Integrated Modeling for Safe Transportation – Driver modeling and driver experiments

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Abstract: The project *IMoST* addresses the problem of capturing the behavior of a car driver in an executable model enabling design-time predictions of the interplay between driver, assistance system and car in realistic traffic scenarios. To this end, a generic cognitive model is instantiated and extended based on data gathered in targeted simulator experiments. The considered example scenario covers the entering of an expressway, with possible support for the driver in the form of an intelligent assistance system. The project plan foresees specific analysis techniques for the resulting heterogeneous models and validation of the driver model both via experiments and simulation.

1 Overview of the *IMoST* Project

Model-based design introduces additional artifacts, namely models, into the development of systems. These models capture relevant parts of the behavior of the system and/or its environment, for instance in an executable way allowing simulation. They serve to enable an early understanding of the dynamics of the system to be developed. In current practice mainly the controller, often the controlled system and even part of its environment are modeled. But lacking adequate models, human operators must today be left out of the scope of modeling. While this is justifiable when purely technical controllers are considered, as their main outputs concern the controlled system, it is obvious that the operator must not be neglected when modeling interactive assistance systems.

IMoST (Integrated Modeling for Safe Transportation) is an interdisciplinary project of the University of Oldenburg, DLR Braunschweig and OFFIS addressing this question. The main goal of the project is to enhance the efficiency of the development process of advanced driver assistance systems (ADAS) by enabling early exploration of designs. By combining a model of the car driver's behavior with models of the car, the ADAS and traffic scenarios, and analyzing the joint behavior, it is hoped that the number of time-consuming and expensive tests in simulators and prototype cars can be significantly reduced. Consequently, the main sub goals are:

1. to get valid models of drivers (i.e., models which mimic their behavior well enough for meaningful assessments of ADAS), and

2. to provide analysis methods capable of predicting the behavior of the complex artifacts which result from combining all involved models.

This paper will be mostly concerned with the first subgoal. It is treated in the coordinated work of two subprojects of *IMoST*, HM (Human Modeling, where C.v.O. University Oldenburg and OFFIS cooperate) and EE (Experiments and Evaluation, DLR). Subproject HM constructs the driver model with a focus on steering and acceleration behavior as well as attention allocation. This is an interdisciplinary task, based on cognitive theories, in which psychologists, computer scientists and physicists cooperate. The test case which is to be handled by the driver model is the entering of an expressway. This includes tasks like lateral and speed control, situation assessment, lane change and so on and can thus be considered as rather complicated. This is in line with the more general goal of HM to advance processes and techniques for modeling human behavior in highly-dynamic real-world traffic situations. And we hope to be able to transfer project results to other scenarios and areas. Subproject EE gathers empirical data for constructing the model, relying on a realistic driving simulation, and later validates it in further experiments. It also provides a specification of an ADAS to support the driver in the test scenarios, derived from experiments in a theater setup.

Two further subprojects of *IMoST*, IM (Integrated Modeling) and PR (Prediction) are concerned with the second goal. The challenge there is to master the complexity arising from both the size of the joined model and its heterogeneity, as it includes discrete, continuous and stochastic components in a tight interaction.

The project operates on a common tool basis for traffic and car simulation provided by the DLR. This enables, for instance, to repeat the very same experiments, which had been done with test drivers in the virtual reality laboratory at the DLR, with HM's model in a simulation environment of PR. HM uses this setup to test, calibrate and validate driver models. The landscape of possible configuration of the experimental/simulation setup is indicated in Figure 1.: Whether experiments are performed in the virtual-reality laboratory using the theater system to test assistance strategies (Figure 1.a), or a model of the assistance system is tested in the laboratory (Figure 1.b), or the combined behavior of a driver model and an assistance system are simulated with the means of PR (Figure 1.c), always the same traffic and car simulations are used, thus achieving a high level of compatibility of results.

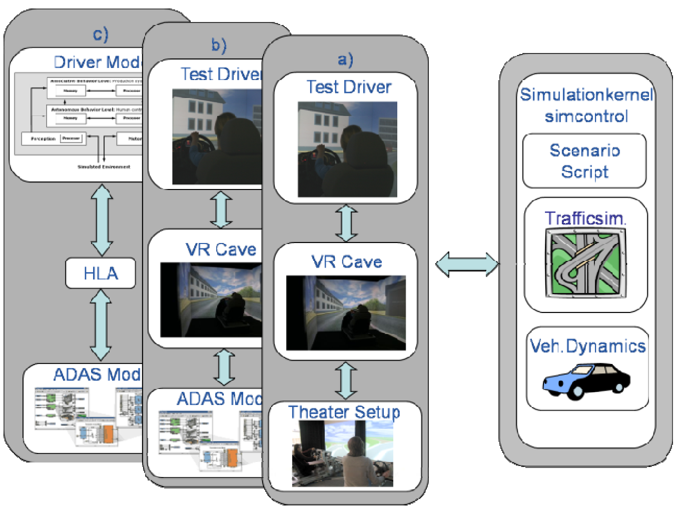

Figure 1: Simulation Platforms for the investigation of driver behavior in IMOST

This paper focuses on the subprojects HM and EE giving an overview of the *IMoST* approach to driver modeling and the results of the first year.

2 Scenario

As scenario for which to build and test the driver model the maneuver of entering an expressway was chosen. This maneuver (see Figure 2) is both complex enough to address real assistant systems of the near future, and demanding for the driver so that assistance makes sense for this maneuver. It involves different levels of the driving task: planning, decision processes at the maneuver level (finding a suitable gap, deciding which gap to choose), and both longitudinal and lateral control at the stabilization level. The maneuver is associated with large workload and a relatively high error and accident frequency and the results can be transferred to similar maneuvers, such as lane change and overtaking. Additionally the maneuver is an excellent basis so that the results on *IMoST* are applicable for real assistant systems of the near future: On the one hand, there is no system yet in the market with the full functionality addressed in *IMoST*. On the other hand there is a first system in the market that addresses some aspects of entering an expressway: The Lane Change Assist that gives a simple, visible warning in the side mirror if there is another vehicle in the blind spot. All major vehicle manufacturers have plans to address assistance for this difficult maneuver beyond a Lane Change Assist, and *IMoST* can provide methods to keep this development safer.

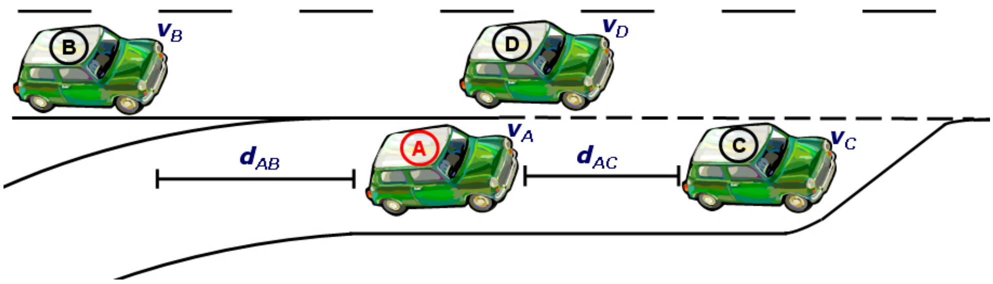

Figure 2: The expressway entering scenario with high complexity for driver A.

In subproject EE a re-analysis of accident reports has been performed leading to a hypothesis about cognitive processes that are most likely often involved in driver errors: (1) lateral and longitudinal control, (2) speed estimation and (3) attention allocation. Subproject HM strives to realize a model of these cognitive processes based on in depth empirical investigations performed in EE.

3 Formal Task Analysis

We performed a task analysis to identify driver actions together with associated environmenttal and temporal action preconditions for the expressway entering task. For this purpose an initial ontology was defined, which served as a basis to build up a Hierarchical Task Network (HTN). By formalizing the HTN, a formal domain theory was developed:

- Ontology: The ontology defines the terminology which will be used for modeling driving strategies. Our ontology focuses on terminology for describing traffic situations including the relative position and speed of other traffic participants.

- HTN: The HTN is a conditional decomposition of driving tasks into subtasks and finally into concrete driving actions.

- Domain Theory: The formal domain theory, in our case, is a formalization of the HTN specifying regularities between traffic scenarios and driver actions.

An initial version of the ontology was created, starting from the work of (Kassner, 2004). She conducted interviews with driving instructors and as a result defined a normative behavior for entering a freeway. Additionally, several studies were reviewed that focused on driver errors, traffic conflicts and accidents associated with entering the expressway. From these analyses relevant situation variables that influence drivers´ performance when entering an expressway were identified. Processing of these variables has to be included in the driver model. These situation variables were:

- A: Ego Car
- B: Approaching rear car on the target lane of the expressway
- C: Leading car on the acceleration lane
- D: Approaching front car on the target lane of the expressway
- pos_A: Position of the ego car (which lane, where on the lane…)
- d_{AB}: distance to rear car in expressway target lane
- d_{AC}: distance to lead car on acceleration lane
- d_{AD} distance to lead car on expressway target lane
- $vdiff_{AB}$: speed difference between ego-car and rear car on expressway target lane
- $vdiff_{AC}$:speed difference to lead car on acceleration lane
- $vdiff_{AD}$: speed difference to lead car on expressway target lane
- d_{gap}: size of target gap between two cars on expressway target lane
- l_{accel}: length of acceleration lane

There are certainly many more relevant situational variables, such as weather conditions, road conditions, day light, that also influence drivers‘ behavior when entering an expressway. These seemed to be not of primary importance when performing this maneuver but seemed to represent moderating factors that can change the effect of the primary factors. The primary factors on the other hand seemed to be essential for successful performance of this maneuver.

The current version of our ontology encompasses Boolean conditions over variables of type Integer and Real allowing to describe for example that the “distance to leading car" is greater than a certain “safety threshold". Some of these variables (e.g. “distance to leading car") are considered as dynamic input for the expressway entering task, to be retrieved from a simulated traffic environment. Other variables are parameters (e.g. “safety threshold") that have to be empirically derived based on experimental data from subproject EE. Starting from the ontology, we used the RCS (Real-time Control System) Task Analysis methodology (Barbera, 2004) to derive the HTN. As a result of the RCS Task Analysis we derived a hierarchically organized task network of informal “if-then" rules associating traffic states with subtasks and driver actions (Weber & Lüdtke, 2007).

The HTN was transformed into a formal specification of the expressway entering task using a rule-based language as well as a set of human controllers. These knowledge types are described in the following two sections.

3.1 Rule-based formalization

The rules have got a Goal-State-Means (GSM) format. All rules consist of a left-hand side (IF) and a right-hand side (THEN). The left-hand side consists of a goal in the goal-part and a state-part specifying Boolean conditions on the current state of the environment. The right-hand side consists of a means-part containing motor and percept actions (e.g. hand movements or attention shifts), memory-store items as well as a set of partially ordered subgoals. Furthermore the right-hand side may contain skill-items to activate, deactivate and configure controllers like braking or accelerating (see next sub section for controllers). Configuration means to change the set point and the input parameters of the controllers.

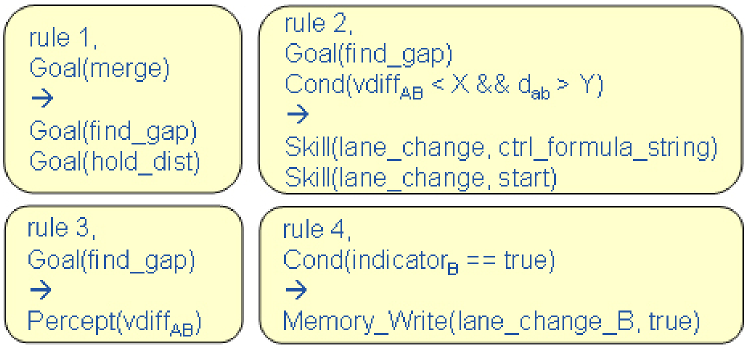

Figure 3: Example rules for expressway entering

Rule 1 in Figure 3 can be informally read as “IF the actual goal is to merge onto the expressway, THEN you need to find a gap and hold the distance to the car in front”. Rule 2 states that if distance and speed difference to the approaching car are within a certain boundary, a steering skill is started which executes the manual steering actions using a specific controller formula. Skills can be started and stopped using the “start” and “stop” keywords. For each goal dedicated rules may be specified to perceive relevant data from the environment (see rule 3 in Figure 3).

Additionally to the GSM-rules we added a second rule type, called reactive rules (see rule 4 in Figure 3). The only difference is that reactive rules have no Goal-Part. While GSM-rules represent deliberate behavior and are selected by our knowledge processing component during the execution of a task, reactive rules (State-Means (SM) rules) represent immediate or reactive behavior which is triggered by visual events in the environment. The rule based language allows to define tasks of different degrees of flexibility:

1. Rigid script based tasks: by using rules with a set of ordered and thus successive subgoals.

2. Highly dynamic tasks: by using parallel (unordered) subgoals and a set of rules where each one suggests alternative actions on the right-hand side with different environmental conditions on the left-hand side.

In the current version the ontology and consequently the HTN contain “crisp" traffic states like “distance to leading car > safety threshold". This is obviously only a first approximation of how human drivers assess traffic situations. It is more likely that humans rely on fuzzy estimates like “the distance to leading car seems sufficient to be safe". In a next step we will extend the ontology and the HTN to better capture this kind of imprecision. In particular, probability distributions for different kinds of driver behavior, to be derived from empirical data, will be used.

3.2 Control theoretic formalization

For more than 50 years control theoretic models have been used to simulate the longitudinal and lateral control of human drivers (Jürgensohn, 1997). All control-theoretic models assume a rational driver, whose gaze and consequently the heading of the car are directed towards the intended driving goal. Deviations are interpreted as errors which have to be minimized (Fajen, 2001). This hypothesis of a view constrained, intention directed rational driver is not always true, especially when speeds are low, maneuver difficulty is easy, driver's expertise is high and the surrounding scenario is interesting (Rogers, Kadar & Costall, 2005).

The generic approach uses a specific mathematical controller formula, which calculates an output value (e.g. an actuator steering signal), depending on an input error signal. The controller interacts with an environment in a feedback loop to generate continuous output. In classical controller theory the formula consists of one or more proportional, integral and differential parts of different order.

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PID controller: Output=P*Input + I*Integral(Input) + D*d/dt(Input)
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Besides the formula the most relevant part is an adequate choice of the input error signal. The fine tuning (e.g. adjusting values for PID) of the controller formula can never succeed, if the input is inadequate. Some driver models for lateral control use input signals like distance to right side of the lane or angle between car and road orientation. More complex models use preview distances or switch their modes for different track conditions. For the longitudinal control the distance to a car ahead or the curvature of the track are often used input variables.

In *IMoST* we have implemented control theoretic models for the longitudinal and lateral control (Hübner, 2007; Schroer, 2007). A critical review of literature relevant for lateral and longitudinal control and personal driving experience (Möbus et al, 2007) raises some doubt concerning the predominant importance of the tangent hypothesis of gaze control (Land, 1998). We think that empirical data supporting this hypothesis is to some degree a result of a bias in experimental conditions. Nearly all relevant driving scenarios in experiments supporting this hypothesis contained single way traffic and lane markings. Driving was performed at rather low speeds (km/h<=60) and small sample sizes (N<10). We propose simulation runs on road sections with two way traffic with different kinds of lane markings and an ecological valid embedding of the road in natural settings. It is planned that two versions of the model (control theoretic, probabilistic) will be conceptualized, implemented and evaluated.

4 Human Modeling

In the first year we reached the goal of building a first version of the executable driver model that is able to perform expressway entering maneuvers in simple traffic scenarios simulated in the platform presented in Figure 1c. Flexible and situation adapted procedure following has been integrated with characteristics of lateral and longitudinal control in an initial model.

The general approach towards driver modeling within *IMoST* follows the principles of cognitive architectures. Human cognition may be seen as a system that gets perceptual input and computes output in form of physical actions (like looking on the street and steering the car). A cognitive architecture describes involved cognitive processes independent from specific tasks in a computational way. From an engineering point of view, a cognitive architecture can be understood as a (human like) vehicle to run and modify formal domain theories (like those described in Section 3). In *IMoST* we develop a flexible layered cognitive architecture (LCA) that allows to integrate techniques from different cognitive models in order to model different behavior levels and their interaction in the same framework (see Figure 4). Behavior levels (autonomous, associative and cognitive level) have been introduced in the literature (Anderson, 2000) to differentiate tasks with regard to their demands on involved attentional control. The *IMoST* architecture integrates the autonomous (acting without thinking) and associative (behavior involving decisions) levels. From a psychological perspective the LCA allows to integrate steering/braking behavior (autonomous) and driving decision based on situation assessment (associative) in the same model. From a technical point of view, the LCA allows to integrate heterogeneous modeling paradigms.

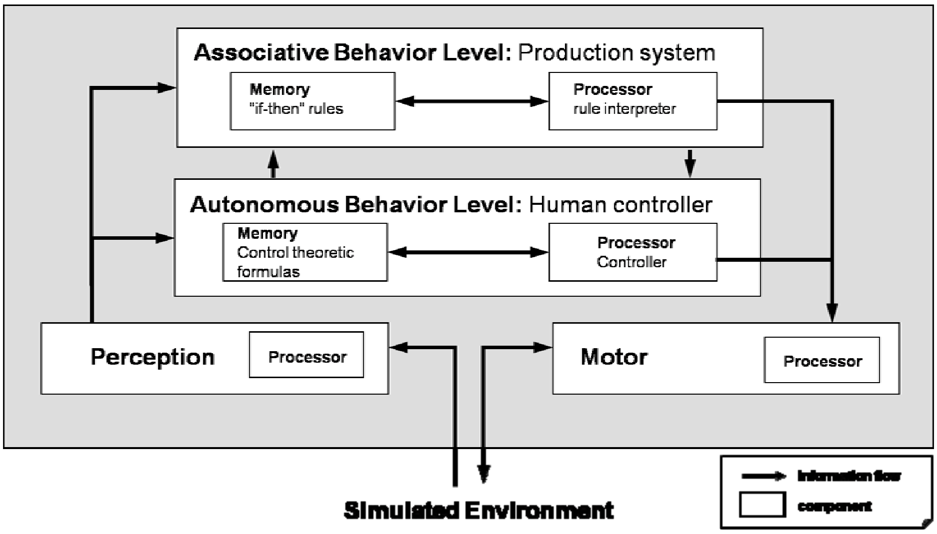

Figure 4: *The two levels of the IMoST Layered Cognitive Architecture*

In the following the environment representation and the individual components and layers of the architecture are described.

4.1 Simulated environment and visual perception

The cognitive model relies on a symbolic representation of the simulated world with which it is intended to interact. Most relevant are data about the other traffic participants and the current state of the ego vehicle. Every car is represented as an Area of Interest (AOI) object with a name, e.g. "approaching_rear_car ", and a set of variables describing the vehicle state. Currently we consider the speed difference ($vdiff_{AB}$ and $vdiff_{AC}$), the distance to the ego vehicle (d_{AB} and d_{AC}), a variable indicting if B is blinking ($indicator_{B}$). Apart from AOI there are visual events like the onset of blinking.

When modeling visual perception, the main focus is on *what can be perceived based on the visual constraints*, and *how much time is needed* to perceive something. In order to answer this we modeled visual focus, visual field, human attention, as well as head- and eye-movements. In our model we assume a visual field of 170 degree horizontal and 110 degree vertical around an optical axis (defined by the gaze direction of the eye). The focus is modeled with an expansion of seven degree around the optical axis. The vision component implements all basic functions of human low level vision (LLV): eye- and also head-movements (including focus and visual field). LLV is a process that performs the necessary steps to move the eyes and head in a certain direction. Top-down perception is initiated when percept actions contained in rules (see Section 3.1) are sent to the percept component. To simulate bottom-up perception each visual event (like the onset of blinking at a certain car) is sent to the perception component. Based on the actual eye position it is determined if the AOI to which the currently processed event belongs lies within the current focus or at least in current visual field. To be in the visual field the AOI must be within 85 degrees of the eye position. If the AOI is in the visual focus no further eye movement is necessary. If it is outside the visual field LLV reacts to this event by moving the eyes in this direction.

Currently, we do not distinguish between moving eyes and moving attention. We assume that if eyes are moved also the attention is moved. This is of course a simplification which does for example not allow to simulate the phenomenon "seeing without noticing".

4.2 Autonomous layer

The memory component of the autonomous layers stores a set of controllers that are dynamically activated and configured by either the associative or the autonomous layer itself. In general the controllers are activated via the “skill”-item either via GSM or reactive SM-rules. The latter can be imagined as an autonomous steering reaction to avoid a collision. As long as they do not use the same motor resources several controllers may be activated at the autonomous layer. Currently, no interleaving is possible to share motor resources between two controllers. In this case the previously activated controller is stopped.

The currently active controllers sample the needed input variables from the memory component and compute corresponding output for steering and braking/accelerating. Via dedicated percept actions it is assured that new input values are requested from the percept component which writes directly into the memory component. If no new values are available (e.g. for the steering controller when the eye is directed towards the outside mirror) the controller keeps on sending to last computed output command.

4.3 Associative layer

The short-term memory of the cognitive model stores the mental image of the current state of the other traffic participants and the surrounding area. Consequently, there is a corresponding Memory Object for every AOI Object. Memory Objects store a subset of the AOI Object attributes. Additionally the short-term memory stores a set of goals which the model has to process (goal agenda). The long-term memory stores the GSM and reactive rules derived during the task analysis.

The processor (KP) component executes a four step cognitive cycle typical for production systems:

- KP1: A goal is selected from the goal agenda in short-term memory.

- KP2: All rules containing the selected goal in their goal-part are collected from long-term memory. Reactive rules are added to this set if new values for the variables contained in their state-parts have been added to the memory component (by the percept component). A request for retrieving the current state of the variables contained in the Boolean conditions in the state-parts of the collected rules is sent to the memory component.

- KP3: After the request has been answered by the short-term memory one of the collected rules is selected by evaluating the state-part. Reactive rules are always preferred to non-reactive rules. If the retrieval of some variables from memory failed because the values are not available and if furthermore no state-part can be evaluated because of the missing values, then a corresponding percept rule for those variables (or a subset of them) is selected

- KP4: The selected rule is fired, which means that the motor and percept actions are sent to the motor and percept component respectively, the subgoals are added to the goal agenda (together with the partial temporal order) and the values contained in memory items are sent to the memory component. Furthermore, skill commands for controllers are sent to the autonomous level.

The cycle time for KP1-4 is 50 ms similar to the cognitive architecture ACT-R (Anderson, 2004). This time may be prolonged depending on the memory retrieval in KP2. In KP2 all variables contained on the left-hand sides of the collected rules have to be retrieved from memory. The retrieval time is influenced by the number of variables.

The currently simplified task model for expressway entering contains 10 goals where the main part of the maneuver consists in alternating between the two goals "find_gap" and "hold_distance". For each goal there are dedicated rules. This allows maximum flexibility because in each cycle the model decides new whether to keep on looking to the left or to look to the front.

In KP1 a goal is selected from a subset of selectable goals. This selection is based on the partial order which is induced on the goal agenda when in KP4 a rule is fired and partially ordered subgoals are added to the agenda. While in older versions of the model the selection was done randomly we are currently modeling a mechanism to select goals based on the mental prediction of the dynamics of the situation: additionally to the goal agenda a dynamic scheduling for selectable goals is implemented using a goal queue which is similar to Salvucci's General Multitasking Executive (Salvucci, 2005). It has the following four features: a) The queue is sortable using deadlines for each goal. The goal with the smallest deadline is selected. b) The mechanism to set deadlines is work in progress, currently a parameter in the procedure language is used, which can be added to a subgoal statement on a rules right-hand side. This means, whenever a subgoal is put on the agenda a deadline is attached to it. c) Continuous goals which need to be interleaved or executed periodically are queued in repeatedly after one KP1-KP4 cycle until they are terminated. d) Furthermore the deadlines need to be adjustable based on information about the environment.

Based on these mechanisms we currently model attention allocation depending on the predicttion of other traffic participants behavior.

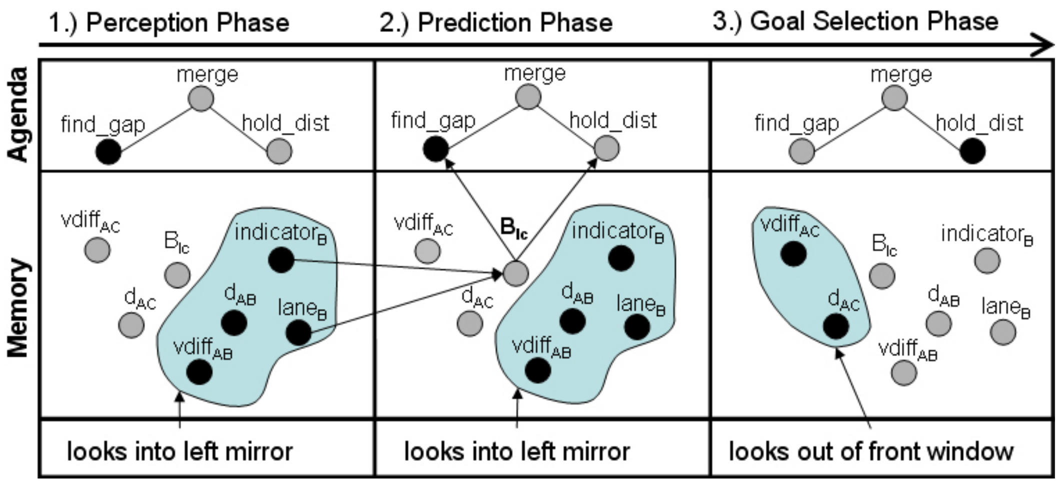

Figure 5: Three phases of shifting attention using the prediction of other traffic participants behaviour.

Figure 5 gives an overview of the modeling concepts which are used for prediction and attention allocation referring to the expressway entering scenario. Driver A currently drives on the acceleration lane and needs to 1) find a gap and 2) hold the distance to a lead car on his lane. These two subgoals are interleaved, periodic subgoals, which have by default equal deadlines.[1] This implies, we have alternating execution of KP1-KP4 for both goals until one or both are done successfully.

- 1.) Perception phase: A pursues the goal “find_gap” (marked black) and allocates his attention to observe the traffic in his left side mirror. Information in the working memory is updated, e.g. the distance (d_{AB}) to an approaching car (B) at the target lane ($lane_B$), an estimation of B’s speed relative to the A’s own speed ($vdiff_{AB}$).[2] Additionally the driver model recognizes a visual event: car B starts blinking ($indicator_B$).

- 2.) Prediction phase: Based on the perceived information the driver model forms predictions over the behaviour of the other traffic participants – in our scenario about B. In the example the prediction is that B will change the lane (B_{lc}). This prediction is modeled using additional reactive predictive rules which are activated by the declarative memory item $indicator_B$. The existence of such a prediction is likely to change the attention allocation of the driver A, because he assumes that the target lane will be free and find_gap needs less attention. The associated predictive rule has two subgoals “find_gap” and “hold_dist”, with different deadlines attached to them. Since these goals are already put on the agenda previously, only the deadline parameter is adjusted.

- 3.) Goal selection phase: Based on the computed deadlines and the reordered goal queue the next goal is selected (“hold_dist”).

[1] We are currently investigating how the gaze is allocated with a number of experiments and situations. But the modelling mechanism is flexible enough to configure different gaze strategies.

[2] The performance of how the driver separate different combinations of those two variables and when they merge before or after B is investigated in experiment 1 (see section 5.1).

5 Experiments and Evaluation

Within subproject EE of the *IMoST* project five goals are pursued: Goal 1 is to provide psychological and behavioral research required for the development of the driver model and the advanced driver assistance system (ADAS); Goal 2 is to validate the driver model developed in subproject HM. Goal 3 is to develop strategies of assistance functions. Goal 4 is to gather data about driver errors, traffic conflicts, accidents in situations without ADAS and with ADAS. Goal 5 is to evaluate the developed assistance functions by comparing empirical results on driver errors, traffic conflicts, accidents when entering an expressway with the ADAS with the results when entering the expressway without the ADAS.

In this section we will focus on the description of experiments conducted to provide the empirical basis for the driver model. To achieve this a series of experiments is planned. This series of experiments is based in the analysis of relevant situation variables described above (Section 3). Each experiment addresses a small set of situation variables that affect driving behavior. It is necessary to focus on a small set of these factors in each experiment to be able to examine the considered factors in detail with sufficient power. The first experiment of this series is already finished and its data are partly analyzed. In the following section we will provide a short overview of this experiment and its results.

5.1 Experiment 1

5.1.1 Background

This experiment was designed to address four questions important for the modeling work in subproject HM. These questions were derived from the analysis of relevant situations variables and their effect on driving performance while entering the expressway. These questions were i) the effect of distance between the ego-vehicle and the nearest car on the expressway and the speed difference between these two cars on drivers‘ perception and evaluation of different situations, ii) the effect of these variables on drivers entering behavior including actual driving behavior and glance behavior, iii) drivers‘ glance behavior when driving through curves with and without oncoming traffic, based on the analysis described in Section 3.2, and iv) driver strategies when entering the expressway to complement the analysis of previous studies described in Section 3.1.

5.1.2 Method

To examine these questions the scenario as shown in Figure 6 was used. The participant (car A) had to enter the expressway while a car on the right lane of the expressway was approaching (car B). This car was either 20, 30, or 40 km/h faster than the participant. Additionally, B was either 20, 30, or 40 m behind the participant at the time when the participant passed the beginning of the acceleration lane (This will be referred to as the “initialization point”). The combination of these two variables led to nine combinations of situations. These nine combinations could be divided into situation where it was possible to safely enter the expressway in front of the B and where this was not possible.

The experimental design made it possible to apply the Signal Detection Theory (SDT) in order to analyze the driver’s decision to enter the expressway before or after the approaching vehicle on expressway. SDT is a general methodological approach in cognitive psychology that allows to distinguish between the ability to perceive a given situation adequately and a person´s response tendency or decision criterion (i.e. conservative/cautious vs. liberal/risky) deduced from the observed behaviour of participants (MacMillan & Creelman, 2005, Wickens, 2002). In terms of the given task – to decide whether a presented traffic situation represents an acceptable gap for entering or not – this theory provides a tool to dissociate, within a given experimental situation, between the driver's perception of the appropriateness to enter and an estimate of the person's response tendency or willingness to enter, respectively.

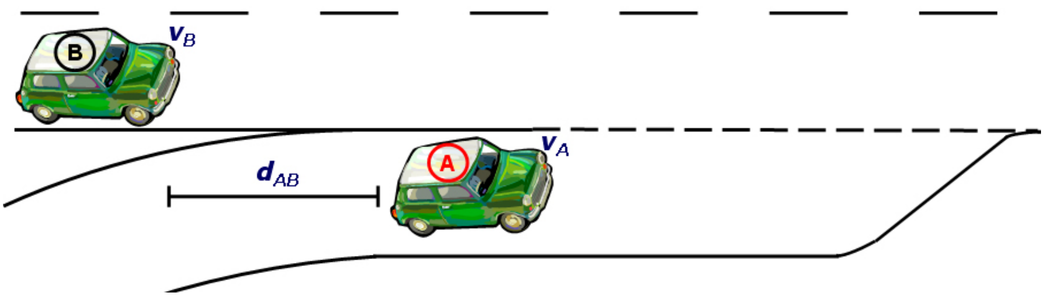

Figure 6: Scenario of the experiment

5.1.3 Results

In this section we will focus the presentation of results on two major aspects: 1) The analysis of the decisions of the participants to enter the expressway in front of B or not in terms of SDT and 2) the effect of the speed difference and the distance between A and B on performing the entering maneuver.

Signal Detection Theory Analysis

The two variables identified as most crucial for the decision to enter the expressway in front or behind B, d_{AB} and $vdiff_{AB}$, were presented at three levels each resulting in a total of nine different experimental conditions. In order to calculate d-prime as a measure of the ability to separate "noise" from "signal", the physical situations had first to be classified into "signals" (= physically o.k. to enter) and "noise" (= physically not o.k. to enter). We defined seven noise situations as "risky to enter" and two situations as "o.k. to enter" (signal). For each of the nine possible traffic situations, the relative frequency of the drivers' decision to enter the expressway in front or behind B on the expressway was collected from the data recording in the driving simulator. These frequencies were used to estimate the conditional probabilities P(decision to enter | entering is o.k.) referred to as a hit and P(decision to enter | entering is not o.k.) referred to as a false alarm.

Additionally the drivers had to rate their confidence of the correctness of their decision. In four of the nine physical situations, the probability of the participants to change lane was zero; therefore, these conditions had to be excluded from further SDT analysis. From the remaining hit and false alarm estimates, the d-prime value for each possible signal/noise pair was computed as a measure of the drivers´ ability to discriminate between traffic situations that are "o.k. to merge" vs. "risky to merge". A preliminary SDT data analysis revealed that the perceptual effects of the two relevant physical variables ($vdiff_{AB}$ and d_{AB}) can be combined into a one dimensional representation, generating a subjective scale (perceived appropriateness to merge) onto which each traffic situation is being mapped. Moreover, the distribution of the probabilities indicate that the participants are most prone to merge when the distance between the ego and rear car is greatest (40 m) and when speed difference is 20 km/h (p= .9125) and 30 km/h (p= .4375), respectively, even if the latter situation is classified as a noise condition.

Effect of Speed Difference and Distance on Driving Behavior

Figure 7 presents six histograms showing the distribution of distance between A and B if the driver decided to enter the expressway in front (upper row) or behind B (lower row). The data of the figure stem from combinations where the distance to the approaching rear car at the initialization point was 40 m.

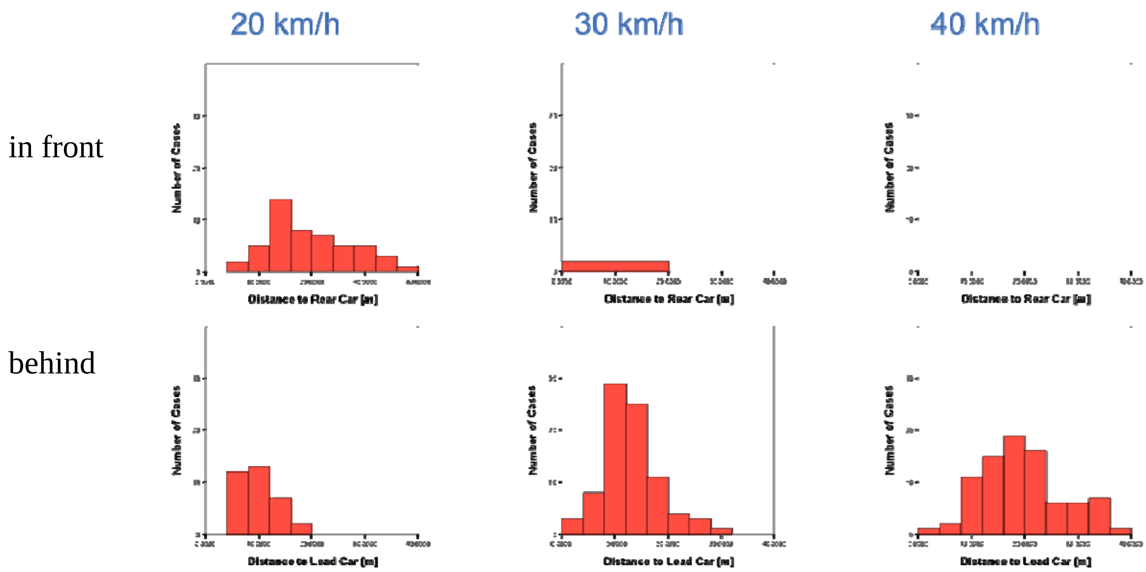

Figure 7: Distribution of distances between driver A and car B on the expressway at the time of the lane change as function of varying speed difference and distance of 40m at initialization point. Upper row: trials where drivers entered the highway in front of the car on the expressway, lower row: trials where drivers entered behind the car on the expressway.

It can be seen that most of the drivers decided to enter the expressway in front of B when this car was 20 km/h faster at initialization point, whereas no driver entered the expressway in front of B when B was 40 km/h faster than the driver at initialization point. If the car on the expressway was 30 km/h faster at initialization point in about half of the trials the drivers entered the highway in front of B and in half of the trials they did not. It can also be seen that the distance to the B at the moment when the driver changed from the acceleration lane to the expressway depended on the distance and speed difference initialization point. When entering in front of B the distance was smaller if B drove faster. When the drivers chose to enter the expressway behind B the distance at the time of the lane change increased with increasing speed of B at the initialization point.

5.1.4 Discussion

The results indicate how the chosen situation variables influence driver’s decision making and driving behavior when entering an expressway. These results will be directly integrated into the driver model in terms of GSM rules about which distances and speed differences are acceptable and which are not and in terms of rules about the drivers‘ reaction to cars approaching from behind on the target lane on the expressway. The SDT results indicate that this framework is promising in terms of describing the parameters underlying the drivers' decision whether to enter the expressway before or after an approaching rear vehicle.

Besides the driver‘s actual driving performance his glance behavior during the merging maneuver as a function of distance and speed difference was examined to get first results about the effect of these two situation variables on the drivers strategies of attention allocation while entering the expressway. These results will be used to advance the attention allocation mechanism for the driver model (Section 4.3). This is essential when the driver has to perform multiple tasks simultaneously, as for example when there is a lead car on the acceleration lane and the driver 1) has to decide whether to enter the expressway in front of the car approaching from behind on the expressway or not and 2) at the same time has to control the distance to the lead car. Further experiments will examine exactly this situation to get deeper insight into the attention allocation and multiple task performance strategies of drivers when entering an expressway. Additionally, a second line of experiments will address the drivers' decision making in more detail. In several experiments more combinations of distance and speed difference to B will be realized to yield a more detailed picture of the influence of these variables on drivers' decision making. Furthermore, the time of the decision whether to enter in front or not will be manipulated and the criterion whether entering at a given combination of distance and speed difference is acceptable will also be manipulated in a further experiment. The results of these experiments will then be analyzed in terms of the signal detection theory.

6 Summary

In this paper we described the first version of a driver model developed in the IMoST project. The driver model integrates autonomous steering and braking behavior with associative decision making and attention allocation for finding a gap and holding distance to a leading car. Human controllers and "if-then" rules have been specified based on a task analysis and a first driving experiment. Dedicated knowledge processing components have been implemented and integrated in a layered cognitive architecture. Within the next two years further experiments with more complex traffic scenarios are planned to extend and validate the driver model. The model shall cast behavior during expressway entering maneuvers similar to human driver behavior with regard to steering, accelerating and the allocation of attention.

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