DRIVERS TAKE-OVER PERFORMANCE FROM PARTIAL AUTOMATION TO MANUAL DRIVING

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ABSTRACT
Difficulties recognizing and analyzing the environment are examples of technical challenges impairing a short-term adoption of full-automated vehicles. Hence, drivers are still supposed to be available for occasional control, but with sufficiently comfortable transition time. This work aims to advance existing knowledge on the influence of non-driving related tasks (NDRT) engagement over driver's ability to regain manual control while conducting a partially automated vehicle under complex situations. For this purpose, experiments with licensed drivers are conducted through a driving simulator hardware running a busy urban scenario within the CARLA autonomous urban simulator, so that driver's takeover performances may be analyzed.

1. INTRODUCTION

Automation is a technology by which a process is performed with reduced or minimum human intervention (GROOVER, 2007), and aims to improve human safety and comfort (SHERIDAN, 1992). Specifically to the automotive context, automation exists as driver support systems (DSS), which make the driving task more efficient, comfortable and safer for drivers (BISHOP, 2000). DSS together with Connected Vehicle (CV) technologies are able to support part of driving tasks such as acceleration or deceleration, as well as keeping the car centered within the road lane without driver interference. Vehicles can even take actions automatically to avoid hazard (YUE *et al*., 2018).

A large number of studies have estimated the effectiveness of DSS technologies, either on field tests or through simulated scenarios (YUE et al., 2018; ENDSLEY, 1999; CICCHINO, 2017; REAGAN; MCCARTT, 2016; GOLD et al., 2016). Yue et al. (2018) summarized most of the Connected Vehicles and Driving Assistance (CV&DA) research involving technologies used in the last ten years in order to provide a general estimation of CV&DA effectiveness. The study analyzed the usage of each CV&DA system alone and integrated, applied to light vehicles and heavy trucks. Results showed that CV&DA technologies could lead to a reduction of 33% and 41% in crashes to light vehicles and heavy trucks, respectively. Furthermore, it was found that CV&DA technologies could lead to a 70% crash avoidance rate while operated in the real-world environment. The paper indicated also that 35% of the near-crash events could be avoided by FCW under fog conditions. The literature suggests that safety is improved significantly with Driver Support Systems (DDS). The more equipped with such technologies a vehicles is, the safer it becomes to its occupants. There are several levels of automation, which a vehicle can operate with. Its classification is usually based on how many and which technologies the vehicle is supported by or the required amount of driver intervention and attentiveness.

The levels of automation are categorized according to the degree to which the system is able to execute the tasks necessary for driving, such as executing of steering, monitoring the environment, determining when to change lanes, turning, using signals, etc. The differences between all levels defined by the Society of Automotive Engineers (SAE) international standards are shown in Table 1 below.

Table 1: SAE International (2014) Automation Levels

SAE level	Name	Narrative Definition	Execution of Steering and Acceleration/ Deceleration	*Monitoring* of Driving Environment	Fallback Performance of *Dynamic Driving Task*	System Capability *(Driving Modes)*
***Human driver* monitors the driving environment**						
0	No Automation	the full-time performance by the *human driver* of all aspects of the *dynamic driving task*, even when enhanced by warning or intervention systems	Human driver	Human driver	Human driver	n/a
1	Driver Assistance	the *driving mode*-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	Human driver and system	Human driver	Human driver	Some driving modes
2	Partial Automation	the *driving mode*-specific execution by one or more driver assistance systems of both steering and acceleration/ deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	**System**	Human driver	Human driver	Some driving modes
***Automated driving system* ("system") monitors the driving environment**						
3	Conditional Automation	the *driving mode*-specific performance by an *automated driving system* of all aspects of the dynamic driving task with the expectation that the *human driver* will respond appropriately to a *request to intervene*	System	**System**	Human driver	Some driving modes
4	High Automation	the *driving mode*-specific performance by an automated driving system of all aspects of the *dynamic driving task*, even if a *human driver* does not respond appropriately to a *request to intervene*	System	System	**System**	Some driving modes
5	Full Automation	the full-time performance by an *automated driving system* of all aspects of the *dynamic driving task* under all roadway and environmental conditions that can be managed by a *human driver*	System	System	System	**All driving modes**

The capacity of monitoring the environment is the bottleneck of a fully automated system. It's not difficult to understand the reason as there are many relevant aspects of the real-world environment that must be taken into consideration so that the system is capable of producing the best solution for each and every situation. Difficulties recognizing and analyzing the environment are examples of technical challenges impairing a short-term adoption of full-automated vehicles. Endsley (1999) even suggests that, by keeping the human involved in some operations, an intermediate LOA may provide better overall performance when compared with highly automated systems lacking any human involvement. Furthermore, there are other issues associated with developing such technology that transcend computational bottlenecks. The human factor is determinant for the future of automation as it depends on how reliable people feel using the technology.

Several studies have reproduced experiment scenarios using driver simulation environments focusing on answering to how drivers manage take-over situations. Eriksson and Stanton (2017) summarized the modality and the takeover-request lead and reaction times found by twenty-five studies conducting take-over time experiments. The mean take over request lead-time calculated for all studies is 6.37s, while the mean take over request reaction time found is 3.04s. According to Petermeijer et al. (2017) switching tasks demands lots of mental effort from a person because he or she needs to use the sensory state, switching his or her gaze from the Non-Driving Related Task (NDRT) to the road, motoric state taking the hands back on steering wheel, and cognitive state, re-configuring response rules or mental task sets. While using NDRT during travel time increases driver workload and decreases take-over quality, a state of cognitive underload may equally affect the driver's take-over performance, as he or she could get tired by monitoring the automated vehicle for an extended period (NAUJOKS et al., 2018).

Most of the studies comprising take-over reaction performance in the last two years were conducted through experiments involving driving simulators (NAUJOKS et al., 2018; ERIKSSON & STANTON, 2017; STANTON *et al*., 2017), and much has been achieved on how drivers manage the so-called take-over situations. However, there is still a long way to go until level of automation 3 or 4 can be safely deployed (KYRIAKIDIS et al., 2017). The majority of the researchers focused on conducting the experiment scenarios in rural areas with high visibility and low traffic density. Consequently, driver's take-over performance still needs to be analyzed while the drivers is subjected to stressful situations, such as under fog or pouring rain, or exposed to complex urban scenarios like crossing a busy roundabout. For example, Shen (2017) suggested evaluating driver interaction with urban scenarios, high traffic density and prolonged NDRT periods engagement before taking over, so that an even slower response to emergencies could be observed.

There are not many simulators capable of reproducing an urban environment for driving simulation purposes, including cross traffic, pedestrians, traffic rules, etc. In order to enable the simulation of these environments, a team of digital artists created the CARLA (Car Learning to Act) Simulator. It has been developed to support training, prototyping, and validation of autonomous driving models, including both perception and control. It provides urban layouts, a multitude of vehicle models, buildings, pedestrians, street signs, etc. The simulation platform supports flexible setup of sensor suites and provides signals that can be used to train driving strategies, such as GPS coordinates, speed, acceleration, and detailed data on collisions and other infractions (DOSOVITSKIY *et al*, 2017).

Figure 1: CARLA Simulator screen (DOSOVITSKIY *et al*, 2017)

The simulator's environment is composed of both 3D models of static objects (buildings, infrastructure, vegetation, etc.) and dynamic objects (vehicles, pedestrians), which share a common scale, proportionally to the sizes of their respective object in reality (figure 1). The non-player vehicles are based on PhysXVehicles, the standard model by Unreal Engine 4. Other behaviors such as lane following, speed limits, decision-making on intersections and respecting traffic lights were also implemented (DOSOVITSKIY *et al*, 2017).

2. OBJECTIVE AND METHODOLOGY

This work aims to advance existing knowledge on the influence of Non Driving Related

Tasks (NDRT) engagement over driver's ability to regain manual control while conducting a partially automated vehicle under complex situations. For this purpose, experiments with experienced drivers are conducted through a driving simulator apparatus together with CARLA simulator in a busy urban scenario, so that driver's takeover performances may be analyzed. The dependent variables considered include hands-on time (HOD), i.e. time between request and hands on steering wheel, take-over time (TOT), minimum time-to-collision (TTC), horizontal gaze dispersion (HGD), brake application and crash probability. Traffic density will be constant throughout the experiment, and only drivers in the early 20's to late 30's will be invited to participate. Each participant will be required to perform five takeover requests, and they will be distributed randomly in two different groups. Half of them will be engaged in NDRT that demands more cognitive workload then the others. Results are expected to show shorter HOT and TOT, longer TTC, increased HGD and lesser brake application and probability of crash to the group engaged in a NDRT less demanding on cognitive workload.

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