A Cognitive Model for Understanding the Takeover in Highly Automated Driving Depending on the Objective Complexity of Non-Driving Related Tasks and the Traffic Environment.

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Abstract

The aim of this study is to refine a cognitive model for the takeover in highly automated driving. The focus lies on the impact of objective complexity on the takeover and resulting outcomes. Complexity consists of various aspects. In this study, objective complexities are divided into the complexity of the non-driving-related task (no-task, listening, playing, reading, searching) and the traffic complexity (relevant vehicles in the driving environment). The impact of a non-driving related tasks' complexity on the takeover is evaluated in empirical data. Following, the cognitive model is run through situations of different traffic complexities and compared to empirical results. The model can account for empirical data in most of the objective complexities. Additionally, model predictions are tested on significant variations in different complexities until the action decision is made. In more complex traffic conditions, the model predicts longer times on different processing steps. Altogether, the model can be used to explain cognitive mechanisms in differently complex traffic situations.

Keywords: highly automated driving; HAD; cognitive modeling; ACT-R; takeover; conditional automation; NDRT; non-driving related tasks; real vehicle study; Objective complexity; traffic complexity; Complexity of NDRT; cognitive model predictions;

Introduction

In the field of Highly Automated Driving, the development of technological innovations is growing rapidly. It is not only necessary to develop working technology, but to understand human cognition, enhance the human-machine interaction (HMI) and improve safety and comfort (Sun et al., 2017). Approaching the next SAE Level of automation (Level 3, conditional automation), where the driver still has to take over the driving task if requested (SAE, 2014), the state of the driver plays an important role. Here, the state is determined as the awareness of the surrounding traffic and necessary action decisions. It depends highly on the situation and its complexity in which the driver has to take over. Different approaches of defining situation complexity exist (Baumann and Krems, 2007; Haerem and Rau, 2007; Schlindwein and Ison, 2004). A key factor concerning the driver is the expectation about the future development of a situation, that is activated when a type of situation occurs (Baumann & Krems, 2007). These types of situations can be distinguished in various ways. They could for example be a traffic situation (congestion, construction zone, intense or low traffic etc.), a type of traffic environment (city, highway etc.), a weather condition or further differentiations.

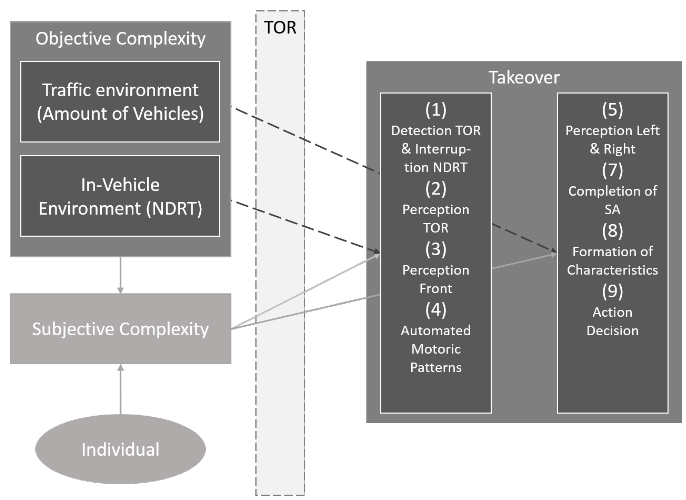

Figure 1: Outline of the Assumed Dependencies, leading to the Approached Hypotheses concerning the Impacts of Objective- and Subjective Complexity on the Takeover Performance. Dark Grey Variables and Interactions are Focus in this Study (Source: own figure).

Due to Schlindwein and Ison, 2004, complexity can be understood as a result of a particular perception of a situation of complexity or resulting from a distinction between expectation and situation development. As we live embedded in situations of complexity, it is important to distinguish between descriptive (objective) and perceived complexity. The perception, that is made by an observer and individually variable, can be determined as perceived complexity (Schlindwein & Ison, 2004). Objective complexity on the other hand describes the complexity a certain traffic situation has. For the first modeling approach presented in this paper, the objective complexity will be the focus of the cognitive model. The impact of the objective complexity on the takeover is analyzed and displayed in the model. According to Paxion, Galy, and Berthelon (2015), the objective complexity of a situation in driving can vary with road geometry (rectilinear vs. curvilinear), the roadside environments (quantity and variability of traffic signs, variability of scenery) and traffic density (low vs. high). Thus, the role played by objective characteristics is very important (Haerem & Rau, 2007) for the takeover task and will be addressed here. The focus is set on understanding the impact of objective complexity on cognitive mechanisms during a takeover on a highway with varying traffic density in the relevant areas of interest. Thus, an explanation of how the visual perception and the resulting cognitive processing is provided and differences that occur due to different complexities can be displayed. To provide a safe and cognitive adequate takeover, it is necessary to understand which cognitive mechanisms influence different behavior of the driver. Based on such a comprehension of the situation the development of a useful HMI in highly automated driving is possible. It can thus incorporate the current situation and adapt and support the driver accordingly to enable a safe and comfortable takeover.

In this study links between objective complexity and the impact on the takeover are assumed and visualized in (Figure 1). Objective complexity is based on the amount of relevant vehicles in the traffic environment as well as the complexity of the non-driving related task (NDRT) in the in-vehicle environment. The subjective complexity on the other hand is assumed to be influenced by the objective complexity as well as by the individual perception of the objective complexity and management abilities. Both complexity versions should have an impact on cognitive mechanisms and the processing stages during the takeover and the resulting action decision. Nevertheless, as mentioned earlier, in the current context, the focus is set on understanding the impact of objective complexity before approaching subjective complexity. This is important, as the subjective complexity can only be measured, if an understanding about the impact of the objective complexity on the takeover already exists.

In order to perceive different stimuli in a complex environment, awareness of the situation has to be reached and sensory information understood (Plavsic, 2010). In driving, the most important human sense is the visual perception, involving several sub-processes. These are seeing, detection and recognition (Plavsic, 2010). To comprehend the impact of complexity on the takeover in highly automated driving, cognitive processes during a takeover and the influence of objective complexity have to be understood. This can be captured and simulated by a cognitive model. Further resulting behavior can be predicted based on the model.

Cognitive modeling is used to understand more precisely, how complexity emerges and subsequently affects the takeover. Thus, the exploitation of the resources in different complexity combinations can be revealed. For the implementation of the cognitive model, the ACT-R (Adaptive Control of Thought-Rational) cognitive architecture (Anderson et al., 2004) was used. It provides a more accurate representation of human abilities than standard programming languages (Salvucci, Boer, & Liu, 2001). Several cognitive patterns can be modeled and clearly distinguished between the different resources. The architecture provides different modules for each resource that can act simultaneously and interact with each other. Especially the visual module is able to illustrate precisely the above mentioned sub-processes of the visual perception. In conclusion, cognitive modeling is used, as it is a valid and useful method to depict human cognition very detailed with respect to the different resources (visual, haptic, auditory). The ACT-R cognitive architecture is chosen, as it is an architecture that incorporates all relevant mechanisms for the takeover task and enables the modeling of the whole task with respect to the different resources and their interactions. To understand underlying cognitive mechanisms as a function of the objective complexity, the cognitive model is established based on empirical data of a previous study (project KoHAF) and run through different levels of objective complexity. As task performance is reliant on the availability of resources (Kahneman, 1973) and auditory perception uses different resources than visual perception does (multiple resource theory; Wickens, 2008), traffic density has a strong influence on the takeover quality in highly automated driving Radlmayr, Gold, Lorenz, Farid, and Bengler (2014). The developed cognitive model gives an understanding about the underlying cognitive mechanisms. This is necessary for future development of the HMI in highly automated driving. In order to test, whether the model correctly depicts the cognitive processes, the following questions are addressed in the examination of this paper:

- Is the cognitive model able to validly display differences in objective complexity that are found in empirical data?
- Is the cognitive model able to generate predictions that significantly vary with different objective complexities in the traffic environment?

Methods

In this paper, the impact of the complexity of a NDRT and the traffic environment is addressed. As non-driving related tasks (NDRT) play an important role when it comes to taking over the driving task (Radlmayr et al., 2014), the impact of tasks with different complexities is investigated. To validate the cognitive model, data of a previous study (KoHAF) was used. In a first step (Step 1) the influence of NDRT-Complexity on takeover stages in empirical data is evaluated. Further, an ACT-R cognitive model for the takeover task per se, that displays underlying cognitive mechanisms during a takeover is developed. The model is run through scenarios of different objective complexities and resulting predictions are compared to empirical data (Step 2). The predictions of the model in environments of different complexities are then tested significant differences in prediction times.

Data Acquisition

The data that is evaluated in this paper comes from a previous study in the project KoHAF. As it includes all the relevant information, necessary for the model, it supports the assumptions, that are addressed in this paper. For the realization of a takeover in a real scenario rather than an simulator, a Wizard of Oz vehicle is used. It allows the passenger to drive the vehicle covertly via a hidden control. Thus, a takeover in a real driving environment is possible, simulating a Level 3 automation. Due to that, participants feel like driving an automated vehicle in real traffic (Ko-HAF, 2017) and can engage into secondary tasks during the mock-automation.

The study was held in 2017 in the area of Stuttgart. Overall data of $N = 14$ participants is evaluated. Takeover requests (TOR) after five different NDRTs are covered. A first evaluation of empirical data shows, that NDRTs have a significant influence on the takeover. Due to this, the complexity of the different NDRTs is rated on a ten point likert-scale by three experts based on resource capacities that are needed to solve the tasks. Conditions without NDRT are rated as lowest complex with one point (1P.). A bit more complex, listening to an audiobook (3P.) is valued as it occupies the auditory channel. This is followed by playing Tetris (6P.). Reading a newspaper (7P.) as well as searching something in the back of the vehicle (7P.) is assessed as most complex, each with seven points. Tetris was rated as less complex than reading a newspaper or searching something in the back, as the tablet was mounted to the center console and participants did not need to hold it. Thus, it is assumed as less resource-demanding with regard to the task of taking over. The data was evaluated by two independent raters concerning the different steps of the takeover and the objective complexity of the scenery (amount of visible vehicles on the road and their position). The overall objective complexity thus consists of the scenery and the traffic conditions and of the driving situation. The scenery has a high influence on the objective complexity of a situation (Rommerskirchen, Helmbrecht, & Bengler, 2013), including possible distraction sources from the in-vehicle driver's point of view (e.g. NDRT's).

Cognitive Model

As the most important factor in driving is the visual perception, the focus of the cognitive model to update situation awareness (SA) during the takeover task lies on modeling the perception behavior. Overall longer takeover times are found in a more complex scenery (Radlmayr et al., 2014). This is realized in the model with the focus on visual perception mechanisms of the relevant objects in the traffic environment. The model interacts with a graphical user interface in Lisp. It represents the ego-vehicle on the center lane of a three lane highway. The surrounding traffic is inserted at random, varying between zero and five vehicles in the environment.

Besides visual perception patterns, the cognitive model for the takeover task incorporates motoric and cognitive retrieval patterns. In the following, the steps, that are undertaken until control is regained during a takeover are defined as well as the realization in the cognitive model (Figure 2). While engaging into a secondary task, the driver is alert on whether a takeover request (TOR) appears. This is due to the drivers awareness of situation and task. As soon, as a TOR is detected (0), the NDRT is interrupted (2) and the gaze oriented to the TOR message (1). The model reacts to a stimulus in the visual or aural module, that fits the condition of a TOR message. The meaning of the TOR message is retrieved from the declarative memory and the TOR visually attended, fixated and processed. Then, the visual resource is oriented to the road center and the front lane (near and far area; Salvucci, 2006) is perceived (4). First sensory-motoric patterns (hands to steering wheel, feet to pedals) are automatically applied (3), resting on automated reactions rather than intentionally directed movements. The visual resource further attends and processes the left and right lane (5), storing the status (car or no car) of the attended areas in chunks. In the data, this is followed by the deactivation of automation (6). This is not implemented in the model though, as deactivation modalities vary and there is no common mechanism yet. The model thus completes the perception phase (7), and forms characteristics of current status. The current status of the environment is compared to the task ((8) status-task-mapping) and a decision made based on that (9). Finally, the motoric module performs the selected action ((10) sensory-motoric intervention patterns) that are either to follow, change the lane to the left or right. The vehicle is then stabilized (11). This final step is not explicitly included in the model though.

The cognitive model incorporates these steps and displays the cognitive processes that occur during each one (Figure 2).

Results

Statistical analysis is used, to show, that the cognitive model is able to depict differences that occur due to objective complexity. The two objective complexity measurements (complexity of NDRT and amount of objects in traffic environment) are evaluated separately. The impact of complexity of the NDRT is evaluated in empirical data. NDRT complexities are then scaled and compared

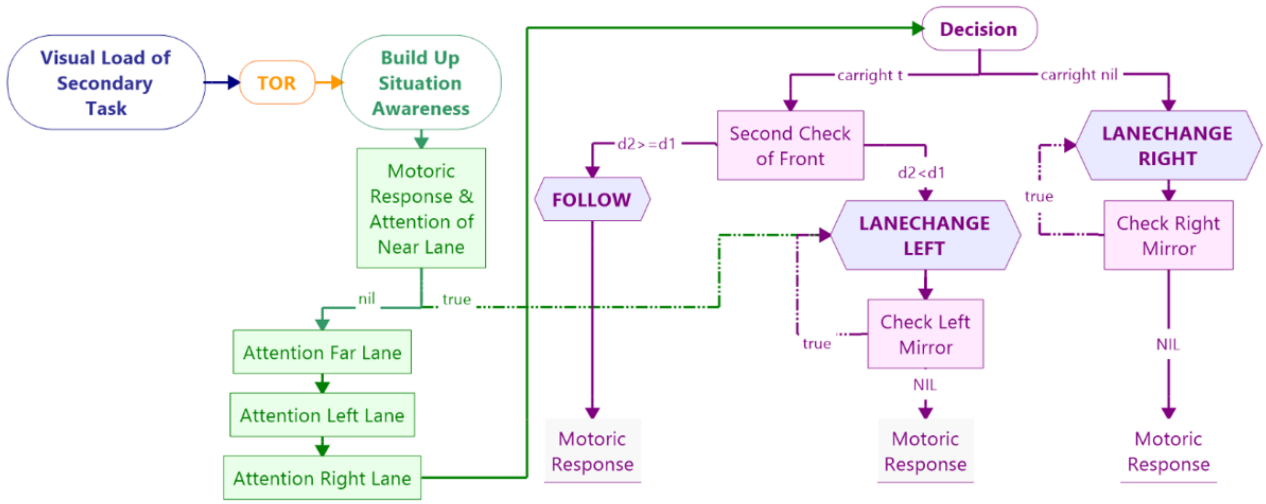

Figure 2: Representation of Main Productions, the Cognitive Model Resolves to Display Cognitive Processes During the Takeover in Highlay Automated Driving (Source: own figure).

to the cognitive model to show, that cognitive model predictions are able to account for empirical data. Based on these results, the model itself is further run through conditions of different traffic complexities and tested on significant variations between those conditions.

The influence of the NDRTs on takeover patterns is tested first using ANOVA for statistical evaluation. Based on that, regression analysis is used to measure the impact of the complexity of the NDRT on the performance of the takeover in empirical data (Step 1). Further, it is examined, whether predictions of the model correlate with the results found in empirical data (Step 2). Finally, model predictions of action decisions are tested on the influence of objective complexity variations (Step 3).

Step 1: Influence of NDRT-Complexity on Takeover Times in Empirical Data

ANOVAs show significant results for the takeover patterns one to four ((1) visual re-orientation and fixation of takeover request (TOR) message, (2) interruption of NDRT, (3) first sensory-motoric patterns, (4) visual orientation to road center). The time until the gaze gaze is directed to the TOR differed statistically significant for the different NDRTs ($F(4, 65) = 3.088, p < .05$). The same applies for the time until the NDRT is stopped ($F(4, 65) = 4.221, p < .01$), the time until the hands are moved to the steering wheel ($F(4, 65) = 12, p < .001$) and the time until the gaze is directed to the road ($F(4, 65) = 5.808, p < .001$). Due to this, the impact of complexity on takeover patterns is evaluated, using regression analysis. Based on the regression equation $y = x\beta + \epsilon$, the impact of the Complexity of the NDRT ($CNDRT$) is tested on significance to reject the null hypothesis. Further, the amount of variance that can be explained by the regression (multiple determination coefficient R^2) is evaluated. Regression analysis is tested on normal distribution of residuals, heteroscedasticity, non-linearity and multi-collinearity by plots (Liborius, 2015; Ligges, 2007). Analysis of empirical data ($N = 14$) on $CNDRT$ on the takeover shows significant effects for all takeover processes (Figure 3).

The time until the Gaze is directed to the TOR significantly rises with higher $CNDRT$ ($\beta = .004, p < .01$). The complexity of the NDRT explains 11.3% percent of variance ($R^2 = .113, t(68) = 2.943, p < .01$).

The effect of $CNDRT$ on the time until the NDRT is stopped ($\beta = .0005, p < .001$), explains 16.4% of variance ($R^2 = .164, t(68) = 3.652, p < .001$). Variance in time until the hands are moved to the steering wheel can be explained with 29,07% ($R^2 = .2907, t(68) = 5.297, p < .001$). The time increases significantly ($\beta = 1.47\mathrm{e}{-06}, p < .001$) with more complex NDRTs. $CNDRT$ also influences the time until the gaze is moved to the road ($\beta = 3.05\mathrm{e}-05, p < .001$). 22.7% of variance can be resolved ($R^2 = .227, t(68) = 4.469, p < .001$). The results show, that the complexity of the NDRT has a significant impact on all four steps of the takeover that were measured empirically (Figure 3). The more complex the NDRT that is performed before the takeover, the longer do drivers need to perform the takeover steps. This shows, that more cognitive occupation during the NDRT occupies relevant resources that need to be freed in order to attend and process objects, that are relevant for the takeover. The more complex a non-driving related task

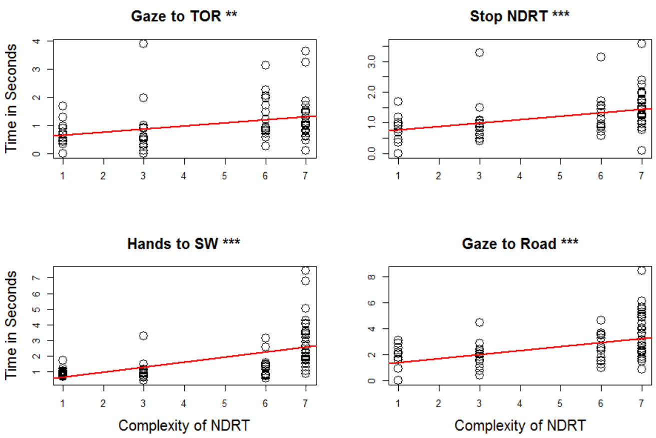

Figure 3: Regressions of the Influence the Complexity of the Non-Driving-Related Task (CNDRT) has on Times of Takeover Patterns (Significance codes: 0 '***' .001 '**' .01 '*' .05 '.' .1; Source: own figure).

is, the longer do drivers need to complete the outlined steps for taking over the driving.

Step 2: Correlation between Model Predictions and Empirical Results of Different Objective Complexities

Further, model predictions under different complex traffic conditions are tested against the results found in empirical data ($N = 14$), that are described above. The comparison of empirical takeover times with different surrounding traffic conditions and model predictions shows, that model predictions correlate with the empirical data for almost all situations of objective complexity (amount of vehicles) significantly (Figure 4). Empirical data (gray) was evaluated for situations with zero to five vehicles in the surrounding traffic. Mean (pink) and median median (red) courses for empirical data are evaluated and median courses correlated with model predictions (green-dotted). For each traffic conditions, model predictions correlate with median values of empirical data. Especially with one, three and four vehicles in the environment, model predictions are in line with empirical data.

Step 3: Test whether Model Predictions of different Complex Traffic Environments show Significant Differences

Finally, predictions of the action decision (9, see section Cognitive Model) of the model are evaluated based on objective complexity measures. In the interaction of the model with different driving situations, it can be shown, that the time for an action decision increases with a more complex driving environment. Overall the model is run through 17 different complexity situations ($N = 17$), varying between zero to five vehicles in the driving environment. The time until an action decision is executed ranges from 1.37s to 4.86s ($M = 1.74$). Regression analysis results in significant regressions for the overall amount of vehicles in the environment ($\beta = 0.04, p < .05$). The parameter resolves 24.91% of variance ($R^2 = .25, t(15) = 2.23, p < .05$). Regarding the vehicle distributon in detail, it can be shown that the amount of vehicles on the right lane has a significant impact on the time until an action decision ($\beta = 0.04, p < .05$). 18.87% of variance ($adj.R^2 = .19, t(14) = 2.3, p < .05$) can be explained. Also the amount of vehicles on the left lane has a small impact on the time until an action decision is made ($\beta = 0.09, p < .1$), explaining 12.13% of variance ($adj.R^2 = .12, t(14) = 1.83, p < .1$). Neither for the vehicle in the front of the ego vehicle a significant impact can be shown. Nor the speed (faster/slower) in relation to the own position has an impact. This shows, that the perception of left and right lane (5), the completion of the perception phase (7) and the formation of characteristics and recognition of the current status (8) need more time in more complex driving environments and lead to a delay of the action decision (9).

Discussion

The results show, that the complexity of the NDRT has a significant impact on the time of takeover patterns in empirical data. It can thus be concluded, that more complex tasks that are done during the automated drive lead to longer takeover times. Portraying the processing patterns that are undergone during the takeover with a cognitive model, similar time trajectories can be shown. This is very important, as results show, that not only the overall time, but also processing steps can be identified and displayed in the model. Further, the model is run through situations with differently complex traffic situations (amount of relevant vehicles). Results show longer times for the processing patterns in more complex environments. The predicted time-lines of the cognitive model are compared to results in empirical data with respect to the traffic complexity. Model predictions correlate with empirically gathered trajectories in differently complex traffic environments. In addition, predictions of the cognitive model are tested on significance in differences between traffic complexities. It can be shown, that the traffic complexity (amount of relevant vehicles) has a significant impact on the time until an action decision is made. These results indicate, that the objective complexity of the NDRT as well as of the traffic situation play an important role concerning processing steps during a takeover in highly automated driving. The takeover behavior as well as the time until an action decision is made, show significant influences of complexity measures (NDRT and traffic environment). Still, the model is slightly faster in the overall performance (0.5 seconds). Since the difference already occurs at the first

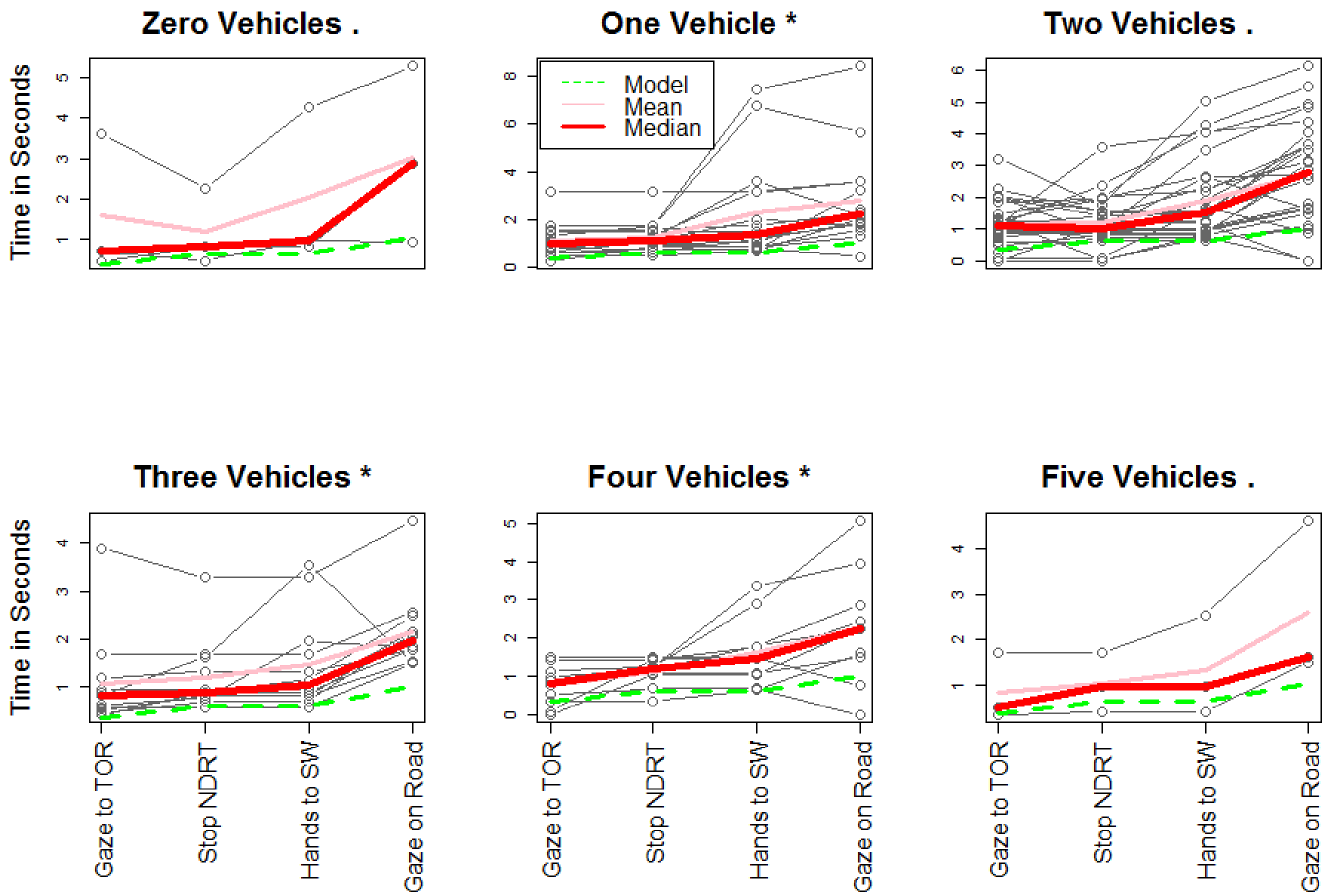

Figure 4: Correlations between Empirical Values and Model Predictions in Different Complex Traffic Situations (Significance codes: 0 ’***’ .001 ’**’ .01 ’*’ .05 ’.’ .1; Source: own figure).

processing step (Gaze to TOR), it is assumed, that cognitive processes before the gaze is directed to the TOR already have an influence. In the remaining sequence no noticeable time differences are observed. Thus, cognitive processes before the gaze is directed to the TOR have to be included into the model. Further, more aspects of the objective complexity have to be incorporated (e.g. notifications in the HMI, relevance of colors). It is though necessary to investigate on complexity measures concerning the takeover and incorporate further aspects of objective complexity. For an efficient development of interaction devices and estimates in highly automated driving cognitive models are important. They uncover underlying processes and should guide the development of highly automated driving. In this study, empirical data was collected in real traffic. The advantage of this is the creation of a more realistic scenario. However, traffic situations were not controllable and action decision patterns could hence not be evaluated. A simulator study in which the traffic conditions at the moment of the takeover request are controllable will thus be executed. This enables the collection of action decision parameters. The action decision is unequal to the action execution, as the decision may take place before the execution is possible due to the traffic environment. Thus, model predictions of the action decision in different complex situations can be validated by empirical data. In further investigations it will also be important to focus on subjective complexity in addition to objective complexity measures to include the individual into predictions. This is a very important factor, as only the consideration of individual differences enables a suitable, adaptable and safe development of the human machine interface. In order to focus on subjective complexity measures validly, it is though necessary to completely understand and control the objective complexity to separately carry out result analysis for subjective complexity measures.

Conclusion

Results of this study provide a first understanding of the impact of objective complexity on the takeover task. In a next step, action decision mechanisms in dependance of the objective complexity will be gathered. These will be incorporated to further investigate in the subjective complexity of participants during a takeover. Additionally, steps that are undertaken during the takeover will be differentiated more detailed. Patterns like action decision, action execution and the quality of the takeover and of the action execution should be included. Later, subjective complexity measures will be addressed, to additionally select model predictions based on the individual.

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