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Development of an automotive data acquisition platform for analysis of driving behavior

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Abstract **-** The main purpose of this work is to develop a low-cost data acquisition platform prototype for automotive telemetry applications such as driving style analysis, fleet management and fault detection. Measurement data, gathered from On-Board Diagnostics (OBD) sensors and an Inertial Measurement Unit (IMU), are logged on the onboard device for remote backup.
An accurate analysis of the collected data has been performed to identify the main parameters able to monitor driver behavior and to define suitable indexes to evaluate the driving performance.
Particular attention has been paid to the analysis of vehicle parameters during braking and gear shifting in order to classify different attitudes and generate driver profiles and trends.
Understanding drivers' characteristic behavior can contribute significantly to road safety, to define insurance premium, to engage user in saving fuel and money and to correlate faults of the car with the driving style.

Keywords: Automotive control, car instrumentation, driving style, telemetry.

I. Introduction

Data acquisition in automotive industry is widely used in everyday applications. Born fifty year ago, the theory of vehicular control deals with system optimization for streamlining the driving style. One of the most popular applications concerns the measurement and control of emission relevant parameters of internal-combustion engines in road cars, bikes and trucks [1], [2] driving behavior studies [3], [4] and fault diagnosis or car accident analysis [5]-[7].

The need for emission monitoring is due to the first pollution regulations like Clean Air Act (CAA) in 1970 [8], which fixes limit emissions from both stationary (industrial) and mobile sources. California Air Act in late 70's opened the way to the first monitoring systems. Several studies have been performed to propose possible solutions for evaluating and controlling air emissions [9]-[12]

This has led the automobile manufactures to directly install on board of the vehicle a complex measurement system for self-diagnostic and reporting (OBD) compliant to the Society Automotive Engine (SAE) Standards [13].

Since the middle of the 90's OBD systems became mandatory in the automotive field for new cars produces in USA, followed in 2001 by Europe with the 98/69/EC Regulation. The OBD acts like a sensor network, which monitors engine parameters and offers standard interfaces for scan tools used by technicians to analyze and solve problems.

Nowadays, the response to rising concerns about global warming and sustainability is researched in several directions, such as energy production from renewable sources [14]-[16], energy consumption measurement and monitoring [17]-[19], energy efficiency and energy-saving habits. In this regard, some studies [3], [19], [21] show that one of the most important factors affecting fuel economy is the driving style. For driver behavior modeling, a suitable analysis based on experimental measurements of main automotive parameters is desirable.

The majority of studies regarding driving style focus on the identification of suitable indicators based on main vehicle parameters [22]-[27]. In [22] a binomial logistic regression model was proposed, based on four indicators which take into account speed variation on a distance, average shift-up RPM's, gear usage distribution.

In [23] three-axis accelerometer data gathered on public transportation have been analyzed to identify five suitable statistical parameters able to discriminate normal and aggressive driving sessions.

A study presented in [24] defines aggressiveness parameters combining speed and acceleration data. In [25] a longitudinal kinematic model combining IMU and GPS speed measurements has been proposed to calculate energy spent moving the vehicle against a realistic reference.

A logging device is presented in [26], which is able to detect high accelerations and jerks by setting thresholds on the acceleration and its derivative.

The aim of proposed work is to evaluate the different behavior of drivers based on gear changes and longitudinal acceleration measured on the same car and track with a purposely developed data acquisition platform. This kind of analysis combines OBD and Inertial measurements data.

In this paper the variations of vehicle speed, acceleration and engine rotation, which happen in the short time interval between the selection of two gears, is analyzed. For this purpose, a gear segmentation algorithm, features definition and gear shift classification are proposed. This analysis, being focused on driving style, is different from other studies in which the behavior during gear shift is not analyzed and the focus is, instead, to find and suggest the optimal gear in order to minimize fuel consumption for given speed, engine rotation speed, vehicle model and traffic flow [28], [29]. The management of gear shift, being it a fast event, is less influenced by external factors, such as traffic flow, and is an indicator of driving style and attitude.

Even though the application described in this paper concerns driving style analysis, it should be noted that the fundamental requisite of fleet management applications, i.e. telemetry, is fulfilled by our system because it is able to remotely communicate vehicle parameters and location. Hence, services such as vehicle tracking, safety, diagnostics and lifecycle management can be developed on dedicated application servers, which integrate the proposed data acquisition platform.

Although there exist different devices for automotive control, the proposed system has been designed to offer low cost without sacrificing flexibility and performance. It allows an easy integration with add-ons such as new sensors and radio interfaces, more onboard memory and remote control. The computing unit, based on Raspberry Pi, offers higher computation capabilities than many other low cost embedded solutions.

This paper is structured as follow: in Sec. II the data acquisition platform is described; the parameters used for driver behavior analysis are detailed in Sec. III; in Sec. IV the classification algorithm is explained; experimental data on the classification of two drivers are provided in Sec. 0; and finally, in Sec. VI are reported the conclusions.

II. System Overview

The data acquisition platform, initially proposed by the authors in [30], consists of four main elements, as shown in Figure 1:

- A single-board computer (SBC), namely Raspberry Pi, which coordinates the operation of sensors and processes and stores data.
- An IMU, model MPU 6050, for accurate measurement of acceleration on 3-axis, which provides useful information about vehicle kinematics and solicitations and is a key element for driving style classification.
- A device, model ELM327, used to communicate with the OBD system of the vehicle and retrieve information such as engine rotation speed. The system can be easily implemented and adapted to any OBD II compliant vehicles. Indeed, the hardware interface with the vehicle is based on SAE 1962 [31] connectors to ensure the highest degree of compatibility.
- A GPS receiver for vehicle tracking purposes.

Figure 1 Scheme of the proposed system

Figure 2 Prototype

The architecture of the proposed system includes also a remote server for data logging and auxiliary devices such as a battery pack and a 3G internet key in order to enable remote monitoring. Figure 2 shows the developed prototype, where the battery pack is visible on the left, and the SBC is on the right. Connected to the SBC there are: an USB Bluetooth adapter, an USB Wi-Fi adapter, a USB 3G internet key and a Raspberry PI shield, which manages electrical power and provides additional USB ports.

Several demonstration tools have been developed to access the available telemetry data. In particular, a LabView™ based client for personal computers was designed to work with remote servers as well as a local logging one. Users can choose the session from a list, then data are downloaded from the server and shown in tables and graphs for all the sensors available in the telemetry session. A web-based interface has been developed as well, which allows one to access the measurement database on the remote server by username and password. For each session a report is generated, which summarizes data about measurement values acquired by means of the sensors, distance travelled, travel time and suitable comments.

It is noteworthy that the use of the low-cost SBC and, as a consequence, the availability of a full Linux operating system, gives maximum flexibility to the system because allows one to rapidly integrate components, among which all the communication devices, and easily develop powerful data processing and storage software leveraged by a programming languages such as Python™ and a complete and reliable Apache-MySQL-PHP server. This means also that the other hardware components, as well as software components, can be chosen among an extended set of possibilities, a feature which was particularly useful when carrying out this research. It should be clear that the software developed for the Linux™ operating system on a given computing platform is easily portable to other computing platforms supporting Linux. This was in contrast with other development options, such as the use of purposely designed microcontroller boards, which would have implied higher hardware and software development costs and times (among which the time required for developing the drivers of all the communication interfaces) and the use of a smartphone [28], which would have implied a reduced availability of programming languages and complete server applications, with increased software development times.

Details about the devices used in the prototype are given in the following subsections.

A. *Raspberry Pi*

It is a SBC developed by Raspberry foundation and based on Linux operating system. The board acts like a controller for all the data sources. A Python script has been used in order to continuously run on the device, receiving data from sensors. Then, measurements and their timestamps referred to the start of the session are stored on an internal MySQL Database, which has been optimized in order to reduce data memory occupation and increase reliability having one table for each sensor source. Measurements are periodically synchronized with a remote server when internet connection is available. The board has an 802.11g adapter for local wireless access and acquisition control.

B. *ELM327*

It is the interface connected to vehicle OBD II system, which communicates with the Raspberry Pi controller via Bluetooth.

OBD II provides a standard automotive fault diagnosis system for manufacturers, describing protocols, messages, connectors and electrical specifications. Its basic operation consists in one or more ECUs (Electronic Control Unit) communicating with powertrain sensors measuring engine revolution per minute (RPM)s, speed, intake pressure, and other parameters. SAE J1979 describes nine different operations called Services, among which are Diagnostic Trouble Code (DTC) and Request Powertrain Diagnostic Data.

When one or more values exceeds a prescribed limit a DTC is generated. DTCs are identified by service codes $03 and $07 while the mode used in our system, i.e. Request Powertrain Diagnostic Data, is identified by code $01. OBD sensor polling is performed by software, sending Parameter ID (PID) request messages and saving the replies.

A subset of PIDs for reading sensor data is given in TABLE I. , where the numeric format of the raw output data as well as the conversion formula used to obtain the quantity value in physical units are detailed and *x* is the raw data reading. The resolution of speed and engine rotation speed measurements can be calculated from TABLE I. , obtaining 1 km/h and 0.25 rpm, respectively. It should be noted that the accuracy of sensors installed by the vehicle manufacturer and integrated through the OBD system are generally unknown to the user. In particular, the accuracies of car speed and engine rotation speed measurements are not stated by vehicle manufacturers and change according to vehicle model. The speed error changes also with tire model and pressure. For these reasons the developed algorithm, described in Sec. III, isn't based on the accurate measurement of car and engine rotation speeds, but on the clustering of their ratio obtained directly from measured data.

TABLE I. EXAMPLES OF OBD PARAMETERS AND CONVERSION FORMULAS

PID	DESCRIPTION	RAW DATA RANGE	RAW DATA LENGHT (BYTES)	CONVERSION FORMULA	UNIT
0C	Revolution per minute	0 – 65535	2	$x/4$	rpm
0D	Speed	0-255	1	x	km/h
04	Calculated Load Value	0-100	1	x*100/256	%
10	Mass Air Flow	0-65535	2	$x/100$	g/s
0B	Intake Manifold Absolute Pressure	0-255	1	x	kPa

C. *MPU6050*

The IMU, model InvenSense MPU6050 [32], has been added to the system in order to provide inertial measurement such as acceleration and angular velocity of the monitored car. It integrates a 3 axis MEMS accelerometer, a gyroscope, an elaboration unit and has digital filtering and triggering capabilities. The unit is able to interface itself with other sensors, like a digital compass, via I2C bus, which is the same bus used to communicate with the Raspberry Pi Board. This sensor has been chosen in order to provide good sensitivity at low Full Scale Ranges that are good enough to describe vehicle dynamics in normal operation. The device offers a high stability performance, assuring low sensitivity to temperature, which is very important for a measurement system that has to be installed on board of the test vehicle. Accuracy specifications are typical of automotive-infotainment sensor's market. Furthermore, its breakout board availability permits easy system integration.

Power saving functionality lets the device to store 1024 bytes of samples in a FIFO buffer before the transmission. The supply voltage of the sensor ranges in 2.37 - 3.46 V assuring the compatibility with Raspberry PI 3.3 V power supply.

The digital motion processor (DMP) has six 16-bit ADCs with programmable ranges: ±250°/s, ±500°/s, ±1000°/s, ±2000°/s for the gyroscope and ±2g, ±4g, ±8g, and ±16g for the accelerometer. The ranges ±2g and ±2000°/s have been chosen. Sample rates are up to 1 kHz.

The device offers a good stability performance assuring low changing of sensitivity as function of temperature. This is very important for a measurement system that has to be installed on board the test vehicle. A summary of metrological specifications of the accelerometer is shown in TABLE II. Complete specifications can be found in [32].

TABLE II. ACCELEROMETER SPECIFICATIONS

PARAMETER	TYPICAL	UNITS
Initial calibration tolerance	±3	%
Nonlinearity (best fit)	0.5	%
Cross Axis Sensitivity	±2	%
Zero-G Initial calibration tolerance X ,Y and Z axis	±50 (X- and Y-axis) ±80 (Z-axis)	mg
Quantization (FS = ±2g)	$4/2^{16} = 0{,}061$	mg
Sensitivity Change vs. Temperature	± 0.02	%/°C

D. *Sirf Star III GPS*

The GPS receiver integrated in the system is based on the widespread and low-cost Sirf Star III Chipset and is connected via Bluetooth too the SBC. The rms of the horizontal position error is 5 m. Software implemented on the SBC reads the NMEA (National Marine Electronics Association) sentence information and translates $GPGGA (Global Positioning System Fix Data) and $GPRMC (Recommended Minimum Specific GPS/TRANSIT Data) sentence codes into decimal Latitude and Longitude coordinates.

III. PARAMETERS FOR DRIVER BEHAVIOR ANALYSIS

The main factors influencing the driver style are the attitude in both braking and gear shifting phases; hence, it is important to identify the parameters, which contribute significantly in these driving conditions.

For this aim three quantities have been taken into account in the proposed study: *vehicle speed* and *engine rotation speed*, both obtained from the OBD interface, and vehicle *acceleration*, measured with the MPU6050 three axes accelerometer unit.

OBD measurements of vehicle speed and engine speed have been performed with an actual sampling time that varies between 0.5 – 0.6 s for the most of measurements with sporadic slowdowns to 0.8 s; this is due to random bus communication errors and sporadic workloads of processes run by the Raspberry Pi operating system. The data so acquired have been software resampled to 10 Hz with linear interpolation in order to reduce the computational load for the following analysis and to have constant time spaced samples.

Accelerometer data have been obtained via the I2C bus with a nominal sampling time of 0.03 s and a jitter limited to 1 ms. For the same reasons discussed before, these data have been software resampled and linearly interpolated with a higher rate of 1 kHz, so that information on acceleration dynamics is not lost. Furthermore, to reduce the noise of the accelerometer data, an augmented Lagrangian filter was used [33].

Initially, the behavior of vehicles speed as function of engine speed has been investigated.

Figure 3 shows the experimental results obtained in a test track including both urban and suburban ways that lasted about 20 minutes. It is possible to note that experimental data are mainly distributed along five straight lines representing vehicle status when gear is engaged (clutch pedal not pressed). Therefore, each straight line identifies a driving condition where a fixed gear was used and the ratio between car speed and engine speed remains almost constant. Data points which are not aligned on the lines represent driving condition where a gear change was performed.

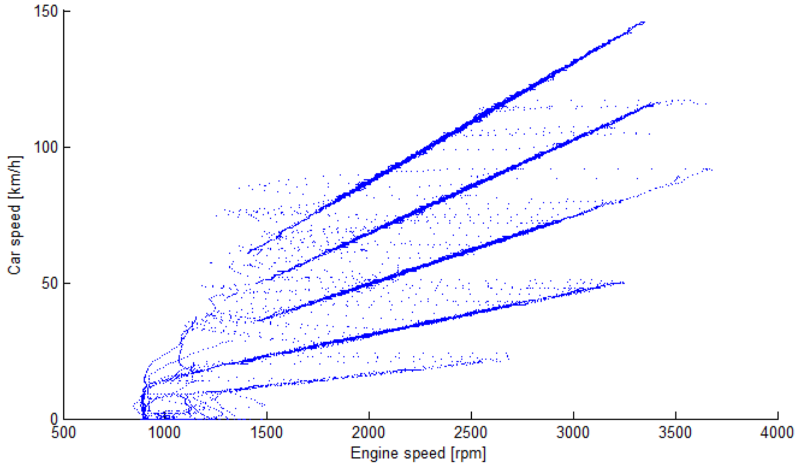


Figure 3 Vehicles speed versus engine speed obtained in a test track

Therefore, in order to analyze the driver style in gear shifting it can be useful to study the behavior of the ratio between vehicle speed, denoted as $v(t)$, and engine rotation speed, denoted as $r(t)$,

$$G(t) = \frac{v(t)}{r(t)} \tag{1}$$

The plot of this ratio versus time, shown in Figure 4 for the same measurement session previously described, highlights that the approximately constant segments are correlated with an engaged gear while the transition phases indicate a gear change.

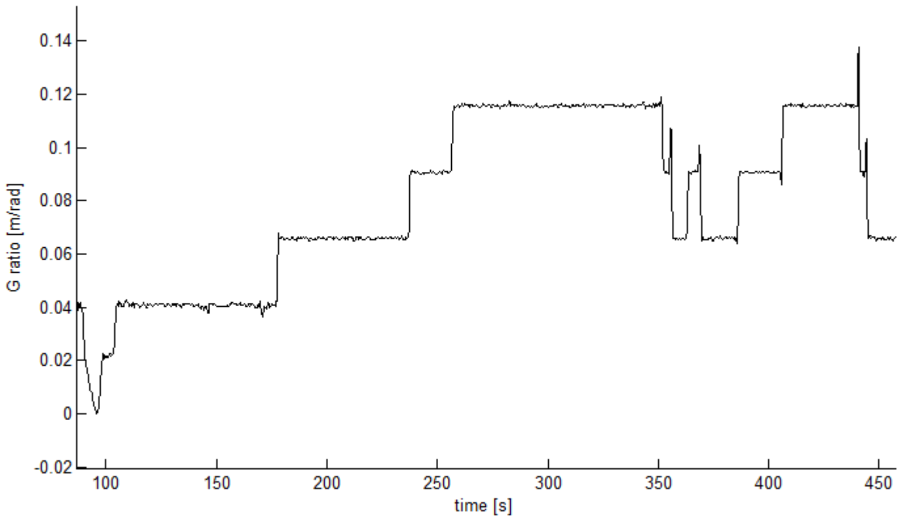


Figure 4 Plot of G(t)

By estimating the straight lines slopes in Figure 3 by means of the least mean square method, we can find constants values of $G(t)$ for each n-th gear, denoted as G_n, with the meaning of meters of development per radiant. These values are listed in TABLE III. for the vehicle under test and vary with the specific combination of gearbox, differential and tires.

TABLE III. METERS OF DEVELOPMENT PER RADIANT, G_n , CALCULATED FOR EACH GEAR

n (gear number)	G_n *[m/rad]*
I	0.0210
II	0.0408
III	0.0655
IV	0.0910
V	0.1157

In the study of G(t), particular attention has been paid to the analysis of transition phases in order to identify the driver attitude in gear shifting. For this aim, $G(t)$ has been initially filtered by using an augmented Lagrangian [33] to limit the overshoots that affect $G(t)$ in downshift, clearly visible in Figure 5. This filtered version of $G(t)$ is denoted as $G_f\,(t)$.

To characterize gear shifting, it is necessary to identify suitable time windows where to limit the analysis of $G(t)$, hence a suitable algorithm has been developed consisting of the following steps:

1. *Calculation of a reference instant for each time window.*

   Each gear shifting event is defined by the gear number before that shift, denoted as B, the consecutive gear number after that shift, A, and the instant t^r individuated by the crossing of $G_f\,(t)$ through the value $\bar{G}_{B,A} = (G_B + G_A)/2$. The quantities $\bar{G}_{B,A}$ are the mean meters of development of the gears A and B, and their actual values can be calculated starting from TABLE III. Hence it is

$$G_f\left(t^r\right) = \overline{G}_{B,A}, \quad k = 1,.....\mathrm{N} \tag{2}$$

   Figure 6 shows the so calculated window reference instants t^r, highlighted by red markers.

2. *Calculation of the time windows*

   Several simulations have been carried out to identify the best time window width able to provide the information required to characterize gear shifting. Then the time window W relevant to any given gear shifting has been defined as follows:

$$W = \left[t^{in} ; t^{out} \right], \quad t^{in} = t^{r} - 0.2s, \quad t^{out} = t^{r} + 0.6\text{s} \tag{3}$$

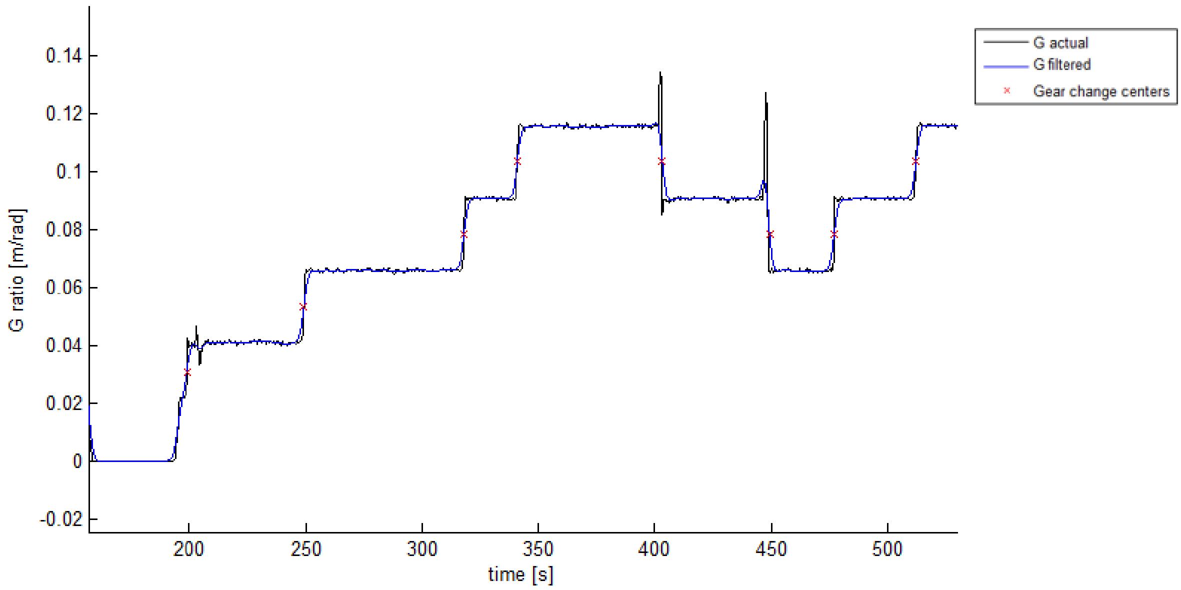


Figure 5 Actual $G(t)$ and its filtered version $G_f(t)$. The red markers represent the reference points for transition analysis.

The sign of the difference of $G_f(t)$ at the boundaries of W, is used to identify the direction of gear shifting. When $G_f\left(t^{out}\right) - G_f\left(t^{in}\right) \geq 0$ the gear change is recognized as *upshift*, otherwise the gear change is recognized as *downshift*.

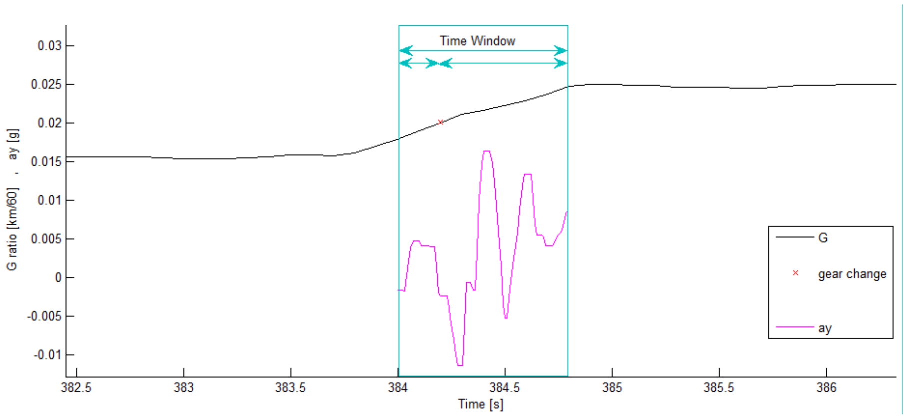


Figure 6 Example of acceleration extraction in a time window

An asymmetrical time window has been chosen because the most significant signal variations were provided after the reference point of the window. Indeed, by analyzing the y-axes acceleration

a_y, which corresponds to the driving direction, it is possible to note that the most relevant variations happen in the last part of the gear change.

For each gear shifting event and window $[t^{in}; t^{out}]$, the parameters indicated in TABLE IV. are calculated.

TABLE IV. PARAMETERS USED FOR THE PROPOSED ANALYSIS

Parameter	Definition	Units	
Vehicle speed variation	$\Delta v = v\left(t^{out}\right) - v\left(t^{in}\right)$	$\frac{km}{h}$	(4)
Engine rotation speed variation	$\Delta r = r\left(t^{out}\right) - r\left(t^{in}\right)$	rpm	(5)
Mean acceleration	$\mu_y = \frac{1}{t^{out} - t^{in}} \int_{t^{in}}^{t^{out}} a_y\left(t\right) \cdot dt$	g	(6)
Standard deviation of acceleration	$\sigma_y = \sqrt{\frac{1}{t^{out} - t^{in}} \int_{t^{in}}^{t^{out}} \left(a_y\left(t\right) - \mu_y\right)^2 \cdot dt}$	g	(7)

IV. DRIVER BEHAVIOUR CLASSIFICATION

For the test session previously described in paragraph III the engine and car speed variations obtained in all gear transitions have been analyzed as function of mean acceleration and standard deviation of acceleration, as shown in Figure 7.

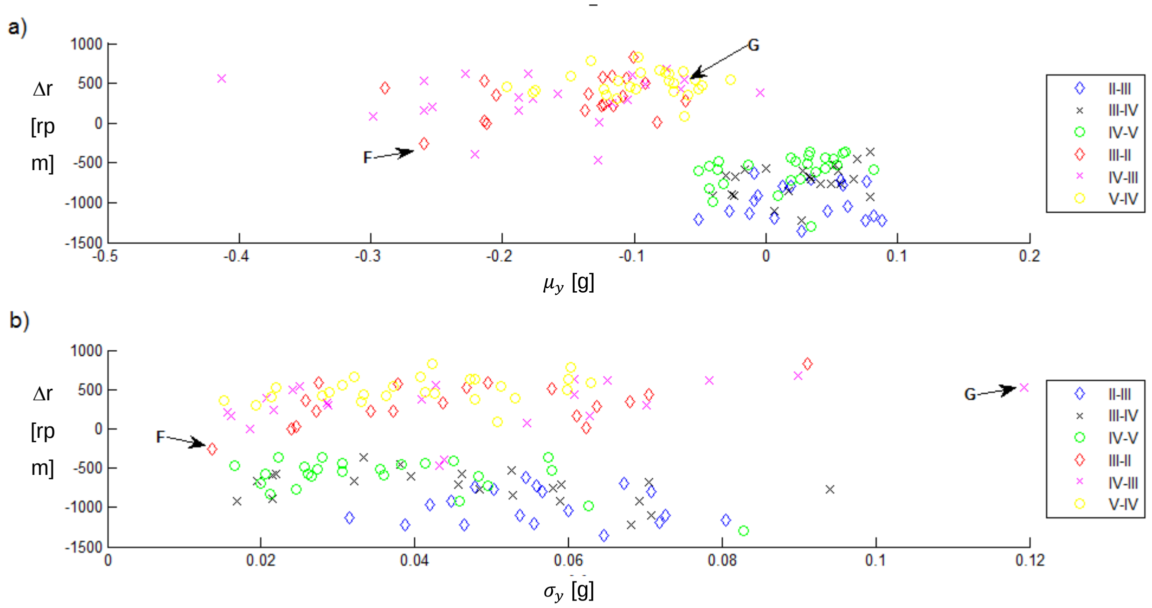


Figure 7 Engine speed variation versus (a) mean and (b) standard deviation of acceleration on y-axis

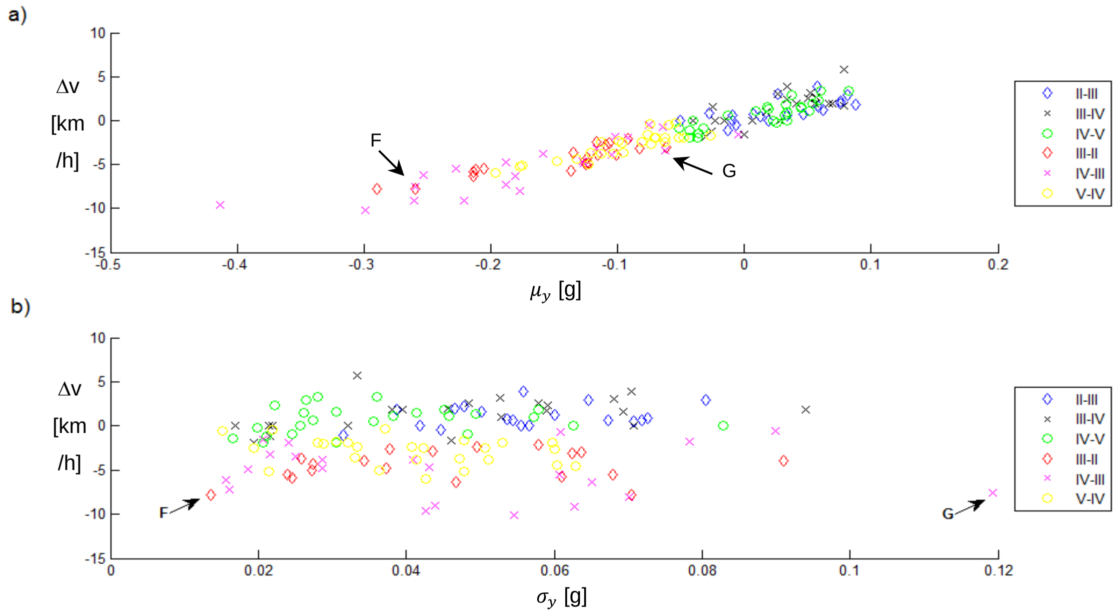


Figure 8 Vehicle speed variation versus a) mean μ_y and b) standard deviation of acceleration on *y*-axis, σ_y

On the basis of these data, an in-depth analysis of gear shifting has been performed and upshifts and downshifts have been classified as described, respectively, in Sec. IV.A and IV.B. In Sec. 0 upshift and downshift behavior is combined to give overall driving style classification.

A. *Upshift*

The upshift is performed by the driver changing from the n^{th} to the $n+1^{th}$ gear. By analyzing the experimental data two different behaviors have been identified.

TABLE V. DRIVING CLASSIFICATION IN UPSHIFT

	Δv	μ_y	σ_y
Soft/cruising (SC)	Low (less than or equal to zero)	Low (less than 0.05 g)	Low (less than or equal to 0.05 g)
Hard/accelerating (HA)	High (greater than zero)	High (greater than 0.05 g)	High (greater than 0.05 g)

Soft/cruising (SC) upshift behavior is done by a driver when he wants to keep a low car acceleration or to maintain constant speed, just running the car at low engine rpm in order to save fuel. Small negative values of Δv and μ_y could happen if the clutch pedal is pressed for too long so that wheels receives no torque from the engine and the vehicle slows down due to frictions.

Hard/accelerating (HA) upshift behavior is adopted by a driver that upshifts during a continuous accelerating phase. In this case the possible decrease of Δv is widely compensated because the driver shifts up while he is pushing the accelerator pedal and his clutch usage is more fast and rough.

B. *Downshift*

Different driver behaviors during braking/downshift events have been investigated. According to brake pedal and downshift usage we can easily identify two different behaviors described as follows.

Hydraulic braking (HB) downshift behavior: driver decelerates the vehicle mostly with the brake pedal, managing the deceleration mostly with foot pressure and shifts down later with low engine speed to avoid engine brake shocks during clutch pedal release. This behavior led to a smoother deceleration, clutch pedal release roughness is less important because speed is already adapted to lower gear ratio.

Engine braking (EB) downshift behavior: downshift happens earlier than previous case with respect to the start of braking. Clutch management is more important because a rough release could led to a shock deceleration which should be compensated by the driver reducing brake pedal load in order to achieve a more smooth deceleration.

TABLE VI. DRIVING CLASSIFICATION IN DOWNSHIFT

	Δv	Δr	μ_y	σ_y

Hydraulic braking (HB)	Don’t care	Low (can be negative)	Don’t care	Low
Engine braking (EB)	Don’t care	High	Don’t care	High

Two different examples of driving classifications during downshift events are marked as F (a III-II downshift) and G (a IV-III downshift) in Figure 7 and Figure 8. Both events have the same strong speed decrement Δv. However, for the event F, σ_y and Δr are lower than G. Hence, According to TABLE VI. the event F denotes HB behavior, while the event G denotes EB behavior. μ_y is smaller for event F than G, however this does not affect behavior classification.

Classification of driving styleThe key aspects defined in previous subsections IV.A and IV.B can be used to classify the whole driver conduct. Upshift and downshift behavior are combined in TABLE VII. in order to describe two combinations in which driving style can be clearly put in evidence, so defining the two classes: *Moderate driving* and *Aggressive driving*. In the former case, Moderate driving, upshift is characterized by soft/cruising behavior and downshift by hydraulic braking; in the latter case, aggressive driving, upshift is characterized by hard/accelerating behavior and downshift by engine braking.

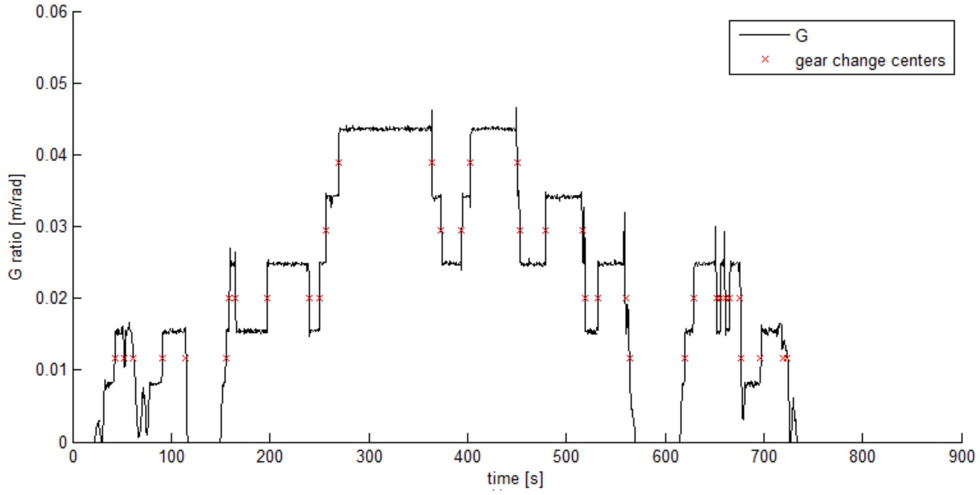
TABLE VII. CLASSIFICATION OF DRIVING STYLE

	Upshift	Downshift
Moderate driving	SC	HB
Aggressive driving	HA	EB

V. DRIVING SESSION COMPARISON

Two different drivers (driver A and driver B) have been compared using the classification proposed in Sec. IV. Both drivers drove the same test car (a Ford Fiesta 1.0l Turbocharged gasoline engine, five-speed manual gearbox) on the same path in a mixed environment (about 70% extra-urban, 30% urban) at the same daytime with almost the same traffic condition.

a)



b)

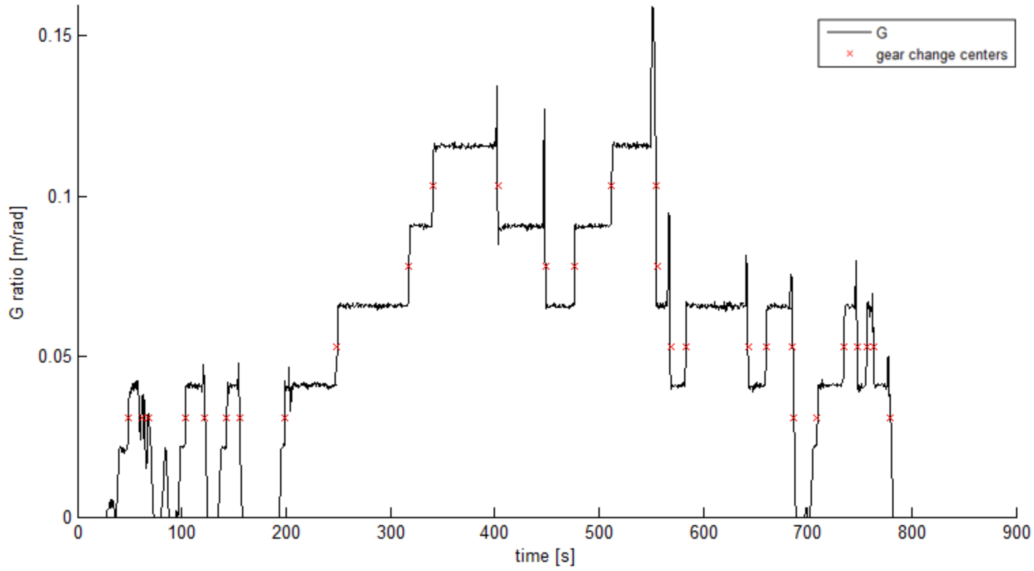


Figure 9 *G(t)* for a) driver A and b) driver B.

Figure 9 shows gear ratio versus time for the same path. Gear distribution is very similar, consisting in lower gears at the beginning and at the end of the path (urban zones) and higher gears in the central part (extra-urban zone). The plot in Figure 9 a) shows that $G(t)$ ends earlier than the plot in Figure 9 b), which means that driver A drove the same path in a shorter time with higher average speed.

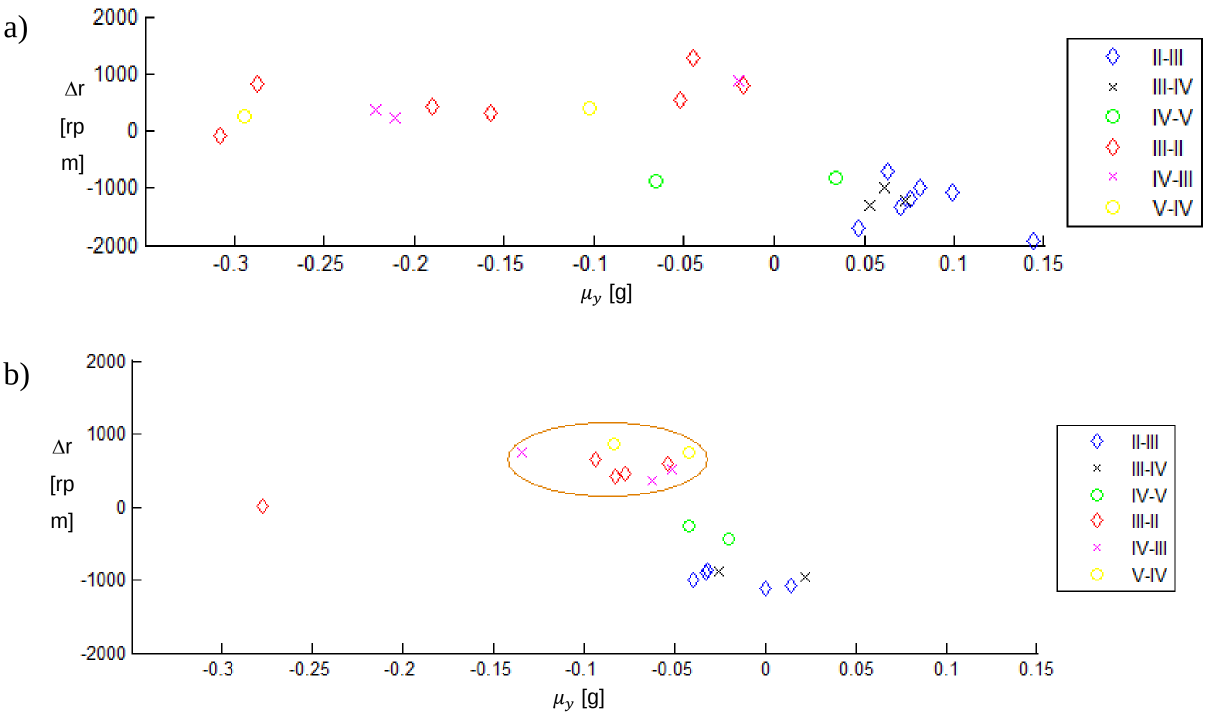


Figure 10 Comparison of engine rotation variation Δr versus mean acceleration μ_y, for a) driver A and b) driver B.

Figure 10 a) highlights upshifts with a net positive acceleration which is larger than Figure 10 b); this means that driver A changes gear up in a more aggressive acceleration phase. Driver B has more negative acceleration markers for upshifts, and this denotes a cruising behavior where gear change is intended for cruising speed with a lower engine rotation speed, which is good for fuel economy.

Looking at downshifts (warm color markers), driver B offers a more homogeneous behavior with the majority of markers close each other with a limited deceleration, and driver A shows more heterogeneous deceleration values and generally higher rotation speed variations.

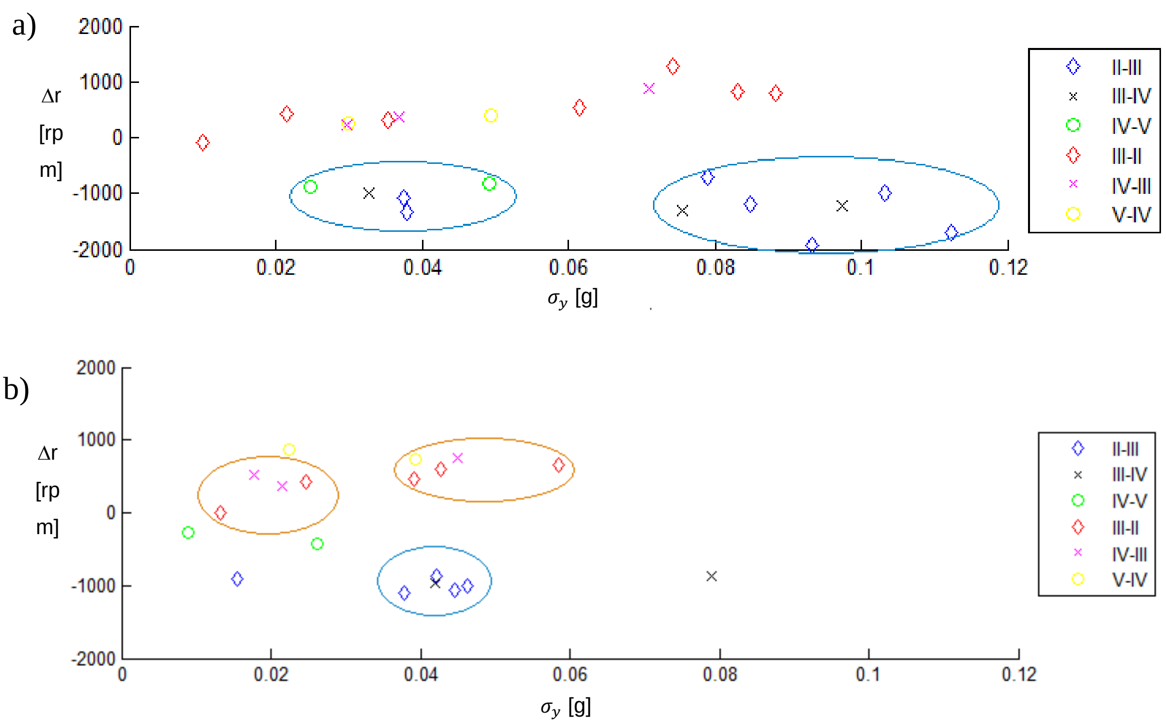


Figure 11 Comparison of engine rotation variation Δr versus standard deviation of accelerations σ_y, for a) driver A and b) driver B.

Figure 11 confirms the tendency of driver B to use less engine brake in downshifts than driver A, because of limited standard deviations of y-axis acceleration in each window. Both drivers' data highlight gear shift clusters that could derive from path characteristics, but taking a glance at the abscissa axis shows that for driver A two separated clusters can be formed, characterized by different aggressiveness in upshifts.

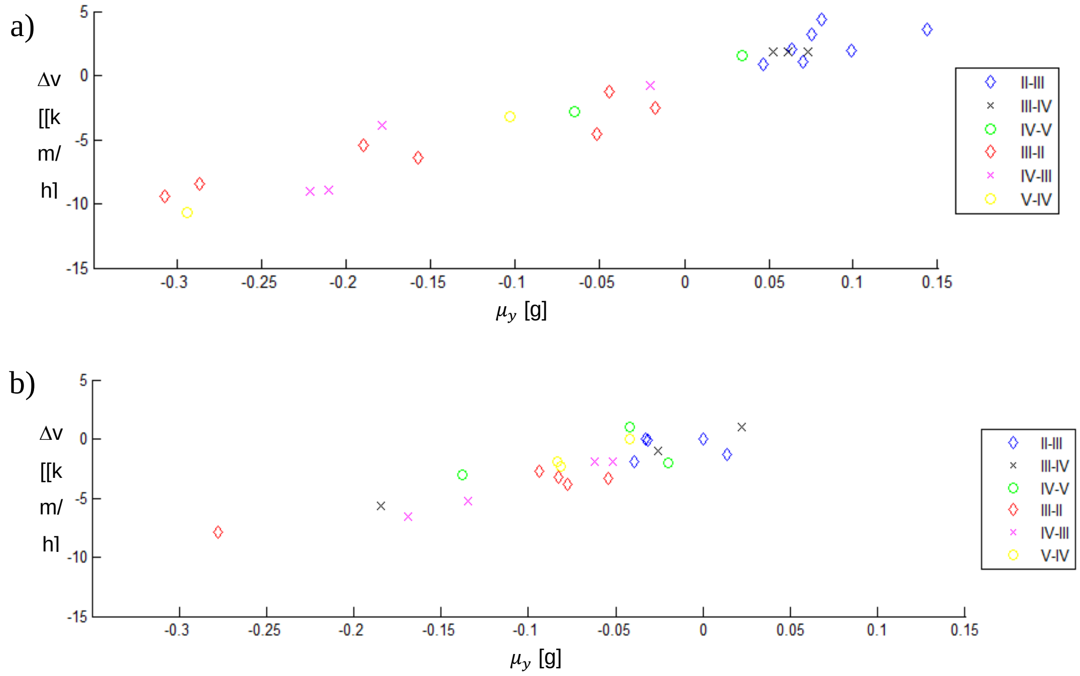


Figure 12 Comparison of vehicle speed variation Δv versus mean acceleration μ for a) driver A and b) driver B.

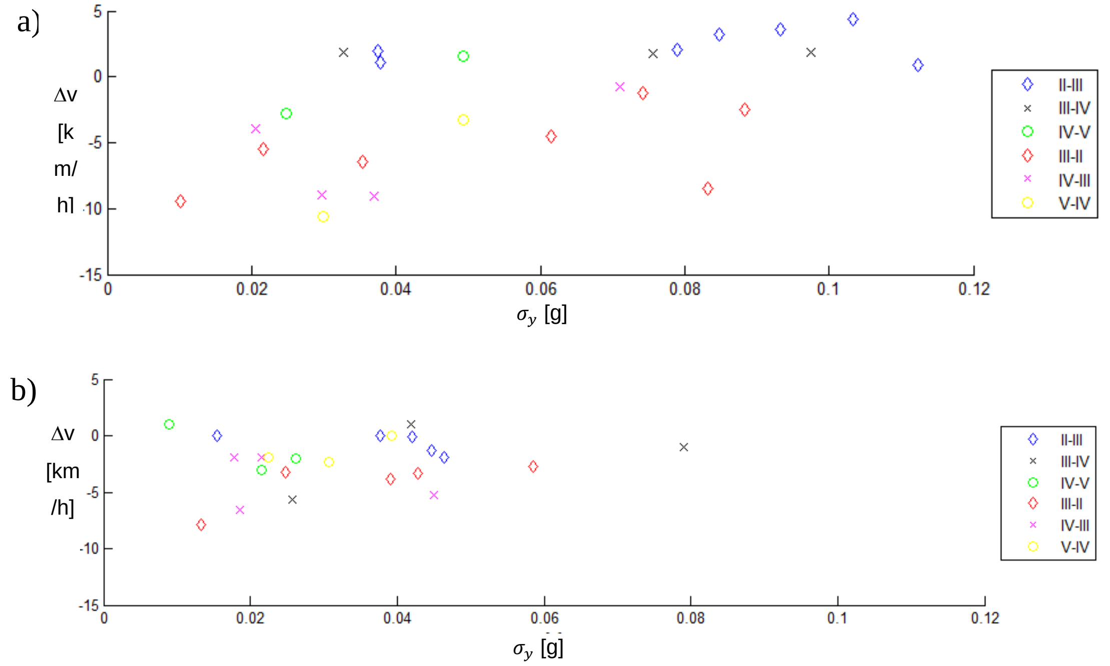


Figure 13 Comparison of vehicle speed variation Δv versus standard deviation of acceleration σ_y for a) driver A and b) driver B.

Vehicle speed variation plots (Figure 12 and Figure 13) confirm the tendency of driver B to shift up with null or negative speed gain, which is the result, for example, of prolonged clutch pedal pressure. Driver A compensates this, showing a more positive speed variation, because he shifts up while the car is accelerating and his clutch usage is more fast and rough. Indeed, if we consider II-III gear changes, Figure 12 and Figure 13 show that acceleration for driver A has both mean and standard deviation higher than driver B.

Summarizing the obtained results, it is possible to observe that Driver A brakes and accelerate harder. He shows a shorter shifting time, characterized by roughness in up shifting, more engine brake usage in average and his behavior is more varied. Hence his behavior is recognized as *Aggressive driving*, including HA and both EB and HB.

Driver B, on the contrary, offers a more constant and mild behavior in both shifting up and shifting down phases. He shows homogeneous downshifts with reduced mean deceleration, less engine braking and a smoother release of the clutch pedal with less shock. That behavior is recognized as *Moderate driver* since it includes HB and HA.

VI. CONCLUSION

A low cost data acquisition system has been proposed which integrates measurements from accelerometers and OBD. The data processing subsystem is based on a Raspberry PI single board computer, which allows the development of custom acquisition software with an open source programming language. The technical feasibility of data collection and telemetry through the proposed system, easily mounted on a car, has been demonstrated by means of a measurement campaign. This approach differs from other systems already known in the literature, based on microcontroller boards and smartphones, showing high flexibility and easy software development.

Among the logged data, the acceleration, the engine rotational speed and the car speed have been analyzed in order to understand the behavior of the gear shift and the driving style. This small selection of parameters has allowed us to individuate two different patterns for upshifts, namely soft/cruising and hard/accelerating. Analogously, hydraulic-brake and engine-brake behaviors have been distinguished for downshifts. Two representative driving style profiles, moderate and aggressive, have been finally defined.

The peculiarity of the proposed approach resides in the fact that features representative of the transition between two gears have been identified in order to classify gear shifting, while previous studies have taken into account only the speed and rpm threshold that triggers (or should trigger) a change of gear, so to ignore the dynamic behavior of gear shifting.

An example, based on experimental data, of the classification of two drivers has been illustrated and has showed two clearly distinct behaviors, which can influence fuel consumption, car reliability and more generally, driving security.

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