Validation of driving behaviour as a step towards the investigation of Connected and Automated Vehicles by means of driving simulators

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***Abstract*—Connected and Automated Vehicles (CAVs) are likely to become an integral part of the traffic stream within the next few years. Their presence is expected to greatly modify mobility behaviours, travel demands and habits, traffic flow characteristics, traffic safety and related external impacts. Tools and methodologies are needed to evaluate the effects of CAVs on traffic streams, as well as the impact on traffic externalities. This is particularly relevant under mixed traffic conditions, where human-driven vehicles and CAVs will interact. Understanding technological aspects (e.g. communication protocols, control algorithms, etc.) is crucial for analysing the impact of CAVs, but the modification induced in human driving behaviours by the presence of CAVs is also of paramount importance. For this reason, the definition of appropriate CAV investigations methods and tools represents a key (and open) issue. One of the most promising approaches for assessing the impact of CAVs is operator in the loop simulators, since having a real driver involved in the simulation represents an advantageous approach. However, the behaviour of the driver in the simulator must be validated and this paper discusses the results of some experiments concerning car-following behaviour. These experiments have included both driving simulators and an instrumented vehicle, and have observed the behaviours of a large sample of drivers, in similar conditions, in different experimental environments. Similarities and differences in driver behaviour will be presented and discussed with respect to the observation of one important quantity of car-following, the maintained spacing.**

Keywords*—Driving behaviour; Car-following; Instrumented Vehicle; Driving Simulator; Connected and Automated Vehicles.

I. INTRODUCTION

Reconciling mobility needs with efficient and more sustainable transportation, hence increased levels of road safety, is a key objective in the transportation sector. Since 95% of road accidents have been shown to be human-error related, driving automation at different levels is seen as having the potential to greatly reduce road fatalities. Such automation levels have been classified in slightly different ways by different organizations. For instance, as reported by [1], the Society of Automotive Engineers (SAE) considers six automation levels, ranging from 0 to 5. SAE level 1 of automation has been deployed for some years (e.g. adaptive cruise control, lane-keeping assistance, etc.), level 2 systems have more recently emerged (e.g. automated parking, adaptive cruise control with stop-and-go and/or truck platooning, etc.) and introduction of level 3 is now discussed (e.g. combination of adaptive cruise control and lane changing/overtaking systems). Interestingly, increasing introduction of automation requires that the driver is even more at the centre of the innovation and design process. Indeed, as automation moves from one level to the next, the required driving performance shifts from full driver responsibility to co-responsibility with assisting or automated systems. Levels 1 and 2 require that the automation logic interacts with driver behaviour to accomplish complete driving tasks, and higher automation levels also require that the driver is kept in the vehicle control loop, since at level 4 he/she is responsible for the transition from automated to non-automated tasks (or between different automated tasks), and at level 3 he/she can also be required to regain control of the vehicle automation should fail.

Connected and Automated Vehicles (CAVs) could save lives by reducing crashes, improve mobility by reducing traffic congestion, and could potentially have many other profound effects as fuel savings and pollution reduction. In the first steps of the development of CAVs the biggest issue was related to the design of the technology needed to monitor the environment and apply the control to the vehicle, while in the recent years one of the most important field of research has been the evaluation of the impact of the addition of CAVs on traffic flow [2]. It is currently difficult, if not impossible, to evaluate these situations in the real world, mainly because of a lack of automated vehicles on the roads, and also a lack of trust, from the safety point of view, in these new technologies. Moreover costs associated with these testing activities are not negligible. Therefore the research problem is currently addressed by modelling realistic CAV behaviours, and carrying out simulations.

The tool most used for CAV performance prediction in traffic engineering is microscopic simulation [3, 4]. However, while software in the loop can provide an effective nano simulation representation of the automated vehicle, both micro and nano traffic simulation can be inadequate in order to take into account some relevant aspects of the CAVs impact, e.g., it cannot capture the nuances of real drivers interacting with automated vehicles.

As a consequence, new methodologies for the testing of autonomous vehicles in mixed traffic conditions (and in general) are being proposed in the literature. [5, 6]. Although this set benefits of the presence of real drivers, the fact that these drivers interact in a virtual environment, is still relevant, and it is paramount that the behavioural validity of the driving simulators be assessed, i.e., the extent to which driver behaviour is similar between reality and simulator..

The scope of this paper is to present results of a large field survey where the behaviours of more than 100 drivers have been compared in several different experimental environments (Instrumented Vehicle, and two different Driving Simulators), in order to draw attention to differences in the driving styles possibly arising from the different cues perceived in each environment [7]. Comparisons are reported with respect to a particular situation, car-following, and with reference to a very important quantity, the maintained spacing (that is, the bumper-to-bumper distance between the leader and the follower vehicles, analysed also with respect to their relationship with the cruising speed.

II. Background

During the past decade, CAVs has been an attractive research area both in control and in transportation. This research have been focused substantially on three aspects:

- impact of the CAVs on the traffic flow [8,9];
- impact of the CAVs on traffic externalities such as fuel consumption [10] and road accidents [11];
- impact of the CAVs on travel behaviours [12].

As introduced above, many research papers [3,4,13] focus their attention on the calibration of microscopic traffic simulator to simulate the interaction between vehicles (driverless and not); in these environments a part of the unpredictability of human behaviour (as a driver or road user) is totally lost. A proper precaution could be then to try to involve humans in the simulations by means of virtual reality [14]. Generally Driving Simulators (DS) are used in this sense in order to observe the drivers' response to functionalities which do not exist, or cannot be safely tested in real cars [15,16]. However a growing interest is arising about the possibility to test multiple human drivers who interact with each other and with simulated automated vehicles [17].

Within the vast field of research on driving support systems, longitudinal control of the vehicle has so far been one of the more addressed aspects. This applies to different driving tasks; for instance, Intelligent Speed Adaptation (ISA) mainly works in free-flow conditions, while Adaptive Cruise Control (ACC) and Automated Emergency Breaking (AEB) mainly work in car-following conditions. Assisting and automation solutions related to car-following conditions are among the most effective with respect to safety, as they deal with relative speed and spacing [18]. This affects the occurrence of rear-end crashes, that represent more than 25% of total crashes [19]. The risk of a rear-end crash increases exponentially as the headway time gap decreases (a recent review of the literature on this topic can be found in [20]), and for this reason statistical distribution in a population of drivers of the adopted headway (or equivalently of the adopted spacing) is usually carried out in order to evaluate safety conditions in car-following.

In real driving conditions, adopted spacing has been shown to be dependent on cruising speed, and to be distributed, within each speed class, with a lognormal distribution [21,22]. Verifying the distribution patterns of this variable in virtual environments represents a fundamental activity, since it is necessary to ensure that quantification of the hazards, and more generally behaviours of the drivers, are consistent with the reality in order to effectively test CAV solutions in car-following by means of driving simulators; it is worth noting that this activity can be related to the general field of behavioural validity of the DS [23].

The validity of driving behaviour observed in virtual environments is a topic often addressed. In the literature, many examples can be found of studies directly aimed at the evaluation of simulator validity with respect to some specific tasks such as speed [23] or cognitive load [24]. With specific reference to car-following, some studies have been focused on the comparison among field data and DS [25] directly, or indirectly by means of surrogate measures of safety [26]. However in both cases the spacing is a variable only partially taken under control. Therefore this paper presents, for the first time in literature, a direct comparison of adopted spacing in different experimental environments, in different speed classes, from the same sample of drivers in the same driving scenario.

III. Experiments carried out and the collected data

The data used in this study were collected within the Italian research project DRIVE IN2 (DRIVEr monitoring: technologies, methodologies, and IN-vehicle INnovative systems); details about the DRIVE IN2 project can be found in [27]. They were collected both in the real world and two virtual environments using an Instrumented Vehicle (IV), a Static DS (S-DS), and a Dynamic DS (D-DS).

The on-road experiments were carried out using the IV owned by the Department of Civil, Environmental and Architectural Engineering (DICEA) at the University of Naples. It is equipped with systems (sensors on pedals and steering wheel, GPS, forward and backward radars, video cameras) that permit the monitoring of the driver's actions, of the vehicle kinematics, and of the surrounding vehicles. The S-DS is also located at the DICEA. It is a fixed-base single cockpit, with all standard driving controls retained. Torque feedback is included at the steering wheel, and adjustable springs provide all the pedals with realistic force feedback. The virtual environment is visualized on three 23" monitors at a total of resolution of 5760 x 1050 pixels. The horizontal field of view is 100° whereas the vertical one is 20°. The frame rate is fixed at 60 Hz. The D-DS is located at CNR Istituto Motori in Naples. It is a six degree-of-freedom motion platform where the motion is reproduced by a Cuesim hexapod with six electric actuators, able to reproduce most of the accelerations that real car occupants feel. The cockpit is one half of a real Citroen C2 with two adjustable seats and a real equipment dashboard. The visual scene is projected to a three channel (resolution of each channel is 1400 x 1050) 180° x 50° forward field of view on three flat screens (3.00m x 4.00m) surrounding the motion platform. The mirror views are replaced by 6.5" LCD monitors. Note that both the DSs were provided with the same traffic-simulation module, allowing for the emulation of the same specific traffic conditions.

A sample of 100 participants was drawn to match the Italian drivers' population on gender, age and educational level according to the information provided by the Italian National Statistics Institute. All the participants took part in two driving sessions: those on-road with the IV and in the S-DS. Twenty-two drivers randomly chosen from the 100 participant sample, also drove in the D-DS.

The driving scenario has been the same in all the three environments. It consisted in a 78 km single loop on three roads near Naples: a first section on the National Highway A1 (14 km with a speed limit of 100 km/h), a second one on the National Highway A30 (30 km with a speed limit of 130 km/h) and the last one on the rural roadway SS268 (16 km with a speed limit ranging from 60 to 80 km/h). The three sectors were preceded by a 10 km acclimatization sector and an 8 km final urban path used to close the loop. In the first section drivers drove naturally in the surrounding traffic., while in the second section they were committed to follow a corporate vehicle, travelling at 80, 100 and 120 km/h; in the final segment they again drove naturally in the surrounding traffic. In the travelled roads a speed value lower than 50 km/h was never observed. Similarly traffic conditions were also replaced in the virtual scenarios.

IV. Methodology

The analyses of the spacing adopted by the drivers in the different experimental environments are based on the concept of Equilibrium car-following conditions.

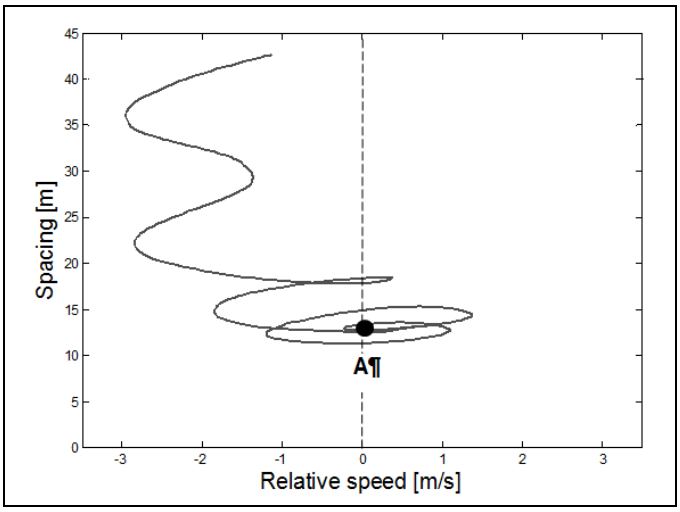

Fig. 1. An example of car-following behaviour in equilibrium conditions; A is the Equilibrium Point

[28] showed that in car-following (CF) conditions drivers respond to changes in the perceived size of the vehicle ahead, arguing that the response is actuated by drivers (by depressing or releasing the gas pedal and/or the brake) at given thresholds of the perceived variation of the apparent size of the vehicle ahead. These thresholds can differ according to whether the distance from the vehicle ahead is increasing or decreasing.

In this condition drivers oscillate within the thresholds and, in the event of the leader's steady-state speed, the centre of this oscillation is an equilibrium point with a null relative speed and a given inter-vehicular spacing. The existence of this Equilibrium Point (EP) is also confirmed by experimental observations, and is consistent with hypotheses of both engineering and psycho-physical car-following models [29]. Figure 1 shows a typical car-following plot, where relative speed is plotted against spacing; in that plot the EP is indicated with A.

Actually, due to changes in the leader's speed or other random effects that interrupt the close-following process, more than one EP can be observed in a CF trajectory. One uniform and uninterrupted CF sub-trajectory in equilibrium conditions (oscillating around the same equilibrium point) is here called a segment.

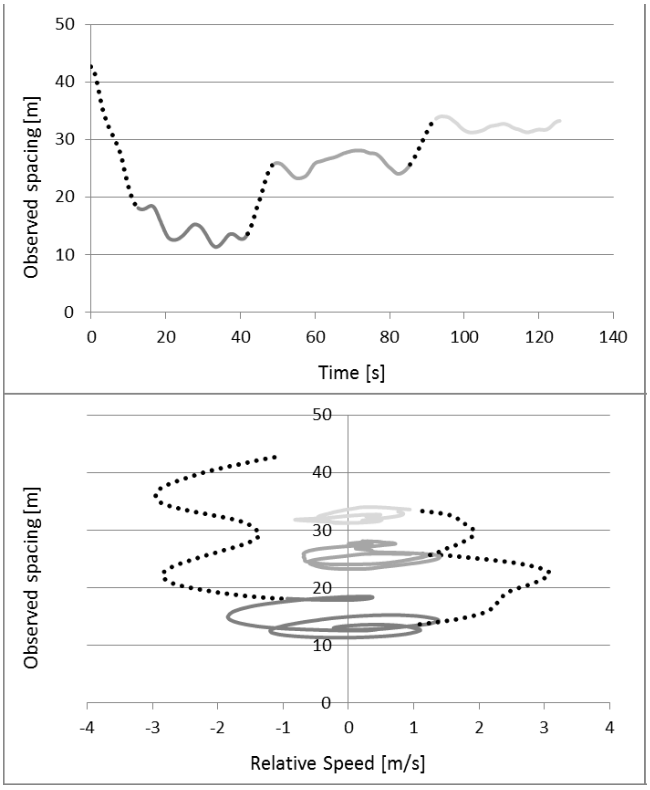

Fig. 2. Three segments evidenced in a car-following trajectory; one Equilibrium Point correspond to each segment

An example is of a segment is provided in Figure 2, where three different segments are evidenced in one trajectory. In the example the changes in the adopted spacing are mainly due to the variations of the speed of the two vehicles. The different equilibria have to be duly identified in order to ensure a proper identification of the equilibrium spacing and of the cruising speed at which the equilibrium spacing holds.

A. Identification of the Segments

The procedure adopted here for selecting segments in each trajectory, and identifying CF equilibria, is a machine learning approach, which allows for automating the process and for applying it to our large amount of observed data. The methodology is based on a clustering algorithm for multivariate time-series segmentation. The algorithm has been proposed in [30] to which the reader can refer for any detail. Very broadly, the clustering technique blends together principal component analysis (PCA) and fuzzy logic. PCA is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The PCA is used to determine in each section the most relevant variables to be taken in account to evaluate the homogeneity of the segments. The full set of variables analysed have been: follower's acceleration, follower's velocity and relative acceleration, relative velocity and relative distance (spacing). The fuzzy logic is used in the algorithm to determine the transition from one segment to another; these points are usually vague and difficult to be associated to a precise instant of the time series.

After each clip has been segmented, the segments actually corresponding to equilibrium conditions have been selected. As represented in Figure 2, at least two kind of segments can be identified in a trajectory. Those corresponding to periods of oscillations around the equilibrium point (three in Figure 2, evidenced with continuous lines), and the transitions between different equilibria (three in Figure 2, evidenced with dotted line); the conditions that triggers these transitions are not studied here, although they also represent a very fascinating topic. Once a segment is determined to concern an equilibrium condition, the average value of spacing in the segment is considered as representative of the EP. The selection of segments concerning equilibrium situations has been automatized also in this case; indeed these segments are characterised by a limited excursion of the values assumed by the considered variables (as a consequence of the oscillation), and thus a measure of these excursions can be used in the recognition process. The chosen measures were the Inter Quartile Range (IQR) value of follower's velocity, relative velocity and spacing; different thresholds have been settled, for every environment, to verify if they affect, or not, the results. The thresholds were [2,3,4] for the relative and follower's velocity, and [15,30,45] for the spacing.

V. Results

The results of the algorithm have been firstly used to investigate the influence of the considered variables on the analysed phenomenon. Indeed, the PCA analysis used for the time-series segmentation evidenced that, with reference to all the experimental environments, in all the analysed cases, the variables were ranked in terms of relevance in this order: (1) spacing, (2) relative velocity, (3) follower's velocity, (4) relative acceleration, (5) follower's acceleration. However the most interesting part arises from the analyses of the relative weight of each variable. Indeed the algorithm showed that in most of the cases, the car-following phenomenon could be described with less than five variables. In particular, in the D-DS the algorithm used in 95% of the cases only the first three principal components. This happened similarly in the S-DS and IV datasets, where the algorithm used only three components respectively in 74% and 70% of the cases. It is worth noting that these three variables (spacing, relative speed, and follower's speed) are the ones most studied in car-following.

Once clips have been segmented, and consequently Equilibrium Points detected, these points were grouped on the basis of the speed value associated to each EP. Four groups have been composed, defining four speed classes, ranging from 50 to 130 km/h, with one speed class every 20 km/h. This choice was influenced by the particular experimental conditions.

The three environments have been compared in terms of dispersion of the observed spacing in each speed class, and impact of the speed value on the dispersion itself.

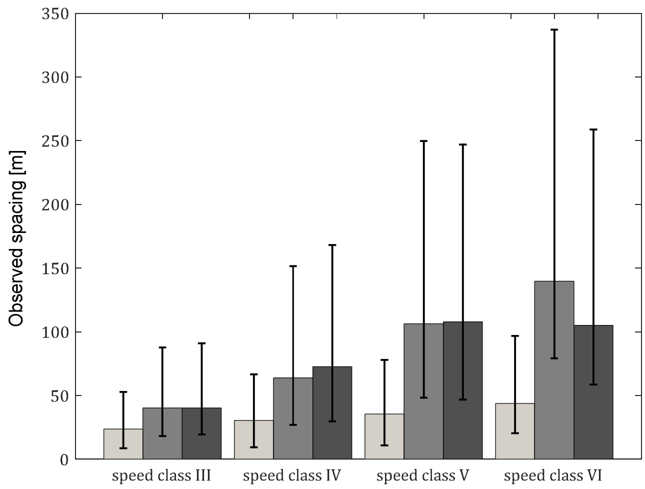

Fig. 3. Mean, 25th and 75th percentile computed for each environment (from left to right, in gray scale: IV, S-DS, and D-DS) and each speed class; each samples is based on all EPs

One plot showing the mean, the 25th and 75th percentiles of the empirical distribution of the detected EPs in each environment, and in the four speed classes has been reported in Figure 3. It should be noted that the spacing observed in the virtual environments have a different magnitude than those recorded on the real road, and in particular they are systematically higher, in terms of both mean and dispersion; similarly happens for the variability within each speed class. Interestingly, comparing each other, the two simulators, very common trends are detectable (except perhaps for the speed class IV where the difference can be attributed to a relative lack of observation, rather than a real different behaviour of the drivers).

With more details, and with reference to each speed class, and each environment, the investigation of the dispersion of the equilibrium spacing has been based on the fitting of an empirical probability density function. The sample considered for the fitting is based on all the EPs, without distinguishing drivers. Different distributions have been tested, consistently with the tests carried out in [20]: (a) Exponential, (b) Inverse Gaussian, (c) Lognormal, (d) Normal, and (e) Weibull. By using Kolmogorov-Smirnov (KS) test, the two distributions which showed the best goodness of fit have been the Lognormal and the Inverse Gaussian; this is based on the analyses of the the p-values associated to KS-tests performed for each speed class and experimental environment. The two distributions are quite consistent internally; in the sense that the null-hypothesis is never rejected for IV and S-DS data, and is rejected just in one speed class in the D-DS environment for both of them. These results are very interesting from the behavioural validity point of view, since they show that independently from the experimental environment and from the speed class, the dispersion of the spacing can be fit with the same statistical distribution law; thus a great consistency between the three experimental environments exists.

The values of the parameters estimated for the two distributions in each speed class and each environment have been reported in Table I. In the same table, also some descriptive statistics concerning the sample are given.

TABLE I. ESTIMATED PARAMETERS AND DESCRIPTIVE STATISTICS

Dataset	Speed Class	Lognormal		Inv. Gaussian			
		μ	s	μ	λ	*Mean*	*SD*
IV	I	3.05	0.47	23.62	95.35	23.62	11.46
	II	3.34	0.40	30.52	174.42	30.52	13.49
	III	3.48	0.41	35.50	190.05	35.50	15.98
	IV	3.60	0.58	43.66	116.88	43.66	29.37
S-DS	I	3.51	0.57	40.24	103.56	40.24	29.94
	II	4.00	0.57	63.95	174.95	63.95	38.50
	III	4.49	0.61	106.19	243.60	106.19	64.69
	IV	4.69	0.74	139.62	205.57	139.62	97.34
D-DS	I	3.50	0.60	40.26	95.10	40.26	28.44
	II	4.14	0.60	72.54	178.64	72,54	36,69
	III	4.53	0.58	107.74	277.99	107,74	55,92
	IV	4.49	0.65	105.15	221.47	105,15	53,52

Table I and Figure 3 show another element of consistency between the three environments. In every environment, the values of spacing increase according to the increment of speed, and also the dispersion of the data (e.g. the standard deviation - SD) increases with speed.

It is worth noting that results reported in this section refer to a specific set of values of the IQR thresholds used to select EPs. However, it was verified that the results are not affected by these thresholds; indeed the same analyses were repeated for all the sets of thresholds and differences in the order of magnitude of parameters estimated for each distribution, in each speed class and experimental environment were comprised between 0 and 3%.

VI. CONCLUSIONS AND FUTURE PERSPECTIVES

We retain that DSs could deeply contribute to the development and testing of CAVs, giving the opportunity to embed human drivers in this process. Undeniably, drivers exhibit driving behaviours in virtual environments which are different from those observed in the reality. Knowing these differences can lead to improved methods and awareness of this process. In this study we presented exhaustive comparisons of the spacing adopted in equilibrium car-following conditions by the same sample of drivers, in the same traffic conditions, but in different experimental environments. In all environments, adopted spacing values seem to depend on the vehicle speed, and an increment of speed leads to an increment of the spacing. The increments are not only in terms of mean but also in terms of dispersion. Another analogy between real and virtual environments concerns the statistical distributions that fit the data; indeed Lognormal and Inverse Gaussian are the two distributions which best fit the data independently from the experimental environment. Thus a consistency of the driving behaviours observed in different environments has been shown, at least with respect to car-following conditions. It should be also highlighted that the absolute values of the adopted spacing (and consequently the values of the parameters of the distributions) are significantly different between reality, and the virtual environments. However, another interesting second-order outcomes of this study, is the presence of a high level of consistency in the behaviours observed in two simulators characterised by very different levels of physical validity. It is worth noting that the visual resolution is significantly different between the two simulators, thus it seems that the resolution did not matter in this specific case. Adopted spacing is only one of the variables which characterise driving behaviours in the virtual environments. Other levels of investigation could be carried out by using data from our experiment both concerning the way drivers interact with the vehicle (e.g. how they control the steering wheel or pedals), and the levels of effort required to drive (e.g. level of workload). All these quantities are relevant from the CAVs development and testing point of view. The two DSs share the same software suite, thus a countercheck of the consistency of driving behaviours observed in different simulators could come from analysing data collected in other experiments, with a different simulation software. Finally, experiments carried out at simulators concern the interaction of one human driver, with some robotic vehicles acting as a leader. Indeed vehicle in the simulators were with a realistic behaviour, but their behaviour was deterministic and pre-determined. Some interesting outcomes could arise from the investigation of the interaction of two real drivers in the same virtual environment.

ACKNOWLEDGMENT

The work reported in this paper was partially supported by the *App4Safety* research project (PON03PE_00159_3) under a grant from the Italian Ministry of Education (MIUR), and by a grant funded under the POR_FESR 2007-2013 program (000009-POR_OPEN_INNOVATION_RIS3). Data used in the work were collected during the research project *DRIVEIN2* (B61H110004000005/PON01_00744) also under a grant from the MIUR.

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