Modelling Workload of a Virtual Driver

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Abstract

In many transportation modes, automation is added to increase comfort, efficiency, or to reduce human errors. Automation has a direct impact on the drivers workload, which can even be higher then without automation. In this paper we propose the development of a virtual driver that can predict human workload in early design phases of automation and assistant systems. We describe the auditory workload model in a closed-loop simulation and an early validation.

Keywords: workload; cognitive modelling; driver model; n-back task

Introduction

In many transportation modes, like in cars, aeroplanes, or on ships, more and more automation is added, with the objective to increase comfort of the passengers, to make transportation more efficient and cheaper, or to reduce human errors. Introducing automation should reduce human workload and consequently human errors, but Metzger and Parasuraman (2005) and others have shown that additional automation can even increase mental workload. They conclude that operators "*should be given an active role in the system to ensure that they can detect and respond to malfunctions in a timely manner*" (Metzger & Parasuraman, 2005, p. 13). This paradigm becomes especially interesting, with the current trend in automotive industry on autonomous driving, where drivers are more and more forced into a monitoring role. In order to allow an evaluation of the workload induced by automation systems on drivers in early design phases, we propose the use of virtual drivers, which predict human behaviour in traffic simulations. Using a virtual driver has many advantages for the automotive industry. First, one can not only use them for evaluations in early design phases, where studies with users are expensive or not even possible, but it also allows to evaluate a lot of different driving scenarios that cannot be covered with driver studies, because it is either to expensive, too time consuming, or to risky.

Our virtual driver[1] is implemented in the cognitive architecture CASCaS (*C*ognitive *A*rchitecture for *S*afety *C*ritical T*a*sk *S*imulation). In the following, we will refer to our virtual driver as "CASCaS driver". In order to allow also prediction of workload, we will extend our cognitive architecture CASCaS with different workload measures. Development of the workload model in CASCaS will be done in iterations, in order to handle the complexity of the workload topic. In a first step, Wortelen, Unni, Rieger, and Lüdtke (2016), described different measures that could be implemented for prediction of workload of different modules in CASCaS, and implemented and validated a first version of a measurement in an open-loop simulation. In this paper, we will describe the second step, the implementation of a closed-loop simulation.

[1] Or virtual tester in general, as CASCaS is domain independent

State of the Art

Cognitive Architectures are tools, which provide executable models of human behaviour based on psychological and physiological models of human behaviour. In this paper we will describe the cognitive architecture CASCaS, which has been developed since 2004 (Lüdtke, 2004) in our institute. Main driver for the development of CASCaS was a more application-oriented approach. In contrast to that, many cognitive architectures like ACT-R (Adaptive Control of Thought Rational, (Anderson et al., 2004; Anderson, 2000)), or SOAR (Lehman, Laird, Rosenbloom, et al., 1996) were developed for creation and evaluation of theories and models of human cognition. Beside that, more and more cognitive architectures are now used to predict also pilot or driver behaviour, for example Salvucci (2006) describes a driver model in ACT-R, and Fuller (2010) describes a driver model in QN-MPH. Beside driver modelling, cognitive architectures are also used in aviation, as described in the Human Performance modelling (HPM) element within the System-Wide Accident Prevention Project of the NASA Aviation Safety Program, where they performed a comparison of error prediction capabilities of five cognitive architectures (Foyle & Hooey, 2007), including ACT-R and (Air-)MIDAS (Corker & Smith, 1993; Gore, 2011). CASCaS has been applied in several projects, in order to model perception (Lüdtke & Osterloh, 2009), attention allocation (Wortelen, Lüdtke, & Baumann, 2013), decision making of drivers (Weber, Steenken, & Lüdtke, 2013) and human errors of aircraft pilots (Lüdtke, Osterloh, Mioch, Rister, & Looije, 2009) and car drivers (Lüdtke, Weber, Osterloh, & Wortelen, 2009).

There are several model-based approaches to assess the level of cognitive workload in a specific situation. The workload model of McCracken and Aldrich (1984) offers a scale, which assigns workload levels to specific kinds of human actions like "recall, memorize", or "visually inspect". It distinguishes four types of workload: visual, auditory, cognitive and psycho-motor. For example, this model was used to annotate behaviour primitives in cognitive models created with the cognitive architectures MIDAS (Gore, 2011) with associated workload levels. However, the model of McCracken and Aldrich is used in an analytical way and does not assess workload of a human operator online.

In the current work, we outline a model-based approach for the online assessment of workload. For real human operators, online assessment of workload is ongoing research, and typically performed based on *physiological* measures. Physiological measures are quite popular as they can continuously record the operators response without actually intruding into the operators task. The most commonly used physiological measures for workload assessment are electrocardiogram (ECG) and electro-dermal activity (EDA). Previous researches have consistently demonstrated that increased workload levels lead to increased heart rate (HR) and decreased heart rate variability (HRV) (Kramer, 1991). Solovey, Zec, Perez, Reimer, and Mehler (2014) recorded ECG and EDA while driving and were able to discriminate three driving situations with increasing control demand. Brain activation measurements may provide the necessary specificity and state quantification required for online prediction of workload.

Modelling

In the following sections, we will describe our modelling approach, starting with a short introduction to CASCaS and the driver modelling, followed by the workload model implemented in CASCaS.

CASCaS

The cognitive architecture CASCaS (*C*ognitive *A*rchitecture for *S*afety *C*ritical T*a*sk *S*imulation) has been developed since 2004 (Lüdtke, 2004), and has since then been continuously improved and used in several research projects (Lüdtke, Osterloh, et al., 2009; Lüdtke, Weber, et al., 2009; Lüdtke & Osterloh, 2009; Weber et al., 2013; Wortelen et al., 2013). Main focus during the development of CASCaS has been the usage in real-time simulators, mainly car and aircraft simulators, to cover complex scenarios as needed for the industrial application as virtual tester. As many cognitive architectures, CASCaS has several components as depicted in Figure 1, which cover different aspects of human behaviour. Main component of CASCaS is the "Knowledge Processing" component, which is based on Anderson's theory of behaviour levels (Anderson, 2000):

- cognitive layer[2]: decision making in unfamiliar situations
- associative layer: rule-based behaviour and decision making
- autonomous layer: processing without thinking in daily operations, i.e. sensory-motor programs like steering, braking

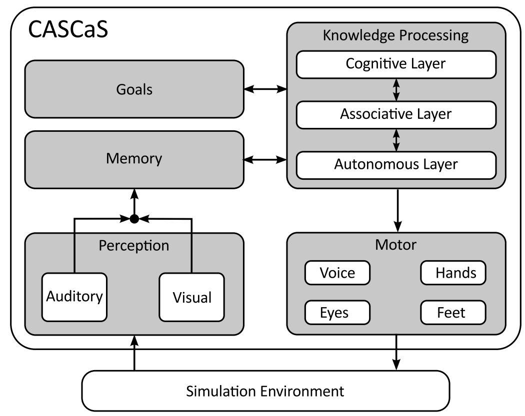

Figure 1: Layered Architecture of CASCaS; (Weber et al., 2013)

For the driver model, only the associative layer and the autonomous layer are used. CASCaS main input is the formal procedure for the associative layer, which describes the interaction with the environment in form of IF-THEN rules. CASCaS procedures are specified in a simple, human-readable, CASCaS-specific text format, allowing also non-computer experts to read, understand, and use the language for modelling without the need to have deep understanding of a programming language. The procedures that are executed by CASCaS are stored in the Memory component, which also contains the declarative memory.

In addition to the Knowledge Processing, additional components for perceptual and motoric processes are part of the architecture, as an interface to the Simulated Environment. The visual component for example, models perception in the focus and in the visual field (Lüdtke & Osterloh, 2009). At each moment, system state and processing of the procedure create the mental model and are expressed as an ordered set of goals and sub-goals that have to be accomplished – the so called goal agenda. Processing of the goal agenda follows these steps:

1. A goal is selected from the goal agenda
2. All rules containing the goal in their Goal-Part are collected, their conditions evaluated by retrieving the needed information from the memory, and organized into a conflict set.

[2] except programming interfaces no model of the cognitive layer is implemented in CASCaS

3. One rule is randomly selected from the conflict set and fired, which means that the motor, percept, and/or memory actions are sent to the motor, percept and memory component respectively, and the sub-goals are added to the goal agenda.

This process is iterated until no more rules are applicable, and all goals are achieved.

Driver Model

The driver model is a combination of a procedure for the associative layer, and some sensory-motor programs on the autonomous layer. The procedure handles decisions that have to be made by the driver, e.g. application of traffic rules, overtaking of other cars, and general interaction with the car and environment. General interaction with the car means operation of possible assistant systems and car interfaces like radio, and GPS by the associative layer. A more detailed description on the driver model that has been used is described in Weber et al. (2013). In our scenario (driving on a German highway), these rules take care of speed limits, and decide if other cars have to be overtaken or to follow them. For this, the traffic is classified onto lanes and positions relative to the ego car, i.e. ahead, behind, left ahead, etc. In addition to that, the distance and speed of the other cars is estimated by the model based on perceived angular sizes.

The motor programs on the autonomous layer cover the actual lateral and longitudinal control, i.e. control of the steering wheel for turns and lane keeping, or control of the pedals for braking and acceleration. For the lateral control, we implemented a simple one point steering control (PD-controller). The longitudinal control has been implemented on the basis of probabilistic models, as described by (Eilers & Möbus, 2014). In general, the probabilistic models are a set of Bayesian Networks, which at each point in time give the probability for a certain output, in our case the braking pedal value and the acceleration pedal value. The probabilities used in the Bayesian Networks are learned from human driver behaviour that has been previously recorded in a highway scenario. Note that the decision to brake, overtake or which speed to drive is made on the associative layer, but the autonomous layer performs the actual motor actions.

Workload in Closed-Loop Simulation

As a first step of the development towards a workload model, Wortelen et al. (2016) implemented a *Working Memory Load* as a mean for workload, which is defined as rate of information elements written to memory, in an open-loop simulation in CASCaS. They tested the working memory load, by using a n-back speed regulation task. N-back tasks have been widely used as a benchmark in the field of neuroscience to influence memory load and task difficulty (Miller, Price, Okun, Montijo, & Bowers, 2009). The n-back speed regulation task requires the driver to follow the speed of the *n*-th speed sign prior to the actual speed sign, as depicted in Figure 2.

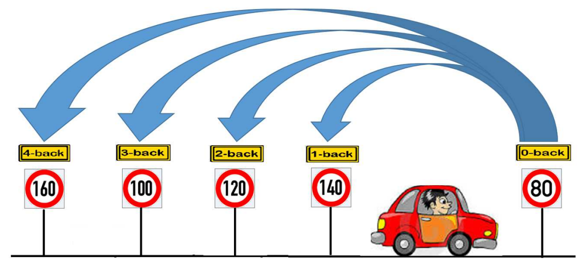

Figure 2: N-back Speed Regulation Task; from (Wortelen et al., 2016)

This approach had two main drawbacks. First, an open-loop simulation has been used, and second the driver model used by Wortelen et al. (2016) was not so sophisticated as the driver model from (Weber et al., 2013). Open-loop simulation in this case meant, that CASCaS was feed with the data from the human drivers, and the steering and acceleration actions of CASCaS are not feed back in a driving simulation. The driver model of Wortelen had therefore only placeholders for the lateral and longitudinal control to mimic multi-tasking. As the objective of CASCaS is to be used as a virtual driver for testing automation and user interfaces in the car, a closed-loop simulation is necessary, i.e. the feedback loop between driver model and driving simulator is closed in a way that the driver model has full control of the simulated car. The closed-loop allows then predictions of the behaviour, without the need of data from real human drivers (with the exception of the data needed for the training of the probabilistic models used for longitudinal control).

The objective of this paper is to describe the integration of Wortelen's workload model in a closed-loop simulation. To achieve a closed-loop simulation, an extended n-back task model from Wortelen et al. (2016) has been integrated with the driver model of Weber et al. (2013).

In a first step, the n-back task procedure for CASCaS has been revised. According to Juvina and Taatgen (2007) humans use two different cognitive control strategies for the n-back task:

1. Phonological rehearsal, i.e. internally rehearsing the list of speeds
2. Time tagging the event

For our model, we have decided to use the phonological rehearsal as strategy for the n-back speed task, as this strategy was, compared to the time tagging strategy, the easiest to implement, due to the lack of a temporal component in CASCaS.

Each time a new speed sign is perceived, the procedure alters a mental list of the speeds. The mental model maintains dedicated associations to the memory chunks at the beginning of the list and it's end, see "list_begin" and "list_end" in Figure 3. When the number of elements is smaller than the current n-back task, the new element is stored into the memory, the "next" association is added from the current "list_begin" to the new element, and then the "list_begin" and "current_rehearsal” associations are moved to the new element. When the number of elements has reached n, the “list_end” association is moved to the “next” chunk to mark the new list end. During the rehearsal, the “current_rehearsal” association is moved over each “next” association from “list_begin” to “list_end”. For each element in the list, an internal speech-

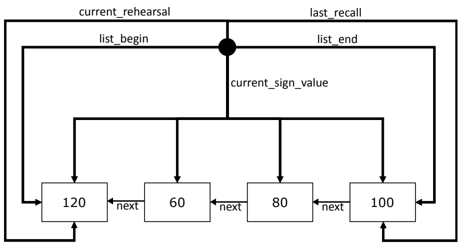

Figure 3: Memory Structure for Rehearsal

action is executed to trigger the phonological loop. Each of this internal speech actions trigger a workload event, which are then accumulated over time as the auditory workload. In our case, we have chosen a seven second interval for the accumulation, because this reflects the response time that is measured with the fNIRS. This is a small difference to Wortelen et al. (2016), as their workload measure captured more than the memory writes from the auditory component, but rather all memory writes from the associative layer.

Then, as a second step, this procedure has been integrated with the driver model. First, the rehearsal has been added at the appropriate places, i.e. the rehearsal is restricted to phases where the driver is driving ahead, and not overtaking. Second, the sign recognition has been replaced with the one described above, such that the list is maintained, and the “list_end” value is set as the current target speed in the longitudinal control at the autonomous layer. Figure 4 shows a screenshot of CASCaS during the simulation. On the left the visualisation of SILAB, the driving simulator, is depicted, and on the right the workload visualisation of CASCaS. The auditory workload is shown in the diagram in the middle.

Validation

For the validation of the workload measure, we have chosen a two step approach. First, we had an internal model validation as a kind of pre-test. With this step, we make sure, that a) the simulator setup and the scenario is working, b) the data recording is suitable for the planned analysis, and c) the CASCaS driver produces behaviour that is plausible (see below for hypotheses). Second, we will perform another experiment in our driving simulator with human drivers. In this experiment, we will record the driver behaviour as well as physiological data (fNIRS) to measure the workload of the humans.

Internal Model Validation

Objective of the model validation is twofold. First this can be seen as a pre-test for the experiment with the humans, where the scenario, the data recording setup, and the data analysis can be tested before the expensive experiment. Second it can be used for model exploration, i.e. checking the plausibility of the CASCaS driver behaviour and improvement of the model subsequently. The plausibility of the model is expressed in multiple hypotheses to be tested before starting the human experiment:

1. The auditory workload can predict the n-back task level.
2. The CASCaS driver will adhere to the correct speed limit according to the n-back level.

As a scenario for the internal model validation, we used the same scenario as described below for the human experiment, but without the traffic.

For hypothesis 1, we calculated Pearson’s correlation *r* between the n-back level and the predicted auditory workload for each of the simulation runs. The mean *r* is calculated with 0.9773, which supports hypothesis 1. In order to analyse hypothesis 2, we analysed how well CASCaS followed the target speed according to the n-back level. For that, in a first step we had to remove the phases where the speed was undefined, because the number of speed signs was lower then the current n-back level. Pearson’s mean correlation *r* between the current speed and the nth target speed of the 15 runs is 0.8445. A more detailed analysis of the speed driven by CASCaS revealed, that in average over all runs, CASCaS

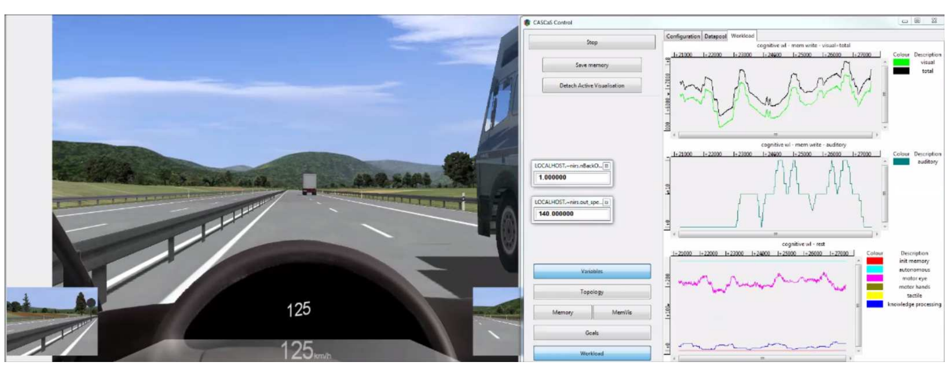

Figure 4: CASCaS workload visualisation while driving; for complete video visit https://hcd.offis.de/wordpress/wp-content/uploads/Workload-02.mp4

made 19 errors of speed out of 169 different speed signs in one run. Error of speed here means, that between two speed limit signs, the actual speed was not in a range of ±10 km/h of the target speed.

Our analysis showed, that when CASCaS had to reduce the speed from a high speed limit (e.g. 140 or 160) to a lower speed limit, the applied braking was not sufficient, such that the new speed limit is not reached before a new sign arrives. An example is shown in Figure 5.

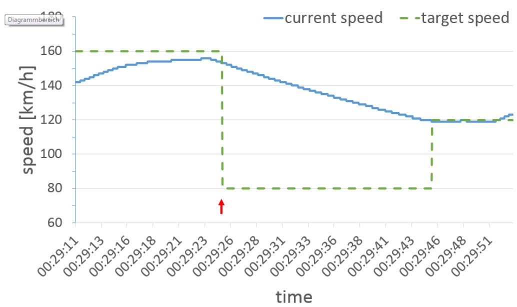

Figure 5: Speed of CASCaS vs. Target Speed

After the target speed of 160 km/h, it goes down to 80 km/h at time 00:29:25. As marked by the red arrow, CASCaS does not decelerate below 90 km/h. The explanation for this is the probabilistic model that is used for the longitudinal control. The probabilistic model has been learned from humans driving in a driving simulator on a normal German highway. In this scenario, subjects never exceeded 130 km/h on the one hand, thus the model has never learned to handle fast driving. In addition to that it can be observed, that the subjects preferred to use the motor break to decelerate, as many people do during normal driving. While this gives a very human-like speed control during normal cruising, the learned probabilistic model does not sufficiently represent driver behaviour for the n-back speed experiment, where active braking and more accurate speed control is required. In future versions of the model, the probabilistic model could be replaced with a mathematical PD controller, to overcome this problem, or re-trained with new experimental data. Beside that, the general driving behaviour, including the overtaking and the rehearsal seems natural, i.e. it shows actual human behaviour.

Comparison with Human Data

For further evaluation, we conducted an experiment with 10 subjects (7 male, 3 female). All subjects where students in an age range between 22 to 42 (mean 27.3 years) with a valid German driving license. Most drivers had more then 10.000 km of total driving experience, 4 had between 5.000 km and 10.000 km, and only one had below 5000 km. During the experiment, subjects where given five different n-back levels, from 0-back to 4-back, and thus five different levels of workload, with 0-back inducing the lowest workload level, and 4-back the highest. Each n-back task lasted around three minutes and consisted of ten different speed changes randomly distributed from 70-140 km/h in steps of 10 km/h. Speed changes where randomly assigned, but we made sure, that speed changes where not larger then 20 km/h at once. We had four repetitions for each n-back task, randomly distributed to avoid sequencing effects. Random distribution of n-back task and speed sequence has been done once for the scenario, and then the same order was re-used for all participants. The scenario had two different traffic situations, half of the scenario had low traffic, the other half had higher traffic. Traffic was always ahead and slow, such that the subjects had to overtake, but no faster traffic was induced from behind. The whole driving experiment lasted for about 60 minutes.

The subjects brain activity was constantly monitored by using a 32 channel neuroNIRX-system (fNIRS). The objective is to use the recorded brain activity data as a source for objective workload measurement, and to correlate it to the CASCaS predictions (similar to (Unni et al., 2015)). The analysis of the brain activity data is still ongoing, nevertheless we analysed the speed driven by the subjects, in order to compare it to CASCaS data on hypothesis 2.

The subjects had a mean r of for their speed of 0.87, and in total over all subjects 17 driving errors where made (mean 1.42 errors per subject). In total, 169 different speed changes had occurred, without initial build-up phase of each n-back task, thus subjects had a error rate of roughly 1%. It could be observed for the subjects, that with the higher n-back levels, also the number of errors increased (1 and 2-back: 2 errors, 3-back 6 errors, 4-back 7 errors). In comparison to that, the model had a mean r for speed adherence of 0.75, and a total of 166 errors (mean 12.7 errors per model run), resulting in an error rate of 7.5%, independent of the n-back task. The decrease in correlation of speed for the model from pre-test to final test can be explained by the added traffic in combination with the probabilistic model for speed control. It can be observed, that the model speeds up for the overtaking (about 10-20 km/h), ignoring also possible speed limits. Especially in high traffic scenarios, overtaking can then take longer then the distance between two speed signs.

Conclusion & Next Steps

Starting from previous work of Wortelen et al. (2016) and Weber et al. (2013), we have integrated a workload model into a closed-loop driving simulation. With that, we extended the workload model to use the phonological loop in CASCaS, so that the auditory workload can predict the n-back level, and thus the workload. For the speed management, a replacement or re-training of the probabilistic model should further improve the model by reducing speed errors.

In addition to that, there are a lot of different workload measures we can implement for the different components in CASCaS, as already introduced by Wortelen et al. (2016). We plan to successively implement more of these measures and validate them against the simulator data, to see if other models can also be used as predictor for the n-back level, which serves as controllable workload indicator.

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