A Smartphone-Based Energy-Oriented Driving Assistance System

Simone Formentin, Carlo Ongini and Sergio Matteo Savaresi

Abstract Recent studies showed that one of the major environmental problems is the transport-related air pollution and road transport alone is expected to be the largest contributor to anthropogenic climate forcing in 2020. The development of more efficient vehicles, the use of alternative energy sources, and the deployment of intelligent transportation systems (ITS) are all solutions toward the decarbonization of the sector. In this chapter, an energy-oriented driving assistance system focusing on the assessment of the current driving style is proposed. In fact, it has been observed that a change of the driving style may provide savings from 5 to 40% of the total energy expenses, as well as reductions of the air pollution. The proposed system is fully integrated in a smartphone application, which acquires the signals related to the vehicle dynamics (e.g., velocity and acceleration) and computes three power-related indices containing significant information about the current driving style. Based on such indices, a feedback communication can be given to the driver (if needed) to induce a change in the driving style, which in turns would result into an energy saving. Differently from the existing studies, the proposed application is vehicle-independent and does not require any connection to the vehicle CAN-bus or OBD-interface. The effectiveness of the proposed approach is assessed via an experimental campaign carried out on urban and extra-urban routes by different drivers. Experimental results show that the proposed driving assistance system may reduce the vehicle consumption up to 30%.

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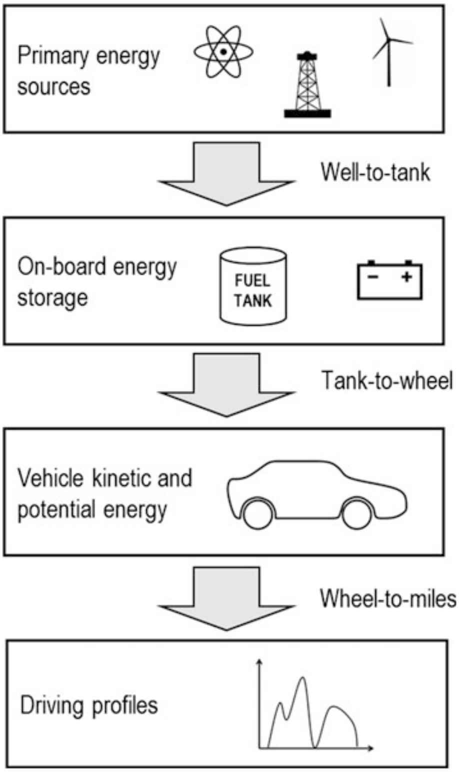
1 Introduction

The complete energy conversion chain related to vehicle energy consumption is depicted in Fig. 1. A first step, commonly referred as "wheel-to-tank", is the conversion of the primary energy carries (e.g., chemical energy in fossil hydrocarbons or kinetic energy in wind, etc.) to an energy carrier that can be stored on-board (e.g., gasoline, electricity, hydrogen, etc.). Then, the energy stored inside the vehicle is converted by the propulsion system into mechanical energy, in the so-called tank- to-wheel conversion. Finally, the "wheel-to-miles" step refers to the dissipation of mechanical energy used to move a vehicle with the speed and the acceleration profiles chosen by the driver.

In order to optimize the total vehicle energy consumption, all the three step efficiencies need to be improved: the "Well-to-tank" conversion by optimizing the upstream processes, the "tank-to-wheel" by optimizing the power train components, architectures, and control strategies, and the "wheel-to-miles" step by reducing vehicle mass and frictions or by influencing the driver's profiles and behavior.

Several research studies in this field have been focused on optimizing the "well-to-tank" and the "tank-to-wheel" energy conversions. The former has been

Fig. 1 Energy conversion chain



enhanced by improving the refinery and transportation of fossil oil. The latter has been improved by optimizing the power train components, architectures, and control strategies.

However, the so-called wheel-to-miles has been less considered until the last decade. This energy conversion step depends on the vehicle characteristics (mass, frontal surface, drag, etc.) and on the vehicle's speed and acceleration imposed by the driver's commands: the so-called driving style. The driving style itself depends on driver's behavior and experience but also on external factors such as traffic and car performance (Brundell-Freij and Ericsson 2005). It is well known that the driving style has a huge impact on vehicle consumption.

Driving style systems can be classified in two subcategories (Corti et al. 2013): active and passive (see Fig. 2).

Active driving style systems (Fig. 2a) control directly the driving style by imposing constraints on the vehicle performance. As an example, (Dardanelli et al. 2011a, b, 2012) propose to limit the acceleration and velocity of a light electric vehicle to manage the battery discharge rate. As shown by these works, the active control of the driving style can decrease the energy consumption and increase the range. However, these systems override driver commands and introduce some drawbacks. First of all, active driving style systems introduce safety issues. For example, they could limit the vehicle performance also in case of an emergency maneuver when the vehicle has to move fast to avoid collision or crash.

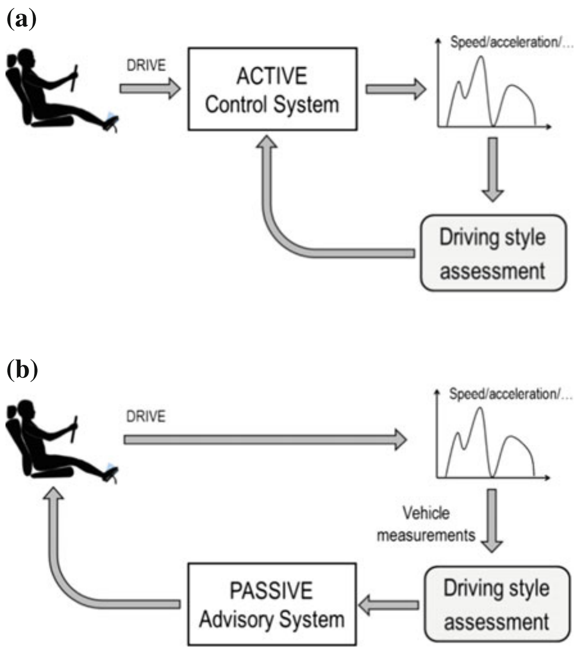


Fig. 2 Driving style systems classification: **a** Active driving style system, **b** Passive driving style system

Furthermore, an ad hoc installation of additional electronic control unit is required for existing vehicles.

An alternative approach is represented by passive driving style systems (see Fig. 2b). This kind of systems does not act directly on vehicle control system but provides a suitable feedback to the driver in order to change his driving style. The interaction between the system and the driver can be performed through different human–machine interfaces (HMIs). Indeed, the main drawback of such an approach is that the effectiveness of the system cannot be guaranteed, as the user may ignore the feedback or not pay attention to the HMI. A huge research effort has been devoted to passive driving style systems, and most of existing studies try to classify the behavior of a driver.

The work in (Murphey et al. 2009) presents a method to classify the driver's style by means of the analysis of the online jerk profile combined with the knowledge of the road type. In (Won and Langari 2005), the driving style is classified in three categories (aggressive, normal, and calm) according to the ratio of the standard deviation and the average acceleration within a specified window and they use the information for the power management system. Likewise, (Tricot et al. 2002) classify the driving behavior into three driving styles applying data classification techniques to vehicle position and driver's actions. Fuzzy systems are used in (Kamal et al. 2007) to determine the driver behavior from noisy data. In (Araujo et al. 2012), a driving style mobile application based on fuzzy system is proposed. The smartphone application gathers vehicle's data through an OBD–Bluetooth interface. In (Lin et al. 2006), Lin and co-authors present a method to classify the driving style in a virtual reality as aggressive or gentle by analyzing the driver's electroencephalogram. In the papers (Syed et al. 2007, 2008, 2009), an advisory system which provides visual and haptic feedback to the driver to change his driving style behavior and reduce the fuel consumption is proposed. Haptic interfaces for improving fuel economy through driving style classification have also been patented (Coughlin 2009). Although all existing systems focus on driving style assessment, they all have two main limitations: (i) the classification of the driver behavior is limited to a finite set of discrete label; (ii) a complete knowledge of vehicle efficiency or the vehicle-dependent measurements is required.

The second limitation is due to the fact that the works are developed just for a particular model of car. The algorithms rely on a deep vehicle knowledge (engine map, gear ratio, gear used by the driver, throttle position). For this reason, the proposed works are not flexible and reusable on different vehicles. Moreover, additional interfaces (like the OBD) are required to read signals from the vehicle CAN-bus.

An alternative is to rely upon inertial measurements. The main advantage of developing driving style application by relying on only such data is the system flexibility. The same system can be used on different categories of vehicles just by adapting few parameters without any vehicle-dependent connection. The first attempt in assessing the driving style via inertial measurements is proposed in (Manzoni et al. 2010; Savaresi et al. 2010). The authors design a method to evaluate the performance of a bus driver. Every time the driver stops, its velocity profile is compared to a realistic reference from an energetic point of view. A synthetic result is provided with a feedback on the bus HMI display. The system was implemented on the buses of Udine in Italy. However, this approach shows some limitation from the user interaction point of view. The feedback is generated only when the vehicle stops so that the driver does not receive any feedback for a long period of time when the vehicle travels without stopping (e.g., highway).

In this chapter, we propose a smartphone-based driving style system based on real-time feedback. A continuous evaluation of the driving style based on inertial measurements is shown to the driver. Differently from the previous works, the proposed system estimates in real-time three indexes related to vehicle power over-consumption instead of classifying the driving style in a finite set of categories. The proposed system is implemented on a low-cost, vehicle-independent device, a smartphone. In this way, we take advantage from an existing pervasive device that integrates all the required hardware (CPU, GPS, accelerometers, and HMI).

An experimental campaign has been carried out with five drivers on a test route for evaluating the performance of the system.

Experimental results show that it is possible to save up to 30% of the total energy.

2 Three Model-Based Indexes

To start with, the considered vehicle model is briefly presented. Then, three model-based indexes to evaluate the driving style are introduced and motivated, as described in Sect. 2.2.

2.1 Vehicle Model

The vehicle longitudinal dynamics of interest can be modeled as

$$P_{iner}(t) = P_{wheel}(t) - (P_{brake}(t) + P_{aero}(t) + P_{roll}(t) + P_{slope}(t)) \tag{1}$$

where $P_{iner}(t) = Ma(t)v(t)$ is the inertial power, M is the vehicle mass, $v(t)$ is the longitudinal speed, and $a(t)$ is the longitudinal acceleration. Further, P_{wheel}(t) is the net power at the wheel, $P_{brake}(t)$ is the braking power, $P_{slope}(t)$ is the power generated by the road gradient, and $P_{aero}(t)$ and $P_{roll}(t)$ represent the power dissipated by the non-conservative aerodynamic and rolling friction forces acting on the vehicle, respectively. Two simplifications will now be made, by neglecting the following terms:

$P_{slope}(t)$, as the system has been conceived for urban environment and the test site is assumed to be flat. It should be noticed that the road gradient may be estimated with a longitudinal accelerometer and/or inferred by road maps made available via Internet connection, see (Dai and Lee 2002; Vahidi et al. 2005).

$P_{brake}(t)$, as it is not measurable and will be treated as a disturbance from now on.

Therefore, one has

$$P_{wheel}(t) = P_{iner}(t) + P_{aero}(t) + P_{roll}(t) \tag{2}$$

The parameters of this model are the vehicle mass M, the rolling drag C_r, the aerodynamic drag Cd, and the frontal surface S. They are approximated as constants (C_r and C_d may in fact vary according to vehicle speed and tires pressure) and depend only on the specific vehicle. Thus, once the vehicle has been fixed, P_{wheel} is a nonlinear function of speed and acceleration, i.e.,

$$P_{wheel}(v(t), a(t)) = P_{iner}(v(t), a(t)) + P_{res}(v(t)) \tag{3}$$

with resistance power $P_{res}(t) = P_{aero}(t) + P_{roll}(t)$ depending on vehicle speed only. The parameters of such a nonlinear dependence can be experimentally estimated by appropriate identification experiments that require measuring only the wheel speed (Dardanelli et al. 2012).

The driver's commands translate into vehicle speed and acceleration, and these are the variables that one must act upon to reduce the energy consumption.

2.2 Cost Function Definition

The cost functions selected to assess the driving style aim at capturing all aspects of power consumption, while being computable in real-time based on inertial measurements only.

The first index $\gamma_1(t)$ is generated as indicated in Fig. 3. It is the high-pass filtered version of P_{wheel}. This cost function stems from considering that $P_{wheel}(t)$ can be split into two parts: a low-frequency one, $P_{LPF}(t)$, which is really needed to move the vehicle, and a high-frequency one, $P_{HPF}(t)$ that represents unnecessary inertial power that is wasted during the process.

The filter order and the cutoff frequency must be tuned to correctly separate the two contributions according to the signal characteristics and to the measurement noise, which are vehicle-dependent. Thus, $\gamma_1(t)$ can be interpreted as the power

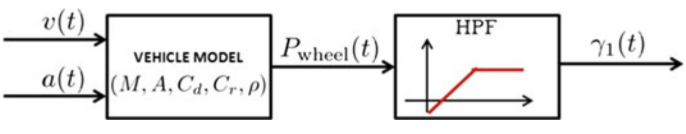


Fig. 3 Block diagram for the computation of γ_1

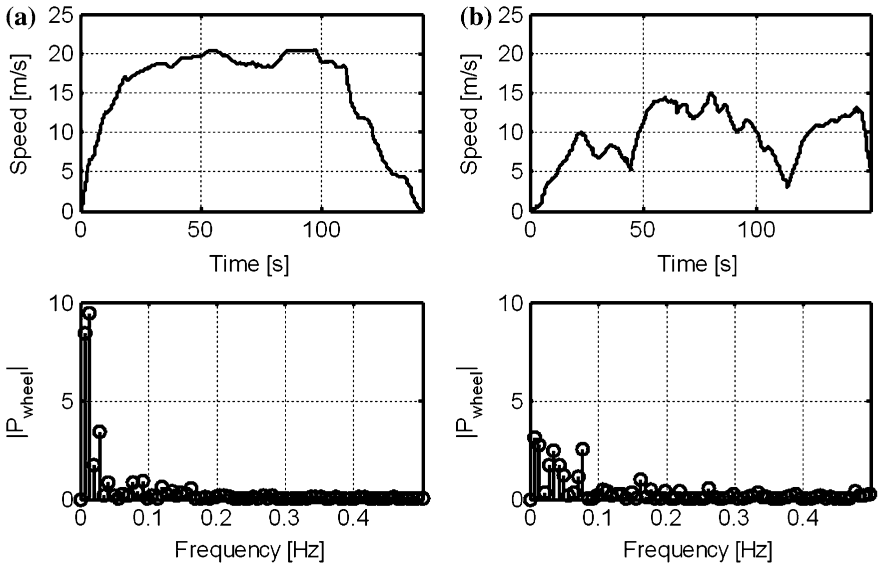


Fig. 4 Examples of two driving profiles. Top plots: time histories of the vehicle speed; bottom plots: spectral content of the signal $P_{wheel}(t)$. Notice that, when the speed is constant, there are no contributions at high frequency

wasted by a fast variation of the vehicle power, a "measure" of the driver aggressiveness. Based on this rationale, the ideal driving style would make the vehicle travel at constant speed (see Fig. 4).

The cost function $\gamma_1(t)$ is, in practice, a measure of the smoothness of the velocity profile imposed by the driver. However, $\gamma_1(t)$ is always equal to zero when the vehicle is proceeding at constant speed (e.g., on a highway).

To increase the driver's awareness about the energy losses due to the cruising speed value, the cost function $\gamma_2(t)$ is introduced as:

$$\gamma_2(t) = P_{res}(v(t)) = 0.5\rho A C_d v(t)^3 + MgC_r v(t) \tag{4}$$

which takes into account the power losses due to friction effects and depends on the cruising speed value $v(t)$, the vehicle mass M, the frontal surface A, and roll and drag coefficients C_r and C_d.

Note that both γ_1 and γ_2 depend on the instantaneous driving style (velocity v(t) and acceleration a(t)). In order to keep track of the driver's behavior over a time window of, say, M seconds, the cost function γ_3(t) is defined as

$$\gamma_3 = \sum_{t=i-M}^{i} \delta^{(M-t)} \frac{P_{res}(t)}{P_{wheel}(t)} \tag{5}$$

where δ is a forgetting factor parameter which allows attributing more importance to most recent data, see (Ljung 1999). Letting $\delta = 1$, γ_3 is the ratio between the power spent by resistance dissipative forces $P_{res}(t)$ and the total power $P_{wheel}(t)$.

Ideally, in this case, an efficient driving style keeps $P_{res}(t) = P_{wheel}(t)$, that is, the energy consumed by the vehicle is due to the chosen speed value and the inertial power dissipated by acceleration/deceleration is minimal.

2.3 System Architecture

The proposed driving style system is entirely developed as a mobile phone application. Using a mobile device is particularly intriguing, due to its pervasiveness and user's acceptance, see also (Dardanelli et al. 2012; Manzoni et al. 2010; Corti et al. 2012). Furthermore, modern smartphones already integrate all the hardware required for a driving style application.

The algorithm has been developed to read the smartphone sensors, process the signals, compute the three cost functions, and provide a visual feedback to the driver. The block diagram of the driving style algorithm is depicted in Fig. 5. The main blocks are the following:

- signal acquisition block is responsible of the acquisition of inertial sensors and GPS;

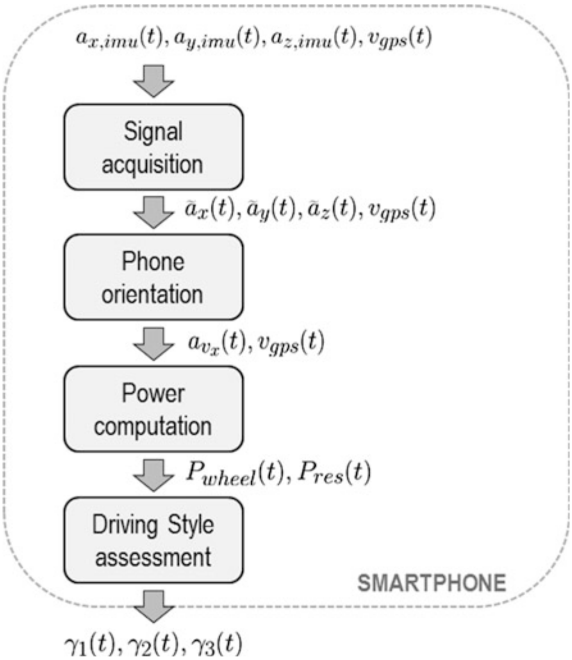


Fig. 5 Block diagram of the driving style algorithm

- phone orientation block performs the estimation of the mobile device orientation, since smartphone acceleration measurements depend on the specific orientation the driver choice in setting the device in the car;
- vehicle power estimation block computes the vehicle power consumption from previous measurements by using data fusion techniques;
- driving style assessment block computes the driving style cost functions and implements suitable interfaces to provide a visual feedback to the driver.

2.4 Experimental Results

The aim of the experiments is to evaluate if the proposed mobile application can improve the energy consumption in a possible mixed urban and extra-urban route.

The test has been performed on a real route in Milan, and it involves a small set of different drivers. The test track, shown in Fig. 6, is 8.8 km long, and it is composed of 5.3 km-long urban route and of a 3.5 km-long extra-urban route. The two parts are generally characterized by different acceleration and speed profiles. In particular, the former is full of traffic because of the presence of several traffic lights and roundabouts, while higher speed and large streets characterize the latter.

The acquisition campaign has been performed with a Tazzari Zero Evo1 (see Fig. 7.

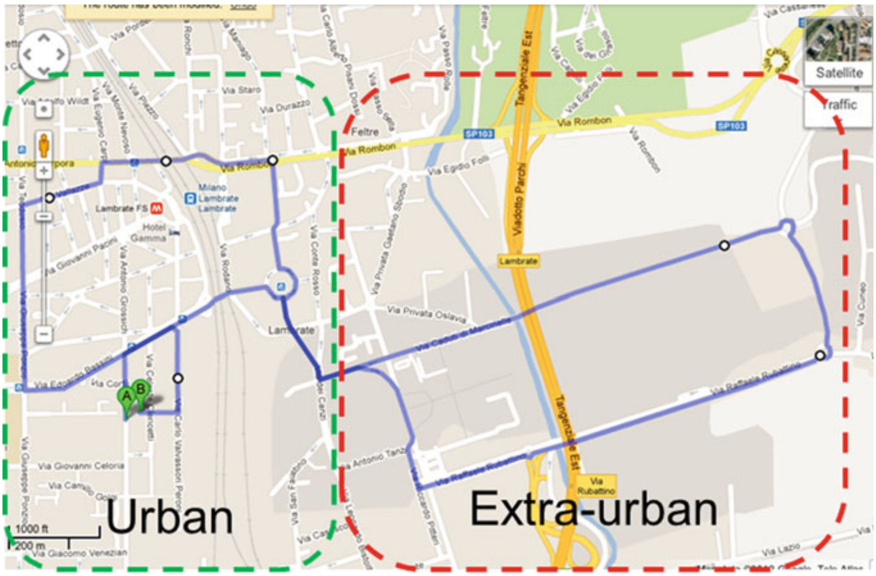


Fig. 6 Map of the experimental track

Fig. 7 Tazzari Zero Evo used in the experimental campaign

Table 1 Tazzari Zero Evo specifications

Weight	540 kg
Frontal surface	2.1 m^2
Max speed	100 km/h
Range	105 km
Battery	lithium-ion 12.8 kWh 80 V
Max power	15 kW
Charging time	Approx. 9 h

See http://www.tazzari-zero.com/ for further details.

The Tazzari Zero Evo is a two-seat, four-wheeled electric car with a driving range of about 140 km and a maximum speed of 100 km/h. The vehicle has a nominal power of 15 kW, a mass of 540 kg, and a frontal surface of 2.1 m^2. The lithium-ion battery pack (160Ah@80 V) requires about 9 h for a full charge (0–100%). Since the heater is powered by the traction battery and its use significantly reduces the range (about one-fourth the total range), it has been switched off for the entire duration of the tests. The main vehicle specifications are synthetically reported in Table 1).

The vehicle is part of a fleet of EVs used for the Green Move vehicle-sharing project and has been equipped with an electronic unit, the Green e-Box (see Fig. 8) which can read signals from the vehicle electronic boards and log them into a micro-SD support. In particular, the considered data are the battery voltage $V_{batt}(t)$ and current $i_{batt}(t)$, sampled every 0.2 s. From these two signals, the power extracted from the battery has been computed as $P_{batt} = V_{batt}(t)\, i_{batt}(t)$. Wheel speed values are also logged and the vehicle speed is computed by simple averaging the wheel speeds over the time. Note that the use of an EV allows an easier and more precise computation of the consumption at the tank, given by the electric power.

Fig. 8 Test vehicle: the iPhone with the driving style application (*left*) and the electronic control unit, Green e-Box (*right*)

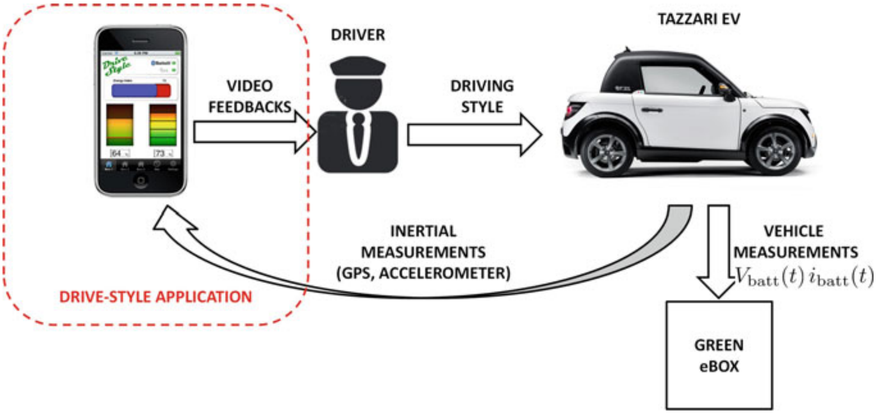


Fig. 9 Block scheme of acquisition campaign setup

Figure 9 shows the block scheme of acquisition campaign setup. The vehicle has been equipped with a smartphone (an iPhone 4) running the driving style application that preprocesses the inertial data, runs the algorithm, and provides visual feedback through the device screen. The electronic box logs the real vehicle measurements.

Three user interfaces (HMIs) will be considered and evaluated separately to assess the amount of energy savings: the first interface (Fig. 10a) reports all the three indexes, the second interface (Fig. 10b) has a single bar with a cumulate γ_1 plus γ_2 indication, whereas in the third interface (Fig. 10c) only γ_1 is shown.

The experimental campaign involved five different drivers (25–30 years old). Each driver performed five different trips on the same route: the first is aimed only at taking confidence with vehicle and route. Another one was carried out without

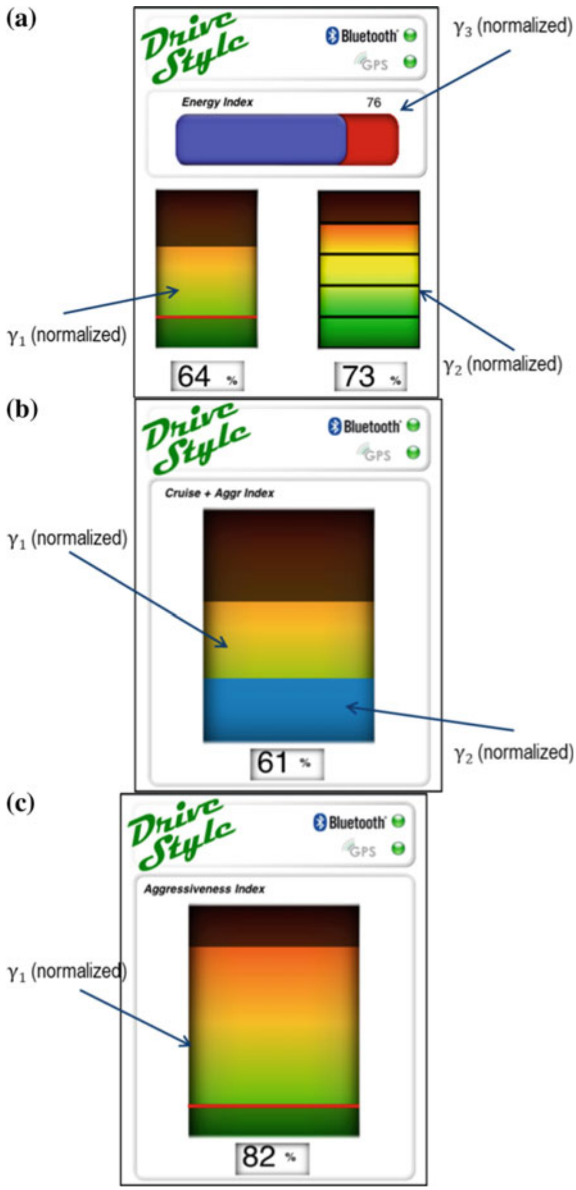


Fig. 10 Three interfaces of the driving style application tested by the different drivers

any interaction with the driving style application. Such a trip is labeled as blind and used as a benchmark to quantify the power consumption associated to the single driver. During the remaining three trials, the volunteers have been driving using all the three interfaces available, one at a time (see again Fig. 10). The order of the blind trial and of the three ones with the driving style application was randomly chosen for each driver, so as to minimize systematic errors in the evaluation of the results.

The experimental results are now illustrated, starting by analyzing those obtained with a single driver and then showing the aggregate results for all volunteers.

2.5 *Wheel-to-Miles*

Figures 11 and 12 show the vehicle speed and the longitudinal acceleration, as functions of distance, imposed by Driver 2 on the test route (the first test is omitted as it served only to explore the route). It can be easily noticed that Driver 2 imposes higher acceleration and speed when no feedback is active (blind trial): in the extra-urban area at approximately 2.5 km, the maximum speed decreases from 23 to 20 m/s, and the same happens between km 7 and km 8 of the urban part of the test route.

Figure 12 shows a similar pattern for the acceleration: in the blind trial, a peak of more than 2 m/s^2 is reached after 2 km. When the same driver gets feedback from the application, this value decreases to less than 1.5 m/s^2.

Further, Fig. 13 shows the energy spent at the wheel, computed using Eq. 3.1. Indeed, since the vehicle, the route, and the distance are the same, the energy spent at the wheel E_{wheel} depends only on speed and acceleration profiles. The energy spent at the end of the trip in the blind trial is 1.12 kWh, while it ranges from 0.78 kWh with version C to 0.75 kWh with version A of the driving style application, therefore assessing the effectiveness of the proposed approach.

To concisely and quantitatively express the results obtained with all drivers, let us define ϕ_i as the percentage of energy savings at the wheel with respect to the blind trial, namely

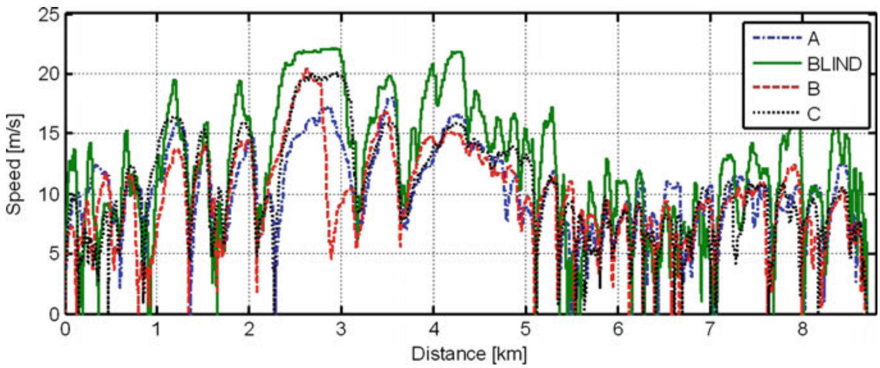


Fig. 11 Speed measured during the four trials of Driver 2 as a function of the travelled distance

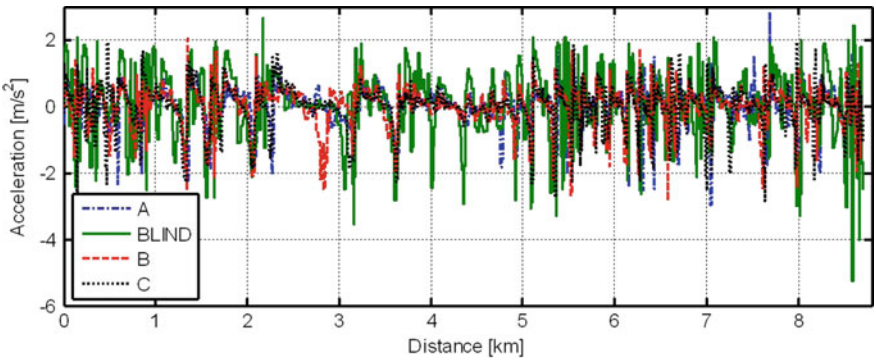


Fig. 12 Acceleration measured during the four trials of Driver 2 as a function of the travelled distance

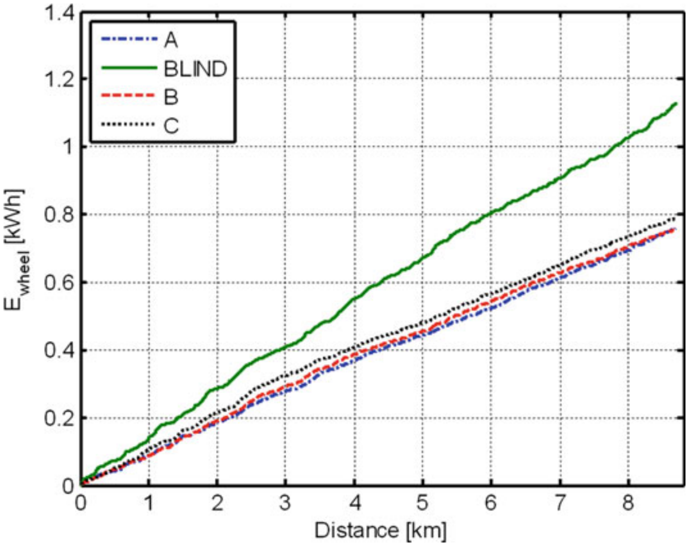


Fig. 13 Energy spent at the wheel by the vehicle with the different versions of the user interface

$$\varphi_i = \frac{E_{wheel,blind} - E_{wheel,i}}{E_{wheel,blind}} \tag{6}$$

where i ∈ A, B, C is the version of the HMI used.

As reported in Table 2, Driver 2 has ϕ_A = 32.8%, ϕ_B = 32.9%, and ϕ_C = 30.1% during the campaign; consequently, more than 30% of energy has been saved with all three user interfaces. Moreover, note that the savings on the extra-urban area are mainly due to the reduction of the average speed. Without any driving style application, the average speed is 15.5 m/s, while it decreases from 11.2 to 12.6 m/s

Table 2 Synthetic results for Driver 2

	Urban	Extra-urban	Total
ϕ_A[%]	32.2	34.0	32.8
ϕ_B [%]	33.8	31.3	32.9
ϕ_C [%]	29.2	31.8	30.1
Avg. speed A [m/s]	7.5	11.4	8.5
Avg. speed B [m/s]	6.6	11.2	7.7
Avg. speed C [m/s]	6.8	12.6	8.2
Avg. speed BLIND [m/s]	7.2	15.5	8.9

with the different application versions. In the urban area, savings are not related just to velocity; for instance, with version A the driver saves more than 32.2% of energy, but he proceeds with an average velocity (7.5 m/s) of 0.3 m/s greater than with blind version.

It should be remarked here that the average velocity might be influenced also by traffic condition. A driver could take less time to finish a trip just because the traffic was lower during the trial. In order to avoid this bias, we explicitly ignore the idle time in computing the average speed.

2.6 Tank-to-Miles

The “tank-to-miles” energy conversion is not influenced just by speed and acceleration profiles, but also by the engine efficiency, which in turns depends on several variables such as the engine type, the gear shift, the clutch dynamics. However, the savings at the tank are the most important ones from the user’s perspective, since they have a direct economic impact related to fuel/electricity consumption.

To analyze this aspect, Fig. 14 shows the energy extracted from the battery pack of the test vehicle during the trials of Driver 2. Note that in the blind trial, the vehicle consumes 1.69 kWh of electric energy, while, when feedback is active, E_{batt} significantly decreases (1.20–1.17 kWh).

Further, let ξ_i represent the percentage of energy savings at the battery with respect to the blind trial, given by

$$\xi_i = \frac{E_{batt,blind} - E_{batt,i}}{E_{batt,blind}} \tag{7}$$

where again i ∈ A, B, C is the version of the HMI used. For Driver 2, ξ_A = 30.9%, ξ_B = 30.8%, and ξ_C = 29.0%. Note that the savings at the battery are slightly less than the ones achieved at the wheel, nevertheless the user saves 30% of electric energy on average.

This proves that optimizing the driving style in the wheel-to-miles phase also enhances the overall fuel consumption.

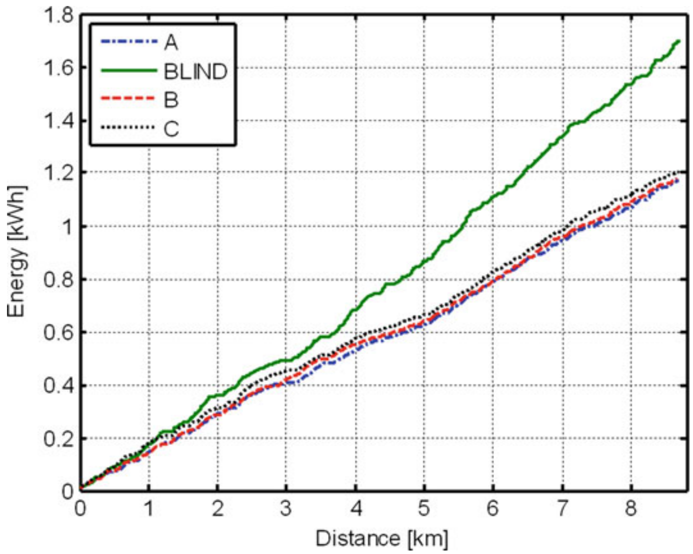


Fig. 14 Energy spent at the battery by the vehicle with different versions of the user interface

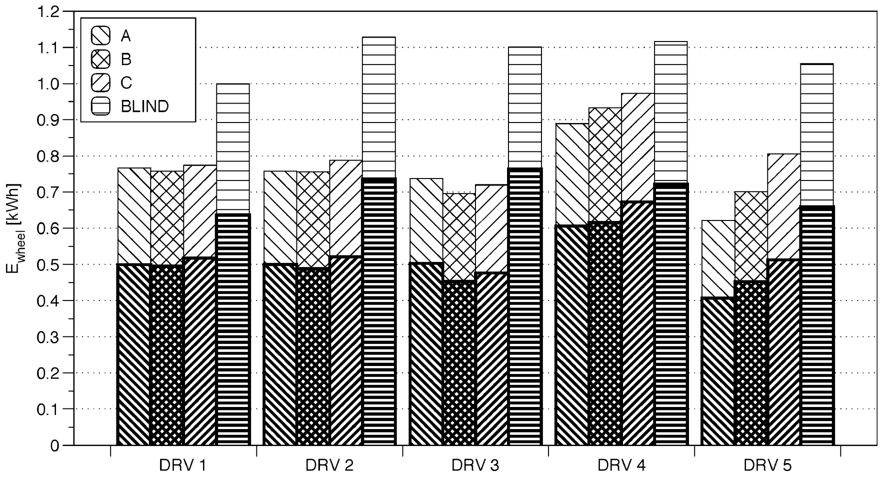


Fig. 15 Comparison between the mechanical energy E_{wheel} consumed by the five drivers. The thicker line represents the energy consumption in the urban area; the thinner one is related to the extra-urban part of the test route

2.7 Aggregate Results

To compare the results considering all five drivers, Fig. 15 shows the mechanical energy consumed at the wheel by all of them. The ticker line represents the urban consumption, while the thinner one represents that obtained on the extra-urban part

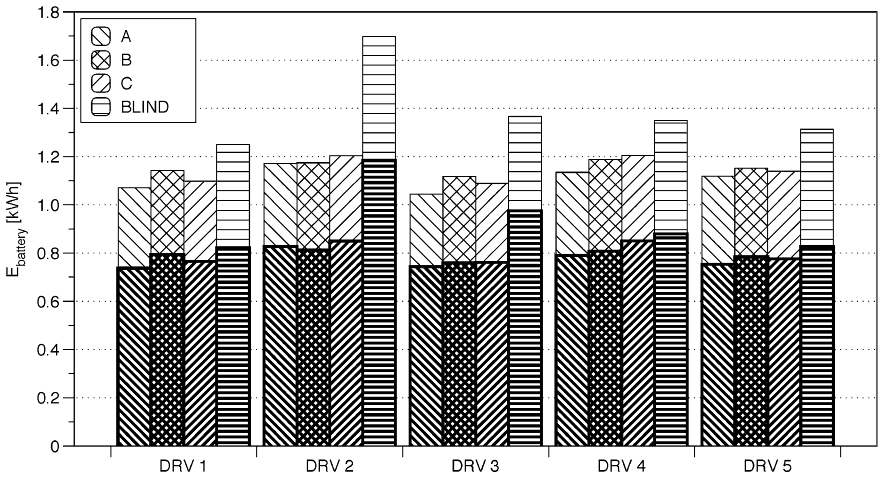


Fig. 16 Comparison between the energy extracted from the battery pack $E_{battery}$ for all drivers. The thicker line represents the urban energy consumption; the thinner line refers to the extra-urban consumption

of the route. By comparing the blind trials, it can be noticed that the five drivers behave quite differently. As an example, Driver 1 saves 100 Wh ($\approx -10\%$) to complete the test route with respect to what done by all the others.

Note that these experimental results demonstrate the effectiveness of the proposed driving style system, as with all user interfaces (A, B, C) the energy consumption is at least 0.2 kWh less than in the blind trial. Nevertheless, it is worth noticing that the percentage of energy savings is: (i) user interface-dependent: Driver 2, Driver 4, and Driver 5 perform better with the more informative interface A, while Driver 1 and Driver 3 perform better with the user interface B; (ii) driver-dependent: different drivers react in different ways to the visual feedback provided by the application. As an example, it can be noticed that Driver 4 saves less energy with respect to the others. Figure 16 reports the energy extracted from the battery pack.

The complete results are summarized in Table 3 which highlights the suitability of the proposed approach. In fact, the system induces all five drivers to save energy when interacting with the driving style application. Driver 2 saves about 30% of the electric energy, while for other drivers the percentage of saving ranges from 10 to 23%. All of them save more energy with the user interface labeled as A. Such HMI can then be considered as the best interface (overall) for the application at hand. This is not surprising, in that it describes a more detailed figure of the driving condition with respect to the others.

Table 3 Energy savings achieved with the three user interfaces by all drivers

	E_{wheel} [%]			$E_{battery}$ [%]		
	ϕ_A	ϕ_B	ϕ_C	ξ_A	ξ_B	ξ_C
Driver 1	23.3	24.1	22.5	14.3	8.6	12.2
Driver 2	32.8	32.9	30.1	30.9	30.8	29.0
Driver 3	33.0	36.8	34.6	23.6	18.2	20.3
Driver 4	20.3	16.4	12.8	15.9	12.1	10.7
Driver 5	41.1	33.6	23.7	14.9	12.3	13.2

3 Conclusions

In this chapter, a novel approach for reducing the vehicle energy consumption by means of a quantitative driving style assessment system has been proposed. The system is constituted by a smartphone application based on inertial measurements, which is vehicle-independent and interacts with the driver by means of visual feedback. Validation results are presented using three human–machine interfaces on an experimental campaign with five drivers. The experiments show that the system improves the driving style and reduces the vehicle energy consumption from about 10 up to 30%.

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