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Data Collection for Traffic and Drivers' Behaviour Studies: a large-scale survey

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Abstract

Studies of driving behaviour are of great help for different tasks in transportation engineering. These include data collection both for statistical analysis and for identification of driving models and estimation of modelling parameters (calibration). The data and models may be applied to different areas: i) road safety analysis; ii) microscopic models for traffic simulation, forecast and control; iii) control logics aimed at ADAS (Advanced Driving Assistance Systems). In this paper we present a large survey based on the naturalistic (on-the-road) observation of driving behaviour with a view to obtaining microscopic data for single vehicles on long road segments and for long time periods. Data are collected by means of an instrumented vehicle (IV), equipped with GPS, radar, cameras and other sensors. The behaviour of more than 100 drivers was observed by using the IV in *active mode*, that is by observing the kinematics imposed on the vehicle by the driver, as well as the kinematics with respect to neighbouring vehicles. Sensors were also mounted backwards on the IV, allowing the behaviour of the driver behind to be observed in *passive mode*. As the vehicle behind changes, the next is observed and within a short period of time the behaviour of several drivers can be examined, without the observed driver being aware. The paper presents the experiment by describing the road context, aims and experimental procedure. Statistics and initial insights are also presented based on the large amount of data collected (more than 8000 km of observed trajectories and 120 hours of driving in active mode). As an example of how to use the data directly, apart from calibration of driving behaviour models, indexes based on aggregate measures of safety are computed, presented and discussed.

Keywords: Driving Behaviour; Data collection; Accident Analysis; Road safety; Microscopic; Advanced Driving Assistance Systems; Intelligent Transportation Systems; Instrumented Vehicle.

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1. Introduction

Identification of driving behaviour represents a fundamental requirement for traffic studies and generates benefits especially in three main fields: road safety analysis; microscopic traffic simulation; intelligent transportation systems (ITS).

Road safety analysis aims to understand the causes of accidents and take measures to prevent them from occurring. Safety can be determined according to different approaches. One is based on statistical considerations and concerns identification of so-called *hotspots* (Montella, 2010). Another approach uses *accident scenarios* and is based on statistical inference (Fleury and Brenac, 2001); recurrent conditions are investigated in observed accidents in order to identify prototype unsafe scenarios related to various aspects, such as the road geometry, road section, vehicle characteristics, the pavement and the weather. A third approach, adopted in this paper, is based on the analysis of driving behaviour, computing the so-called *surrogate safety measures* (Tarko, 2009). All approaches require a non-negligible amount of data, often related to car-following conditions, rear-endings being one of the most frequent causes of injuries (excluding accidents that involve vulnerable road users).

Identification of driving behaviour is also a key task for microscopic traffic models, developed to improve the detail of traffic flow studies by explicitly representing the interaction between the single components of a traffic stream. The choices of each vehicle, in terms of spacing with respect to the vehicle(s) ahead, lane changing, gap acceptance, etc., are identified by analytical models. A review of some of these models can be found in Toledo (2007). A major task for microscopic traffic models is their calibration, given that a large number of parameters have to be estimated for each of the modelling components, including car-following.

ITS are advanced applications that embody decision-making and/or operational intelligence in order to provide innovative services. These applications allow both safer and more efficient use of the road by travellers and enhanced traffic management. In the field of ITS, Advanced Driver Assistance Systems (ADAS) represent a real opportunity to both improve road safety and support efficient transportation systems. Not only do ADAS directly influence the interaction among vehicles and thus affect traffic flows and characteristics., but they also control the driving task directly, reducing drivers' errors and shortening reaction times. The development of such systems is not straightforward and many issues have to be addressed, not only from a technological point of view. For instance, it is crucial to be sure that any proposed system considers driver expectation and behaviour and ensures there is a minimal mismatch between the system behaviour and the driver's normal behaviour, thus increasing driver acceptance (Simonelli et al., 2009; Bifulco et al., 2013a). Indeed, an ideal ADAS needs to be based on a good understanding of driver behaviour, particularly in car-following which still represents one of the main fields of application for solutions like ACC (Adaptive Cruise Control) and AEB (Advanced Emergency Braking).

This paper presents the data-collection activities carried out within the Italian research project DRIVEIN^2 (DRIVEr monitoring: technologies, methodologies, and IN-vehicle INnovative systems). The project involves eight partners and focuses on defining methodologies, technologies and solutions to capture driving behaviours, with special emphasis on road-safety solutions. The DRIVE IN^2 project (Bifulco et al., 2012a) falls within the field of ADAS and, among others, aims to implement a Driver-In-the-Loop (DIL) laboratory based on a multidisciplinary approach which involves knowledge of automotive solutions, transportation engineering and traffic psychology. The project relies on driving data collected by means of both an instrumented vehicle (IV) used for naturalistic (on-the-road) observations and a driving simulator (DS). How the IV is equipped and how it is employed in our experimental framework is described in Bifulco et al. (2012b). The reciprocal validation of DS and IV is an on-going task, with first results recently submitted (Bifulco et al., 2013b).

In this paper, after a review of current advances in microscopic data collection (section 2), the experiment is described in detail (section 3). An application of the collected data to road safety analysis is presented in section 4. Finally, the results are discussed and conclusions are drawn.

2. State of the art in microscopic traffic data collection

Several tools are available to observe driving behaviour, some of which operate road-side and others on-board. In the case of road-side sensors, an unaware driver is monitored while driving on an instrumented site; various technologies can be used for this purpose, with the most popular today being video cameras, that allow to track the trajectories of vehicles via image processing. This method was recently employed in the Next Generation SIMulation program (NGSIM), a public-private project between the Federal Highway Administration of USA and several commercial micro-simulation software developers. Data are public and available for all scientists from the project website (www.ngsim.fhwa.dot.gov). An alternative approach is to obtain motorway individual vehicle data (IVD) as proposed in Wilson (2008). It is based on the use of data collected with inductive loop detectors (in a double loop configuration). Accurate estimates of speed and vehicle length can be recorded together with the time at which they are detected. Such data are generally oriented to aggregate measures of the characteristics of the traffic stream, typically referred to time-lengths of over one minute. However, Wilson suggests recording single detections. Using the speed detected at an upstream double-loop detector, the arrival time of the vehicle at the downstream one can be predicted. Compatibly with the predicted arrival time at downstream the best-matching record is searched, using the detected vehicle's length to help matching. Thus the vehicle is traced across two consecutive (double) loops. The reliability of data is strictly related to the distance between detectors. The method has been applied in the Motorway Incident Detection and Automatic Signalling (MIDAS) project, which consists of a network of traffic sensors installed on several (highly congested) UK motorways. A major advantage of both the NGSIM and MIDAS approaches concerns the amount of data that can be collected. The major disadvantage is that drivers can be observed only for a few seconds, on a limited portion of the instrumented site. Moreover, it is not possible to have information on the driver's characteristics and only combined drive-and-vehicle behaviour can be observed.

On-board sensors, installed on IVs, allow longer observations under more flexible experimental conditions, with the possibility of observing in a controlled way some manoeuvres of particular interest. An instrumented vehicle can be represented as a standard car whose kinematics is recorded in order to be analysed (Bifulco et al. 2012b). Several research projects have been based on IVs, aimed at analysing and modelling driving behaviour or the interaction between vehicles in terms of car-following and/or lane-changing (Boyce and Geller, 2001).The dispersion of driving styles with respect to different personal characteristics, such as age, gender and driving experience, represents the target of an increasing number of IV-based studies, such as that of Ranjitkar et al. (2004). Moreover, IVs have been used for psychophysical analysis of the state of drivers, especially their fatigue or mental workload (Harms and Patten, 2003). Other studies have employed IVs to analyse drivers' responses to route guidance systems. IVs also allow analysis of drivers' behaviour in the absence of interaction with other vehicles but with respect to different geometric features of roads (Perez Zuriaga et al., 2000).

From a broader perspective, Bishop (2000) provides an overview of the possible applications of instrumented vehicles in ITS, with particular reference to Intelligent Speed Adaptation. Of course, IVs are mainly used in order to gain insights into normal driving behaviour. Critical behaviour and/or unsafe situations may also be observed (hopefully rarely; McLaughlin et al., 2008); however, these cannot be deliberately induced in road experiments, because of evident ethical reasons. As a result, only surrogate measures of safety can be produced in most safety-related cases (Yan et al., 2008). That said, the ability to collect and record data about the relative kinematics of the IV with respect to vehicles ahead and/or behind represents a prerequisite for studies involving the observation of car-following conditions. Observation can be carried out (Brackstone et al., 2009) both in *active* mode (the driver observed is in the instrumented vehicle and the car-following process is defined with respect to the vehicle ahead) and in *passive* mode (the leader is the instrumented vehicle and the observed driver is the one in the vehicle behind. Of course, it is also crucial in this framework the ability to use such techniques as filtering and fusion (Bifulco et al., 2011) to handle the large number of both data and sources of data.

3. The on-road survey

3.1. Definition and recruitment of the sample

A sample of 100 participants was selected for experimental purposes, drawn in order to match the population of Italian drivers. The following levels were considered in the stratification of the population:

1. Gender: male and female;
2. Age, 4 classes:
   - class 1, from 20 to 24 years old;
   - class 2, from 25 to 40 years old;
   - class 3, from 41 to 64 years old;
   - class 4, over 65 years old;
3. Educational level attained, considered *low* (until high school diploma) or *high* (after graduation).

The admissible combination of the previous features allows the sample to be split over 14 layers (Table 1 below).

Table 1. The sample

Layer	Age	Gender	Educational Level	Relative incidence	Layer Cardinality (over a sample of 100)
1	20-24	M	L	0.2*0.429*1	9
2		F		0.2*0.571*1	11
3	25-40	M	L	0.3*0.483*0.5	7
4			H	0.3*0.483*0.5	7
5		F	L	0.3*0.517*0.5	8
6			H	0.3*0.517*0.5	8
7	41-64	M	L	0.3*0.491*0.5	7
8			H	0.3*0.491*0.5	7
9		F	L	0.3*0.509*0.5	8
10		F	H	0.3*0.509*0.5	8
11	≥65	M	L	0.2*0.674*0.5	7
12			H	0.2*0.674*0.5	7
13		M	L	0.2*0.326*0.5	3
14			H	0.2*0.326*0.5	3

The cardinality of each layer depends on the relative incidence on the population given by official data, such as those provided by the ISTAT (Istituto [Nazionale] di STATistica – Italian National Statistics Institute), as updated to the latest available year. In order to fill in missing information, we also used data from the DATIS project, carried out by the ISS (Istituto Superiore della Sanità – Italian National Health Institute, http://www.iss.it/chis/?lang=2) to define the distribution of gender in each single layer.

Having defined the desired cardinality of each layer, we recruited individuals among those responding to an advertisement requesting volunteers for a study on driving behaviour. Selection was carried out in three steps:

a) *Contact*, 100 drivers were needed; however, we decided on a preliminary basis to select 150 drivers, distributed according to the desired stratification. Thus a preliminary sample was considered by increasing each of the sample layers by 50%;

b) *Administration of the pre-selection questionnaire* to those showing interest in participating in the experiment. This questionnaire consisted of four distinct parts: Personal Data; Traffic Locus Of Control Questionnaire (T-LOC); Marlowe Crowne Social Desirability (MCSD); Dangerous Driving (DDDI).

   T-LOC, MCSD and DDDI, were administered in random order to respondents, to avoid distortion phenomena, as most people tend to provide the last answers hastily due to the annoyance.

   Analysis of the questionnaire responses achieved three purposes:

- it confirmed that the respondents belonged to the layer he/she had been contacted for. If the layer was not confirmed, the respondent was switched to the appropriate layer. If, after verification of all respondents a layer was under-represented with respect to the desired classification, the sample was supplemented with new respondents;
- it classified the respondents by employment status: student (if appropriate for the considered layer, depending on age), employed vs. unemployed, retired (if appropriate for the layer);
- it divided individuals into clusters. Three categories were created according to responses given to the T-LOC, MCSD and DDDI tests by using two-step cluster analysis (TSC, SPSS Inc. 2001): aggressive drivers; non-aggressive drivers and fatalists; non-aggressive and non-fatalistic drivers;

c) *Final selection of the sample*: from 150 contacts 100 respondents were selected. For each layer, respondents were selected, obtaining a good balance with respect to employment status and clusters.

3.2. The experiment

The experiment lasted from September to the end of October 2012. It was organised into daily experimental sessions, each consisting of several driving sessions. In order to schedule the driving tests, the drivers made their own reservations for one of the experiment day through a web application. Driving sessions were sequenced every two hours, accommodating driving time and the time required to answer two questionnaires (pre and post-driving). Each daily session involved at most five driving sessions (from 8:30 a.m. to 6:30 p.m.). Since the sun sets before 6 p.m. only in last days of October, similar sunlight conditions were established for each session.

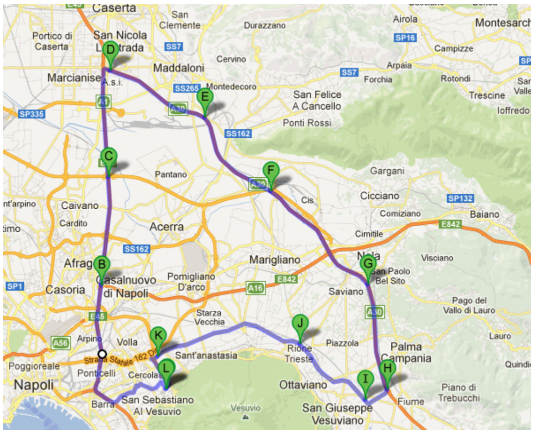

Fig. 1. The experimental path

The following steps were carried out:

- observation of the 100-driver sample;
- each driver drove on the same tour (see Fig. 1) by using an instrumented vehicle (for a detailed description of the IV refer to Bifulco et al., 2012b), detecting the behaviour of the driver with respect to the vehicle ahead and the behaviour of the driver of the vehicle above with respect to the instrumented vehicle;
- the tour is 78 km long, each driving session lasting about one hour; the route consists in a single loop, mainly evolving over three roads near Naples for a total length of 60 km:
  - National Highway A1 (from B to D in Fig. 1, about 14 km), consisting of a dual carriageway and three lanes for each traffic direction, with a designated speed range of 80-120km/h (speed limit 100 km/h). Here the driver is immersed in a traffic stream that moves at about 100 km/h. Thus natural car-following data are

obtained, in the sense that the driver is not asked to perform special tasks;

- National Highway A30 (from D to H in Fig. 1, about 30 km), with the same characteristics as National Highway A1, apart from the speed limit (130 km/h). Here the driver interacts with a vehicle taking part to the experiment (corporate vehicle) which carries out several standard manoeuvres. In particular, the driver is asked to perform three approaching manoeuvres with the leader at a constant speed of 80, 100 and 120 km/h;
- The "Vesuvius" State Highway SS 268 (from I to K in Fig. 1, about 16 km), consisting of a single carriageway with one lane per traffic direction, at-grade intersections and design speed interval of 60-100 km/h (speed limit 90 km/h). Here the corporate vehicle is not present; however car-following data are obtained.

For part of each of the three main sections a workload experiment was carried out on the drivers, aimed at estimating their mental workload. This refers to the portion of the driver's information processing capacity (or resources) that is actually required to meet requirements in the driving task (Eggemeier et al., 1991). The starting point for driving sessions was Via Gianturco, a major urban road in the eastern part of Naples, due to the availability of public transport services, thanks to the Gianturco underground station, and quick access to the A1 Highway. Having been met at the beginning of the test-driving route, selected drivers were given a pre-driving questionnaire, comprising the DCQ (Driver Coping Questionnaire) and the DSI-Pre (Driver Stress Inventory-Pre) as described in Matthews et al. (1996), as well as the Italian version of the PANAS (Terracciano et al., 2003). The tests aimed to investigate the driver's mood prior to driving and to interpreter his/her driving behaviour in light of it. Before point B, a period of acclimatization (from L to B in Fig. 1) was introduced, where the driver familiarized him/herself with the instrumented vehicle, to prevent the driving behaviour being biased by lack of familiarity. A final section was introduced (from K to L) allowing the driver to come back to the starting point. Finally, a post-driving questionnaire was posed to drivers in order to ascertain in what way the driver's mood was influenced by the experiment. The questionnaire comprised the DSI-Post and the NASA-TLX tests adapted for workload (Hart & Staveland, 1988; Bracco & Chiorri, 2006). Workload was used, amongst others, to validate an associated experiment carried out using a driving simulator, as presented in Bifulco et al. (2013b).

4. Using collected data for road-safety analysis

4.1. Data reduction

Using the IV, we thus recorded the trajectories of each driver (and of the surrounding vehicles) also supported by video. In this way we analysed the car following phenomena in active and passive modes (Brackstone et al., 2009). In particular, in active mode, on-board sensors are used to obtain measures relative to the vehicle ahead, and the instrumented vehicle acts as the follower and its driver is the (aware) subject of a behavioural experiment. In passive mode, the sensors measure the relative kinematics with respect to a vehicle behind and the (most probably unaware) subject of the experiment is the driver of this vehicle. While active mode enables recording of long sessions for the same subject (possibly involving several leading vehicles), the passive mode allows the recording of shorter sessions but of many different subjects (with respect to the same leader).

Data presented in this section concern the third section of the experiment (Vesuvius State Highway SS 268), where unsafe driving conditions are often reported and accidents more frequently occur.

In order to analyse this phenomenon, we divided each car-following trajectory into clips. For each clip it was imposed that: the vehicle behind or ahead of the IV (respectively for passive and active mode) is the same; the length of the clip is at least 20 sec; the spacing is less than or equal to 150 metres. Analyses identified 123 clips in active mode and 94 clips in passive mode; for a total of 476.870 km (more than 7 hours) in car-following. The characteristics of the resulting dataset, relative to clip extension in space and time, are summarised in Table 2.

Table 2. Synoptic characteristics of dataset clips

Mode	Clip length (km)				Clip Duration (s)			
	Mean	STD	Max	Min	Mean	STD	Max	Min
Active	2.305	1.218	6.145	0.360	130.02	65.93	320.11	21.16
Passive	2.056	1.102	5.645	0.335	114.06	58.93	343.16	21.66

4.2. Surrogate measures of safety

Having selected the clips, we carried out dispersion analysis of the behaviour observed, taking several traffic variables into account. Our analysis especially concerned the safety of the flow conditions and was disaggregated by active and passive mode, based on the concept of surrogate safety measures. A general definition for these measures is somewhat vague, but basically, in accordance with Tarko (2009), the concept is that a surrogate measure should be based on an observable non-crash event, related predictably and reliably to crashes, which may in practice correspond to crash frequency or severity.

Measures typically considered are vehicle speed, the adopted headway (H) and the time-to-collision (TTC). Headway measures the time required, under unchanged conditions, for the vehicle behind to reach the position occupied by the leading one. TTC (when relative speed, measured as leader's speed minus the follower's, is lower than zero, and the follower approaches the leader) represents the time after which a collision between the two vehicles will occur if the collision course and the speed difference are maintained (see e.g. Hyden, 1996). The two parameters can be computed for each instant *t* using respectively with $H=\Delta x/V_f$ and $TTC= \Delta x/ \Delta v$.
Where Δx, Δv and V_f are, respectively, the spacing (measured bumper to bumper), the relative speed and the follower's speed; all required measures were collected by the IV in both the active and passive mode.

4.3. Results

The distributions of the average follower's speed observed in each clip are reported in the box and whisker plot depicted for both the active and passive modes (Figure 2 left-hand side). Similarly, a box and whisker plot is also produced for the distribution of the average headways adopted (Figure 2 right-hand side).

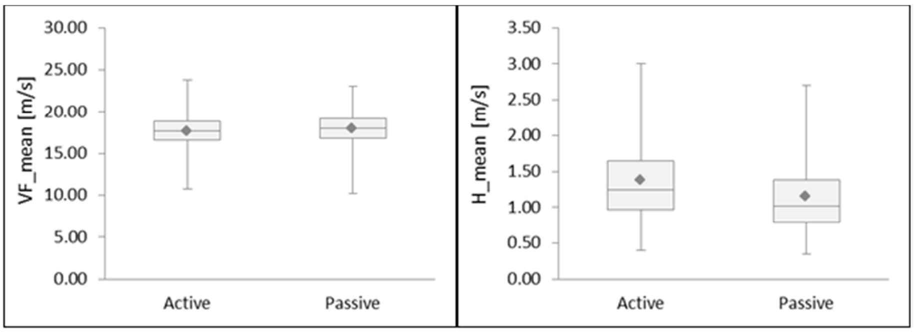

Fig. 2. The box and whisker plot of the average speed and headways

The instantaneous values of Headway and TTC observed in each clip were also used to analyse safety conditions based on Vogel (2003), who proposed to combine the two parameters to determine instantaneous safety conditions for drivers. In particular, four zones can be defined by setting two thresholds. The four zones are depicted in Fig. 3 with respect to a value of six seconds for both the thresholds and for both active and passive mode data; in this case the behaviour of the drivers is never considered safe but situations of "imminent danger" occur very rarely (time frequency < 0.5%). However, it is worth noting that the width of the four zones

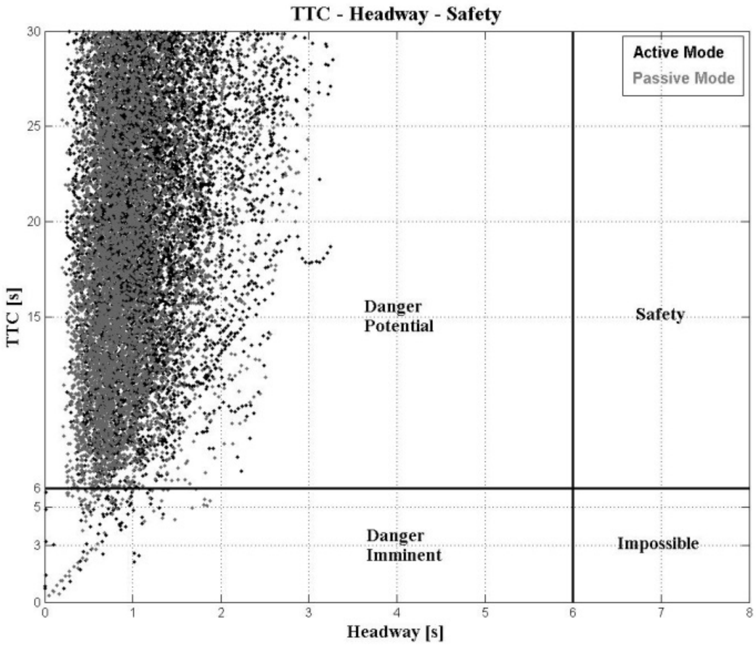

Fig. 3. An analysis of safety conditions according to Vogel

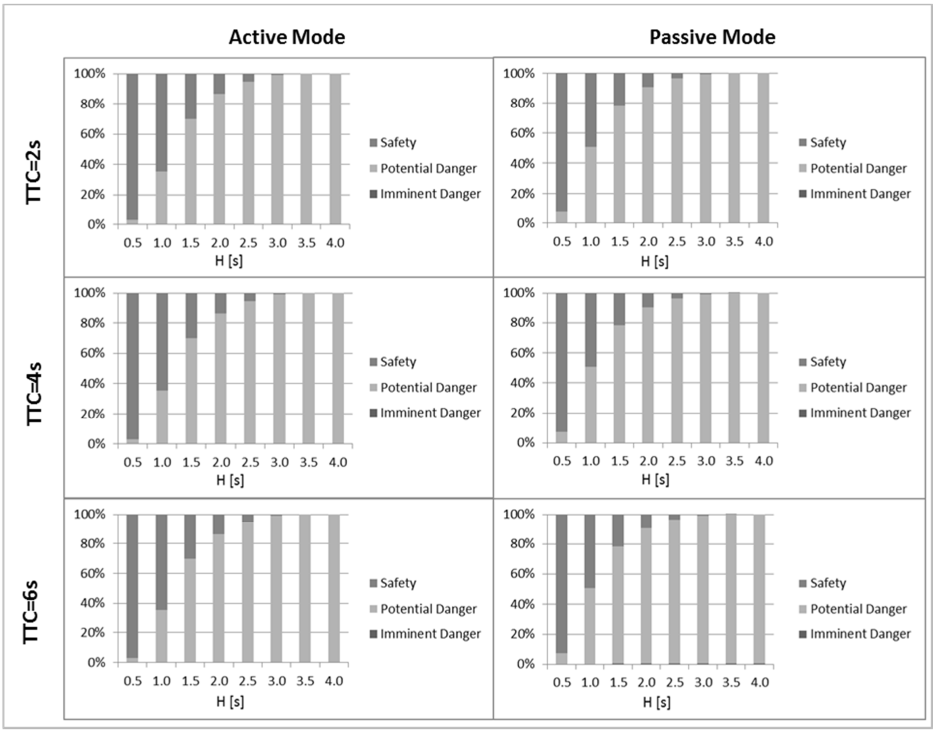

Fig. 4. Sensitivity analysis of safety conditions with respect to different values of TTC and H thresholds

depends on the thresholds. Hence, in Fig. 4, a sensitivity analysis was applied with respect to different values of the thresholds. In particular, three TTC threshold values were chosen (2, 4 and 6 seconds) and, for each the headway threshold was varied (from 0.5 to 4 seconds). Given these thresholds, the percentages of time in which the drivers were in safety, potential danger and imminent danger conditions were computed and plotted in the figure for both the active and passive mode.

5. Discussion and conclusions

In this work we presented a large-scale survey aiming at the observation of driving behaviour. The data which we collected were used for safety analysis. Observations show that the speeds are not dispersed across drivers and along the road stretches concerned. Moreover, they are similar both in average and deviation for active and passive observations. More heterogeneity between drivers is observed with respect to the headway the drivers adopt, which is lower in passive mode.

Vogel's analysis shows that more than 80% of the time potentially dangerous conditions are found if the H threshold chosen for the analysis is 2 seconds, while an H threshold around 1 second has to be chosen in order to obtain safety conditions for about 50% of the drivers. The safety condition seems to be independent of the chosen TTC threshold. Observations in passive mode exhibit slightly more dangerous behaviour.

Driving behaviour during car following were investigated to verify whether active and passive experimental conditions induce different driver performance. The tests concerned the mean speed and mean headway of each clip. The resulting samples are not normally distributed. A non-parametric test, two-sample Kolmogorov-Smirnov, was applied. The difference between headways in the two experimental conditions is statistically significant (t=0.0022), whereas that between speeds is not (t=0.4955). Equal speeds for active and passive observation are expected, given that overtaking is not allowed on the route under analysis. However, an influence of the observation technique was evidenced. The drivers unaware of taking part in an experiment tended to maintain a lower headway with respect to the active drivers. This confirms early findings in motorway studies of McDonald et al. (1997).

Acknowledgements

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