Modeling Pilot and Driver Behavior for Human Error Simulation

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Abstract. In order to reduce human errors in the interaction with in safety critical assistance systems it is crucial to consequently include the characteristics of the human operator already in the early phases of the design process. In this paper we present a cognitive architecture for simulating man-machine interaction in the aeronautics and automotive domain. Though both domains have their own characteristics we think that it is possible to apply the same core architecture to support pilot as well driver centered design of assistance systems. This text shows how phenomena relevant in the automobile or aviation environment can be integrated in the same cognitive architecture.

Keywords: Human Error Simulation, Cognitive Architecture, Pilots, Drivers.

1 Introduction

Today assistance systems are a common and widely accepted means to support human operators in performing safety critical tasks like driving a car or flying an aircraft. The aim is to reduce the number of human errors in order to reach the ambitious goal of zero-accidents. Considering the ever increasing complexity of the traffic environment, be it air or surface traffic, human error will remain the most important challenge in order to reach this goal.

During design and certification of assistance systems it has to be proven that human errors are effectively prevented and no new errors or unwanted long-term effects are induced The current practice is based on engineering judgment, operational feedback from similar aircraft, and experiments with test users when a prototype is available. Methodological innovations are needed to sustain existing quality levels and to guarantee an affordable analysis despite the increasing complexity of the overall aeronautical system. It is necessary to develop a methodology that allows to accurately analyze systems from the operators' point of view already in early design stages when design changes are still feasible and affordable. Our approach is based on modeling and simulation of driver and pilot behavior using a cognitive architecture. It has to be said that the term "human error" is very controversial and often used to blame accidents "ex post facto" to humans. We share the view that human errors in the context of highly automated complex systems are often more a "symptom, not a cause", highlighting weaknesses of the systems that need to be improved.

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Section 2 of this paper presents our approach and describes our core cognitive architecture which can be instantiated in order to derive pilot as well as driver models. Section 3 describes model instantiations for the analysis of pilot behavior and section 4 for driver behavior. Section 5 gives a summary and sketches next steps of our research.

2 Modeling and Simulation Approach to Human Error Analysis

Our approach to the analysis of human errors is based on the development and simulation of integrated closed-loop man-machine-environment models. In this approach human models are used as virtual system testers in order to analyze a vast number of scenarios already in early development phases to identify potentially hazardous scenarios and to iteratively improve the design.

Executable cognitive models are intended to describe mental processes of human beings like assessing situations and choosing actions resulting in time-stamped action traces. These cognitive models usually consist of two parts: a cognitive architecture, which integrates task independent cognitive processes and a formal model of task specific know-how (e.g. flight procedures or traffic regulations). In order to simulate behavior the task model has to be "uploaded" to the architecture. Thus, a cognitive architecture can be understood as a generic interpreter that executes task specific knowledge in a psychological plausible way.

An overview of cognitive models is provided in [2]. The most prominent representatives are ACT-R and SOAR. We decided to build our own architecture because existing ones have complementary strength and weaknesses, but none covers a comprehensive executable model of those human capabilities that are relevant for human behavior in complex dynamic environments. To build such a comprehensive architecture we adapt, extend and integrate heterogeneous modeling techniques (e.g. production system, control theoretic models, semantic networks) from different existing architectures.

A key concept underlying our architecture is the theory of behavior levels [1] which distinguishes tasks with regard to their demands on attentional control dependent on the prior experience: autonomous behavior (acting without thinking in daily operations), associative behavior (selecting stored plans in familiar situations), cognitive behavior (coming up with new plans in unfamiliar situations).

Fig. 1 shows the structure of our cognitive architecture. It encompasses one layer for the autonomous behavior level and one for the associative level. A third layer is formed by the percept and motor component that implement the interface to a simulated environment. On the layer for autonomous behavior we model manual control behavior for tasks like steering and braking using different modeling techniques like control theoretic formulas. These models have been described e.g. in [6]. This paper focuses on the associative layer which is the basis for the main phenomena that have been modeled.

Knowledge is stored inside the memory component in form of Goal-State-Means (GSM) rules (Fig. 2). 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 together with associated memory-read items to specify variables that have to be retrieved from memory.

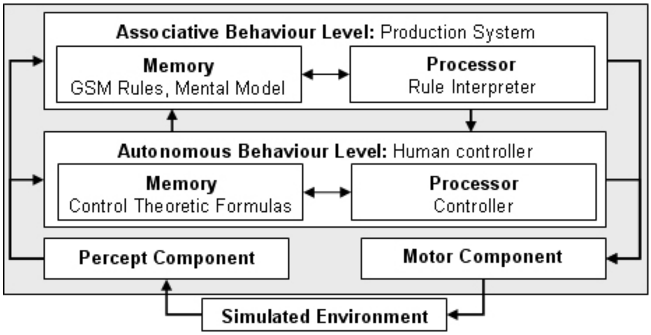

Fig. 1. Layered Cognitive Architecture

The right-hand side consists of a Means-Part containing motor as well as percept actions (e.g. hand movements or attention shifts), memory-store items and a set of partial ordered sub-goals. The rule in Fig. 2 defines a goal-subgoal relation between GEAR_UP and subgoals CHECK_GEAR_UP, CALLOUT_GEAR_UP. The term “After” imposes a temporal order on the subgoals.

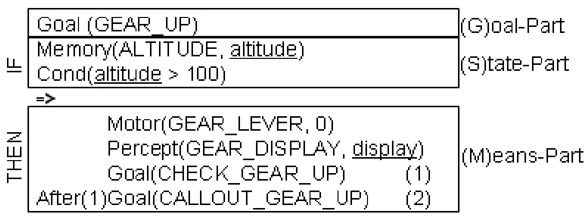

Fig. 2. Format of GSM rules (variables are underlined)

Apart from the rules the memory component stores a ”mental model” of the current situation (e.g. position of other cars, states of instruments) and furthermore an ordered set of goals and subgoals that have to be pursued and which we call Goal Agenda.

The rules are processed by the processor component of the associative layer in a four step cognitive cycle typical for production systems: A goal is selected from the Goal Agenda, all rules containing the selected goal in their Goal-Part are collected and a memory retrieval of all state variables in the Boolean conditions of the selected rules is performed. After the retrieval one of the collected rules is selected by evaluating the conditions. Finally the selected rule is fired, which means that the motor and percept actions are sent to the motor and percept component respectively and the subgoals are added to the Goal Agenda. This process is iterated until no more rules are applicable. The cycle time is 50 ms plus memory retrieval time like in ACT-R. Like in ACT-R one rule can be fired at the same time. But contrary to ACT-R our architecture allows parallelism between the autonomous and associative layer in order to model that humans can concurrently steer a car and operate a CD player.

We use the same approach and in particular the same cognitive core architecture for modeling and simulating both, driver and pilot behavior. While sharing the generic architecture the instantiation of the architecture with task specific knowledge as well as some specific extensions of the architecture are fundamentally different. It is out of question that the two domains, automotive and aeronautics have fundamental differences as well as some similarities. One major difference between driver and pilot behavior is that driver behavior underlies a wider range of variance, then pilot behavior. Main reasons for this are the strict selection process for pilots, the high training standards in aviation, and the standardization of procedures in cockpits. In contrast to this, a large variety of people can drive, which are often only trained once in life. Drivers develop many individual driving routines, therefore strict goal-subgoal relations as in pilot models are less common. The rule base task model allows to model both behaviours: (1) rules allow to formalize rigid script based tasks by using rules with a set of ordered and thus successive subgoals, (2) furthermore highly dynamic tasks can be modeled by using parallel (unordered) subgoals. Individual differences in driving are modeled by adding rules for all relevant driving strategies which can be selected randomly.

Further differences between our driver and pilot models exist, because certain features are more only relevant for one of the two domains. For example, simulating manual steering and braking behavior on the autonomous layers of the architecture is more relevant for driver modeling.

In order to allow execution of the cognitive model within realistic flight or traffic scenarios we interfaced it to simulation platforms that are normally used for experiments with human subjects. In this way we are able to use the same environment for experiments with both, human subjects and the cognitive model. This is a crucial prerequisite for comprehensive model validation.

The following sections describe four extensions of the cognitive architecture for modeling aspects of pilot and driver behavior.

3 Pilot Modeling

Automation systems in aircraft systems are equipped with a huge number of system modes. A mode may be understood as a system state in which it delivers a distinguishable function. Modes allow to use the same system for different maneuvers but at the same this may induce mode errors where an action is performed that is correct in some modes but not in the present one. Often, the pilots' mental model of the automation systems is inappropriate or incomplete. In order to mitigate mode errors display designers try to control the attention of pilots by using flashing graphical elements to highlight mode changes.

3.1 Learned Carelessness

The extension of our cognitive architecture to include the phenomenon Learned Carelessness (LC) can be used to analyze how pilots' might mentally transform the task model of flight procedures while they gain experience with a system.

Interaction phenomenon. The focus is on discrete pilot actions for operating a system (like pressing buttons of an autopilot). We assume that the operation can be defined normatively in form of procedures that prescribe admissible action sequences and preconditions. Of interest for the system designer are especially action preconditions that involve checking the current mode. Using our model we analyze the probability that pilots neglect mode conditions and that this may lead to hazardous flight situations. The goal is to iteratively improve the system design to make it robust with regard to likely mode errors.

Involved cognitive processes. The theory of LC states that humans have a tendency to neglect safety precautions if this has immediate advantages, e.g. it saves time, and allegedly allows to keep the same safety level. In the context of avionics systems safety precautions may be understood as checking the current state or mode of the systems before performing critical actions. LC is characteristic for human nature because we have to implicitly simplify in order to be capable to perform efficiently in a complex environment. Resulting behavior is highly adapted to routine scenarios but, unfortunately, may lead to errors and hazards in non-routine situations. Thus, it is crucial to identify those interaction sequences where LC may lead to hazardous situations. More details can be found in [5].

Modeling idea. To model LC inside our cognitive architecture we added a learning component which produces new simplified rules by merging existing normative rules. Figure 3 shows some rules from a climb procedure. Rule 25 specifies that the vertical speed (VS) button must be pressed as long as the mode annunciation (MA) does not show the flashing letters "ALT" (flashing "ALT" indicates that a mode called Altitude Capture is active). Using rule 21 the current value of MA is perceived. Rule 23 stores the perceived value into the memory. Most of the times when the pilot tries to press the VS button the Altitude Capture mode is not active and the percept action in rule 21 delivers "ALTS" which indicates that the current mode is Altitude Select and not Altitude Capture. We hold the hypotheses that due to this regularity a pilot would simplify his mental model of the procedure into a version, where the MA value is no longer perceived by looking at the cockpit instrument but is just retrieved from memory. This is modelled by merging two rules into one rule by means of rule composition. The crucial point is that in this process elements that are contained on the right-hand side of the first and also on the left hand side of the second rule are eliminated. This process cuts off intermediate knowledge processing steps.

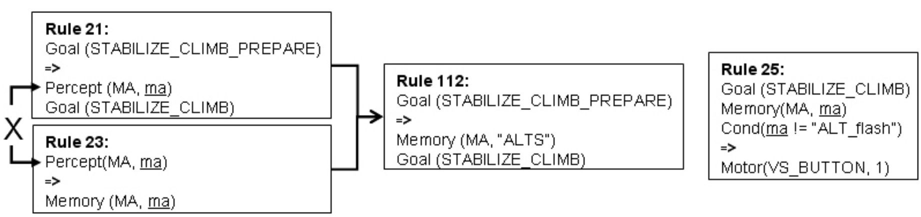

Fig. 3. Composition of *Rule 21 & 23 leading to Rule 112*

Fig. 3 shows the composite rule 112 that was formed by composition of rule 21 and 23. The percept action has been eliminated and the new rule always stores the value "ALTS" in memory. Rule 112 is appropriate in scenarios that are similar to those in which the rule has been learned (MA does not indicate Altitude Capture mode). In deviating scenarios (MA does indicate Altitude Capture mode) applying Rule 112 results in careless behavior: pressing the VS button independent from the current mode annunciation (Rule 112 followed by Rule 25).

Validation activities. We performed three case studies involving auto pilot systems to evaluate the cognitive pilot model. In one study we compared the model behavior with human pilot behavior and were able to successfully reconstruct nine mode errors [5]. In the remaining two studies subject matter experts performed a review of the model behavior and acknowledged that the behavior is in general plausible with respect to the investigated tasks and compatibly with the limitations of the investigated scenarios [4]. Extensive validations where the model predictions will be compared with the behavior of 24 pilots are planned for this year in the European project HUMAN.

Transferability. We hold the hypotheses that the LC mechanism can be applied in the automotive domain for analyzing the discrete interaction with e.g. navigation systems where the driver has to input and select information to set up the system for a new destination.

3.2 Selective Attention

The extension of our cognitive architecture towards Selective Attention can be used to investigate if attention capturing graphical elements are adequate to mitigate errors like those induced by LC.

Interaction phenomenon. One important part in human error analysis is the analysis of the ergonomics of the graphical user interface. In aircraft this includes the analysis of flashing boxes around flight mode annunciations (MA), which are supposed to automatically drag the attention of pilots to mode changes. Here, display designers make use of a phenomenon called “Selective Attention” (SA).

Involved cognitive processes. SA is understood as the phenomenon describing automatic shifts of attention triggered by the onset of a salient stimulus, e.g. a flashing light, or a moving item [11]. Recent studies have shown that certain characteristics of displays may undermine the effect of SA. The study of Mumaw, Sarter and Wickens [7] showed that only 30-60% of pilots recognize a MA change within the first 10 seconds (while the box is flashing). One important reason is that visual context may undermine the SA effect [8].

Modeling idea. In addition to a basic temporal model of human vision (with visual field, focus, and eye-movements) as a low-level percept component, we modeled context dependent SA. In this model the probability that a stimulus is recognized depends on the saliency of the display neighborhood, e.g. the probability is lower, if the neighborhood contains colorful and dynamic displays. Each stimulus received by the cognitive model is processed by the SA mechanism in three steps: The first step *(SA1)*, determines if the area of interest (AOI) to which the stimulus belongs lies within the current focus or visual field. If the AOI is focused, the associated event is marked as recognized and SA3 is started. If the stimulus is outside the visual field, the associated event is marked as unrecognized, and SA1 is restarted with a new stimulus. If it is within the visual field but not in focus, SA2 is initiated in order to determine recognition. In the second step *(SA2)*, it is determined if in a neighborhood of 15 degree (derived from experimental setup in [8]) around the AOI other stimuli have occurred. A probabilistic choice dependent on the dynamics of the neighborhood, based on data from [8], is computed to determine if the event is recognized or not.. If the event is recognized, SA3 is started, else SA1 starts again with the next stimulus. In the last step *(SA3)* a shift of attention is initiated. Then SA1 processes the next stimulus.

Validation activities. In order to illustrate the plausibility of our model we investigated flashing mode annunciations of an autopilot [9]. We simulated a number of scenarios highlighting situations in which pilots might miss the mode indication. In a next step we will compare our data with human data. This validation will be achieved in combination of the validation activities for LC described above.

Transferability. Although the SA model has been developed for pilot behavior it is also usable in driver modeling, e.g. for detecting flashing indicator lights on other cars or warning lights of driver assistance systems.

4 Driver Modeling

Recent analysis of accident data has identified inattention (including distraction) as the primary cause of car accidents, accounting for at least 25% of the crashes. Consequently guidelines for the design of driver assistance systems require to investigate the impact of automation on drivers' attention allocation. In the following we present two extensions of our cognitive architecture with regard to factors influencing attention allocation.

4.1 Divided Attention Based on Prediction of Other Traffic Participants

The extension of the cognitive architecture towards the influence of predictions of other traffic participants on attention allocation can support designers to create effective assistance systems which prevent inadequate assumptions about the dynamics of traffic situations.

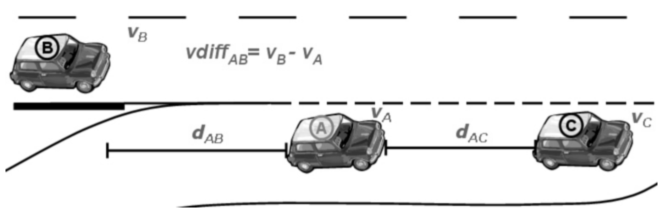

Fig. 4. Freeway merging scenario

Interaction phenomenon. Drivers often find themselves in complex traffic situations which require attention allocation to different traffic participants and the integration of diverse information into a mental model of the situation. Estimations of the behavior of other drivers have an impact on attention allocation. Inadequate estimations can lead to incorrect situation assessment and accidents. We perform several simulator studies with human participants to investigate these aspects.

In a first study we investigated the influence of 9 different combinations of speed differences ($vdiff_{AB}$) and gap size (d_{AB}) (see Fig. 4) on merging behavior to build up an initial model for gap acceptance and lane change.In a second study we consider a lead car (C in Fig. 4) which also enters the freeway. Here we investigate drivers divided attention between the Tasks “hold distance to C” (T1) and “looking for a gap” (T2). In a reference scenario, B does not change its lane and we analyze the attention allocation of A. In following test trials B gives different lane change cues: B turns on his left indicator (Cue1), B suggests a lane change by moving to the left-most lane (Cue2). Finally, B either changes or not changes the lane (Cue3).

Involved cognitive processes: Compared to the reference scenario we expect drivers to increase their attention allocation either to task T1 or T2 in the test trials. Referring to Wicken’s SEEV Model [10] we interpret this as a consequence of the attention parameter “value of information”. Both tasks have a certain value for the driver therefore both need to be considered. The smaller the distance to C, the higher the value of having exact information about C because C might brake suddenly. In consequence, the priority of T1 will be high. Concerning T2, more safety related drivers who perceive Cue1 might search for additional cues which support their prediction of a lane change of B. They invest more attention in observing B to get more reliable information. Risky drivers may consider Cue1 as predictive enough to assume lane change of B therefore spending less attention.

Modeling idea. Task priorities are modeled by extending the Goal element in the Means-Part of our rules (Fig. 2) with a priority parameter. Priorities of goals are used to initiate successive execution of the same goal: the higher the priority, the larger the probability to execute the goal once more before switching to the next one. The more often a goal was executed successively, the less its probability to be executed again. In our model cues in the traffic environment have a direct influence on goal priorities. These quantitative dependencies are derived from experimental data.

Validation results. The current state of the model is rather basic, results have not yet been validated systematically. Detailed validation studies are planned for this year. The main measure for model validation will be the gaze behavior of drivers.

Transferability. A dual task structure of continuous, interleaved goals can be found in pilot tasks as well. Prioritization of tasks is a very important aspect in time critical multitasking situation. We assume that the aspired priority mechanism is flexible enough to model dual-task scenarios e.g. during aircraft takeoff as well.

4.2 Divided Attention Based on Event frequencies

The extension of the cognitive architecture with regard to the influence of event frequencies on attention allocation can be used to identify a potential negative influence of assistance systems on the attention and situation awareness of the driver in cases where (s)he gets out of the loop of the driving task.

Interaction phenomenon. Out-of-the-loop effects may be caused when a certain task is fully controlled by the system. For example an ACC (Automatic Cruise Control) system reduces or completely removes the necessity for the driver to correct the distance to the lead car. The driver might rely too much on the system and might allocate too little attention to the longitudinal control tasks. As a consequence the driver might fail to take over control in situations where the ACC reaches its limits.

Involved cognitive processes. Wickens & McCarley [10] and Horrey et.al. [3] postulated four main influences on the process of attention allocation - salience, effort, event expectancy and value. With these values they created the SEEV trade-off model to describe how humans distribute visual attention. The probability that an information sources will be paid attention to, is a function of the four influence factors. Horrey et. al. [3] conducted driver studies focusing on collision avoidance where they gained good results though only considering the factors expectancy and value. We focused on the expectancy factor, that describes how likely it is that the driver expects new information at an information source. For the collision avoidance task it is based on the bandwidth of events the driver has to react on. The more events have occurred on that source, the more will the driver expect further events to occur.

Modeling idea. Following the SEEV attention allocation model we currently implement the correlation of event bandwidth and attention allocation. The implemented process relies on a percept mechanism: an Area of Interest will be scanned by the model if the goal which requires this information, is selected in the cognitive cycle. For task T1 "hold distance to C" (see Fig. 4) the required information would be d_{AC}. Perceived information is used in the State-Part of rules.

Fig. **5** shows two rules for the goal hold_distance. Their conditions will trigger a rule that perceives current_distance. The new value may trigger rule 1 or 2. In that case an event for the model has occurred, because the model has to react on outside information. The time of occurrence of this event will be stored together with the goal. It is then used to influence the goal selection process in the cognitive cycle. Tasks with higher event bandwidth will be triggered more often. As a result of the simulation the model will adapt its scan rate to the event bandwidth of the information source.

```
Rule 1:
Goal (hold_distance)
Cond(current_distance < lower_threshold)
=>
Motor(accelerator, reduce)
```

```
Rule 2:
Goal (hold_distance)
Cond(current_distance > upper_threshold)
=>
Motor(accelerator, intensify)
```

Fig. 5. Rules for keeping safe distance to front car

Validation results. Like in the preceding section validation studies focusing on gaze behaviour will be done this year.

Transferability. The described phenomenon is not only applicable in the driving domain. In fact the SEEV trade-off model is used in general for the design and analysis of human machine interfaces. As has already been shown by Wickens [10], pilots scan control instruments with a high event bandwidth more often. In that approach the bandwidth is derived as a constant value from the features of the instruments. In our approach we derive the bandwidth from the dynamics of the environment and consequently the bandwidth can change dynamically.

5 Summary and Next Steps

In this text we presented an approach to support the design of safety critical assistance systems in aircraft and cars. This approach is based on a cognitive core architecture which is used in both domains. We described four extensions of the core architecture.

Our future work will concentrate on a detailed validation and improvements of the four extensions which includes a validation of the transferability of the cognitive mechanisms. The validation requires a complex design of experiments in which our models as well as real pilots/ drivers perform the same scenarios. This will allow a comparison between the model and human behavior along parameters like error rate, eye-movements, action sequences or timing.

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