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What factors influence drivers' response time for evasive maneuvers in real traffic?

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ABSTRACT

Distraction and inattention contribute to 80% of traffic accidents by delaying or hindering driver responses. However, distraction and inattention are not the only factors increasing response times. In addition, the extent to which different factors-related to the driver, the vehicle, or the environment-influence response times in real traffic is still uncertain. Such knowledge may significantly help the development of countermeasures to distraction and inattention.

Naturalistic driving data promises to help determine the causes of distraction and inattention by understanding driver behavior in real traffic. Further, large naturalistic datasets are now publically available from a few sources such as UMTRI (University of Michigan Transportation Institute) and VTTI (Virginia Tech Transportation Institute). However, analysis of such data is made difficult by the intrinsic nature of the data: it is large and complex and the variables of interest are hard to control.

This study used the public 100-car and 8-truck naturalistic data from VTTI to show how the NatWare toolkit developed at SAFER (Vehicle and Traffic Safety Center at Chalmers) can be used to determine the influence of several factors on response time. Among these factors, attendance to secondary tasks and eyes-off-road, which are indicators of driver's distraction and inattention, significantly delayed response times; the type of incident and response maneuver also affected response times; and finally, truck drivers responded more quickly than car drivers.

1. Introduction

As intelligent communication technologies (ICTs) evolve, the driving task changes. ICTs can make driving more comfortable, environmentally friendly, and safe (Pauwelussen and Feenstra, 2010; Park et al., 2009; Navarro et al., 2011), respectively. Although active safety ICTs may increase safety, other ICTs such as nomadic devices may challenge the driving task by offering new opportunities for distraction. Concerns about the effect of ICTs on distraction were raised long ago and have been both supported and disproved in different studies using driving simulators or small real-traffic studies (Ioannou and Stefanovic, 2005; Stanton and Young, 2005; Lin et al., 2008).

A major safety concern is that ICTs may increase response times, thus delaying drivers' reaction to possible hazards (Alm and Nilsson, 1995). Response times are not easy to quantify and, as Green (2000) points out, the search for "canonical" reaction time applicable to any situation is neither theoretically nor practically grounded. In fact, several factors, such as expectation, urgency, age, gender, and cognitive load, impact response time (Green, 2000). Summala (2000) also warns that response time should take situational and driver-center variance into account. Also, response times from simulator studies are not always consistent with real-traffic data (Green, 2000). Finally, some experimental set-ups favor collection of data representing the drivers' maximum performance when drivers are maximally alerted (Summala, 2000), thus underestimating response times under normal conditions.

In this paper, we focused on response time in near-crash situations collected in real traffic in a naturalistic fashion. We assumed that drivers were not simply adjusting safety margins (Summala et al., 1998) or trying to minimize deceleration and avoid braking (Fuller, 1984), because the criticality of the situation (but not necessarily the urgency) was substantial and similar across events. We tested the hypotheses that factors such as eye-off-road or distraction increase response time in such safety–critical events. Such hypotheses were formulated by Summala (2000); however, they have not been exhaustively tested for real-traffic data yet because of the lack of "any good unobtrusive real-life data" (Summala, 2000). This paper proposes the use of naturalistic data from safety–critical situations to test such hypotheses in real-traffic.

Naturalistic driving studies collect unobtrusive real-life data, and promise to address many safety concerns by assessing driving behavior in real traffic and collecting enough data to enable

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epidemiological analyses. Naturalistic studies and field operational tests have already proven their worth by, for instance, demonstrating the advantages of in-vehicle systems such as collision warning systems (Sayer et al., 2011) and the disadvantages of using mobile devices to text while driving (Olson et al., 2009). Real-traffic data also offers the opportunity to measure driver response time and how it is affected by factors related to the driver, the vehicle, and the environment. This measure may be used to infer the effect of distraction on safety, which is impossible to estimate from other data sources such as accident databases. Further, the effect of distraction and other factors (Consiglio et al., 2003; Siliquini et al., 2011) on response time could be incorporated into a warning system, which uses a threat function to dynamically adjust the threshold for intervention in a specific situation by estimating the time for the driver to respond, based on the current values of known factors.

Naturalistic driving studies and field operational tests, also increasingly popular in Europe, US, Japan, and Australia (e.g. euroFOT, SHRPII, SmartWay, and NSW ISA, respectively), will provide extremely large datasets for a number of new analyses in the near future. Such data will also be useful to better understand driver behavior and improve driver models, especially in safety–critical situations such as crashes and near-crashes. However, the opportunities from naturalistic data come with a cost: naturalistic data analysis is complicated, and challenged by the intrinsic nature of the data. In fact, these datasets are (1) extremely large, (2) complex, since they comprise several types of data, and (3) exposed to a variety of confounding factors. Thus, analysis of naturalistic data requires the employment of new software and methods which enable the analyst to (1) manage large datasets, (2) combine different data types, and (3) filter confounding factors in an efficient, and hopefully user-friendly, fashion.

Following Summala's recommendations that "More emphasis should be given to analyzing (and producing) real-life data on driver reactions as a function of situational and driver-centered variables" (Summala, 2000), this study used the public 100-car and 8-truck naturalistic data from VTTI (820 near-crashes in total; (Dingus et al., 2006) and (Olson et al., 2009), respectively) to investigate the relation between drivers' responses to the precipitating event and a number of factors related to the vehicle, the driver, and the environment in near-crash situations. This paper also takes a pedagogic approach by describing how the free NatWare toolkit could support and significantly simplify such analysis. Finally, this paper discusses the main analysis challenges of the present study in a more general context, by relating this study to the analyses in progress in euroFOT (currently the largest ongoing naturalistic field operational test in Europe; euroFOT-Consortium).

2. Materials and methods

2.1. Datasets

The analysis presented in this paper is based on two studies publically available at VTTI (VTTI-Data-Warehouse). The first, the 100-car study (Dingus et al., 2006) was the first large-scale collection of naturalistic driving data. 100 instrumented cars collected 43,000 h of data in real traffic, including: vehicle dynamics (i.e. speed and yaw rate), driver control inputs (i.e. brake pedal position and steering wheel angle), radar data, and lane marking information. In addition, video data was also collected and annotated for specific events such as crashes and near-crashes (Dingus et al., 2006). A total of 760 near-crashes and 68 crashes were annotated. Video were described with a short narrative, and video annotation included information about the driver (e.g. gaze, distraction, reaction maneuver) and the environment (e.g. incident type, lighting, weather). 38 female and 56 male drivers were responsible for the events; the average age was 35 and the range was 18–68. A complete list of all data collected along with video annotations for the 100-car study can be found on the Virginia Tech data warehouse.

The second study is part of the data from a bigger study aimed at assessing distraction in a fleet of commercial heavy vehicles (Olson et al., 2009). Data was collected from 8 trucks for a total of 735,000 miles and included information similar to that for the 100-car study. 60 near-crashes and 5 crashes were individuated in this dataset and annotated similarly to the 100-car naturalistic driving study. 2 female and 38 male drivers were responsible for the events; the average age was 42 and the range was 21–65. A complete list of all data collected and video annotations for the 8-truck study can be found on the VTTI website (VTTI-Data-Warehouse).

2.2. Analysis tools

Analysis was carried out using the NatWare toolkit (partly presented in Dozza (2010) and available on the net at (SAFER-website) and R). The NatWare toolkit comprises intelligent software and data structures for visualizing and processing naturalistic data. The NatWare software is intelligent because it recognizes different data structures from different naturalistic studies (100-car and 8-truck) and adapts its look and features to the dataset. The data structures are intelligent because they provide enough information for the NatWare software to be able to adapt and present different data types in an organized and synchronized format. For example, NatWare can easily provide the analyst with time series, narrative, direction of gaze, video annotations, and quality information of one event in one glance. Three main NatWare components were used in this analysis: (1) a file system, in which each file contained an event from either the 100-car or the 8-truck study in a common data structure, (2) an event structure capturing the whole dataset in one single structure, and (3) three different graphical user interfaces (GUIs) to analyze specific events and visualize the properties of the overall dataset.

2.3. File system

The file system created from the VTTI data combined all data types (time series, video annotations, descriptive narratives, sensors status, and gaze direction) into a common, harmonized data structure so that each file corresponded to a different event.

2.4. Event structure

An event structure containing information from the file system was created to enable rapid visualization of the whole dataset. The structure, similar to a table in a SQL database, could be queried to visualize the data's statistical properties (e.g. distributions and regressions).

2.5. Graphical user interfaces (GUIs)

The first GUI enabled the user to automatically apply a script which could compute new measures in the whole dataset. The new measures were then visualized on an event-by-event basis using a second GUI. This second GUI was also used to make new time annotations to the individual files: by loading each event into this GUI and plotting the time series, the user was able to annotate the maneuver response point (RP, the point when the driver reacted to the precipitating event either by braking, or steering, or a combination of the two). Finally, the third GUI was used to visually query the event structure obtained after annotating RP in all events, in order to plot distributions, pie diagrams, regressions, and box plots for the overall events dataset.