that collects naturalistic drive trips [19].

Following the introduction in the first section, Sect. 2 reviews the literature; Sect. 3 presents the methodology and data; Sect. 4 describes the two proposed modules for (i) RT driving feedback and (ii) trip-level eco-drive categorization; Sect. 5 presents the analysis, assessment and a simulated case study; Conclusions and future work are given in Sect. 6.

2 Related Work

Several studies have shown the benefits of providing eco-driving advice in reducing FC and emissions using different approaches. [20] proposed a control strategy to drive efficiently using fuzzy logic (FL) by determining the adequate speed and gear. [21] presented a driver evaluation system for assessing driver's skills, based upon the achieved fuel efficiency and acceleration using in-mobile sensors and car's OBD-II system. [22] developed a smartphone fuzzy application to reduce energy consumption via providing hints to drivers using statistical analysis of speed, acceleration and FC.

Driving- and travel-related SGs can have a range of objectives such as encouraging the use of different transport mode and route choices [23]. Studies have also used gamification's motivation towards more fuel-efficient driving (e.g., [24]) and safer driver behavior (e.g., [25]). Some of those motivations were achieved by combining gamification with social networks. [26] developed an incentive system for comparing individual driver's FC average with the average FC of all drivers in a group that is formed with similar vehicles, routes, and time of day. [27] presented a social awareness system to promote eco-driving and safe-driving by implementing some social experiments on a website through communication technology that gathers information about driving patterns using GPS and motions sensors. [4] implemented a driving game to encourage drivers to save fuel, comparing the vehicle telemetry with other users with similar characteristics. Drivers can share their scores with others, e.g., via social networks. Their experiments (on three routes by 36 drivers) showed that gamification tools and eco-driving assistants, help drivers to not lose interest in fuel saving.

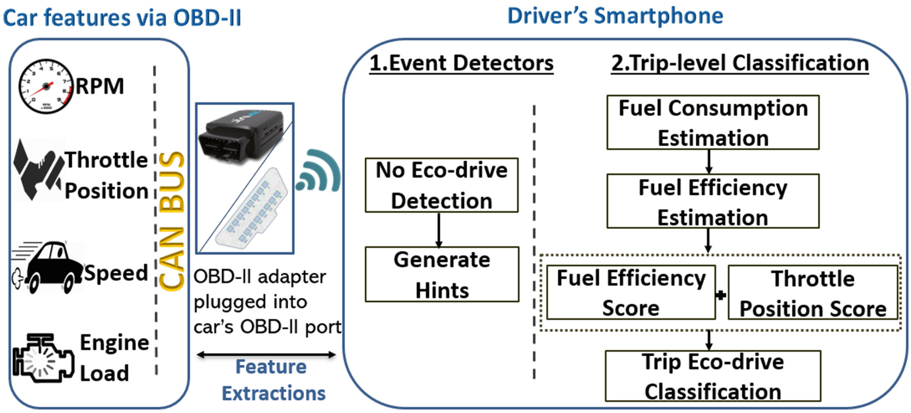

Fig. 1. Methodology – in-car features' extraction via OBD-II system used as inputs for the two modules (running in drivers' smartphones): (i) RT driving feedback when inefficient manoeuvres are detected and (ii) eco-drive classification after a drive

3 Experimental Environment

3.1 Methodology

Figure 1 depicts the followed methodology. The inputs are periodically captured from the vehicle OBD-II interface, through an OBD-II adapter and delivered to a driver's smartphone via a Bluetooth connection. A careless (aggressive) driving style results in more FC than a normal one. Our system thus detects in RT aggressive/inefficient driving manoeuvres by analyzing the three signals (TPS, car speed and RPM) and triggers warnings on what actions the driver could do to better control the fuel economy. Beside RT event's detection, we also estimate instant FC for fuel efficiency's calculation after a trip, which might be used as a part of self/peer competitions (e.g., [10]). FC is not directly accessible through the OBD-II interface, as the 'Engine fuel

Rate' is not supported by all cars (not mandatory in the OBD-II standard protocol) [19]. Thus, it has to be estimated from the available OBD-II signals and information.

3.2 Experimental Data

We analysed the requested OBD-II enviroCar data – a community-based open data collection platform for gathering pseudonymized naturalistic driving car sensor data (cars are just identified by ID numbers for the privacy of drivers) [19]. Data was sampled at regular time intervals (every 5 s, for most of the tracks we used), together with GPS information for spatial-temporal analysis. Derived parameters, such as FC and Carbon dioxide (CO_2) emissions, are computed post-hoc and added to the server.

To build our dataset, we developed a software system that requests the data through a JSON (JavaScript Object Notation) interface, using the enviroCar REST APIs. Data is then stored in a local relational database for querying purposes. For our analysis, we considered 8726 different gasoline tracks, with 983, 291 measurements for gasoline engines that were recorded mostly in Germany in the period 2012-01-01–2016-06-15.

4 Real-Time Event Detectors and Trip-Level Eco-Drive Categorisation

4.1 Event Detectors

(a) *TPS*, ranging from 0% to 100%: It regulates the air and fuel intake into the engine, making it run slower or faster. It is one of the parameters that are controlled directly by drivers, reflecting their habits in dealing with the accelerator pedal.
(b) *Car speed,* measured in km/h: Speeding requires fuel burning. Likewise, overspeed is a crucial metric to characterize driver safety compliance. Overspeeding events are triggered if the car's speed is greater than the legal speed limit, which is obtained through a web service access, based on OpenStreetMap (OSM) [28]. Table 1 presents the driving classification with this indicator.
(c) *RPM* expressed as the number of revolutions per minute: The higher the RPM, the more the fuel is consumed [1, 29]. Optimal RPM value differs between cars (e.g., engine characteristic) and depends on road type (e.g., uphill or downhill).
(d) *Engine Load (calculated),* ranging from 0% to 100%: It measures how much air and fuel are sucking into the engine. The more the engine is loaded (close to 100%), the more the fuel is burned. We categorised this feature into three classes low-loaded 'LL', typical 'T' and Loaded 'L', when its ranges in 0–39, 40–59 and 60–100 respectively.

In [1], we modelled FC resorting to FL, exploiting TPS, speed and RPM signals. Table 2 presents the driving feedback, extracted from our deduced fuzzy rules for the case FC is high 'H' or very high 'VH' [1].

Table 1. Driving profiling with overspeeding (CS: current speed, MS: OSM maximum speed).

Speed (km/h)	Class	Recommendation
CS < MS–5%	M	–
MS–5% $\leq$ CS $\leq$ MS + 5%	M	Be careful, reaching the legal speed limit
CS > MS	A	Overspeeding, slow down for safety and fuel saving

Table 2. Extracted fuzzy rules and proposed feedback in case FC is High or Very High (L: Low, M: Medium; H: High, VH: Very High).

	FL rules
1	if RPM is L & TPS is H & Speed is H then FC is VH
2	if RPM is L & TPS is H & Speed is VH then FC is H
3	if RPM is H & TPS is M & Speed is M then FC is H
4	if RPM is H & TPS is M & Speed is (H or VH) then FC is H
5	if RPM is H & TPS is H then FC is H
6	if RPM is VH & TPS is M then FC is H
7	if RPM is VH & TPS is H then FC is VH
Corresponding driving feedback	
F1	Whether upshift the gear or slow down
F2	Whether upshift the gear or slow down
F3	Downshift the gear
F4	High RPM caused by high speeds, downshift the gear to drive at a lower speed
F5	High RPM caused by high speeds, downshift the gear to drive at a lower speed
F6	Downshift the gear
F7	High RPM caused by high speeds, downshift the gear to drive at a lower speed

4.2 Trip-Level Eco-Driving Categorization

We implemented an eco-driving categorisation for a trip as a trade-off between the two indicators, fuel efficiency (75%) and TPS (25%). TPS is introduced to balance the impact of driving patterns and other factors on fuel economy (e.g., weather conditions) [2]. This could be a powerful indicator of fuel efficiency and driving style simultaneously. The trip is classified as (1) Saver ‘S’ for a score is in 60–100; (2) Typical ‘T’ if the score is in 40–59; (3) Careless ‘C’ for a score is in 0–39.

(a) *Quantitative FC estimation:* In [2], we proposed a FC predictor for gaming via three vehicular signals TPS, RPM and car speed, using Random Forests (RF). FC is impacted by other factors in addition to driving styles [29]. Consequently, we involved the calculated ‘engine load’ sensed from OBD-II, as a further FC predictor. In the analysed data, we consider the computed FC (l/h) by enviroCar following the formula given in [30], focusing on gasoline engines, as their FC estimation provides the best accuracy [19]. For implementing the RF model, we used the ‘RandomForestRegressor’ of the ‘Sklearn.ensemble’ python library [31], dividing our dataset in 80% learning and 20% testing. We have adjusted its two most important settings, (1) the number of trees in the forest 'n_estimators' and (2) the number of features considered for splitting at each leaf node 'max_features'. In addition to 'max_depth', which is the max number of levels in each decision tree.

(b) *Eco-driving categorization:* Fuel efficiency relates distance travelled by a vehicle and the amount of fuel consumed. For estimating the fuel efficiency score, we followed the proposed approach in [21] (Fig. 2). It compares the fuel efficiency achieved by a driver with the current maximum recorded fuel efficiency value by any previous driver, who is driving a similar car model. The TPS score is an average of the instantaneous values obtained as 100-TPS. The higher the TPS score, the better the driver's estimated performance.

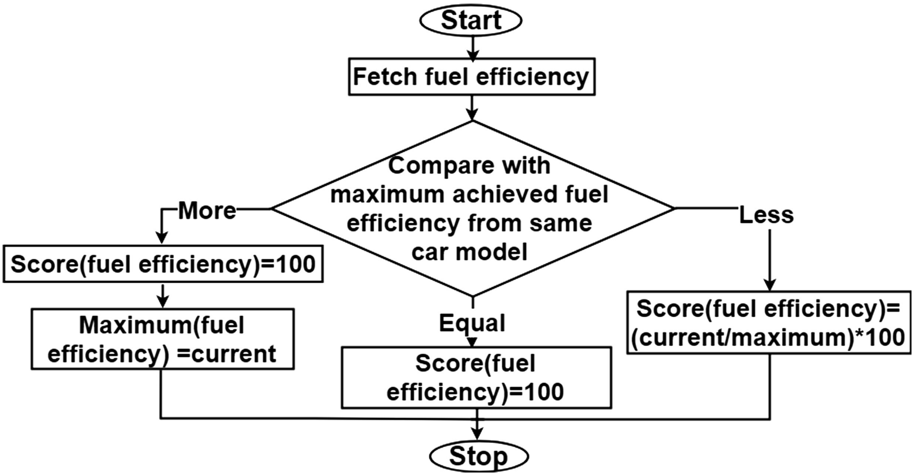

Fig. 2. Fuel efficiency score algorithm [21].

5 Results Case Study and Discussion

For our analysis, we selected from the enviroCar database, a 71 km and 50 min track, with 575 measurements, recorded in Germany in 2016, with a Volkswagen Polo 9 N 2009, gasoline engine. Figure 3 shows the analysis done for the considered indicators. The trips were mostly driven on a highway. The last picture at the bottom of Fig. 3, visualizes the time evolution of FC predicted by the RF model versus the actual enviroCar estimated one for the studied track. We considered 800 trees, 100 levels and square root of the number of features to split at each leaf node, as found in [2]. Involving engine load, increases the performance of the model, giving a lower Mean-squared-error (0.82 vs 1.5) and a slightly higher squared correlation coefficient (0.94 vs 0.896) than without it. Figure 4 shows the fit of the RF model.

Speeding requires a high RPM, leading to a drop in fuel efficiency. On the motorway (the speed is higher than 60 km/h), the values of RPM are higher compared to urban roads at the start and the end of the trip, where the OSM speed limit is about 70 and 30 km/h respectively. In those cases, the values of engine load are higher, since the engine has to work harder for moving the car at high speeds, which implies more FC. Further, the FC fluctuates more than RPM on motorways. This is caused by engine load variations which is clear from the engine load timeline. This might be due to car configuration changes (e.g., caused by the use of heated seats and demister blowers in cold weather as the trip was recorded at the beginning of February) or changes in the use of car accessories such as playing the entertainment system more loudly. This is the reason for involving the engine load in the FC estimation.

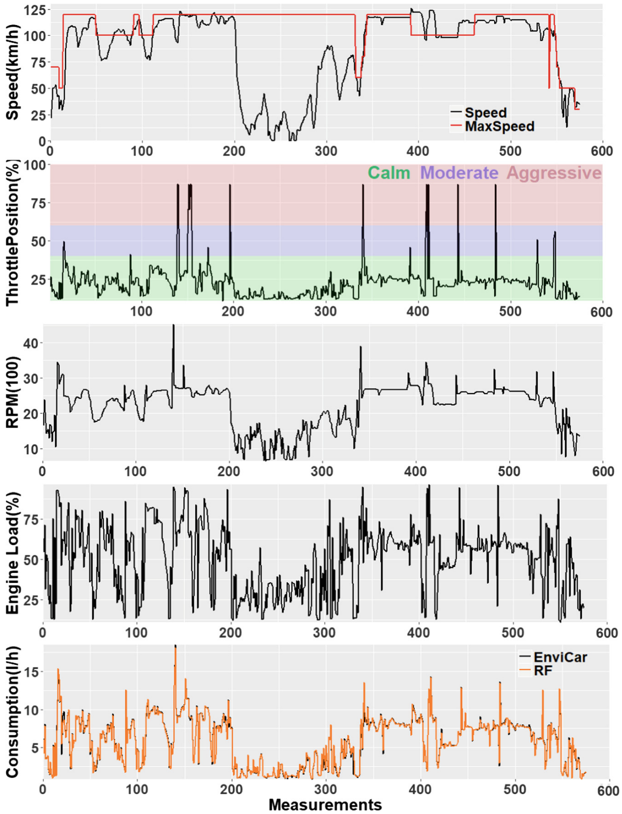

Fig. 3. Car data behavior along with the trace: speed, TPS, RPM, engine load and FC (RF prediction vs enviroCar estimation).

Higher values of TPS are translated into higher FC values, regardless of other factors. Also, when a driver releases the accelerator pedal, the FC decreases. This validates involving TPS in the eco-driving profiling, since it affects strongly the fuel economy and it is directly controllable by a driver. Table 3 shows an example of an instant driving recommendation.

The achieved fuel efficiency for the studied trip is 0.021 km/l/h, while the maximum efficiency achieved by 111 tracks for the same car type, in the same region is 0.037 km/l/h. Hence, the score of fuel efficiency is 56.25 over 100 (normal trip). The score for the TPS is 77 over 100 (calm, saver trip). The eco-driving score for the trip is 61.44 over 100, which again indicates a saver behavior.

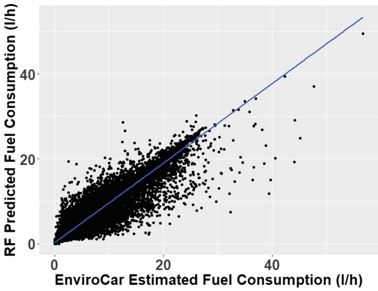

Fig. 4. RF model fit (test set 20% of the data).

Table 3. Example of driving feedback for a measurement of the studied track.

Event detectors	Values	Classifications
RPM	4530 rpm	VH
Car speed/OSM speed	117.36/120 km/h	H, respecting the legal speed limit
TPS	87%	H
Engine Load	93%	Loaded
****** Driving Recommendation ******		
High RPM caused by high speeds, downshift the gear to drive at a lower speed		

6 Conclusions and Future Work

As SGs are gaining momentum also in the transportation sector, this paper has proposed two modules employable as virtual sensors for driver's behavior assessment. The first algorithm detects no eco-driving events and provides instant related recommendations for keeping the driver aware of fuel economy. Source signals are accessed from the OBD-II standard interface for estimating a driver's style and fuel economy. These are numerical values and verbal messages, that can be easily encapsulated into a variety of game mechanics inside a RESG (e.g., as points, energy, bonuses/maluses) [32].

The second algorithm processes data sampled from a whole trip to classify it with respect to three classes, 'Saver', 'Typical' and 'Careless'. The algorithm exploits two indicators: (i) the achieved fuel efficiency (the most important metric in eco-driving) and (ii) the throttle position, which is a good indicator for the driving style, also considering the influences on FC by other factors (e.g., environmental). As above, the provided quantitative score for each drive can be exploited through proper game mechanics. Those games' motivation elements are expected to encourage continuous improvement towards more fuel-efficient and safer driver behavior.

Our future work will focus on improving validation. Drivers will be evaluated under different driving conditions in order to tune feedback provision to improve fuel economy. We believe that this work opens significant perspectives, as similar algorithms may be designed and integrated into SGs (e.g., as software services [33]) in order to improve the field performance in various types of activities.

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