Published in IET Intelligent Transport Systems
Received on 27th September 2012
Revised on 13th February 2013
Accepted on 25th February 2013
doi: 10.1049/iet-its.2012.0148

Special Issue: Human-Centred Design for Intelligent Transport Systems

ISSN 1751-956X

Identifying critical incidents in naturalistic driving data: experiences from a promoting real life observation for gaining understanding of road user behaviour in Europe small-scale field trial

Anita Tontsch, Pedro Miguel Valero-Mora, Ignacio Pareja

INTRAS, Universitat de València, Institute of Traffic and Road Safety, C/Serpis 29, 46022 Valencia, Spain
E-mail: anita.tontsch@uv.es

Abstract: The methodology of naturalistic driving observation aspires to observe the driver and his environment while driving in natural driving settings. It is of great importance in research on road safety as this method of observing road users eliminates the disadvantages of traditional methods like simulator studies or interviews. However, it produces vast such amounts of data and challenges data reduction and data analysis. Therefore automatic methods for filtering critical incidents based on thresholds for numerical data are often applied to select the data to be analysed. This study reports a small-scale field trial in Valencia, Spain, which was conducted within the promoting real life observation for gaining understanding of road user behaviour in Europe project. The analysis of the numerical data using thresholds resulted in a great number of false alarms and did not identify safety-critical sequences. In contrast, video analysis revealed a number of critical events that had not been previously detected using the numerical parameters. The study conveyed the importance of continuous video recording in these kinds of studies and showed that the methodology of data reduction for naturalistic driving studies requires further development in order to be able to capture all the relevant incidents automatically.

1 Naturalistic driving observation

Naturalistic driving (ND) investigates driving behaviour in on-road measurement studies. Initiated as a way of overcoming the limitations of crash data collected by police, in-depth investigations or other sources of accident data, naturalistic research brings about the possibility of understanding the factors involved in collisions directly instead of having to infer them from indirect sources. These studies involve the interaction with other road users as well as the driver's behaviour behind the steering wheel or the handlebars. Naturalistic driving studies were pioneered by the Virgina tech transportation institute (VTTI). In the 100 cars study, the participants' own cars were equipped with technology that enabled the recording of driving parameters, the driver and his environment. Hundred drivers participated over a period of several month driving their usual ways and being captured continuously while driving [1]. After this project, about 40 naturalistic driving studies have been undertaken around the world according to the count of Regan *et al.* [2], mainly in US. They have researched cars, trucks and two wheels vehicles, with different number of subjects and durations, exploring issues such as driver characteristics [1], driver error [3, 4], driver distraction/inattention [5–7], driver fatigue/sleep deprivation [8–10] interactions between vehicles [11] and so on. In Europe, the promoting real life observation for gaining understanding of road user behaviour in Europe (PROLOGUE) project, which was co-funded by the European Commission, aimed 'to demonstrate the usefulness, value and feasibility of conducting naturalistic driving observation studies in a European context in order to investigate traffic safety of road users, as well as other traffic related issues such as eco-driving and traffic flow/traffic management' [12, p5].

In naturalistic driving studies, by equipping cars with data loggers and cameras, drivers are unobtrusively observed in their everyday driving. Performing the studies in realistic context tries to eliminate the many disadvantages of other more subjective or artificial investigation methods enabling the researchers to 'objectively observe various driver- and crash-related behaviour' [12, p9]. Naturalistic driving observation can provide a large amount of information about real driving behaviour and might help to answer some of the unsolved questions we still have regarding road safety. However, in order to attain this goal, naturalistic driving studies need to resolve a number of technical and methodological problems, many of them related with the large amount of data collected and how to draw the important information out of it. This paper focuses on the problem of detecting critical events in a study using the values that stand out more in certain variables (speed, braking, swerving etc.) against using the video data. However, before we start with a description of the data gathering process as it is usually performed in this kind of studies (Section 2), and then we will proceed with the results found in our study (Section 3).

2 Data gathering

In naturalistic driving studies, driving data can be collected through in-car technological devices that gather many different measures [12]. The data are captured with data loggers that either dispose of certain sensors themselves or are connected to vehicle-based sensors (for a detailed listing of sensor specifications see Welsh *et al.* [13, p19]). Video is captured using installed cameras that may record both the driver and his environment [12, 14].

2.1 Data reduction and analysis

Driving data in naturalistic driving studies are usually captured continuously while the vehicle is moving. Consequently, even short trials result in vast amounts of data. Naturalistic observations are optimally carried out during long-term periods of time [14]. As a consequence, the data collected can be very large and hard to manage. Therefore finding the specific parts of the data relevant for the research questions may require special methods for filtering out the non-relevant parts [13]. This problem has been attacked using specific thresholds for the numeric parameters that identify the parts worth being analysed in detail.

The research questions determine the difficulty and extent of this filtering process. Thus, for example, if analysing speeding sequences is the objective of the study, identifying all data where participants drive over the mandatory speed is straightforward. In this example, the speed limit works as the threshold in the filtering process. However, if the study aims to study events that are not so easily defined, specifying the threshold may become a much more difficult process. Thus, safety-critical events can be identified using braking pressure, sudden deceleration, or brisk swerving. However, many safety-critical events may not produce any measurable effect on these parameters and using them as filters would leave many of them undetected. Also, badly selected thresholds could lead to high analysis time, because of the high number of filtered events or, as mentioned before, to miss important events [13].

2.2 Event triggering

An alternative that facilitates data collection is to pull the filtering process one step forward. By defining thresholds for certain driving parameters, some data loggers are able to log data and video recording just for some defined time before and after the parameters reach the predefined value [13]. Thus, data collection and video recording is limited to events that reach some conspicuous driving values and are therefore likely to be safety relevant. Some devices collect basic data like travel time and global positioning system (GPS)-signals on every trip. Data can also be triggered to certain predefined geographical locations. That is, if the instrumented car reaches a predefined GPS-position, data collection (and/or video recording) is activated for some time.

The amount of captured data is clearly reduced by this methodology. However, this method has certain disadvantages. Welsh *et al.* [13] name as the most significant issues that the calibration can be affected over time or refuses to work at all without notifying the researcher. Similar to the previously named issue of bad selected thresholds, important events could be missed by not reaching that predefined value. However, with the difference that, in this case, missed events are not even captured in the data and one is limited to the data that has been gathered [13].

3 Experiences from a Spanish field trial

3.1 Spanish field trial of the PROLOGUE project

Within the PROLOGUE project, a small-scale field trial was conducted in Spain by the University of Valencia. Five experienced drivers drove a highly instrumented car for four days each. While driving, their driving performance and behaviour were recorded continuously. Sensors captured car dynamics and five cameras recorded the driver's face, the scenery in the front and in the back. On two of the four driving days, the participants used a navigator to find their destinations and could choose whether to make use of any in-vehicle information systems (IVISs). On the other two days, they were asked not to use any IVIS while driving. These two days per driver have been the control group. Participants picked up the car at 8 am and drove about 2 h to different destinations in and around Valencia. They could choose by themselves which route to take in order to reach the destinations.

Approximately 40 h of driving have been collected with the four drivers. Data analysis aimed to identify safety-critical incidents during the two conditions (with/without the use of IVISs) [13].

This study provides an indication of the effectivity of the threshold-based identification of events against the review of videos for identification of safety-critical incidents.

3.2 Safety-critical incidents

In-depth analysis of safety-critical events requires understanding of not just the event itself, but also the time before and after the event. This involves analysing the driver's behaviour while driving as well as his road behaviour and the road behaviour of other included road users. This analysis supplies information about causes, sequences of events and driver reactions in case of critical incidents. It is of great value in accident research, but also to investigate what leads to successful avoidance of impending crashes. It also helps to evaluate the role of driving assistance systems in critical incidents.

Safety-critical incidents were defined using a five-category system that has been used by the VTTI for a big naturalistic driving study, also known as the '100 car study' distinguishing between crashes, near-crashes, crash-relevant conflicts, unintentional lane deviation and illegal manoeuvres [13]. Definitions of these categories are provided below:

- Crash: any contact with an object, either moving or fixed, at any speed, in which kinetic energy is measurably transferred or dissipated. Includes other vehicles, roadside barriers and objects on or off of the roadway, pedestrians, cyclists, or animals.
- Near-crash: any circumstance requiring a rapid, evasive manoeuvre by the subject vehicle, or any other vehicle, pedestrian, cyclist, or animal to avoid a crash, or any circumstance that results in extraordinarily close proximity of the subject vehicle to any other vehicle, pedestrian,

cyclist, animal, or fixed object, where, because of apparent unawareness on the part of the driver(s), pedestrians, cyclists or animals, there is no avoidance manoeuvre or response. A rapid, evasive manoeuvre is defined as a steering, braking, accelerating, or any combination of control inputs that approaches the limits of the vehicle capabilities.

- Crash-relevant conflict: any circumstance that requires a crash avoidance response on the part of the subject vehicle, any other vehicle, pedestrian, cyclist, or animal that is less severe than a rapid evasive manoeuvre (as defined above), but greater in severity than a 'normal manoeuvre' to avoid a crash OR any circumstance that results in close proximity of the subject vehicle to any other vehicle, pedestrian, cyclist, animal, or fixed object, where, because of apparent unawareness on the part of the driver(s), pedestrians, cyclists or animals, there is no avoidance manoeuvre or response. A crash avoidance response can include braking, steering, accelerating, or any combination of control inputs. A 'normal manoeuvre' for the subject vehicle is defined as a control input that falls within the 99% confidence limit for control inputs for the initial study data sample. Examples of potential crash-relevant conflicts include hard braking by a driver because of a specific crash threat, or proximity to other vehicles.
- Unintentional lane deviation: any circumstance where the subject vehicle crosses over a solid lane line (e.g. onto the shoulder), where there is not a hazard (guardrail, ditch, vehicle etc.) present.
- Illegal manoeuvre: any circumstance where, either the subject vehicle or the other vehicle, performs an illegal manoeuvre, such as passing another vehicle across the double yellow line or on a shoulder. For many of these cases, neither driver performs an evasive action.

3.3 Event identification using numerical thresholds

Identificaiton of safety-critical events was firstly carried out using numerical thresholds. So, we selected the following parameters as indicators for possible critical incidents:

- Frontal distance.
- Lateral distance (left and right).
- Brake pressure.
- Speed of steering wheel rotation.
- Angle of steering wheel rotation.
- Sudden speed changes.

We identified critical values of these parameters for our instrumented car during explorative test drivers. These values served as thresholds for a filtering process in order to identify the critical events. Results of the filtering process were analysed in-depth by screening the video material [8].

3.4 Results of data filtering

The video analysis of the filtered driving moments showed that the events identified by the thresholds were mostly false alarms. In fact, video sequences associated with these events did not display any serious happenings during them. Instead, the thresholds were exceeded in rather innocuous incidents such as when braking in front of a traffic light. As it happened, normal driving in urban traffic was full of these types of incidents.

In the 100 car study, previously defined trigger variables were continuously tightened in order to reduce the number of false alarms and missed events [1]. However, in our study, many of the safety-critical incidents were not filtered out by thresholds, especially not when they were adapted in order to reduce the number of false alarms. We did not want to blame the limited scale of the study for not finding any incidents and decided to screen the whole video material. The result was a number of 16 safety-critical incidents; six crash-relevant conflicts, one unintentional lane deviation and nine illegal manoeuvres. No crash or near-crash happened; however, such an event would probably have been identified with our thresholds. The data of the six crash-relevant conflicts have not been conspicuous at all.

After identifying the safety-critical incidents by watching the entire video material which is in fact a very time-consuming activity, certain factors have been discovered that complicate incident detection by numerical data analysis:

High number of false alarms:

- values of driving parameters are much more conspicuous in urban traffic as it constantly leads to sharp speed changes or close distances between road users (e.g. at traffic lights); and
- cultural driving differences might influence the analysis as, for example, braking pressure seems to be, in general, high in Spanish traffic because of late braking.

Missing incidents in driving data:

- critical incidents do not always result in conspicuous data (see Fig. 1);
- driving in lower urban speed does not always result in extraordinary values for braking, for example;
- the observed driver is not aware of the conflictive incident and does not perform an evasive manoeuvre; and
- if the other participant of a conflictive incident performs (predominantly) an evasive manoeuvre, there is no conspicuous data produced by the observed driver.

These results should make obvious the importance of video data for the analysis of naturalistic driving trials. Video

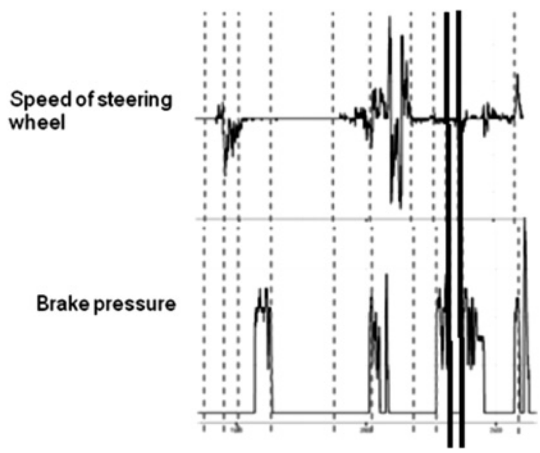

Fig. 1 *Example of a safety-critical incident that shows no conspicuous kinematic values (incident occurred between the two bold lines)*

IET Intell. Transp. Syst., 2013, Vol. 7, Iss. 2, pp. 198–202
doi: 10.1049/iet-its.2012.0148

material helps to identify possible events and excludes unimportant ones [15]. It helps to interpret numerical data, to decide which sequences are of real importance and enables an in-depth analysis of the occurrences during safety-critical events. Cameras should be situated in such a way that an extensive view of traffic environment and of course the driver himself are recorded.

4 Discussion

Naturalistic driving observation is of great importance for research on traffic and road safety. This methodology enables to observe drivers and their driving behaviour in an unobtrusive way in their natural driving environment [12]. Naturalistic driving studies are meant to be long-term observations that continue over months or years.

Data collection over this period of time is obviously challenging and results in vast amount of data. Data can be gathered continuously or restricted to sequences of interest. The latter reduces data in an early stage and can be applied if the research questions are specific and allow this limitation. One example is the interest in the driver's behaviour at certain GPS locations, that is, just when the driver reaches this programmed locations data collection are activated. Other thresholds could be set when one is interested in exceeding speed limits or when certain driving assistance systems are activated. When reaching such a threshold, data collection devices are able to save time frames retrospectively, for example, 10 s before an assistant system was activated. Consequently, data recording are restricted to these sequences and just activated if a parameter (like GPS location) reaches a predefined threshold. Data collection by the use of conspicuous values (thresholds) seem practical as unimportant data can be excluded. However, the use of predefined triggers for reducing the recorded data seem critical as important information obtains lost and cannot be recaptured.

Nevertheless, naturalistic driving is not just a method for investigating very specific parameters. It rather enables to build up a data source by recording and storing all data without any restrictions. These data source later permit to analyse topics of interest in the complete data set without data loss.

The highly instrumented car we used has the capacity to collect and store vast amount of data. In consequence, instead of predefining thresholds for data collection, we decided to perform a continuous data recording and capture all driving and video data of all trials.

Obviously, this method results in a vast amount of data challenging data reduction and analysis. In order to find the critical incidents in traffic that we were interested in, we performed a numerical data analysis. We defined critical thresholds for certain parameters and applied them in a numerical data analysis. Afterwards, we verified the resulting time frames with the video material checking whether they are actually incidents. The result was disappointing as the majority of time frames were false alarms. Modifying the thresholds reduced the number of false alarms. The lack of uncovered incidents through this method sent us to analyse the whole video material. In this way, we revealed incidents that were missing through the previous data reduction method. Analysing them, we uncovered that some did not have any extraordinary numerical values making it impossible to find them through numerical reduction. Furthermore, it was obvious that incidents, during which the driver was not aware of the critical moment, neither showed any conspicuous values as the driver did not perform any correcting manoeuvre. The same issue occurs in cases where other road users perform an evasive manoeuvre to avoid a crash. These kinds of incidents cannot be found by a single analysis of numerical data, but rather requires to analyse the video data.

This paper has shown that identifying critical incidents in naturalistic driving data using only numerical data are a critical method with a couple of issues. So, in our case, this method resulted in many false alarms and missed incidents. During most near-crashes and crashes, drivers would perform a sharp evasive manoeuvre, which can easily be found in the numerical data. However, other safety-critical events like crash-relevant conflicts, driving errors and illegal manoeuvres may not necessarily lead to conspicuous numerical data in most of the cases. Consequently, finding them by only filtering the critical values proved to be a daunting, almost impossible, task.

The previous conclusion, however, admits a number of caveats that are also important to take into account.

First, highway data with its higher speeds may also result in clearer data that may lead to an easier identification of events. In turn naturalistic driving data of urban areas seem a more difficult area to apply the threshold-based selection of events because of its special conditions (i.e. irregularity of traffic, constant braking and accelerating). In this case, the resulting high number of false alarms and missed events challenges the methodology of data reduction and analysis.

Second, in our trial, no crash or near-crash incident occurred. Indeed, it is very possible that incidents of this type are more easily detected using numerical thresholds, as their seriousness make them much more conspicuous to the driver and consequently a bigger reaction can be expected.

Finally, an advanced refinement of thresholds like the one performed in the 100 car study [1] may lead to a better ratio between false alarms and missed incidents. However, in our experience, there will still be safety-critical incidents that will not produce anything conspicuous. Note that, although these incidents cannot be identified by a preliminary selection of the numerical data, they are of high relevance for traffic safety, as they may point to situations where the driver is unaware of the danger and, despite an incident has happened, he does not react at all to it.

In Europe, the number of urban crashes is higher than highway crashes [16], and consequently, the naturalistic driving observation in urban settings is of special importance and requires further development of the ND-methodology.

5 Conclusions

As manual video analysis is very hard to perform in large-scale naturalistic driving studies because continuous data recording of various car drivers over a long period of time produces vast amounts of video data that cannot be analysed manually, and there are important events that may remain undetected using only the sensor data, alternative approaches for the exploration of video data should be examined. For example, an alternative approach could be to carry out image processing of the video data such as in [17]. In this work, reactions from the driver are identified by software in the video, with the consequent gains in objectivity and savings in effort that this implies. This approach, however, is not free of caveats, as the identification of incidents does still depend on the driver reacting to the event in some way. Nevertheless, future developments of this idea might wind up providing practical solutions for the automatic processing of video data that would solve the current problems highlighted in this paper.

6 References

1 Neale, V.L., Klauer, S.G., Knipling, R.R., Dingus, T.A., Holbrook, G. T., Petersen, A.: 'The 100 car naturalistic driving study, phase 1 – experimental design'. Report no.: DOT HS 809 536, Blacksburg, Virginia, 2002

2 Regan, M.A., Williamson, A., Grzebieta, R., Tao, L.: 'Naturalistic driving studies: literature review and planning for the Australian naturalistic driving study' (University of New South Wales, Sidney), available at http://www.acrs.org.au/wp-content/uploads/57_Regan-PR.pdf, downloaded 2/13/2013

3 Uchida, N., Kawakoshi, M., Tagawa, T., Mochida, T.: 'An investigation of factors contributing to major crash types in Japan based on naturalistic driving data', *IATSS Res.*, 2010, **34**, (1), pp. 22–30

4 Klauer, S.G., Sudweeks, J., Hickman, J.S., Neale, V.L.: 'How risky is it? An assessment of the relative risk of engaging in potentially unsafe driving behaviors' (AAA Foundation for Traffic Safety, Washington, DC, 2006)

5 Hanowski, R.J., Perez, M.A., Dingus, T.A.: 'Driver distraction in long-haul truck drivers', *Transp. Res. F, Traffic Psychol. Behav.*, 2005, **8**, (6), pp. 441–458

6 Koppel, S., Charlton, J., Kopinathan, C., Taranto, D.: 'Are child occupants a significant source of driving distraction?', *Accident Anal. Prev.*, 2011, **43**, (3), pp. 1236–1244

7 Stutts, J., Feaganes, J., Reinfurt, D., Rodgman, E., Hamlett, C., Gish, K., *et al.*: 'Driver's exposure to distractions in their natural driving environment', *Accident Anal. Prev.*, 2005, **37**, (6), pp. 1093–1101

8 Dingus, T.A., Neale, V.L., Klauer, S.G., Petersen, A.D., Carroll, R.J.: 'The development of a naturalistic data collection system to perform critical incident analysis: an investigation of safety and fatigue issues in long-haul trucking', *Accident Anal. Prev.*, 2006, **38**, (6), pp. 1127–1136

9 Hanowski, R.J., Hickman, J., Fumero, M.C., Olson, R.L., Dingus, T.A.: 'The sleep of commercial vehicle drivers under the 2003 hours-of-service regulations', *Accident Anal. Prev.*, 2007, **39**, (6), pp. 1140–1145

10 Wiegand, D.M., Hanowski, R.J., McDonald, S.E.: 'Commercial drivers' health: a naturalistic study of body mass index, fatigue, and involvement in safety-critical events', *Traffic Injury Prev.*, 2009, **10**, (6), pp. 573–579

11 Hanowski, R.J., Hickman, J.S., Wierwille, W.W., Keisler, A.: 'A descriptive analysis of light vehicle–heavy vehicle interactions using in situ driving data', *Accident Anal. Prev.*, 2007, 1; **39**, (1), pp. 169–179

12 Backer-Grøndahl, A., Phillips, R., Sagberg, F., Touliou, K., Gatscha, M.: 'Naturalistic driving observation: topics and applications of previous and current naturalistic studies'. PROLOGUE report no.: deliverable D1.1, TØI Institute of Transport Economics, Oslo, Norway, 2009

13 Welsh, R., Reed, S., Talbot, R., Morris, A.: 'Data collection, analysis methods and equipment for naturalistic studies and requirements for the different application areas'. Prologue report no.: D2.1, University of Loughborough. PROLOGUE, Loughborough, UK, 2010

14 Valero-Mora, P.M., Tontsch, A., Welsh, R., *et al.*: 'Is naturalistic driving research possible with highly instrumented cars? Lessons learnt in three research centres', *Accident Anal. Prev.*, DOI: 10.1016/j.aap.2012.12.025

15 Soccolich, S.A., Blanco, M., Hanowski, R.J., *et al.*: 'An analysis of driving and working hour on commercial motor vehicle driver safety using naturalistic data collection', *Accident Anal. Prev.,* DOI: 10.1016/j.aap.2012.06.024

16 CARE: 'Community database on accidents on the roads in Europe'. 2011

17 Dozza, M., Gonzalez, N.P.: 'Recognizing safety critical events from naturalistic driving data', *Procedia – Soc. Behav. Sci.*, 2012, **48**, pp. 505–515

doi: 10.1049/iet-its.2012.0148