Evaluating a custom-made agent-based driving simulator

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Abstract

We present the design and evaluation of a custom-made driving simulator, which was conducted through an experiment with users. Objective and self-reported measures of driving behaviour are used to validate the simulator. Objective data include situation awareness and workload measures, quantified with SAGAT and physiological estimates, while self-reported data focused on driving behaviour perceptions from a standardised driving style questionnaire. To evaluate the simulator, we firstly check that the synthetic environment does not overload the participants and enable them to have a sufficient level of situation awareness. Secondly, a correlation analysis is conducted between observed and self-reported driving style to examine the level of their covariance and similarity. Results showed that participants exhibited a similar driving behaviour as that reported with self-reports. This indicates that the simulator provides realistic driving conditions that encourage participants to behave in a realistic way.

1. Introduction

Driver related factors, according to the literature [Evans, 1991; NHTSA, 2015a] constitute the main cause of accident in three out of five crashes, while they contribute to the occurrence of 95% of all accidents. The National Highway Traffic Safety Administration -NHTSA [NHTSA, 2015a], classified driver-related accident causes into recognition errors, decision errors, performance errors, and non-performance errors [Reason et al., 1990]. The most frequent of these errors (more than 40%) are recognition errors which include driver's inattention, internal and external distractions, and inadequate surveillance. Decision errors, such as driving too fast under certain conditions, too fast for given curves, false assumption of others' actions, illegal manoeuvres and misjudgement of gap between other vehicles or others' speed, account for more than 30% of accidents [NHTSA, 2015b]. Performance related errors such as overloading, poor directional control, etc., account for 11% of the crashes. Sleep is the most common critical reason among non-performance errors that accounts for about 7% of the crashes. These categories however, are highly interrelated. For instance, overloading will affect decision and recognition that could lead to a crash.

Driving style is directly linked to accidents. Many studies analyse driving style, and particularly aggressive driving, since this is highly related to crashes. Evaluating the effect of different driving styles on accidents can be performed in different ways, one of which is through driving simulation. Alternatively surveys such as the Manchester Driving Style questionnaire [Reason et al., 1990] can be used. Simulation can be described as a method of reproducing a situation similar to reality. To test driving style, it is necessary to design an environment with identical stimuli to a real situation. In the field of driving, simulations are used to generate situations that produce the same response to participants as real-life driving, without having the risks of injury. Driving simulators have been developed ranging from small-scale such as the NADS miniSim [FHA, 2013] to large scale models such as the Daimler-Benz [Kading, 1995]. The advantages of using simulators as a research tool include the design of experiments that are easily replicated and the dynamic collection of relevant drivers' variables for safety analysis. Driving simulators are designed for specific purposes and hence require validation in order to produce correct results. However due to the inherent complexity of such systems the prediction of travellers and drivers' behaviour is becoming increasingly harder. For these reasons, agent-based simulation, which adopts an individual-centered approach, is one of the most relevant paradigms to design and implement such applications [Mastio et al., 2018].

Human driver behaviour modelling has been the subject of many studies. The car-following model [Reuschel, 1950] has been used to describe driver behaviour at the micro level and is based on control theory (predictive control, optimal control, etc.). The model expresses how vehicles follow one another on a roadway, the minimum space and time gap between them and the behaviour of the driver with regards to keeping a "safe distance" from the leading vehicle, driving at a desired speed, or choosing acceleration pattern to maintain a comfortable range from the vehicle in front. The aim is to mimic different driving styles, such as: Aggressive driving, that has high accelerations and deceleration patterns with almost no anticipation, eco driving style, where sufficient anticipation is evident to avoid unnecessary acceleration and braking, and normal driving, an intermediate driving style between the above two styles. Alternative driver behaviour modelling methods include neural networks, and fuzzy logic. The latter models human perceptions by fuzzy sets and fuzzy mathematics combined with knowledge-based logic. These methods are often used to mimic processes that have complicated mathematical models. Fuzzy logic has gained attention in modelling tactical driver behaviour [Khaisongkram et al., 2010], however, it requires a large number of experimental data.

The use of driving simulation in driver behaviour analysis is considered essential due to the difficulty in eliminating confounding effects on control measures in field experiments. However, unrealistic simulation conditions may affect the driving behaviour of participants in experiments which could influence the validity of any study. Commercial driving simulators, on the other hand do not provide the required level of customisability necessary for researchers to design experiments. Therefore, most experiments are designed using custom made simulators. The main limitation of driving simulation studies is that by removing the risk of harm to participants, their driving behaviour may be altered. Therefore, the conclusions made could be inaccurate. This paper contributes in resolving this problem by addressing the following research questions: (1) Does self-report driving behaviour of participants differ from the observed objective driving behaviour in the simulator? The assumption here is that drivers should demonstrate similar driving style as their self-report in the driving behaviour questionnaire. (2) Does the simulator enable the drivers to have sufficient situation awareness? The assumption is that a realistic driving simulator should enable drivers to have a minimum situation awareness (SA), which is the capability of understanding what is going on around them and make decisions accordingly. (3) Is aggressive driving associated with situation awareness? (4) Does the simulation environment overload the drivers? This examines if the workload of participants is within the accepted levels. An indication of overloading in a normal driving scenario could indicate a problem with the realism of the simulator. (5) Do imprudent drivers consume more cognitive resources than prudent drivers?

The paper is organised as follows. The next two sections describe the literature relating to driver behaviour, SA, workload and driver simulation. The next section describes the process of designing a custom made driving simulator, followed by a section that addresses its validation process. The paper concludes with the main results of this study.

2. Driving behaviour, Situation Awareness and workload

Driving performance is associated with driving skills that are manifested on driver behaviour which, in turn, affects driving style. Driving skills include information processing and motor skills, which improve with experience. Driving behaviour describes driving habits that define the way a driver chooses to drive [Lajunen et al., 2011]. The Driver Behaviour Questionnaire (DBQ) [Reason et al., 1990] is one of the most widely used instruments for measuring driving style. According to Reason et al. [1990] driving errors and violations are two different groups of behaviour, which is overall categorised into violations, errors, slips and lapses. Violations are deliberate deviations from practices believed necessary to maintain safe operation of a potentially hazardous system, while errors are defined as the failure of planned actions to achieve intended outcomes. The research instrument DBQ developed by Reason et al. [1990] considers this classification. Slips and lapses refer to attention and memory failures such as: attempt to drive away from the traffic lights in wrong gear, forgetting where you park the car etc. Violations are more serious and include close following vehicle ahead (tailgating), speeding, risky overtaking etc. Errors refer to behaviours such as failing to notice pedestrians-crossing, missing Give Way signs etc. A further classification [Lawton et al., 1997] divides violations into aggressive violations, and ordinary violations, which are deliberate deviations without aggressive behaviour.

An important skill that affects driver safety is anticipation of events. Experienced drivers can predict the traffic situation, hence are ready when a hazardous event occurs. This ability is referred to as driver's situation awareness. Gaining situation awareness involves perception and pattern recognition, attention and comprehension, and decision-making [Ensley, 2012]. Hence, drivers identify, process, and comprehend the critical information cues from the environment to predict how future events could unfold. Drivers' decision-making process is not only based on the current environmental state, but also extrapolates the current situation to future projections. Well aware drivers analyse the current state of their environment using multiple information sources, then predict the next states. Situation awareness is an important feature in driver safety. In normal condition an average driver has a minimum level of situation awareness, which is required in order to navigate the vehicle. This driver property can be used as an indicator of the quality and realism of a driving simulator, assuming that an unrealistic simulator will not enable drivers to maintain minimum situation awareness. In this study, self-reports of driver style gives an indication of capability to maintain sufficient situation awareness, along with driver behaviour. Therefore, a driver that reports in DBQ that he/she is making a few errors and lapses is expected to demonstrate sufficient situation awareness in the simulator.

Amongst the various methods for assessing drivers' situation awareness, this study employs the Situation Awareness Global Assessment Technique SAGAT [Endsley, 2004; Endsley & Jones, 2012], which is a dynamic query technique that questions participants' recent memory of the situation by freezing the simulation and hiding all information.

Measuring driver workload is of great significance for improving the understanding of driver behaviours and supporting the development of driver assistance systems. Workload expresses the demands placed on the driver from secondary tasks that could potentially interfere with the primary driving task. Workload is defined as the competition in driver resources (perceptual, cognitive, or physical) between the driving task and a concurrent secondary task, occurring over that task's duration. Driving tasks for instance, require physical and cognitive resources that are dynamically varied under different driving conditions.

There are three main methods to measure cognitive workload: subjective, performance-based, and physiological. Subjective knowledge acquisition techniques such as surveys, interviews, and observations are commonly used to assess cognition workload during tasks [Lehto et al., 1992]. Performance based measures are usually classified as either primary task or secondary task performance. Depending on the type of secondary task performed, objective measures of workload include lane departures, and lateral deviations. Additionally, performance based assessments include task time, reaction time, accuracy, and error rate. Physiological measures encompass audiology, cardiovascular, urodynamic, gastrointestinal, respiratory, neurophysiology, and ophthalmic physiology [Rusnock, 2018]. Using physiology is advantageous, as assessment occurs continuously in real-time. Physiological quantitative data of a subject's state can be linked to complex constructs such as mental workload, fatigue, situation awareness, health, and emotion [Endsley, 1996; Kelly, 2003]. By assessing a user's physiological state, a designer will receive feedback that cannot be expressed verbally or written by the user.

In this study drivers' workload was measured by electroencephalography (EEG) and lateral deviation. The algorithm implemented in the NeuroSky EEG device measures the attentional resources consumed while the participant performed a task. Data from the EEG was monitored on a simulation time-step basis and automatically mapped to road sections. The optimum level of driver performance is achieved with a medium level of workload [Gregoriades et al., 2006], which implies an EEG reading around 50%. Hence, as part of the simulator validation, it is hypothesised that a normal driving scenario should not overload the participants. Overloading users in a simple scenario could indicate unrealistic driving conditions that require participants to devote extra cognitive resources to process unfamiliar task-related situations (unexpected acceleration, steering etc).

3 Driving simulation

By definition, driving simulators are complex systems of software and hardware which simulate real life environments, behaviours and physical systems. Driving simulators are used in a variety of applications, from training new drivers in a safe environment to testing new car technologies. They are often developed as part of traffic modelling and driver behaviour research, prototype intelligent transportation systems validation and training.

There are different categories of driving simulations. Microsimulation is widely considered as a method to study drivers' behaviors, as in the example of parking choice simulators PARKIT and PARKAGENT [Bonsall and Palmer, 2004]. Among micro-simulation programs, multi agent-based modelling simulation environments, such as NetLogo [Sklar, 2007] and Archisim [Doniec et al., 2008], allow researchers to investigate the connection between micro-level behaviors of individuals, and macro-level patterns coming from their interactions. Intelligent agents in multi agent systems perform three functions: they perceive the dynamic conditions from their environment, they perform actions, and reason to interpret perceptions, solve problems, draw inferences, and determine best course of actions.

Traffic models are also classified into microscopic and macroscopic models. The latter analyse traffic flow as a whole, while the former focus on specific actions of the driver and the physical laws of motion. Thus, in the case of macroscopic models, overall shockwaves are analysed but do not consider each car individually. Macroscopic models are not suitable for driving behavior modeling since they do not examine individual vehicle behaviours. Microscopic approaches are more suitable for driving behaviour analysis and are based on the models of: car-following [Brackstone and McDonald, 1999], intelligent agents [Hidas, 2002], fuzzy logic [McDonald et al., 1997], and cell transmission [Daganzo, 1993] for simulation of traffic. Car-following theory is an effective method to study the interaction between vehicles in a microscopic simulator. The method used in this work is based on a microscopic model utilising the agent-based approach, with each vehicle represented by a software agent having autonomy to behave based on some predetermined rules that define basic driving styles.

The aim of this work is to provide a simulation environment that is fully customisable. This is necessary to eliminate the effects of confounding variables from a driver behaviour experiment due to unfamiliarity with the infrastructure. Hence, it was necessary to model the road network in the simulator prior to the analysis.

4 Designing the driving simulator

Much effort has been put in implementing driving simulators in the last years [Biurrun-Quel et al., 2017; Rossetti et al., 2013; Almeida et al., 2013; Gonçalves et al., 2012, 2013; Alves et al., 2013]. These methods and tools allow the representation of complex, realistic traffic situations for evaluating specific traffic situations or testing new technological applications and their influence on the driver. The simulator was implemented using UNITY game engine which appraises rapid application development through a component-based software engineering approach. The driving environment was designed using generic models that make up driving conditions and road infrastructure. The modelling of the road network was achieved by extracting a section of the Nicosia road network from OpenStreetMap to generate a 3D model of the cropped area in UNITY. The selection of the road network was based on identified accident black spots [Gregoriades, 2013] on the road network: roads suffering from high accident rates. The assumption is that drivers consume more cognitive resources at these locations hence they are more susceptible to accidents. The selection of the car models was based on car types and brands currently used in Cyprus, in order to enhance the realism factor of the simulated environment. Traffic conditions were specified though the use of autonomous agent-based vehicles that are able to navigate independently in the network based on pre-set driving behaviours. The vehicle behaviours were based on a preliminary analysis of traffic routing in the modelled traffic network. The accident time statistics of the modelled section of the road network were used to pinpoint the most critical time on the selected black spot and accordingly replicate the traffic conditions in the simulator.

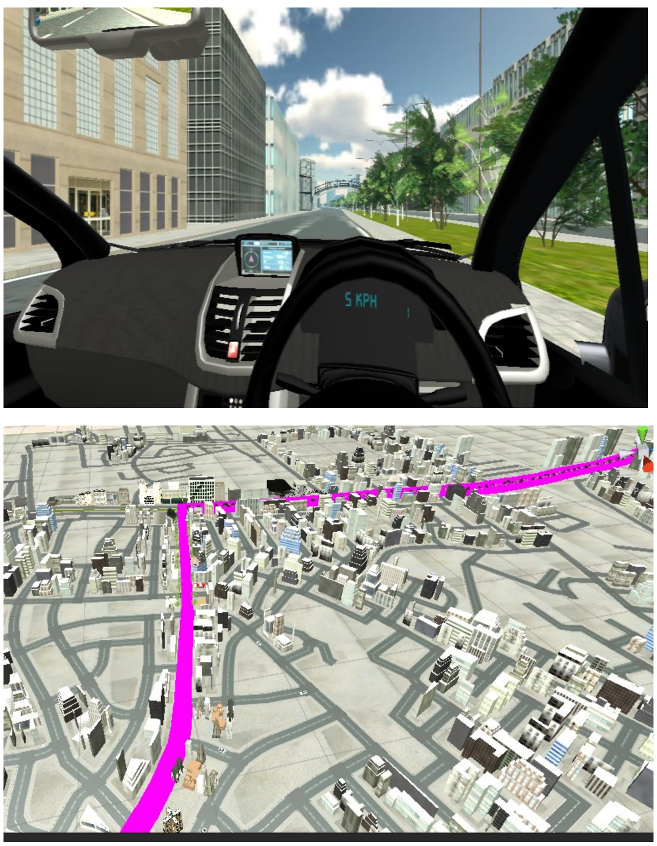

Figure 1: Screenshot of the virtual road design (bottom) and the first-person-view from the driver's seat (top)

Interactivity between the user and the simulator was realised in Unity through C# scripting languages. Finally, the simulator was designed with the capability to record in log files the driving behaviour of users in real-time. Specifically, for each simulation time-step the simulator records drivers' headway, lateral deviations, speed, acceleration and deceleration. Thus, it enables the analysis of the data collected on a section-by section basis. A screenshot of the simulator's user interface from the driver's perspective is depicted in Figure 1 along with the road network under study divided into 63 sections.

The main components of the simulator are: i) the Unity game engine that controls the physical and environmental aspects of the simulation; ii) the host vehicle controller that enables the navigation of the host vehicle using the pedals and steering wheel; iii) the data-logger that records the driving behaviour of participants in experiments, along with additional data relating to the traffic conditions; iv) the Multi screen controller, that is responsible for the synchronization of the 4 screens in the cave automatic virtual environment (CAVE) facility; v) the autonomous multi agent vehicle controller, that controls the vehicle-agents in the simulation. This component is responsible for recreating different traffic conditions depending on the scenarios that need to be modelled. Each autonomous vehicle agent dynamically decides its route, avoids obstacles in its way and alters its speed depending on the traffic. vi) The final component, is the road infrastructure manager component is the facility used for the development of the road network and the surrounding environment.

4.1 Autonomous vehicle agents

In order to mimic a real driving experience, it is essential to model all external environmental factors such as surrounding vehicles dynamics, traffic lights and so on. The behaviour of vehicles around a car is modelled based on the car-following model and using the agent-based paradigm. The goal here is for participants to experience the same feelings as if they were in the real vehicle in naturalistic settings. This is achieved by embedding each agent with a driving behaviour model with the following features: path finding, speed selection, obstacle avoidance, and acceleration and deceleration models. Each vehicle agent interacts with other vehicle agents and with infrastructure and traffic control agents as shown in Figure 3. The exchanged messages enable each agent to achieve its goals which are to avoid colliding with other vehicles or the infrastructure, maintain a normal speed, abide to the traffic regulations (drive on left lane etc.). The route followed by each agent is dynamically defined, however collectively all agents device routes that mimic realistic traffic conditions.

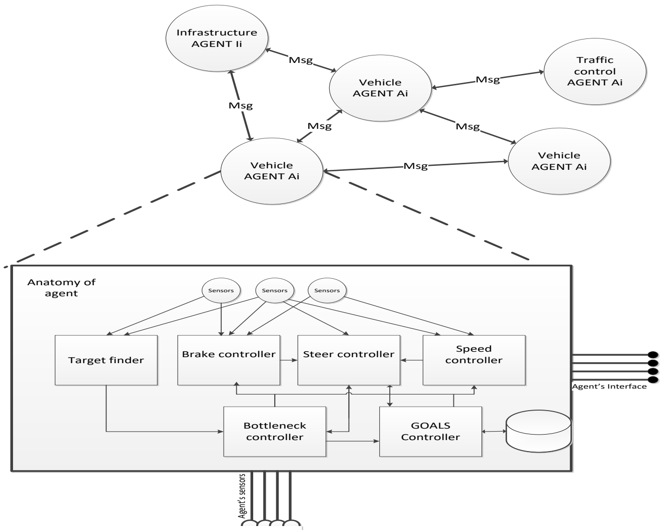

Figure 2: Multi agent system architecture

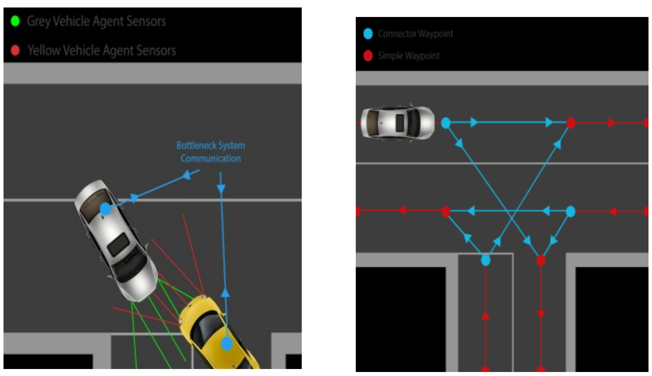

Figure 3: Vehicle Path finding component

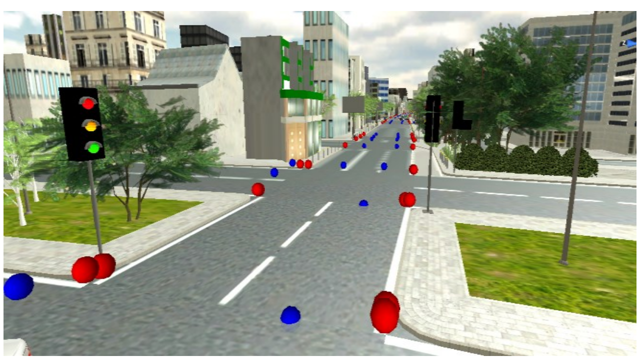
Figure 4: Waypoints on the infrastructure, for vehicle path finding

Path finding refers to the process of finding the path to follow in order to reach a destination or an objective. For instance, an agent might be seeking the shortest path to a destination, or the path with the smaller number of obstacles or traffic. Path finding agents analyse all available paths, and based on their objectives and restrictions, decide which one to follow in a similar way as Navmesh method [He et al., 2016]. Agents choose their path at runtime, hence deciding the path based on what is currently happening around them. For this study vehicle agents had no specific destination. Their role is to move autonomously, in a non-predefined path, in the road network under study, to mimic the traffic condition at the specific network. The driving behaviour model used was the car-following and the traffic volumes for the particular part of the road network was specified based on results from a previous study using the VISTA macroscopic simulation model [Gregoriades et al., 2013].

For the path finding model to be operational, the road network was modelled using waypoints (Figure 3). This enables vehicle agents to know their location on the network, the number of lanes at each point and the flow direction at each lane. Waypoints represent all the possible paths a car can take on the network. Waypoints are connected in a way that each road lane has a predefined direction. Two types of waypoints were used: simple and connector waypoints. Simple waypoints are used by the vehicle agents as targets to follow on a path, which resembles the road lane they are currently on (Figure 4). Connector waypoints are used as simple waypoints, with the added functionality to connect two different road sections. For example, in an intersection, you exit the road section you are currently on to enter a different section on your path. In this case, these two sections are connected with connector waypoints.

Vehicle agents follow waypoints, to create a path to follow. As mentioned before, the path is not specified at the beginning of an agent's life. Instead they start by defining the first two target waypoints and each time a target is reached, the agent changes its target to the next waypoint it had already selected before, while choosing a new "next" target. The selection of a target waypoint is done randomly, based on where the target waypoint is connected to, along the direction of the car. All possible connections from each waypoint are stored in an array, and are dynamically accessed by the vehicle agent at each time-step of the simulation.

To implement this functionality, all waypoints were prespecified on the network model in the form of invisible event-based UNITY objects (Figure 4). Waypoints' objects act as placeholders of infrastructural information that autonomic cars utilise. Vehicle agents access this information when targeting a waypoint, or when they are in the process of selecting a new target waypoint. In order to mimic the driving conditions of the road network under study, the autonomous agents' controller assesses the number of vehicles that are on the road at each time-step of the simulation and accordingly increase or reduce the traffic volume so as to replicate the expected traffic conditions.

Vehicle steering and acceleration is performed after the vehicle has selected its next target. As soon as a car has a new target to reach, it starts calculating the steering angle and acceleration required to effectively reach the target waypoint.

The steering angle is adjusted dynamically depending on the position of the vehicle, its desired destination, and speed. The steering functionality also addresses issues with regards to obstacles or bottlenecks. In case of obstacles, the steering to be applied is calculated based on the direction the car needs to follow in order to avoid the obstacle. Acceleration and speed are calculated based on distance to the preceding vehicle. Lane change behaviour is stochastic.

5. Validating the Simulator

To be confident that the driving simulator correctly mimics reality, two validation studies were conducted: a preliminary validation and a more extensive human factors validation. For the former, a number of professional taxi drivers were asked to drive in a modelled road section in the VR settings using the virtual host vehicle. Experts tested vehicle's steering sensitivity, acceleration and deceleration, and evaluated the realism factor of the virtual environment. Initially, several problems were identified with regards to vehicle steering, acceleration and deceleration behaviours. In addition, the early versions of the driving simulator suffered from low refresh rate that led to motion sickness. In order to overcome these issues, several modifications were performed to the simulation scripts until a satisfactory vehicle behaviour was achieved. The revised version of the simulator was revalidated by 5 taxi drivers who all agreed that its behaviour was realistic.

The main simulator validation study aimed to identify the suitability of the developed synthetic environment for human factors analysis. Therefore, for this purpose an experiment was conducted with participants in a hypothetical driving scenario of a replica road section of Nicosia, with the same infrastructure, traffic control and similar traffic conditions. The simulation was performed in the VR cave with physical steering wheel and petals. The research was conducted in three stages: before, during and after the experiment. Before the experiment, participants completed the Manchester Driving Style questionnaire [Reason et al., 1990] and after the driving experience questionnaire.

Seventeen participants from the local population, with a valid driver's licence and either 20/20 vision or wearing corrective glasses or lenses were involved in all stages of the experiment. Given that driving skill is a significant factor in the visual search strategies of drivers, and subsequently SA [Underwood, 2007], the subjects selected had at least seven years' driving experience and were under 55 years old. Prior to the experiment, participants were screened for colour blindness. They were introduced to the various simulator controls, made adjustments to the seat and were given a five-minutes training session in a road section other than the section used in the experiment. The average age of participants was 37.1 years and the gender distribution was 55% female to 45% male.

The main variables of interest in this study were workload and Situation awareness (SA), hypothesising that a realistic driving environment would enable participants to have adequate level of SA and workload. During the experiment participants were informed to drive in their normal driving style in a pre-specified path in the road network. During the experiment the simulator was collecting data regarding their speed, acceleration, deceleration, EEG, headway, lateral movements and breaking patterns. Upon completion of the experiment participants completed the post-test questionnaire about their driving experience in the simulator. Post-experiment questionnaire addressed the following dimensions: realism of the simulator's general features, user interface, ease of learning, capabilities, usefulness, ease of use, how the simulator supports their situation awareness. Each dimension was assessed on a 1-7 point response scale with 1 being negative ratings and 7 positive (figure 5). Results show percentage of positive scores (scores of 5 and above).

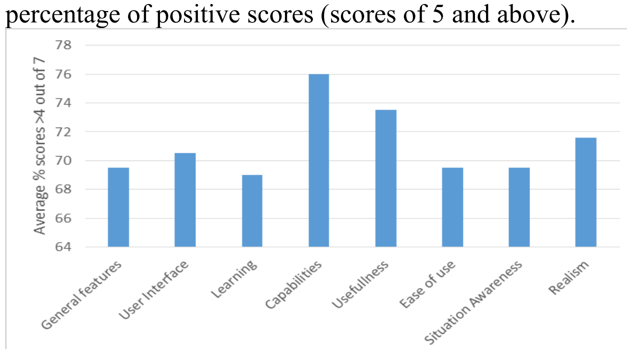

Figure 5. Percentages of positive responses above 4, in each of the measured dimensions

Participants' post-test response shown as percentage of positive responses (above 4) in Figure 5, reveal that overall the simulator was perceived as satisfactory in mimicking a realistic driving situation. Moreover, the level of realism was adequate (71%). However, in one case the participant suffered of a minor incident of motion sickness.

During the objective SA assessment, the simulator was stopped at different points and participants were asked a number of questions relevant to the driving situation to the freezing point. Questionnaire responses from this process were assessed on a 0-100 score and analysed by comparing the actual situation with what the participants reported in their results for the 3 freezing points. Answers from these questions were analysed and an average collated score for all questions designated the level of SA. Results showed that all participants maintained an adequate level of SA with an average score of (69.6%) in 3 freezing points. This was slightly less than the subjective rating of participants as shown in Figure 5 which was about 72%. However both indicate a satisfactory level of SA. An additional evaluation of SA was conducted using objective data from lateral deviations as recorded by the simulator for all 63 road sections. These were analysed to identify points of reduced SA due to sharp lateral movements. This is phenotype behaviour related to both overloading and low SA. From the diagram in Figure 6 it is evident that the deviations are relatively smooth which indicates an acceptable level of SA. This, in turn, shows that participants were actively engaged with the driving task. Moreover, smooth deviations also indicate a relatively easy task undertaken by participants. The three points with high deviations (sections 23, 47 & 58) represent the points with the pre-set obstacles.

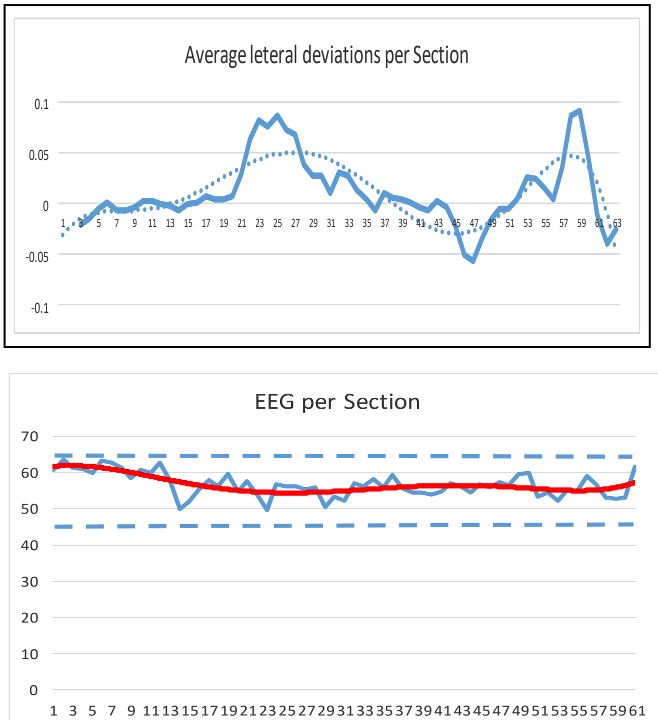

Figure 6: Workload (bottom) and Lateral deviations (top) of all participants per road section

Driver Style Analysis

To answer the first research question it was necessary to investigate the extent of the association between participants' self-reported and observed driving style. The assumption is that, if self-reported and observed driving behaviours are similar then the simulator provides the means for participants to behave in a realistic manner and hence is considered as valid.

For the self-report stage, participants were asked prior to the experiment, to fill in the Manchester Driving Style questionnaire [Reason et al., 1990]. This aimed to elicit the driving style of participants, along with demographic information. Their observed driving style data were collected by the simulator for each time-step of the simulator and assigned to relevant road sections.

Collected data underwent pre-processing and subsequently analysed in SPSS to investigate the magnitude and significance of the link between observed (simulator) and self-report (questionnaires) behaviours. Results in Table 1 indicate that aggression variable is correlated positively (and significantly) with the variables "serious violation", "errors", "lapses" and "aggressive acceleration". Observed aggressive acceleration was positively correlated with "errors", "lapses" and negatively correlated with "SA". This means that aggressive driving reduces drivers' SA while it increases errors and lapses. Essentially, our initial assumptions regarding self-report driver behaviour and observed driver behaviour were met. Specifically, self-reported aggressive behaviour was found to be positively related to increased speed and acceleration patterns in the simulator, hence indicating that the simulation environment provides a realistic setting that enables participants to drive in the same manner as they do in their everyday life. This, as a result, is a promising indicator towards the validity of the designed simulator

	Serious (SR)	Errors (SR)	Lapses (SR)	Acceleration (O)	Aggressive acceleration (O)	Tailgate (SR)	Situation awareness (O)
Speed (O)	-0.267	-.288*	-.296*	0.396**	-.325*	-0.268	0.212
Aggression (SR)	0.512**	0.401**	.518**	-0.204	.277*	-0.189	-0.151
serious(SR)		.622**	.507**	-0.245	0.275	.333*	-.302*
errors(SR)			.857**	-0.241	.389**	0.125	-0.155
lapses(SR)				-0.133	.402**	-0.012	-0.197
Aggressive acceleration (O)						0.068	-.416**

Table 1. Pearson correlations (and significance level) among observed (O) and self-reported (SR) behaviours (N=50 or 51, *p<0.05, **p<0.01)

Workload analysis

To answer the fourth research question in relation to drivers' workload, both EEG readings and lateral deviations per road section (Figure 6 &7) were utilised. The former is a physiological objective measure and the latter a phenotype objective measure. Given that the participants were driving in a normal driving scenario with easy traffic conditions, the assumption here was that there would be no overloading of participants. If that occurred then it could indicate a problem with the simulator's level of realism. The hypothesis is that drivers under optimum driving condition (no hazards and low traffic flow) should not experience overloading. If this occurs then it could designate that the simulator requires the drivers to utilise extra cognitive resources to figure out how to drive optimally in the synthetic environment. It is evident from these results that on average all participants experience an optimum level of workload. This was between 45 to 65 in terms of EEG readings (Figure 6). Similar results are depicted in the 3D analysis of the frequency distribution of EEG ratings (Figure 7) per road section. This shows that the majority of participants experience optimum level of workload in all road sections. The EEG ratings are slightly high at the first road sections but still within the acceptable range of optimality. The second measure of workload utilised here is lateral deviations. Results of Figure 6 show that there was no significant deviations by participants and hence indicating that the level of workload was optimal throughout the experiment.

	Aggressive (SR)	Serious (SR)	Errors (SR)	Lapses (SR)	Tailgating (SR)
EEG	.225	.477**	.181	.320*	.148

Table 2. Pearson correlations (and significance level) among observed EEG (O) and self-reported (SR) behaviours (N=50 or 51, *p<0.05, **p<0.01)

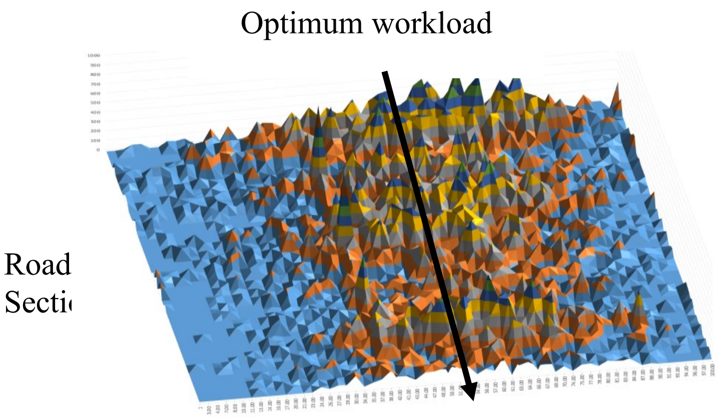

Figure 7: 3D EEG frequency distribution per road sections (vertical axis) and EEG level (horizontal axis), showing the concentration of frequency peaks around the optimal level of workload

To answer the fifth research question, an analysis was conducted to examine the link between drivers' style and workload. Correlation results showed that drivers who are characterised as inattentive (i.e. commit high level of lapses) in their self-report driving style experiences high readings of EEG (Table 2). This confirms the assumption that careless and inattentive drivers (imprudent) consume more cognitive resources to engage with the driving scenarios.

6. Conclusions

The paper describes the design and validation of a custom made driving simulator for driver behaviour analysis. The developed driving simulator is agent-based with the infrastructure being developed using a component based approach. This allows the analyst to easily customize the road infrastructure for what-if scenario analyses and the design of experimental settings for a variety of scenarios.

Results from the analysis of the data collected during the experiment, revealed that the simulator satisfies the minimum requirements for vehicle control since participants maintain satisfactory level of SA and workload. Additionally, results indicate that what the users experienced during their interaction with the simulator and what they actually denoted as their opinion in the post-test questionnaire point to the same conclusion. Finally, self-reported driver style of participants was correlated with observed behaviour during the use of the simulator, pointing to the conclusion that the artificial settings did not alter their driving style, hence it is realistic and considered as valid.

Limitations of this work concentrate on the simulator's level of immersion factors and the issue of motion sickness known in VR settings. Simulated settings do not currently offer the resolution of the real world, and so these may affect driving behaviour and human factors analyses.

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