Modeling the Human Operator's Cognitive Process to Enable Assistant System Decisions

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Abstract

Human operators in human-machine systems can be supported by assistant systems in order to avoid and resolve critical workload peaks. The decisions of such an assistant system should at best be based on the current and anticipated situation (e.g. mission progress) as well as on the current and anticipated cognitive state of the operator, which includes his/her beliefs, goals, plan, intended action, interaction with the environment, and subjective workload. The more of this can be assessed, the easier and the earlier human errors can be recognized and corrected by assistant system initiative. Multiple approaches to enable an assistant system to correctly decide whether, when, and in which way to take initiative are currently under research at the Universität der Bundeswehr München, e.g. mixed-initiative mission planning, which includes assuming the human operator's plan and estimation of operator workload by means of human operator behavior models. We here give an overview of these approaches and present our position in favor of an overarching framework for modeling a human operator, which is based on our Cognitive Process model.

Introduction

The Universität der Bundeswehr München (UBM) is conducting research in the field of aeronautical human-machine systems. During the development of complex human-machine systems (such as an aircraft), often models of human operators are used in order to optimize system behavior. In contrast to this it is not common in such systems that the machine reasons upon the human's cognitive state during runtime.

In our current main application we regard a helicopter cockpit crew consisting of two persons (cf. figure 1). One of them is the helicopter commander, who is at the same time the operator of a smaller number of Uninhabited Aerial Vehicles (UAVs). The other person is the helicopter pilot. In this context the UBM is developing prototypes of artificial cognitive systems that aid the cockpit crew in coping with high work demands caused by multi-vehicle guidance and mission management (Strenzke et al. 2011). To be more precise, both crew members shall be supported by an assistant system for each workstation. In future, the decisions of such an assistant system shall be based on the current and anticipated situation (e.g. mission progress) as well as on the current and anticipated cognitive state of the operator, which includes his/her beliefs, goals, plan, intended action, interaction with the environment, and subjective workload. The more of this can be assessed, the easier and the earlier human errors can be detected and corrected by assistant system initiative. Multiple approaches to enable an assistant systems to correctly decide about taking initiative (whether, when, and in which way) are currently under research at the UBM.

In this article, we first present our Cooperative Automation paradigm for assistant systems and then give an overview of our research work. Finally, an overarching framework for modeling a human operator is proposed, which is based our Cognitive Process model.

Figure 1: Helicopter Crew in Manned-Unmanned Teaming

Cooperative Automation Approach

The Cooperative Automation approach (Onken and Schulte 2010) is an answer to the vicious circle of automation engineering, which is observable in the evolutionary development of supervisory control systems (Sheridan 1992). In brief, this vicious circle describes the increase of automation to counteract human errors, which thereby in turn provokes human error through automation complexity and opacity. The Cooperative Automation approach is intended to build automation functions that do not accept orders from the human operator in a supervisory control fashion. Instead these functions work upon the same objectives as the human does in a human-machine-team relationship.

According to (Onken and Schulte 2010) a cognitive assistant system shall be designed as such a cooperatively functioning automation. It is furthermore defined by the following basic requirements. The assistant system shall guide the attention of the human operator to the most urgent task. In case the human operator cannot accomplish or should not work upon this task (due to overtaxing, risk or cost), the assistant system shall take initiative to transfer the situation into one which can be handled by the operator (by generating proposals or executing actions on own initiative). Thereby, an assistant system shall provide improvement of the operator's situation awareness, reduction of subjective workload, as well as error avoidance and correction.

Current Assistant System Research

This chapter describes several research aspects concerning the mentioned two helicopter crew assistant systems.

Knowledge-Based Assistant System

The UAV operator assistant system is realized as a knowledge-based system that supports the UAV operator upon detection or anticipation of suboptimal behavior. It mainly holds knowledge about the modes of interaction with the human operator. See figure 2 and (Donath, Rauschert and Schulte 2010) for further information.

In assistance cases, the system has three options to aid the operator. It can provide a warning, suggest an action proposal, or initiate an action (e.g. reconfiguration of some system). To communicate with the operator, the assistant system instantiates a dialog or makes an announcement via speech synthesis and the displaying of a message box in the task-based UAV guidance GUI. Whenever appropriate, this message box includes a few buttons that allow the operator to invoke further aid by the assistance system or to either accept or reject its proposals. See (Strenzke and Schulte 2011) for more detail.

To decide whether, when, and in which way assistance should be provided to the UAV operator

- the assistant system has to be able to anticipate, which tasks the operator has to execute and when he/she is supposed to do this (i.e. plan is incomplete and has to be evolved soon due to time constraints), and
- the assistant system has to be able to notice insufficient quality in the past planning process of the operator (i.e. his/her plan is of too low quality).

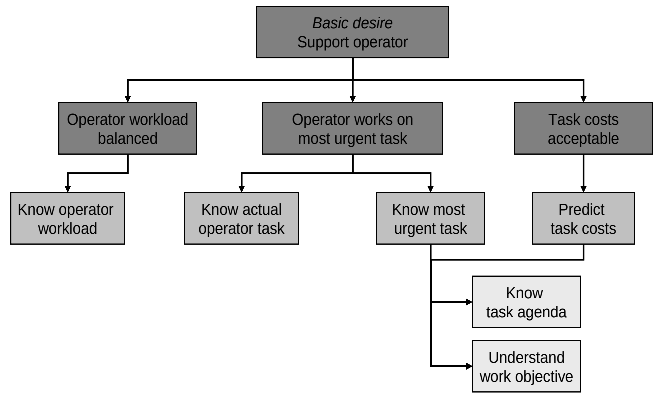

Figure 2: Goal structure of a cognitive assistant system

In principle, the assistant system needs to solve the following questions through target-performance comparison:

- What is the operator planning?
- Is his/her plan good enough?
- Does he/she pursue the plan or make errors?
- Is he/she overtaxed w.r.t. to mental resources?
- What is he/she currently doing?

Clearly, these questions are difficult to answer by a technical system. In the following sections we present our research approaches to these problems.

Mixed-Initiative Mission Planning

The UAV operator generates and modifies the multi-UAV mission plans incrementally. The above-mentioned assistant system is able to evaluate, complete, and generate such mission plans with the aid of the Mixed-initiative Mission Planner (MMP). As shown in figure 3, the MMP generates two types of plans: *Reference plans* and *assumed human plans*.

The assumed human plan can be regarded as the assistant system's assumption about the best possible plan the human has in mind after he/she revealed a partial plan[1] by entering UAV tasks into the UAV guidance system (*system plan*, cf. figure 3). The assumed human plan is generated by completing this partial plan through adding the tasks the machine supposed that the human should add to the system

[1] The human can either be aware of the plan being incomplete or he/she is not, but the machine concludes that the plan is only partial due to missing mission-relevant tasks.

plan (at some later point in time). In this process it takes into account constraints concerning human goals (which are known by the machine because they are shared in the Cooperative Automation approach), fragments of the human plan, and the current actions of the UAVs. This approach can be seen as plan recognition by planning. The assumed human plan can be used by the assistant system as a list of tasks to be worked upon by the UAV operator at (or before) the specific times that have been scheduled by the MMP. These operator tasks can be either the execution of an already planned UAV task (already included in the system plan) or the planning of a UAV task that is missing in the system plan.

The reference plan is generated by the MMP without regarding any human input, simply by solving the UAV mission problem through automated planning. The assumed human plan can be evaluated by comparing its costs to those of the reference plan. In addition to that, the reference plan can be offered by the assistant system to the human in case there is the need of complete mission replanning. I.e. if there is a difference between the reference and the assumed human plan, the reference plan stands for what the machine supposes the human should do instead of what he/she has planned.

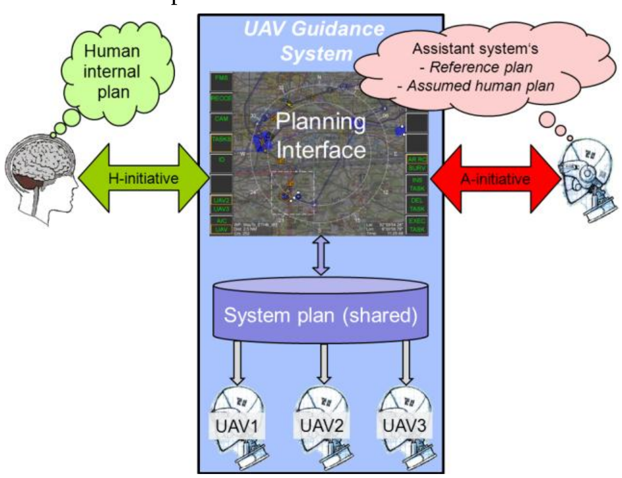

Figure 3: Mixed-initiative planning concept for the MMP

The assistant system has the choice to urge the human operator to make the system plan converge to either the assumed human plan or to the reference plan. The decision of the assistant system can be based either on certain use cases (e.g. major change in the tactical situation or reception of follow-up mission order) or on a cost comparison (target-performance comparison) between the reference and the assumed human plan. Further information about this and the MMP in general can be found in (Strenzke and Schulte 2011).

The current implementation of the MMP is based on PDDL 2.2 (Edelkamp and Hoffmann 2004) world modeling. We intend to improve the MMP by taking advantage of the expressiveness of PDDL 3.0 (Gerevini and Long 2006) and by plan validation / plan repair with VAL (Howey, Long, and Fox 2004).

Operator Workload Estimation

In a similar application context we experimentally analyzed the correlation between the subjective workload and the behavior of a UAV operator guiding multiple UAVs from a helicopter cockpit, i.e. using them as remote sensor platforms for the reconnaissance of the helicopter route. Especially the changes of his/her behavior can be used as an indicator for high workload situations due to the application of so called self-adaptive strategies (SAS). A human operator will apply suchlike strategies in order to keep the subjective workload within bearable limits and to retard possible performance decrements (Canham 2001; Schulte and Donath 2011). Since such a change in human behavior occurs prior to grave performance decrements, recognizable changes in human operator behavior can be used as trigger for assisting functions. Therefore, for each operator task an assistant system needs different human behavior models, representing behavior within normal workload situations and modified behavior as a consequence of SAS (cf. figure 4). By the use of such models an assistant system can be enabled to anticipate workload-induced human error and take initiative prior to the occurrence of the error.

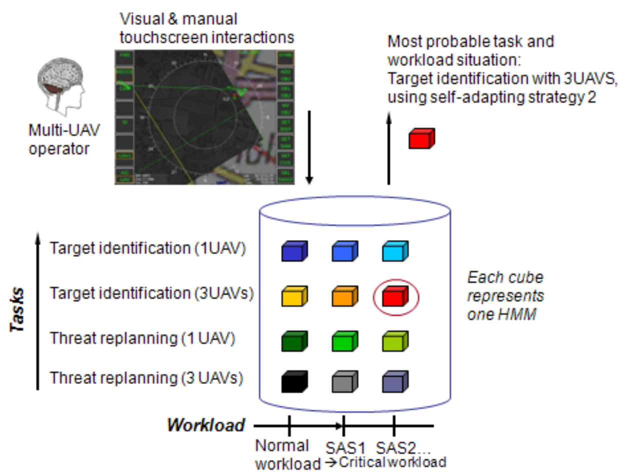

Figure 4: Subjective workload recognition by behavior models

In the experiment, human operator behavior was captured during a certain, recurring task situation. The operator had to identify objects (ground vehicles) along the route observed by the reconnaissance UAVs. The object identification task consists of essentially three subtasks, the *recognition and marking of a hotspot* in the photos made by the UAVs, the *object classification process* via the video stream generated by the UAVs, and the *entering the classification result* into the mission management system. We analyzed gaze tracking and manual interaction (touchscreen button pressing) data to decide if the behavior corresponds with a normal workload situation or a high workload situation respectively. The following SAS were observed (Schulte and Donath 2011):

- Proactive task reduction (e.g. using fewer UAVs for task accomplishment than available)
- Less exect task performance (e.g. watching video stream from a suboptimal UAV/camera position in relation to the object to be identified)
- Omission of subtasks (e.g. classifying the object without entering the result into the system thereafter)
- Total neglect of the object identification tasks within a complete mission phase
- Purposeful delay of task accomplishment (i.e. interruption / task switching and then continuing)

Each of the mentioned SAS indicates excessive workload and can therefore be used to enable an assistant system to decide to take initiative and offer assistance.

Our approach is to use Hidden Markov Models representing person-specific, task-specific human operator behavior within normal workload conditions in the first step. In future, further HMMs will be added to represent human operator behavior within high workload situations, i.e. the change of operator behavior caused by the use of SAS (cf. figure 4). See (Donath, Rauschert, and Schulte 2010) for further details. So far, the analysis process is only done offline. Hence, our assistant systems are currently not able to invoke functions based on workload estimation by behavior recognition.

Optimization of Information Channel Selection

In the cockpit setup described above, the pilot flying needs to take over additional responsibilities and tasks from the helicopter commander in order to enable the latter to accomplish the UAV guidance task. Therefore, the pilot flying is also in need of an assistant system, which aids him/her in navigation, aircraft system configuration, and timeliness in the mission plan. This assistant system has to decide whether, when, and through which information channel to inform the pilot about his/her most urgent task and anticipated or detected errors.

As stated before, there is no online workload estimation by behavior patterns in place. Therefore, (Maiwald and Schulte 2011) take the approach to predict the workload on the basis of task models for different task situations and current mental resource demands. By means of a resource model the assistant system is enabled to predict the operator's workload for a certain task situation (see figure 6). Cases of an impending overtaxing can thereby be identified beforehand and prevented by resource-oriented planning of the machine-initiated interactions. E.g. if the pilot is currently performing a radio transmission his audio processing resources are occupied and therefore the assistant system's information should be passed on via a message display. But in this case for example, the assistant system also needs to check if the pilot is currently watching the designated display. In addition to that, it would be useful to check if the pilot has noticed or read the corresponding message.

Improving Gaze Tracking Data by Task Context

For the above-mentioned reasons our assistant systems need access to gaze tracking data. In a realistic aircraft cockpit (cf. figure 1) it is very difficult to achieve gaze data quality that is accurate enough to determine in which period of time which object was looked at. This is especially true in the case of online data processing, which is needed for assistant system decision-making. Therefore, the data quality has to be enhanced by feedback loops as shown in the lower part of figure 5. Its upper part is dedicated to pilot task detection by gaze tracking, which includes the recognition of fixations out of the eye movement data as well as the mapping of fixations to objects in the simulator cockpit (e.g. an aircraft symbol in the moving map display). This data can also be used to make assumptions about the pilot's current situation awareness (e.g. he/she has read a certain message or not) (Maiwald, Benzler, and Schulte 2010).

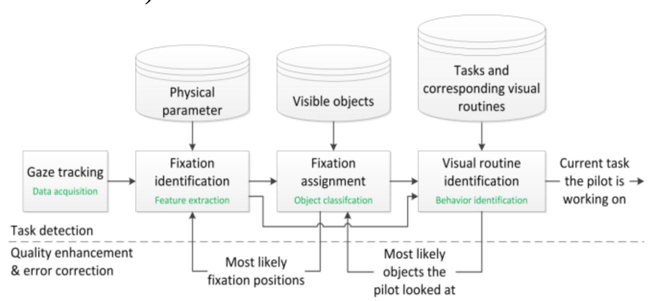

Figure 5: Using and enhancing gaze data by task context

The data quality improvement and error correction shall be accomplished by applying strategies known from human visual perception, which are the stimulus-based *bottom-up strategy* (Yantis and Jonides 1984) and the knowledge-based *top-down strategy* (Land and Lee 1994).

We intend to use Kalman Filtering for fixation correction towards areas in the display that hold relevant information for the pilot. The detection of the currently processed task by recognizing gaze routines is a candidate for Hidden Markov Modeling. More details about this can be found in (Strenzke et al. 2011).

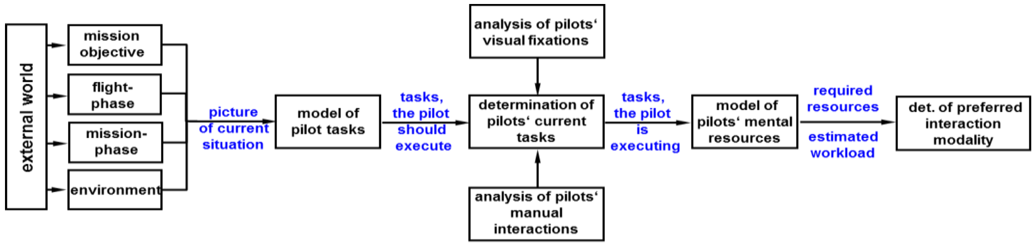

Figure 6: Mental resource-oriented information channel selection for assistant system initiative (Maiwald and Schulte 2011)

A More Complete Human Operator Model

When modeling the behavior of a rational agent, a world model has to be built. An assistant system is such a rational agent, but it has the specialty that it also needs a model of the human operator to be assisted. He/she can be seen as a rational agent as well, because we need the model rather to generate reference behavior (to which the actual measured behavior can be compared), than to predict the actual human behavior. The reason for this is that an assistant system has its focus on recognizing erroneous and suboptimal behavior as well as high workload situations. Therefore it needs to generate a reference behavior dynamically for current situation, to which the actual behavior can then be compared. In contrast to this, the prediction of actual human operator behavior (e.g. human has high workload, will make certain error in near future) is not so important and also much more difficult to cover with a human operator model.

In the previous section it has been shown that there are numerous interdependencies between the operator's goals, plans, actions, behavior, errors and workload. But the current approaches to assess these constructs rely only on simple operator models, which focus only on a specific part of his/her cognitive state and process. A more complete human operator model would allow more thorough reasoning upon the human's cognitive state and cognitive process. E.g. if there are assumptions about his/her goal(s), it is of course easier to assume what he/he is planning. Also, in case there are assumptions about his/her plan, the recognition of the current action is facilitated.

In the following we depict our model of the Cognitive Process (Onken and Schulte 2010) and then add relevant psychological constructs to it in order to enable more sophisticated assistant system decisions upon a model of the human operator's cognitive process.

The Cognitive Process

Figure 7 shows the Cognitive Process that is already used by the UBM to build knowledge-based assistant system behavior as well as cognitive agents (Artificial Cognitive Units, ACUs) for Uninhabited Aerial Vehicle guidance. It has not been used to model the cognitive process of a human operator so far. Due to its dedication to beliefs, goals, plans, and actions (instructions), the Cognitive Process model seems well-suited to unite the above-mentioned approaches to operator modeling and incorporate their interdependencies. A detailed description of the Cognitive Process can be found in (Onken and Schulte 2010).

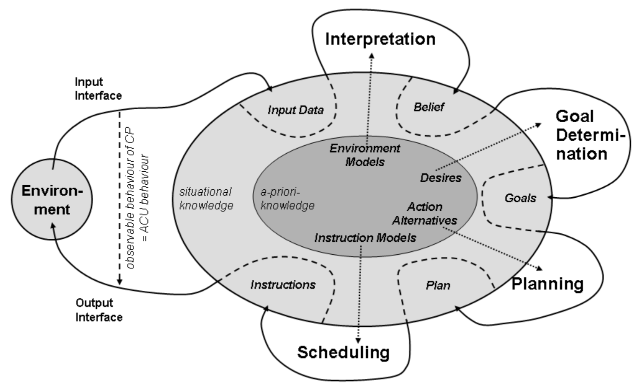

Figure 7: The Cognitive Process (Onken and Schulte 2010)

Adding Behavior, Workload, and Error

As we have shown in the overview of our current research topics, a model of a human operator needs to include constructs of *behavior* (which includes more than the intended action, e.g. sweating), mental *workload*, as well as *errors*. Figure 8 shows the enhanced model differentiated by the human operator's conscious internal world and the external world, in which his actual behavior (e.g. eye movement, manual interactions) occurs and can be measured. Workload may induce errors (deviations) in the different steps of the cognitive process. Of course, workload is not the only source of human error, but for a start we focus on it in this application-driven model.

The error taxonomy of (Reason 1990) allows the attribution of error origin and temporality. *Mistakes* are made during planning phase, *lapses* are missed actions (e.g. memory problems), and *slips* refer to errors in the task execution. The mentioned three error types are mapped to the steps in the Cognitive Process as follows. Mistakes happen during planning (e_p), lapses during action selection (e_a), and slips during action execution, i.e. behavior (e_b). Furthermore, errors can take place during information processing (e_i) and goal inference (e_g).

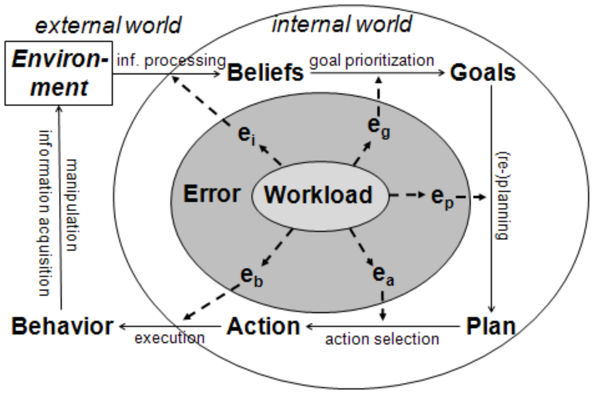

Figure 8: A more complete model of the human operator

Future Work

In future research we will explore implementation approaches for the human operator model presented here. Our novel cognitive system architecture (Cognitive System Architecture with a Central Ontology and Specific Algorithms, COSA²) is based on the Cognitive Process (see figure 7) and able of deliberative planning (Brüggenwirth, Pecher, and Schulte 2011). Integrating a model of the human operator into COSA² could either be achieved by updating the system's beliefs about the cognitive state of the human operator or by adversarial or cooperative planning. The latter means that the machine and the human player have the proposition to solve a problem fully cooperatively and are also able to anticipate each other's behavior. In this case the actions of the human and of the machine can be calculated by means of a uniform planning process. Planning can be seen as top-down determination of plans out of beliefs and goals. The current task or action can be recognized by probabilistic methods as mentioned above (facilitated by assumptions about the human's plan) and then be induced as a constraint into the planning problem. The exploitation of feedback loops as in the mentioned example remains future research work as well.

Acknowledgments

The authors acknowledge the scientific contributions of Diana Donath (UBM), Andreas Benzler and Felix Maiwald ("Military Rotorcraft Associate – Teaming" UBM project staff), as well as Andreas Rauschert ("Manned-Unmanned Teaming" UBM project staff).

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